Unravelling the causal associations and path dependencies between Foreign Direct Investment and social development: the case of Panama

UNRAVELLING THE CAUSAL ASSOCIATIONS AND PATH DEPENDENCIES BETWEEN FOREIGN DIRECT INVESTMENT AND SOCIAL DEVELOPMENT: THE CASE OF PANAMA

R. MURILLO HERRERA

DBA

2023

Unravelling the causal associations and path dependencies between Foreign Direct Investment and social development: the case of Panama

Rodrigo MURILLO HERRERA

Submitted for the degree of
Doctor of Business Administration (DBA)

Faculty of Management, Law and Social Sciences
University of Bradford
2023

ABSTRACT

Rodrigo MURILLO HERRERA

Unravelling the causal associations and path dependencies between Foreign Direct Investment and social development: the case of Panama

Keywords: Foreign direct investment, social development, social progress, social performance, social spillovers, public social policy, developing nations

Academics have majorly explored the positive and negative economic spillover and linkages effects of FDI on economic growth, local wages, productivity and technological knowledge. Nonetheless, alternative benefits induced by FDI on social development have been neglected to be explored in-depth, constraining scholarly contributions to welfare economics. Although preceding works have studied social development factors, they traditionally have been addressed as either positive, negative or neutral in different pockets of academic literature. Moreover, none of them offers a robust empirical/structural framework linking FDI and social development. Panel data figures of MNEs classified as FDI recipients in the Republic of Panama are employed in proposing an empirical/structural framework explanatory of the bidirectional association and causal mechanisms between FDI and social development, using the Social Progress Index as a proxy, moderated by proxy variables of productive linkages and household income. A lop-sided circle, negatively inclined on the association flowing from social development to FDI, is suggested to exist. A 'weak' positive effect of FDI on social development is found, supported by a locked-in stable loop of FDI yearly feeding on MNEs profit's reinvestments. Social development is also found to be in a locked-in stable loop, directly exerting a 'strongly negative' impact on FDI, which suggests being a constraining determinant for the country to attract 'green field' FDI. The empirical/structural framework herein proposed aims to guide future academic research in welfare economics and also serve policymakers in Panama for understanding and structuring national policies to unlock the self-reinforcing path dependency mechanisms preventing social development potential from being unleashed.

ACKNOWLEDGEMENTS / DEDICATIONS

To Gaby -my beloved wife- who was aware of my doctoral plans since the time we were dating and who has been my support ever since, sharing with me all the sacrifices that this personal project has implied.

To Hector, my classmate and partner in this long journey since we started our MBA, for continuously encouraging me to align plans despite the drawbacks encountered.

To my parents and my mother-in-law (R.I.P) for supporting me both directly and indirectly in reaching this professional goal.

TABLE OF CONTENTS

LIST OF CHARTS

LIST OF TABLES

1 CHAPTER ONE: INTRODUCTION

Although from a worldwide perspective, Foreign Direct Investment (FDI henceforth) inward stock has shown a feeble 1% CAGR (Compound Average Growth Rate) between 2008 and 2019 (years 2020 and 2021 are ignored due to the atypical figures as per the effects of the COVID-19 pandemic), the fact is that FDI globally increased by an 8% CAGR between 2000 and 2007, in addition to its 20% growth figure before 2000 (UNCTAD, 2019). Furthermore, particularly regarding emerging/transitional economies which have exhibited rapid population growths since 1950 (James *et al.* 2012), FDI inflows increased by 2% in 2018, accounting for 54%[1] of the total FDI worldwide and was suggested to maintain a rising trend in the forthcoming years (UNCTAD, 2019). As per the latter figures, FDI has been contended by Sharma & Gani (2004) when quoting Raghavan (1996), Mallampally & Sauvant (1999) having "*superseded trade as the most important mechanism for international economic integration*" enhanced by its characteristic of openness to a global economy (Kolstad & Tøndel, 2002; Asiedu, 2002). In passing, under Kolstad & Villanger (2008), the tertiary industries have been the most positively impacted ones. Hence, FDI constitutes a present business/trade/social science phenomenon of significant importance (UNCTAD, 2019) worth researching, particularly for emerging/transition economies. As Suliman & Elian (2014) reported, empirical research associating FDI and several other factors, particularly economically inclined ones, has majorly focused on developed nations, suggesting these phenomena have been explored to a lesser extent for emerging/transition host economies.

From the 1960s on, a plethora of diverse theoretical and empirical research works could be found in the literature concerning the FDI topic. It is worth noting, however, that one common characteristic of all available empirical studies is their lack of consensus regarding causal associations (Lim, 2001) since positive, negative[2] and even neutral effects of FDI on host countries (Blomström

---

[1] In passing, for the first time in history developed nations were surpassed in total figures by transitional/emerging economies since 2012 (Deloitte, 2014).

[2] MNE may introduce market distortion in host countries (Sharma & Gani, 2004, pp2-4), as for instance: 1) Location preference favors of urban areas leading to interregional disparities in incomes and opportunities in the host country, 2) Employment results have been less than

& Kokko, 1997; Faeth, 2009 and Tocar, 2018) are reported depending on the type of researched factors. However, as contended by Perri & Peruffo (2016), empirical research studies have majorly concentrated on economic-based factors as valid and reliable predictors of FDI, which coincides with the quote of Tocar (2018, pp166-167): "*the analysis of specialised literature demonstrates that the group of economic factors is the most frequently studied, which was expected due to economic nature of the concept of Foreign Direct Investment*". Hence, literature generally suggests that economic growth is positively stimulated and enhanced by the spillovers[3] triggered by FDI (Yi *et al.*, 2015; Suliman & Elian, 2014, Gökmenoğlu *et al.*, 2018 when citing Amighini & Sanfilippo, 2014 and Lall & Narula, 2004 pp34). In this sense, FDI has traditionally been considered to improve macroeconomic outcomes in host nations by lifting populations out of poverty, leveraged by employment creation, increases in associated wages, and rising internal expenditure per capita, simply mentioning a few economic-based indicators classicly considered proxies for social development. Interestingly, various non-economic-related factors may also offer significant statistical power in explaining FDI inflows (and their potential effects). According to Spark *et al.* (2014), economic-based factors are suggested from the explanatory power percentual perspective to contribute only around 22,5 % of the variation of FDI inflows in host countries. Complementary, the remaining 77,5% explanatory variation may be statistically due to an array of other factors, which are simply non-economic in nature, suggested being frequently ignored or reduced merely

optimal as in cases of capital-intensive technology FDI what is sought are incentives in taxes and subsidized/forgivable loans. Moreover, paying higher wages may foster a job-hopping environment amongst local workers, 3) Influencing government decisions -at the macro-policy level- by means of threat of reducing investments and/or asking home government to pressure the host government. Furthermore, in some cases economic power has been used to manipulate trade unions in host countries.

[3] Impact that phenomena, events, or policies of a sector have on other groups that were not those that participated or to which a given event was directed to. One of the most common cases is the dissemination of knowledge. Once you have invested in the human capital (human stock) on some individuals, a spillover (positive in this case) is likely to occur on the productivity of production factors in other sectors. Spillovers are generally studied when implementing productive development policy programs as measures encouraging innovation, technological adoption, entrepreneurship, export promotion, among others. When considering the investment in a sector, agents incorporate the spillover effect on their decision and so may have incentives to invest less amount that maximizes their benefits. However, the total benefit will be perceived by multiple sectors (not only the one in which the initial investment occurred) and, therefore, the private return on investment is usually less than the social one. This difference between returns, is in passing the incentive that should be given by the government to reach an optimal level of investment socially speaking.

to be mentioned without also exploring their statistical explanatory predictive power. Such an array of factors includes social development-related ones.

The social development dimension, as deeply explained in subsection 2.1, is conceptualised under the *capabilities approach,* which in general terms, enhances the opportunities of individuals to achieve their highest potential as human beings, thus distantly differing from this classic *utilitarian approach* which majorly focuses on the economic-related dimension, which suggests social advancement does not exclusively stem from the mere access to consumable goods and services as reported in the literature (Rojas, 2011; Gökmenoğlu *et al.*, 2018). Under this lens, Gross Domestic Product per capita purchasing power parity (GDP PPP henceforth) and other economic measures -classically assumed to gauge social development properly- may be questionable as they only inform about a limited side of the story. Thereby, -regardless of its economic achievements- one may debate considering a society successful if it fails to: 1) meet the basic needs of its members, 2) generate conditions to improve the quality of life of its citizens, 3) protect the environment and 4) offer opportunities for the majority. Consequently, due to its 'economic-based nature', FDI can neither be argued to contribute to societal development if it cannot induce a positive, inclusive and sustainable impact on the general wellbeing of host countries' populations. Furthermore, FDI and economic growth effects alone - although they may, for instance, benefit all societal strata from a disposable household income perspective in a particular host country- may also lead to social exclusion and unrest (Grömling & Klös, 2019; Ravallion, 2012; Gohou & Soumaré, 2012), as the expected income inequality reductions' effects are not created automatically (Bruno *et al.*, 1996; Orbes *et al.*, 2019) so that requiring of governmental social policy intervention.

Given the latter argumentations, assessment and benchmarking of societal success may directly imply gauging social development via applying systematic measurements to its multiple dimensions and constituent factors, seeking to fully understand the causes, drivers, and catalysers of social advancement. Barrington-Leigh & Escande's (2018) work reports 82 social development measurements created since the 1980s. However, as exhaustively explained in the literature review chapter, Greve (2017) informs that only 12 out of those 82 measurements have been often researched during the past two decades[4], notably the Human Development Index (HDI henceforth). The Social Progress Index[5] (SPI henceforth) is another of those 12 currently researched indicators. Launched in 2013 on its worldwide beta version- is, according to its developers (Porter *et al.*, 2013; Porter *et al.*, 2017; Fehder, 2018 and Porter *et al.*, 2018), an actionable, solid and holistic instrument targeting to fill the void for a social and environmental performance measure in complete alignment with a 'fresh social indicators' movement', considered having been 'reborn' in the last decade with the seminal work of Fleurbaey (2009). Within this range of up-to-date measures available, SPI comprises the most (54 in total) diverse constituent factors[6], focused on gauging outputs (e.g. years in school) rather than inputs (e.g. % of GDP spent in education). This 'outcome-focused' perspective is foundational in considering SPI to provide a robust framework to gauge social development properly.

From an empirical and theoretical standpoint, as profoundly explained in the Literature Review section, the generally assumed causal direction, as buttressed by common wisdom, is that FDI positively affects the host country's economic growth, which in turn causes improvements in social development. This last association between economic growth and social performance is further reported to be bidirectional (Omar, 2020) to the extent of exhibiting *vicious, virtuous, lop-sided* circle patterns as contended in the research works of Ramirez *et al.* (1998), Ranis *et al.* (2000), Ranis & Steward (2001), Ranis (2004), Ghosh (2006) and Joshi (2007).

Under this perspective, if the *vicious* circle potential effects are considered, one alternative causal path may also be FDI inducing positive economic growth effects in the host country, although negatively impacting social development by

[4] 1) Social Progress Index 2) Global Age Watch 3) World Happiness Report Index 4) Gallup-Global Well-being 5) OECD´s How is Life: Satisfaction 6) Overall Life Satisfaction Index 7) Human Development Index 8) Gender Equality Index -Rank- 9) Eurofound Quality of Life 10) EUL (3 Indicators) 11) Legatum Prosperity Index 12) Happy Planet Index

[5] As later explained, although the SPI was formally launched in 2014, the Social Progress Imperative, which is the NGO in charged of keeping track of the index around the world, constructed the time series for the missing years 2011, 2012 and 2013 in some cases (50 countries were part of the beta test the index in 2013).

[6] Ranging from shelter to healthcare, electricity availability to environmental sustainability and access to basic education to personal/political rights.

not generating improvements in the quality of living of their citizens. Under CEPAL(2020), Hausmann *et al.* (2017), Fernandez (2021) and Garcimartin (2021), the Republic of Panama in Central America (See Appendix 1 for an overview of the Republic of Panama) is one nation that has been contemporaneously contended to exhibit such a contradictory robust increase in FDI attraction and economic growth but a deficient social development pattern. Table 1 depicts up-to-date figures for GDP PPP, FDI PPP and Social Progress Index (used as a proxy for social development) for Panama and for comparative purposes of the Republic of Costa Rica, which is Panama's neighbouring country and the most comparable nation within the Central American region due to its economic, social, institutional, and democratic features. The same figures for the remaining 4 countries that comprise Central America are also shown in Table 1, where it is quite noticeable that Panama and Costa Rica outperform each of those countries (World Bank, 2020; Social Progress Imperatives, 2020; CEPAL, 2020).

Table 1. Comparison of GDP PPP, FDI PPP and Social Progress Index for the 6 Central American countries for 2020.

Country	GPD PPP (Current International $)	FDI PPP (Current International $)	Social Progress Index (SPI)
Panama	**$32,761.0 (1st)**	**$2889.8 (1st)**	**76.55 (5th)**
Costa Rica	**$21,792.4**	**$853.6**	**83.01 (2nd)**
El Salvador	$9,139.7	$236.6	67.25
Guatemala	$8,995.5	$136.5	61.67
Honduras	$5,965.4	$227.0	62.42
Nicaragua	$5,631.2	$224.6	64.02

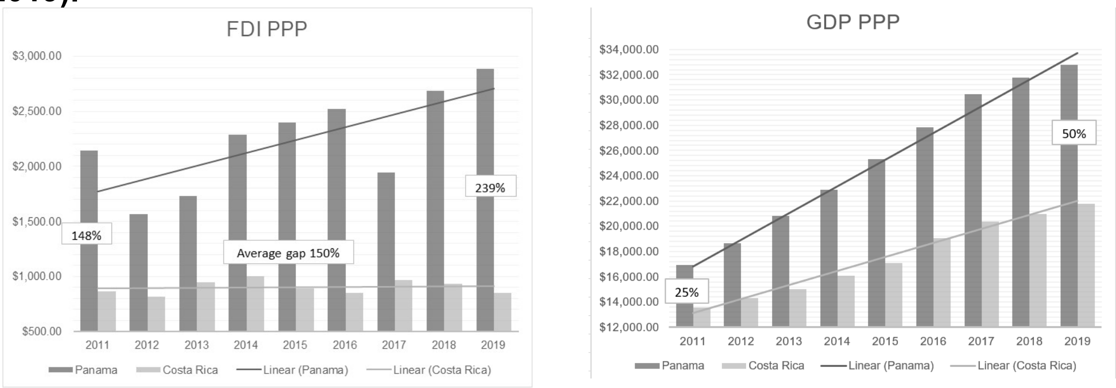
Source: World Bank (2020); Social Progress Imperative (2020) and CEPAL (2020)

Note 1: In parenthesis, the ranking position within the Latin American countries.
Note 2: Figures related to 2020 refer to 2019, as data are generally published with a 1-year lag. It is important to mention that figures for 2021 (which will be published until 2022) and 2020 (published in 2021) were not included since, as per COVID-19 disruptions, both years are not considered typical for comparison purposes.

Under CEPAL (2020), Panama has been the only Latin American nation continuously growing in FDI magnitudes for the past 10 years, ranking 1st concerning FDI PPP figures (current international $) while also becoming 5th in Latin America and 1st in Central America as regards to FDI attraction in absolute values. As majorly informed by the theoretical and empirical literature, FDI is suggested to have positively impacted economic growth as the nation also ranks 1st regarding GDP PPP in Latin America (World Bank, 2020). Nevertheless, despite exhibiting such high indicators of economic prosperity, Panama is suggested to have lately lagged in social development achievements, ranking 5th in Latin America regarding the Social Progress Index. In this context, ranking 1st in FDI PPP, which is suggested to have induced the positive effect for the nation to rank 1st in GDP PPP terms also, but not encompassing social development as per its 5th rank when employing the SPI as a proxy, is an unfortunate evolution pattern for the Panamanian society, appearing to comply with the *vicious* circle characteristics reported in the works of Ramirez *et al.* (1998), Ranis *et al.* (2000), Ranis & Steward (2001), Ranis (2004), Ghosh (2006) and Joshi (2007). Contrarily, even when respectively showing up-to-date FDI PPP and GDP PPP figures lower by 240% (CEPAL, 2020) and 50% (World Bank, 2020) in comparison to Panama, the Republic of Costa Rica ranks 2nd in Latin America in terms of social development when also using the SPI as a proxy. As follows, this comparative analysis is longitudinally extended to previous years.

As per Chart 1, differences between Panama and Costa Rica have been drastically broadening when FDI PPP figures are employed since the average percentage gap between Panama and Costa Rica is 150%, increasing from a 148% figure in 2011 to 239% in 2019. From a classic economic standpoint, one may assume that the average Panamanian citizen would obtain more economic benefits from FDI inflows than the average inhabitant of Costa Rica. Furthermore, as additionally depicted in Chart 1, the percentage gap in GDP PPP has also been broadening between Panama and Costa Rica in the past decade. The gap has increased from Panama exhibiting a GDP PPP figure 25% higher than Costa Rica's in 2011 to reaching a 50% figure in 2019. Under the assumption that FDI PPP induces a positive effect on GDP PPP, one may also assume that each Panamanian citizen has increased their wealth following a growth rate pattern that surpasses the wealth of the average citizen in Costa Rica.

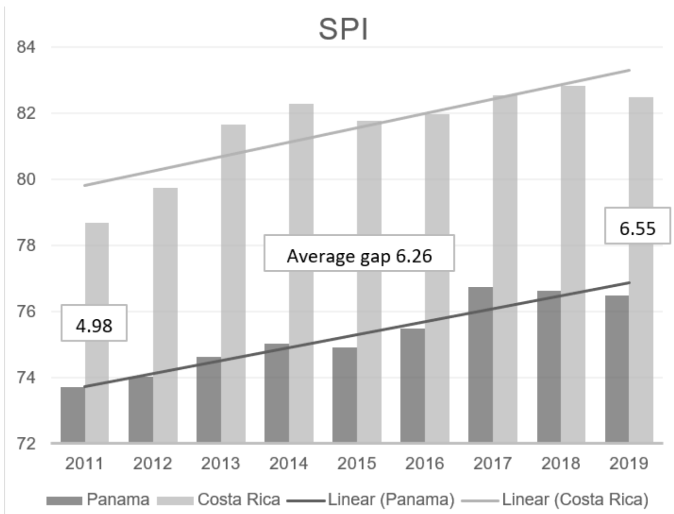
Chart 1. GDP PPP / FDI PPP figures for Panama and Costa Rica (2011 to 2019).



Source: The author based on data from World Bank (2020)

Nevertheless, and in contrast to Panama, Costa Rica ranks second in Latin America as abovementioned (just behind Chile) and 6.55 points above Panama (ranked 5th) when employing the SPI as a social development proxy (Social Progress Imperative, 2020). As shown in Chart 2, one may notice that Costa Rica has surpassed Panama in the past decade by 6.26 average gap points in what pertains to SPI, even though Costa Rica's GDP PPP and FDI PPP figures have been dramatically lower than Panama's. Moreover, the growth effect -in smaller magnitude, however- appears to be shown by Costa Rica instead of Panama.

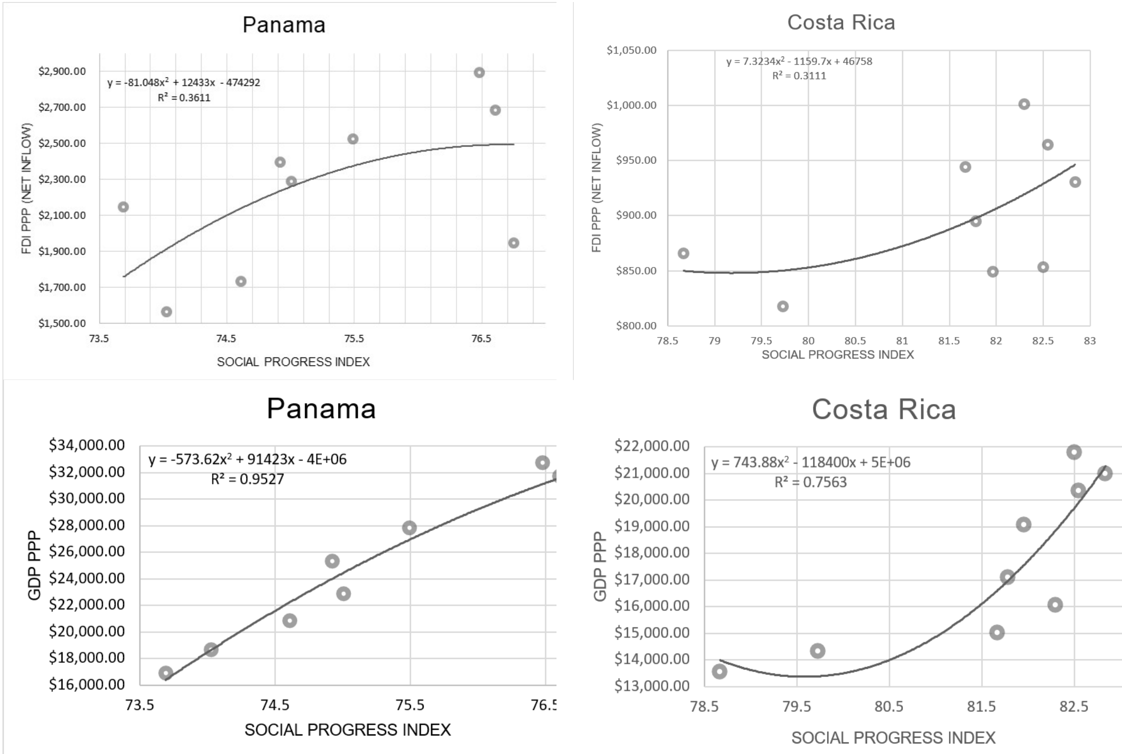
Chart 2. SPI figures for Panama and Costa Rica (2011 to 2019).



Source: The author based on data from Social Progress Imperative (2020)

The latter time series figures for FDI PPP, GDP PPP and SPI and related growth rates suggest that a country like Panama, even when aggregately possesses the capabilities to create wealth, lacks capabilities to appropriately transform this economic prosperity into social advancement for its population. If FDI PPP vs SPI and GPD PPP vs SPI are plotted for Panama and Costa Rica (between 2011 to 2019), as depicted in Chart 3, two different association patterns between economic advancement and social development are suggested to emerge.

Chart 3. Comparison of SPI vs GDP PPP graph patterns between Panama and Costa Rica from 2011 to 2020.



Source: The author based on data obtained from World Bank (2020) and Social Progress Imperative (2020)
Note 1: Quadratic best-fit trendlines were employed for both graphs.

Panama's graphs show a declining association trend, under which economic growth creation measured via GDP PPP in association with SPI and FDI PPP when directly linking it to SPI and not via GDP PPP, are not suggested to encompass social development creation. Interestingly, this current pattern between economic growth and social development has not always been the case for Panama as the country, as also reported in Rannis *et al.* (2000), had been characterised by a *virtuous* circle pattern between 1960 and 1980 and an *HDI lop-sided* pattern between 1980 to 1992, which means that instead of displaying a *virtuous* circle, the nation was more inclined to strengthen the association flowing from social development to economic growth. Contrarily, Costa Rica, even in the absence of equal capabilities to reach a similar economic advancement as the one achieved by Panama, appears to be a better-suited nation to transform economic prosperity into social development for its population (Porter *et al*., 2013; Fernandez, 2022), although more inclined to strengthen the association flowing from social development to economic growth, as corroborated in the research work of Ranis *et al.* (2000), in which Costa Rica is reported to have been exhibiting an *HDI lop-sided* pattern since the 1960s,

Differences in the latter patterns are not negligible. Although both nations are emerging/transitional economies, Costa Rica is suggested to surpass Panama's social development even when its economic advancement is much lower. One may argue that the declining pattern between economic growth and social development exhibited by Panama may be traditionally explained upon the premises of the Solow-Swan (1956) neoclassical theoretical models as an effect of *decreasing return*s or even some assumptions of endogenous growth model stemming from the work of Romer (1992). One may additionally argue that this may be explainable due to the social development growth rate -as per its lagged variable nature- incapable of coping with the economic growth rate pace, according to some assumptions stemming from the Rostow (1960) model as suggested in Deloitte (2014). Alternatively, one may also hypothesise about the existence of some underlying mechanisms which characterise the economic and societal nature of Panama, which are preventing the country's economic advancement from evolving into an expected inclusive and sustainable set of social initiatives and policies (Hausmann *et al.*, 2017; Hausmann *et al.,* 2016a; Hausmann *et al.,* 2016b; Fernandez, 2021 and Garcimartin, 2021). The latter is particularly relevant when considering that in previous decades -as mentioned above- the country exhibited such living conditions for their citizens' social improvement pattern.

Those underlying mechanisms may eventually be explored based on theoretical endogenous growth models stemming from Romer (1992) and complementary empirical frameworks engaging in researching this direct link between economic growth and social development, which, as reported in the literature, has mainly employed HDI as the classical proxy variable. Alternatively, one may understand those underpinning mechanisms by exploring the association between FDI and social development, which, as below argued, appears to be an exploration scarcely reported in the literature. Furthermore, similarly in which, the work of Ghosh (2006) and Joshi (2007), Omar (2020), Ramirez *et al.* (1998), Ranis *et al.* (2000), Ranis & Steward (2001) and Ranis (2004) inform about the existing bidirectional association between economic growth and social development, one may have the academic curiosity, both from empirical and theoretical standpoints, in exploring the potential existence of a bidirectional relationship between FDI and social development, especially considering the economic nature of the FDI (Rojas, 2011). One may hypothesise that this relationship stems from mutually reinforcing forces, where a possible scenario may be FDI directly promoting or deterring social development, which paves the path or prevents further FDI attraction, thereby exhibiting similar *virtuous, vicious* or *lop-sided* circles characteristics as the ones argued to exist between economic growth and social development in accordance to Ranis *et al.* (2000). *What mechanisms cause an emerging/transitional nation to improve or prevent social conditions for its citizens even when an economic advancement magnitude such as FDI PPP is higher than other nations? Are there vicious or virtuous circles, so FDI and social development* co-evolve, positively or negatively, impacting each other? *If existent, which long-term patterns characterised this reverse causality association? Do causal path dependencies patterns also characterise this reverse association between FDI and social development?* Examining such an association may offer a rich, interesting, and novel research topic promising to add to the body of knowledge in the welfare economics arena for an emerging/transitional nation such as Panama, mainly if SPI is employed as a proxy for social development, in contrast to the traditional use of HDI. As one may expect, such an exploration requires a conceptual/structural framework founded on theoretical propositions buttressed by statistically sound and robust empirical findings.

When deeply exploring this link via SPI and any other proxy variable or indicator regarding social development, besides endogenous growth economic theoretical models based on the work of Romer (1992) and other potential theoretical approximations based on the neoclassical works of Solow-Swan (1956), literature perusal, unfortunately, did not render a theoretical framework explanatory for the direct association between the two dimensions. Nonetheless, regarding empirical studies linking both dimensions, a limited number of pieces of research were found, as deeply explained in section 2.3. Preceding literature reviews, and especially quantitative works in scholarly publications such as Kolstad & Tøndel (2002), Sharma & Gani (2004), Gökmenoğlu *et al.* (2018) and Orbes *et al.* (2019) informed about this association, majorly employing the HDI as a proxy for social development, where the latter two studies propose statistically robust conceptual/structural frameworks explanatory of this linkage. Nonetheless, as further explained in the literature review chapter, only two up-to-date attempts were identified directly, specifically researching FDI and SPI, the proposed variable, as a proxy for social development. One is the working paper of Deloitte (2014) which employs SPI country-based data for 2013. The other is the working paper from Dechprom & Jermsittiparsert (2018) utilising an aggregated SPI figure (independent variable) in a cross-sectional study. Both studies -although practitioner-oriented- rather than being discarded, become valuable pieces of work for extending knowledge in welfare economics; since, as argued by Van de Ven (2007), practitioner knowledge not only stems from academia but vice-versa. Unfortunately, although 'academically inspiring', both studies lack robustness and statistical rigour to be proposed as foundational 'conceptual/structural frameworks'. This lack of statistical rigour is critically important in the case of the study of Deloitte (2014), which claims the existence of a *virtuous circle* between the dimensions, a proposition that unfortunately remains unproven due to its cross-sectional nature. Nonetheless, as per Garcia (2020), the study remains one of the best up-to-date available references of a model linking FDI and SPI[7] as a social development measure, especially by researchers in some social and economic development regional institutes, e.g. CLADCS at the INCAE Business School in Costa Rica. In summary, after the literature perusal, to the best of my knowledge, no peer-reviewed journal has yet published research of such a 'conceptual/structural framework', particularly explanatory of bidirectional causal reinforcing effects.

[7] This scant number of studies directly researching FDI and social performance, particularly by using SPI as a proxy indicator, may be explained by SPI panel data still being scarce due to its recent launch in 2013. Although SPI has been in production worldwide since 2013, Panama has only directly and officially estimated it for 2019 in a province-disaggregated fashion; hence figures back to 2012 are to be calculated employing yearly surveys carried out by the Panamanian National Institute from Statistics and Census.

In this void of an economic-based theoretical model explanatory of the potential direct association of the FDI and social performance and also of empirical research proposing a statistically robust and rigorous framework linking both dimensions, one may turn to other alternative theoretical frameworks via an intermediate variable, seeking theoretically grounding this dissertation's research design. Thus, 1) the linkage between FDI and economic development and 2) the linkage between economic growth and social development are proposed as theoretical frameworks. However, finding the most suitable theoretical foundations becomes paramount when employing an intermediate variable such as economic growth distances from the initial target of a direct association between the dimensions. Thereby this dissertation finds 'inspiration' in an FDI-economic growth-social development framework.

Considerable research has been focused on the relationship between FDI and economic growth in societies. As mentioned earlier, conventional wisdom points to the positive effect of the former over the latter, even in the absence of consensus about these effects (positive, negative or neutral). As deeply explained the section 2.4.1 in the Literature Review, the theoretical linkage between FDI and economic growth extends to a widely cited empirical model proposed by Borensztein *et al.* (1998). This model is supported by the preceding research of Romer (1990), Grossman & Helpman (1991) and Barro & Sala-i-Martin (1995), which considers technological progress stemming from different forms of capital (infrastructure, equipment, other physical capital, human capital, know-how, among others). On the other hand, the link between economic growth in societies and social development is theoretically grounded in the *capabilities conceptual approach* upon which HDI is constructed (Sen, 1984; Robeyns, 2016; Streeten *et al.*, 1981; Fei *et al.*,1985). Although less extensive compared to the FDI-economic growth link, classicly employing HDI as a proxy has already been reported to be bidirectional as per Omar (2020), Ghosh (2006), Joshi (2007), Ramirez *et al.* (1998), Ranis & Steward (2001) and Ranis (2004) to the extent of reporting *virtuous, vicious or lop-sided patterns* (Ranis *et al.*, 2000), as extensively explained in section 2.4.2.

While there have been unsupported discussions pointing at the possible direct and indirect effects of FDI on social development, the literature scrutiny did not provide a formal robust and statistically rigorous conceptual/structural framework, neither theoretical nor empirical, explanatory of the association between both dimensions. Based on empirical data of MNEs of an emerging/transitional economy (Panama and its provinces), this relationship's microeconomic dimension is explored via economic growth as a connecting variable. The effects of FDI on economic growth have been pointed out in plenty of research works to significantly vary depending on the type of industry/MNE comprising the FDI function. By using disaggregated MNEs figures, the 'bulk FDI conflation issue' is proposed to be circumvented, as findings are expected to differ depending on the type of industry. Such differentiation is crucial in a host country like Panama, where Foreign Portfolio Investment (FPI henceforth) has historically accounted for figures ranging between 19.9% and 23.9% of its nominal GDP in recent years (IMF, 2022). The proposed research design specifically seeks to fill this void in the literature by proposing a 'conceptual/structural framework' which may exhibit a bidirectional reverse causal association between FDI and social development. This reverse casual association may potentially match *virtuous, vicious or lop-sided* circles as characterised in the work of Ranis *et al.* (2000), as explicitly reported for Panama to be *virtuous* and *social development lop-sided* for the association between economic growth and social development since 1960 as earlier exposed. Furthermore, from a rigorous statistical perspective, such a conceptual/structural framework would adequately test the general claim about an existing virtuous circle between FDI and social development (Deloitte, 2014), which is in an unproven bidirectional relationship also suggested in the work of Gökmenoğlu *et al.* (2018).

The general hypothesis to be tested is if FDI via economic growth induces a positive effect on social development in a society and vice-versa, intending to test whether social development could potentially impact -positively or negatively- on FDI. The theoretical and empirical underpinnings for such a reverse causal association are formally grounded in the literature review. In general terms, and under the assumption that there is no conflation issue regarding FDI, theoretical and empirical literature suggests the primary causal direction pointing to higher FDI enabling economic growth, which may lead to higher social development achievements. However, one may alternatively hypothesise that this relationship could stem from mutually reinforcing forces, under which an alternative scenario may also be social development paving the path for FDI attraction. Econometrically testing such dynamics would potentially unveil the existence of circle/cycle patterns between FDI and social development, as in the case of Ranis *et al.* (2000)'s empirical findings. Such a bidirectional association is hypothesised to be moderated by two classicly considered economic spillover effect variables: 1) Productive Linkages and 2) Household Income. The hypothetical rationale is that both economic spillover effects must initially derivate as a positive economic effect of FDI, as thoroughly argued in a plethora of research studies linking FDI and economic growth reported in section 2.4.1. This latter effect may, in turn, subsequently create a positive direct social spillover effect, as reported in section 2.4.2, regarding the linkage running from economic growth and social development. Once emerge, their impact may be employed as moderating variables which one may hypothesise as capable of strengthening/weakening the association running from FDI to social development. The latter may also be considered a social spillover effect (theoretical underpinnings found in the literature review section 2.4.1: linkage FDI-economic growth) and the association flowing from social development to FDI (theoretical underpinnings found in the literature review section 2.4.2: linkage economic growth-FDI).

Hence, a core hypothesis (H1) is posed seeking to confirm/discard the existence of underlying bidirectional causal mechanisms between social development (using SPI average factor figures per industry as a dependent variable under the assumption it is a proper and robust proxy measure for social development) and FDI (independent variable for which aggregated income figures per industry are employed). By introducing moderating variables, two additional hypotheses are posed to confirm/discard if this bidirectional causal association between the two variables is stronger for industries spending higher amounts in Total Compensation benefits for their employees (a proxy for Household Income) and weaker when lesser amounts are spent (H2). Complementary, this same moderating effect (H3) is sought via another variable referred to Third-Parties Expenditure which accounts for the subcontracted services from other local firms (a proxy for Productive Linkages). Those moderating variables, in addition to the control variables, were chosen for their hypothesised relative importance in impacting FDI and SPI and vice-versa, as per the literature review gaps identified, particularly in the work of Tocar (2019) and theoretical and empirical references found in sections 2.4.1 and 2.4.2 in the literature review.

Although the literature perusal rendered a great deal of research works associating various economically inclined measures to different social development aspects, the direct link between FDI and social development has rarely been explored, which this dissertation aims to add to the scant body of knowledge. Overall, the up-to-date literature on welfare economics appears to be lacking in two respects. Firstly, literature in development economics must go beyond the classic narrow focus on FDI simply creating productive MNEs' spillovers to a broader exploration of FDI additionally impacting social development, which may potentially enhance the understanding of social spillovers' creation in the host countries. Second, welfare economics literature requires a more balanced perspective on the effects of FDI on social development, as positive, negative or even neutral effects may potentially occur in both directions in the same way that *virtuous, vicious, or lop-sided circles* are reported in the literature for the two-way relationship between economic growth and social development. As further explained in the literature review chapter, four main features make this research excel within the preceding/existing works in welfare economics: 1) employs figures for MNEs in different industries/sectors intending to avoid potential 'conflation' issues, 2) employ SPI figures at a province disaggregated level. 3) concentrates on one specific country (Panama), and 4) by focusing on Panama, it extends the knowledge of emerging/transitional economies for which specific welfare economics studies are scant. Fulfilling the knowledge gaps in this promising research arena becomes a direct response to the 'academic calls' and the growing importance of welfare economics studies (Stiglitz, 2019; Fleurbaey, 2009; Atkinson, 2011).

Individual 'path dependencies' (meaning the reinforcing effects of previous periods are explanatory of the current behaviour of a given variable) are confirmed to exist for both FDI and SPI as the social development proxy. 1) FDI function is suggested to be in a stable locked-in mechanism[8], meaning that FDI may 'continue running' in a long-run loop of FDI inflows from previous periods self-feeding current periods (positive self-reinforcement). 2) As per the same token, although with a lower magnitude, social development is suggested to be governed by a locked-in stable loop long-run self-feeding mechanism (persistent positive self-reinforcement). FDI directly and positively impacts the Productive Linkage creation function confirming the *productive spillover effect*, and its effect on social performance is also positive, suggesting the creation of a '*social spillover'*. Nonetheless, FDI is found to exert a contradictory negative effect on Household Income, although the subsequent impact of Household Income on social development is reported as positive, also suggesting the creation of a '*social spillover'*. Unfortunately, the moderating effect of both productive spillover variables is found to induce negligible effects.

In general terms, findings further extend the existing knowledge of the classical *productive spillover effects* (knowledge transfer, technology transfer, and skills transfer, among the significant related gains) to a dimension of *social spillovers*. When the effects are accounted for, results suggest FDI -directly and indirectly via igniting the Productive Linkages and Household Income- inducing a total combined positive impact on social performance. Nonetheless, the effect of social development on FDI resulted as a negative, which suggests a restriction of Panama's economy to attract 'greenfield' FDI. This link's magnitude is higher than that of the link running from FDI to social development, complying with a bidirectional causal pattern described as a *lop-sided circle, negatively inclined on the association running from Social Development to FDI*. Understanding this latter pattern associated with the path dependency loops' effects is paramount for the Republic of Panama, particularly for policymakers. The proposition of national social and economic policies should be primarily directed to dismantle the 'locked-in' FDI and social development loops so, in general terms, the full potential FDI to transform into social development advancement and social

[8] Although Vergne & Durand (2010) conceptually define 'path dependencies' through a series of conditions met by a particular event, for this research purposes (as suggested in the literature review), Garud *et al.* (2010) define the concept as the self-reinforcing impacts that large past FDI inflows exert on contemporary inflows (the same exploration also applies to social performance figures).

development could be unleashed to become a determinant factor of 'greenfield' FDI attraction.

Moreover, the 'methodological funnel' followed towards convergence to the 'conceptual/structural framework' proposed implied the prior construction of what will be referred to in Chapter 6 as static and dynamic structural models and their related equations, a secondary gain of this dissertation for general research purposes in this field. Complementary, the elaborated and detailed description of this 'methodological funnel' in identifying the different misspecification issues, discerning between static proposed structural models via GMM-System and related causality tests, and dynamic structural models via the PVAR method, to ultimately proposing the conceptual/structural framework, also represent another secondary contribution of this dissertation[9].

This dissertation is organised as follows: Chapter 2 explores a gamut of different literature sources for both conceptualisations purposes, theoretical and empirical frameworks and also to ultimately identify the research gaps in the field; Chapter 3 engages into explaining the characteristics of the panel data employed and the research design this study is based upon; Chapter 4, delves into detail about the methods used in obtaining the results to both identify and overcome the misspecifications (endogeneity, heteroskedasticity, autocorrelation, cross-sectional correlations and autoregression issues) associated the panel data and the research design, as prior steps required to engage into model development; Chapter 5, focuses on explaining the results associated the GMM-Sys basic conceptual/structural frameworks and supportive robustness tests; Chapter 6 engages into causal effects and mechanisms testing for the conceptual/structural framework based upon PVAR model, Grainger Causality Test and IRFs; Chapter 7 refers to the conclusions, practical contributions and further research that could potentially stem from this study. As further explained in this last section, it is important distinguishing that this research majorly complies with the characteristics of a PhD study, despite its DBA nature.

[9] From this perspective, it offers the potential to serve as a methodological guide to academics, researchers, and even non-specialists in econometrics in the application Dynamic Panel Data (DPD) Models, particularly on the latest *xtdpdgmm* Stata17® community-contributed command for GMM-System estimations and related tests, where the importance of the conjoint specification tests is suggested to surpass the traditional coefficients' p-value significance thresholds.

2 CHAPTER TWO: LITERATURE REVIEW

The following literature review section aims to gain knowledge about the ongoing debate on theoretical and empirical frameworks that explain the underlying causal mechanisms of FDI associated with social development. This critical exploration of the extant available literature is engaged from theoretical, conceptual, and methodological standpoints, pursuing a deep understanding and a comprehensive overview of related welfare economics and affine topics. Its goal is to identify the knowledge voids of such conceptual/structural frameworks linking both topics and, therefore, the potential contributions this dissertation may offer to the welfare economics[10] research arena. Additionally, in pursuing to put the country into context, key figures concerning FDI and SPI as a proxy for social development are detailly explored for the Republic of Panama. Although this dissertation is based upon +290 reference sources (focused on research gaps, research design and methodological approaches), the following literature review section (ultimately concentrated on knowledge voids identification) is supported by +212 works. Reference sources are either concretely (specific quotes), partly or thoroughly reviewed, ranging between peer-reviewed journal articles, book chapters, working papers and practitioner-like reports, besides the account of interviews and databases.

This chapter is structured as follows: subsection 2.1 engages into detailly describing the main conceptualisations employed throughout this dissertation targeting to establish a common conceptual perspective for Foreign Direct Investment and Social Development, in addition to Social Development Measures and the Social Progress Index structural description; subsection 2.2 delves into putting FDI and SPI for the Republic of Panama in this research context; subsection 2.3, pursuing the identification of a conceptual/structural framework directly linking FDI and social development, exhaustively explores contemporary literature in welfare economics for those two dimensions via the inclusion of Literature Review studies and Literature Review sections of specific quantitative studies, besides of the in-depth analysis their methodological,

[10] As per Fleurbaey (2009) is "*the theory of social choice, the theory of fair allocation, the capability approach, the study of happiness and its determinants, in conjunction with new developments in the philosophy of social justice and the psychology of wellbeing*."

findings, conclusions and further research sections; subsection 2.4, in absence of finding a sound conceptual/structural model, either theoretical or empirical, associating FDI and social development, economic theory is further explored for the association between FDI and social development via a economic growth as an intermediate variable: underlying theory linking FDI and economic growth and a framework explanatory of the theoretical relationship between economic growth and social development; and lastly subsection 2.5 identifies the research voids this dissertation concretely targets to fulfil.

2.1 Conceptualisations

As follows, Foreign Direct Investment and Social Development conceptualisations are provided, seeking to set a common understanding in the context of this dissertation. The conceptualisation of Social Development is further explored by describing the evolution timeline of Social Development Measures within which the Social Progress Index is highlighted.

2.1.1 Foreign Direct Investment

As per Moosa (2002), FDI is a subset of international factor movements (cross-border investment) characterised by controlling ownership of a business company in a host country for a company based in another (home country). Investment may be made by buying a company (inorganically) or by expanding existing business operations in the host country (organically). Host countries often try to channel FDI[11] into new infrastructure and other projects to boost development[12] (Echandi *et al.*, 2015). Additionally, the investing company simply

[11] As per World Economic Forum (2013), four types of FDI are distinguished 1) Horizontal: companies duplicate its home country-based activities in the same host country's value chain. 2) Platform: FDI flowing from a home country into a host country for the purpose of exporting to a third country. 3) Vertical: company moves upstream/downstream in different value chains through FDI i.e., companies perform stage by stage vertical value-adding activities in a host country. 4) Conglomerate: investment overseas setting up business unrelated the home country one.

[12] According to UNCTAD (2000), there are several forms of incentives to FDI: 1) Low corporate tax and individual income tax rates, 2) Tax holidays, 3) Other types of tax concessions, 4) Preferential tariffs, 5) Special economic zones, 6) EPZ– Export Processing Zones, 7) Bonded warehouses, 8) Cross border assembly plant (Maquila), 9) Investment financial subsidies, 10) Free land or land subsidies, 11) Relocation & expatriation, 12) Infrastructure subsidies, 13) R&D

transfers old production capacity/machines in many instances, which may still be used to host countries due to technological lags (OECD, 2002).

As per World Bank (2008, pp355), FDI is the "*sum of equity capital, long-term capital, and short-term capital as shown in the balance of payments*". Following Clegg *et al.* (2017, pp520), FDI broadly includes "*mergers and acquisitions, building new facilities, reinvesting earned profits from overseas operations, and intercompany loans*". However, there is no detailed, authoritative, and universal FDI definition. Thus, the Organization for Economic Co-operation and Development (OECD) has recognised the need to agree on a standardised definition[13] for statistics compiling purposes and benchmarking by highlighting key characteristics (OECD, 2008, pp50): 1) Lasting interest in a company, 2) Long-term relationship and 3) Significant degree of influence of at least 10% ownership of voting power. Nonetheless, there are still grey areas regarding this 10% voting shares' control threshold[14]since, depending on the Multinational Enterprise (MNE henceforth), even in cases of smaller shares' blocks, technology, management, and access to core resources may confer de facto control in widely held companies (Chandra, 2016, pp380). Moreover, proving the existence of control and/or influence varies in scope depending on the applicable law in host countries, as some jurisdictions do not make distinctions between different forms of FDI (UNCTAD, 2003 & UNCTAD, 2010).

It is as regards this notion of control that precisely distinguishes FDI from Foreign Portfolio Investment (FPI), as some host nations may potentially account for FPI inflows as FDI. FPI involves making and holding a hands-off (passive investment of securities) with the expectation of earning a more liquid return dependable upon the market's volatility. Securities can include stocks, American

---

support, 14) Energy, 15) Derogation from regulations (usually for very large projects), 16) Excluding the internal investment to get a profited downstream.

[13] Since 1983, the OECD adopted a 'Benchmark Definition of Foreign Direct Investment' to provide a comprehensive set of rules to improve statistical measures of FDI. As of MNEs and other business combinations financing structures evolve in an increasingly globalized market, the OECD adapts the statistical measures to changing economic and financial realities to standardize the way FDI statistics are measured around the world.

[14] The foreign direct investor may acquire voting power of an enterprise in an economy through any of the following methods: 1) By incorporating a wholly owned subsidiary or company anywhere, 2) By acquiring shares in an associated enterprise, 3) Through a merger or an acquisition of an unrelated enterprise, and 4) Participating in an equity joint venture with another investor or enterprise.

Depositary Receipts (ADRs), or global depositary receipts (GDRs) of companies headquartered outside the investor's nation. These securities may also include bonds or other debt instruments issued by these companies or the host nation's government, mutual funds, or Exchange Traded Funds (ETFs) that invest in overseas assets. In this sense, as a passive investment with no active involvement in the company's management, FPI technically does not provide the investors with direct ownership of a company's assets (OECD, 2008; UNCTAD, 2010).

Some market risks affect FDI to a lesser degree than FPI. By being financial assets and not property or a direct stake in a company, FPI is inherently more marketable. In addition, they are more liquid than FDI, offering the investor a chance for a quicker return on investment as exit barriers are lower than FDI. FPI is bound to be withdrawn from the host country of investment in uncertain or negative political or economic news that may escalate into more aggravated issues in the short or middle term. The latter implies -as in the case of most short-term horizon investments- that FPIs are more volatile than FDI. In any case, FDI and FPI are essential funding sources for most economies. On a macro level, FPI comprises a structural part of the host nation's capital account, shown by its Balance of Payments (BOP) measures money flowing from one country to another over one monetary year. An individual investor would more likely search for investment opportunities outside their own country via FPI instruments. On the other hand, although they may also use FPI, institutional investors, ultra-high-net-worth individuals, and MNEs would likely choose to follow an FDI path regarding their investment decisions.

2.1.2 Social Development

The term 'development' has been classically linked to 'economic development' even though it may equally apply to political, social, and technological progress (Jacobs & Asokan, 1999) as these sectors are intertwined among each other in a society (neatly separating them becomes a cumbersome task) and are suggested to be governed by the same underlying mechanisms (International Commission on Peace and Food, 1994).

Nonetheless, ‘economic development’ and ‘human development may not mean the same. Even when -economically speaking- it is often assumed that economic growth leads nations to reach different stages of ‘development’, such ‘development’ may not necessarily reach out to the entire society and induce improvements, which would exclude the ‘human development’ dimension out of this definition (Anand & Sen, 2000; Sharma & Gani, 2004; Stiglitz, 2006). From a broad standpoint, ‘human development’ depends on a series of factors such as social and physical conditions, healthcare and access to education (Sen & Bhattacharya, 2001). Strategies and policies in a particular society may raise ‘economic development’ in a nation, despite its impact on the living standards of the average members of this society. Conversely, social-oriented policies and programs may improve health, education, living standards, and other quality-of-life measures without special emphasis on ‘economic development’. For this dissertation’s purposes, ‘social development’ will be understood from a ‘human development’ perspective, totally detached from this ‘economic development’ conceptualisation.

Conceptual antecedents of human development may trace back to the earlier basic needs approach of the International Labour Organization (ILO) and the World Bank (Streeten *et al.* (1981) and Fei *et al.* (1985)) in addition to the *capabilities conceptual approach*[15] stemming from the work of Sen (1984) alternatively conceived in the welfare economics. The capabilities approach is a “*normative approach to human welfare that concentrates on the actual capability of persons to achieve their wellbeing rather than on their mere right or freedom to do so.”* (Robeyns, 2016). The rationale behind this is that these capabilities are construed in terms of the ‘substantive freedoms’ (such as the ability to reach a high life expectancy, participate in economic transactions or engage in politics), which are valued by human beings rather than on a ‘utility approach’ which centres on happiness as desire-fulfilment. As argued by Sen (1993), humans are entitled “*to achieve outcomes that they value and have reason to value*”.

[15] As per Sen (1984) there are 5 components when evaluating capabilities: a) importance of real freedoms in the assessment of a person's advantage, b) Individual differences in the ability to transform resources into valuable activities, c) multi-variate nature of activities giving rise to happiness, d) balance of materialistic and nonmaterialistic factors in evaluating human welfare, e) concern for the distribution of opportunities within society

The capabilities approach distantly contrasts the classic 'functioning approach', which advocates access to resources such as income, commodities, or assets, which fits the classic use of economic measures as proxies of social development. In this sense, the capabilities approach focuses on how human beings function and how they have access to capabilities that are practical choices in nature. The capabilities approach thereby centres on people's choices and gauges people's real opportunities to access social development factors (Sen, 1984; Sen, 1985; Sen, 1993; Sen & Bhattacharya, 2001, Anand & Sen, 2000). Freedom of choice, individual heterogeneity and the multi-dimensional nature of well-being are foundational in the capabilities approach. In this sense, social development comprises the enlargement of people's choices, enabling society members to live longer, healthier and more fulfilling lives (UNDP, 1990). Contrarily, from this standpoint, poverty, ignorance, government oppression, lack of financial resources, or false consciousness are to be understood as capability deprivations (Robeyns, 2016). The capabilities approach is consistent with the choice handling concept related to the conventional microeconomics consumer theory, although its conceptual foundations enable acknowledgement of the existence of claims, like rights, which normatively dominate utility-based claims (Sen, 1979).

As argued by Anand *et al.* (2009) and Dowding *et al.* (2009), the capabilities approach is the predominant paradigm for policy debate in social development after strengthening with the contributions of Martha Nussbaum (political philosopher), Sudhir Anand (development economist) and James Foster (economic theorist). It additionally laid the foundations for creating the UN's Human Development Index (UNDP, 1990[16] which has been operationalised with a high-income country focus as per the work of Anand *et al.* (2009) and out of which other closed related indexes such as the a) Gender-related development index, b) Gender empowerment measure c) Gender inequality index and d)

[16] The Human Development Index (HDI) is a composite index comprising indicators used for country ranking into 4 tiers of human development: 1) Income (GDP PPP) as a proxy for a decent standard of living, 2) Education (adult literacy rate -weighing two thirds- and the combined primary, secondary and tertiary gross enrolment ratio (with -weighing one-third-) and 3) Life expectancy at birth. It was developed by the Indian economist Amartya Sen (Nobel Laureate) and the Pakistani economist Mahbub ul Haq.

Human Poverty Index, have also been structured. The United Nations Development Programme's Human Development Report Office extensively uses the latter indexes to measure a nation's social development (Stanton, 2007). Furthermore, it has also served as fertile ground for political theorists, philosophers, and social scientists discussions, particularly after launching the Human Development and Capability Association in the early 2000s (Dowding *et al.*, 2009). Furthermore, as contended by Dowding *et al.* (2009), many of the other prevailing measures of social development still in production (as further explained in the following subsection) had their genesis during and after the 1980s, for which the capabilities approach (Sen, 1993) played a foundational role by either extending, complementing or critiquing it. Contemporarily, it is noteworthy that the *utilitarian approach*, which states that the most desirable actions are the ones that better raise peoples' psychological happiness or satisfaction (Alkire 2009), has lately been gaining strength under a *subjective well-being* conceptual framework which is also explained in the following subsection.

From a complementary theoretical standpoint, 'social development' targets to explain qualitative structural changes in a society, which particularly aids this society in improving the realisation of their common goals and objectives. Jacobs & Asokan (1999, pp152) conceptualised social development as an "*upward ascending movement featuring greater levels of energy, efficiency, quality, productivity, complexity, comprehension, creativity, mastery, enjoyment and accomplishment, which in a way it applies to all societies at all historical periods*". Following the International Commission on Peace and Food (1994, pp163), social development is a process of social change, not simply sets of instituted policies and programs seeking some specific results. The core mechanism driving social change is ignited when a society reaches a point of awareness that a better organisation is achievable and a sparking motive is triggered. This motive has to be mighty enough to overcome impeding obstructions for social change to occur. If a society realises that potential emerging opportunities may lead to progress and prosperity, it is bound to develop new organisational forms to exploit these opportunities successfully. Those new forms of organisation are considered more suitable to harness skills and resources (e.g. capital, technology, and supporting infrastructure) found in that society, seeking the improvement of its members as a whole (Jacobs & Asokan, 1999). From this perspective, social development stems from the societal capacity to organise resources, face challenges and take advantage of opportunities, governed by several determinants which may influence the developmental efforts' results. As Streeten et al. (1981) argued, pioneer members frequently introduce new ideas, practices, and habits that conservative members of society initially resist [17]. Subsequently, other members accept, imitate, organise, and use such innovations.

Social development is suggested to be a research field in evolution in the light of academics, practitioners and policymakers emphasising that globalisation and foreign capital have been classically studied from a market-country perspective while heavily overlooking their effects on people (Streeten *et al.*, 1981). Concretely providing answers about societies improving or worsening appears to be a blurry scenario. Hence, the conceptualisation and deployment of social development measures emerge as an opportunity area to research and implement new proposals of appropriate and well-designed indicators (challenging the prevailing *functioning approach*) capable of gauging inclusive growth and societal success (Stiglitz, 2019, Stiglitz *et al.*, 2009; Fleurbaey, 2009). The 2 subsections that follow seek to support the latter assertion by initially explaining in detail the evolution of the Social Development measures and subsequently extending to the Social Progress Index (SPI) as an emerging measure specifically employed in this dissertation as a proxy for social development.

2.1.2.1 Evolution of Social Development's Measures

As afore argued, although the economic dimension is essential, GDP PPP (or any other economic measure used as a proxy for income per capita) may simply be a means to reach an utterly human goal of well-being (Grömling & Klös, 2019). Nonetheless, during the late 20th century and much of the first decade of the 21st century, gauging material well-being in terms of economic-related measures (mainly using GDP PPP and economic growth) has been the norm in

[17] Society passes through well-defined stages in the course of its development: nomadic, hunting and gathering, rural agrarian, urban, commercial, industrial, and post-industrial (Jacobs & Asokan, 1999)

understanding social development. Interestingly, its adoption has occurred despite the explicit advice of Simon Kuznets -the economist behind the development of the GDP gauging system during the 1940s- that this measure was never intended to assess wellbeing (Coyle, 2014).

Those contrasting perspectives, primarily questioning GDP adequately capturing the goodness of life (Rojas, 2011), have contemporarily become a subject of debate in academic and practitioner circles, paving the path for the emergence of contenting gauging systems argued to assess social development more appropriately. As per Mulgan (2013), questions concerning the characteristics of a good life or society and how social development and goodness in people's lives should be assessed are still a philosophical debate topic as they have been for 3 millenniums.

GDP was a measure developed with the primary purpose of informing about the production outputs of nations, seeking to fulfil public and private material needs (Coyle, 2014), which undoubtedly became core gauging means in economics. However, this has not necessarily been the case for other disciplines. This segregation perspective stems from a historic disciplinary division of knowledge, which became detrimental when assessing societal well-being, resulting in being studied from an academic-construed viewpoint instead of a human being's stance (Rojas, 2007). Thus, economists and statisticians have focused on developing national accounting systems to measure GDP and complementary theoretical models and frameworks to explain their short-run and long-run behaviours. On the other hand, sociologists, politicians, and political scientists have employed GDP to instead focus on different angles, such as electoral systems, political participation, access to public services, and social stratification, among others.

Many questions regarding GDP have historically been unanswered: 1) Are all goods incorporated in GDP indeed goods? 2) Must other goods -not currently considered- be incorporated in GDP accountings? 3) Is GDP adequately weighing societal successes and pitfalls? As per Fleurbaey's (2009, pp1031) quote: "*many official reports swiftly gloss over the fact that economic theory has established total income as a good index of social welfare under some* *assumptions (which are usually left unspecified).*" Such criticism is rooted in scepticism on how gauging social development, mainly because GDP is not considered as important to citizens as it is relevant to economists, politicians and businesspeople. For instance, although GDP may adequately be used for macroeconomic and political discussions (Ward, 2015), it may not be as relevant to citizens who, in general terms, may disagree with this measure properly reflecting their social development reality and their standards of living. Those misalignments between social development and citizens' perceptions about the costs and benefits of government policies arrays have positively impulsed a growing awareness of economists, policymakers, and empirical researchers about economic measures' incapability to fully capture social development phenomena, urging them to expand the up-to-date available battery of social development measurements (Easterlin, 2013) to 'fresh' and more appropriate measures. Following Fleurbaey's (2009, pp1030) quote: "*the fact that monetary measures still predominate in all such contexts is usually interpreted as imposed by the lack of a better index rather than reflecting a positive consensus".*

Notably, criticisms of economic-based measures to asses social development are not new and date back to the late 1960s and early 1970s (Nordhaus & Tobin, 1972). Back then, as quoted in Land & Michalos (2018), the Social Indicators' Movement pursued to "*establish a system of social accounts that would facilitate a cost-benefit analysis of more than the market-related aspects of society already indexed by the National Income and Product Accounts*." Additionally, the Easterlin Paradox[18] (Easterlin, 1974; Diener *et al.*, 1999; Fisher, 2010), which is still considered a high research interest topic as no explanatory causes have been reported regarding the GPD PPP growing curve stopping at some point even when highly correlated to life quality indicators, also dates back to the 1970s. As argued by Hicks (2012), this Social Indicators Movement faded away at that moment in time due to an overestimation of

[18] In 1974, Richard Easterlin, then professor of economics at the University of Pensilvania and the first economist to study happiness data posed a paradox that states that at a certain moment in time happiness and income -among and within nations- vary directly. However, at some point over time, happiness does not follow and upward trend as in the case of income that continue growing. The paradox as an empirical generalization is rooted in this contradiction between the point-of-time and time series findings. Up to date, several theories have attempted to explain it.

computer technology and data availability and/or to its precociousness to generate clear and compelling consensus for a unifying framework.

This quest for new social development gauging indicators is suggested to have been contemporarily reborn since, as per Land & Michalos (2018, pp848) quote: *"interest in social indicators revived, and the field has been in an expansionary phase since the mid-1990s*." Moreover, as extracted from Barrington-Leigh & Escande (2018, pp894): "*the last decades have witnessed a surge in empirical research concerned with notions of social progress, green accounting, sustainability, quality of life, and wellbeing*." In this sense, Fleurbaey's (2009) work may be considered seminal on the topic as it comprises a set of alternative social welfare and well-being measures. Additionally, the Stiglitz Commission (comprising five Nobel laureates) presented in 2009 a report on the Measurement of Progress of Societies required in 2008 by French President Sarkozy (Stiglitz *et al.*, 2009) considered by some scholars, practitioners, and policymakers, another contemporary seminal work, part of a 'fresh' growing global wave to awaken the field of welfare economics. The report emphasised 3 areas requiring the attention of policymakers and national governmental statistical offices: 1) Improvements gauging goods and services accounted by GNP[19], 2) Consideration of sustainability issues, and 3) Quality of life/welfare measurements.

The social development arena has lately been enriched by an emerging *subjective well-being approach* based upon the previously mentioned *utilitarian approach* (Rojas (2011, pp170) when citing Kahneman (1999); Argyle (2001); Diener (2002); Diener & Oishi (2000); Veenhoven (1988, 1992); Easterlin (1974, 2001); Clark & Oswald (1994); Frey & Stutzer (2001); and Van Praag and Frijters Praag et al. (1999)). Those subjective well-being measures started to be developed during the 1990s, as Barrington-Leigh & Escande (2018) reported, many of which are still in production. Fisher (2010, pp385) states that subjective

[19] Gross National Product (GNP) is a term related to GDP. It is an estimate of total value of all end services/products delivered by the means of production owned by a country's residents in a period. It is usually calculated adding up all personal consumption expenditures, private domestic investment, government expenditure, net exports (difference between country exports goods/services imports) and any income earned by residents from overseas investments; and subtracting the earned income within the domestic economy by foreign residents.

well-being "*is usually seen as having two correlated components: judgments of life satisfaction (assessed globally as well as in specific domains such as relationships, health, work, and leisure), and affect balance (having a positive feelings preponderance and relatively few or rare negative feelings).*" Subjective well-being focuses on asking people to describe their well-being rather than presuming and/or prescribing normative and/or standardised characteristics of what is considered a 'good life' (Rojas, 2011). For instance, the GDP measure wrongly prescribes that people´s living standards be reached through consumable goods and services. Furthermore, the Human Developing Index assumes a normative position by considering a GDP PPP and/or life-expectancy figures an 'accurate approximation' of social development. In this sense, the well-being approach is advantageous as it works directly on people, so the relevancy of presumed variables could be directly tested on them. Thereby, the development of subjective well-being measures has become the latest social policy challenge and a growing research trend in the social development arena (Deeming, 2013; Barrington-Leigh & Escande, 2018; Land & Michalos, 2018). Hence, by quoting Helliwell *et al.* (2012, pp96): one *"can well envisage a parallel system of evaluation taking shape over time where policies are judged by the changes in happiness that they produce per unit of net public expenditure*".

The recent survey work of Barrington-Leigh & Escande (2018) mentions a broad range of 82 measurements related to the social development created since the 1980s. As per Greve (2017), 12 leading indicators have been often used and researched in the past two decades. They comprise either a *capabilities approach* or a *subjective well-being approach* based ones: 1) Social Progress Index, 2) Global Age Watch, 3) World Happiness Report Index, 4) Gallup-Global Well-being, 5) OECD´s How is Life: Satisfaction, 6) Overall Life Satisfaction Index, 7) Human Development Index, 8) Gender Equality Index -Rank-, 9) Eurofound Quality of Life, 10) Eurofound Quality of Life (3 Indicators), 11) Legatum Prosperity Index and 12) Happy Planet Index. Besides, Barrington-Leigh & Escande (2018) also report the availability of various methods with different targets or goals being implemented for recording levels and changes in social development, where indices and unaggregated measures could be distinguished majorly driven by Governmental and NGOs.

The work of Hagerty *et al.* (2001) and Michalos *et al.* (2011) focuses on identifying the qualities and validity criteria for assessing well-being, quality of life and progress indices, many of which are shared of the 8 dimensions highlighted in the work of Stiglitz *et al.* (2009, p14): *"material living standards; health; education; governance and civic participation; social connections, relationships, and community; environment; culture, accounts of time-use, and various forms of security*". From this perspective, although the survey's work of Wolff *et al.* (2011) informs about the latter 12 leading indicators sharing some common themes when these 8 dimensions are considered as 'desirable features benchmarks', it appears to be no existing consensus about their appropriateness as social development measures. Nonetheless, this lack of consensus is an expected scenario, majorly rooted in the existing philosophical division between the capabilities and subjective well-being approaches. For instance, Rojas (2011, pp175) -when commenting on the Stiglitz Commission Report (Stiglitz *et al.*, 2009)-, highlights the importance of making a "*clear distinction between objective and subjective indicators as it asks for keeping track of both kinds of indicators".* The importance of making this distinction precisely lies in the existence of two schools of thought, one which 'trendy' advocates that social development could only be adequately assessed via the use of subjective indicators, and another one supportive of social development being more properly gauged by employing objective indicators. Subjective indicators have some significance for measuring the quality of life from the perspective of individuals' assessments (e.g., self-reported health, satisfaction with life as a whole) in complete alignment with the *subjective well-being approach* (Land & Michalos, 2018). Examples of subjective indicators comprise measures of subjective well-being such as individuals' self-reported health statuses, how satisfied individuals are with their life as a whole, with specific life domains (e.g., work life, social life, and family life), and frequency of positive over negative feelings they may have experienced during the last week or so. For instance, the World Happiness Report, Index Gallup-Global Well-being, OECD´s How is Life: Satisfaction, Overall Life Satisfaction Index or the Happy Planet Index fall within this classification. On the other hand, objective indicators have some significance for assessing the quality of life from the perspective of any independent observer (Land & Michalos, 2018) and upon which the *capabilities approach* is construed. Examples of objective indicators include unemployment rates, crime rates, estimates of life expectancy, health status indexes for a specific population, school enrollment rates, average achievement scores on a standardized test, and rates of voting in elections. The Social Progress Index and the Human Development Index fall within this classification (although it also include a 'functioning approach' economic measure such as the GDP PPP per capita as a proxy for individual income). Furthermore, in their recent work, Barrington-Leigh & Escande (2018) have also recommended separating social development measures from sustainability and environmental measures due to distinct conceptual objectives, as the former entirely derives from short-term experiences and events and the latter are influenced by non-anthropogenic long-term events.

This scenario of social development measures is dynamic. As per a quote from Land & Michalos (2018, pp859), "*the field of social indicators and quality-of-life research likely will see several decades of such index construction and competition among various indices—with a corresponding need for careful assessments to determine which indices have substantive validity for which populations in the assessment of the quality-of-life and its changes over time and social space.*" In this venue of dynamism, out of the 12 indices abovementioned, many would likely become 'obsolete' in the medium-term in response to the transformation of the global academic, practitioner and policymaker scenarios. For instance, as reported by Hagerty *et al.* (2001) almost 20 years ago: *"for an early overview of different kinds of indices -22 indices were reviewed-, the Human Development Index and Eurobarometer seem to be the only indexes left."* Besides, as per Barrington-Leigh & Escande's (2018, pp900) work, *"Systems of accounts have a low survival rate from a peak of innovation in the early 2000s. Indices (excluding those shown under the subjective well-being category) have an overall survival rate of about 50% to date, while unaggregated sets of indicators have fared significantly better. Nearly all the most recent subjective wellbeing-oriented indicators are still in production."* In this sense, a longer survival rate of subjective well-being measures is expected. The latter does not imply that objective-based measures will be extinct shortly. However, it may seem reasonable to expect one particular social development measure to become the most researched standard, as in the past decades has been suggested to be the Human Development Index. The underlying reason for facilitating its adoption, diffusion, and cross-sectional/longitudinal comparisons of the same variables has been based on its simplicity, as it comprises a few single indicators. As per Rojas (2011), it appears advisable that the shorter the number of comprising factors on a composite measure, the higher the chances of adoption and becoming a spread-out standard for gauging social development. For instance, GDP's historical positioning as a single economic progress indicator could be solely explained by its relative ease of understanding. (Barrington-Leigh & Escande, 2018)

At this point, one may divagate which approach appropriately assesses social development. Proposing the 'best tool' for such purposes would be a rash suggestion since electing one approach over another depends entirely on the end user (Academics, researchers, practitioners, policymakers) and how they expect to harness the stemming results. For instance, among academics and public policy officials, social development measures are significant for the quality of life broadly construed for the society as a whole (or specific subpopulations, segments, or components) so that becoming valuable tools in social reporting to the general public and for evidence-based public policymaking (Land, 2014). Without consensus on the superiority of an objective-based approach over a subjective well-being approach or vice-versa, it would appear reasonable to take advantage of both via a combination approach. By mixing different measures - about specific aspects of life or domains of well-being- into a *composite measure,* one may obtain a more acute overview of the overall quality of life or social development for specific countries, societies or populations (Land, 2014). Such *composite measures* have been criticised (Ravallion, 2012) for the arbitrary convergence of different variables into a measure incapable of adequately capturing social development and for statistical errors induced by the data (Wolff *et al.*, 2011). However, as reported by Hagerty *et al.* (2001), Michalos *et al.* (2011), Land (2014) and Land & Michalos (2018), the reality is that many precedent social development measures constructed, operationalised and researched have emerged out of this compositing process. By following Hagerty *et al.* (2001), Michalos *et al.* (2011), Land (2014), and Land & Michalos (2018) also, the most influential ones have generally intended to assess or theoretically operationalise well-developed concepts that include quality of life, wellbeing, human development, economic prosperity, ecological sustainability, and so on.

An example of such a measure is the Social Progress Index, the chosen proxy for gauging social development in this dissertation.

2.1.2.2 The Social Progress Index as an emerging social development measure

As per Porter *et al.* (2013), while still in production, many of the existing social development measures mentioned above are laudable efforts to measure this social construct; they are only capable of capturing -uneven in breadth and scope across countries- limited aspects of social development. Thus, SPI emerged in a worldwide scenario in 2013, argued to be a social and environmental metric complementary to GDP PPP and the HDI, designed for societies to gauge the results of policies directly implemented for improving people's well-being (Porter *et al.*, 2013; Stern & Epner, 2019, Fehder *et al.*, 2018).

The SPI was initially conceived by the Council on Philanthropy and Social Investment of the World Economic Forum in Davos in 2009 as a framework for measuring social and environmental performance. It was also considered a success parameter to catalyse progress and identify priority areas of action and intervention. The development of the conceptual framework and the methodological instruments for the SPI construction originates in academia: professors Michael Porter of the Harvard Business School and Scott Stern of the School of Administration and Sloan Business Management of the Massachusetts Institute of Technology (MIT). The initiative was then materialised by the joint efforts of its creators and an NGO formed in 2012 with the collaboration of economist Michael Green, called Social Progress Imperative (based in Washington, D.C.). Social Progress Imperative aims to provide a more comprehensive measure of people's quality of life complementary to economic measures, which can be used to construct a more prosperous society by decision-makers of different governments worldwide, companies, civil society and citizens in general. Over time, several strategic partners have joined in this effort: Fundación Avina, Cisco, Rockefeller Foundation, Deloitte Touche Tohmatsu Ltda. (Deloitte Global), the Skoll Foundation and Compartamos de México. Regarding Latin America, particularly in Central America, the INCAE Business School (Central American Institute of Business Administration as translated into English) and its adjunct Latin American Center for

Competitiveness and Sustainable Development (CLACDS) collaborated in the SPI construction.

The SPI is an *objective well-being* measure which complies with the characteristics of the *capabilities approach* earlier explained. As quoted by Porter *et al.* (2013, pp7) and Stern & Epner (2019, pp3), *"Social progress is the capacity of a society to meet the basic human needs of its citizens, establish the building blocks that allow citizens and communities to enhance and sustain the quality of their lives, and create the conditions for all individuals to reach their full potential".* Stern & Epner (2019) argue SPI's strengths reside in 5 characteristics that successfully distinguish it from previous efforts (referring to the 12 abovementioned indicators under Greve, 2017) and which potentiate it as a holistic and *objective-based* measure of social development: 1) Based exclusively on non-economic indicators, 2) Based exclusively on outcome indicators, 3) A large number of indicators integrated into an aggregated social progress score, 4) Structured to allow empirical investigation of relationships between dimension, components and indicators, 5) Breadth of indicators makes it relevant for countries at all income levels. Following Porter *et al.* (2013), Porter *et al.* (2017), and Fehder *et al.* (2018), SPI is based upon 3 overarching statements: 1) Economic development is necessary but not sufficient for social progress, 2) Overall level of development in a country masks social and environmental strengths and challenges, 3) Areas of underperformance and success for countries at all income levels could be shown at a disaggregated level.

As per Porter *et al.* (2013), Porter *et al.* (2017), and Fehder *et al.* (2018), SPI's primary goal is to provide a rigorous tool to benchmark and stimulate social development within countries, which in turn depends on policy choices, investments, and implementation capabilities of multiple stakeholders (government, civil society, and private business). Following Greve (2017), policymakers, businesspeople, and citizens in each nation could use an index with the characteristics possessed by SPI to compare their country against other countries on different social development facets seeking the identification of specific areas of strengths or weaknesses. Informing and motivating stakeholders to work together is expected to accelerate and develop a more integrated approach to social development. Hence, SPI is argued to become valuable in strategic planning, resource targeting, monitoring, prioritisation and periodic actions assessment in private and public environments, especially when policy intervention is required.

SPI disaggregates into 3 basic structural dimensions (Stern & Epner, 2019): 1) Basic Human Needs, 2) Foundations of Well-being, and 3) Opportunity[20]. Each dimension comprises 4 components that explode into 3 to 5 specific indicators, so SPI has 54 constituents. Overall SPI score is the simple arithmetic average of the 3 dimensions, as each dimension is the simple arithmetic average of its 3 to 5 components. See Chart 4 for the Social Progress Index Structure (Dimensions and Indicators)

Chart 4. Social Progress Index Structure (Dimensions, Components and Indicators)

Source: Social Progress Imperative (2019, pp.5)

[20] 1) Basic Human Needs: Does a country provide for its people's most essential needs? Assesses how well a country provides for its people's essential needs by measuring access to nutrition and basic medical care, if they have access to safe drinking water, if they have access to adequate housing with basic utilities, and if society is safe and secure. 2) Foundations of Wellbeing: Are the building blocks in place for individuals and communities to enhance and sustain wellbeing? Assesses whether citizens have access to basic education, can access information and knowledge from both inside and outside their country, and if there are the conditions for living healthy lives. Foundations of Wellbeing also measures a country's protection of its natural environment: air, water, and land, which are critical for current and future wellbeing. 3) Opportunity: Is there opportunity for all individuals to reach their full potential? Measures the degree to which a country's citizens have personal rights and freedoms and can make their own personal decisions as well as whether prejudices or hostilities within a society prohibit individuals from reaching their potential. Opportunity also includes the degree to which advanced forms of education are accessible to those in a country who wish to further their knowledge and skills, creating the potential for wide-ranging personal opportunity. One of the distinguishing features of the Social Progress Index framework is that it encompasses Opportunity, an aspect of human wellbeing that is often overlooked or separated in thinking about social progress from more foundational and material needs such as nutrition and healthcare. (Stern & Epner, 2019).

Per Stern & Epner (2019), SPI indicators must comply with a series of requisites to ensure appropriate measurements within a given country. The methodology must be consistent as SPI indicators have been tested for internal validity (See Appendix 2. Figure 1. Indicator Selection Tree).

As per Porter *et al.* (2013), SPI's first 2013 'beta' results covered an initial sample of 50 countries (representing 75% of the world's population). After its formal launch in 2014, SPI use has been extended and improved. Better results are increasingly obtained as its methodology is updated[21] , and the number of countries and support of worldwide partners also increases (See Appendix 2. Figure 2: SPI Strategic Partners). In its 2019 version (Stern & Epner, 2019), the report included 149 countries (comprising 90% of the world´s population). Additionally, 77 additional countries and territories were contemplated, calculating component scores when enough data was available. Thus, SPI is reported to currently measure at least some aspects of the social development of 99% of the worldwide population. Table 2 depicts a comparison of the Social Progress Index for 2020, its 3 dimensions, and their comprising 12 indicators for the 6 Central American countries (which includes Panama and Costa Rica), Argentina, Brazil, Chile, Colombia, Uruguay and the United Kingdom (Social Progress Imperative, 2020).

[21] SPI methodological flexibility allows continuous update and enrichment provided there is availability of indicators, for which measurements must be made by the same organization and geographic availability must be assured.

Table 2. Comparison of Social Progress Index figures for the 6 Central American countries, Argentina, Brazil, Chile, Colombia, Uruguay and the United Kingdom

		Social Progress Index			Basic Human Needs				Foundations of Wellbeing				Opportunity			
	Social Progress Index	Basic Human Needs	Foundations of Wellbeing	Opportunity	Nutrition and Basic Medical Care	Water and Sanitation	Shelter	Personal Safety	Access to Basic Knowledge	Access to Information and Communications	Health and Wellness	Environmental Quality	Personal Rights	Personal Freedom and Choice	Inclusiveness	Access to Advanced Education
United Kingdom	88.54	94.36	90.21	81.06	98.24	99.80	97.72	81.70	92.46	96.42	83.48	88.48	93.48	86.78	62.99	80.98
Panama	76.55	86.00	79.83	63.82	90.48	87.86	95.14	70.52	81.13	70.88	77.24	90.06	87.14	61.20	49.76	57.19
Costa Rica	83.01	89.88	84.62	74.51	95.67	97.20	96.99	69.67	88.78	81.69	79.20	88.82	93.44	75.99	70.39	58.22
El Salvador	67.25	77.62	68.87	55.26	91.06	80.74	91.83	46.87	68.35	70.50	62.54	74.08	75.38	63.12	43.56	38.99
Guatemala	61.67	68.32	71.33	45.35	76.38	71.70	76.11	49.12	70.24	72.26	62.17	80.65	63.01	55.34	28.85	34.21
Honduras	62.41	73.72	66.38	47.12	85.36	80.46	80.76	48.29	66.65	55.48	58.20	85.18	62.16	56.13	35.19	35.01
Nicaragua	64.02	75.09	72.83	44.13	87.30	78.38	80.21	54.46	77.31	53.25	71.27	89.49	44.10	57.33	39.72	35.38
Brazil	73.91	82.69	76.59	62.46	93.45	89.62	95.74	51.94	79.27	80.66	65.61	80.82	73.53	67.47	45.45	63.41
Colombia	74.00	83.31	80.09	58.59	92.67	91.85	96.46	52.28	78.86	81.96	73.82	85.72	67.02	64.05	41.42	61.89
Argentina	80.66	87.73	80.05	74.20	94.33	95.79	95.49	65.33	88.50	85.67	69.55	76.50	88.36	69.77	63.14	75.53
Chile	83.34	90.79	81.87	77.35	96.94	96.66	96.44	73.12	84.95	86.31	75.95	80.27	92.16	80.33	59.45	77.46
Uruguay	82.99	88.64	82.59	77.74	95.62	97.45	97.22	64.25	88.59	87.64	74.36	79.77	95.30	78.83	76.19	60.66

Source: Adapted from Social Progress Imperative (2020)

Additionally, as per Social Progress Imperative (2018, 2019), SPI is entirely aligned with Sustainable Development Goals (SDGs)[22], measuring 16 of 17 objectives and recording 131 of 169 sub-goals of the framework. In that sense, SPI is complementary to SDGs, avoiding the risk of focusing on only some objectives and goals. Moreover, being a *composite measure* allows for clear communication of progress concerning the full SDG agenda (See Appendix 2. Figure 3: Relationship between the Social Progress Index and the Sustainable Development Goals). Moreover, although supported by the same SPI collaborations [23], the Multidimensional Poverty Index (MPI) [24] -targeting

[22] The SDG (Sustainable Development Goals, 2015-2030), are an initiative promoted by the United Nations to continue the development agenda after the Millennium Development Goals (MDGs). There are 17 objectives and 169 goals proposed as a continuation of the MDGs including new areas such as climate change, economic inequality, innovation, sustainable consumption and peace, and justice, among other priorities. After a negotiation process on the SDGs. 193 United Nations member states approved on September 25, 2015 during a summit held in New York at a high-level plenary meeting of the General Assembly, an agenda named “Transform our world: the 2030 Agenda for Sustainable Development " which entered into force on January 1, 2016.

[23] SPI is designed to generate multi-sector partnerships to support projects at local government and private sector levels, seeking improvements in population’s wellbeing.

[24] Jointly developed by the United Nations Development Programme (UNDP) and the Oxford Poverty and Human Development Initiative (OPHI) at the University of Oxford, offers data for 101 countries, covering 76 percent of the global population. Per UNDP and OPHI (2019) it provides a comprehensive and in-depth picture of global poverty – in all its dimensions – and monitors progress towards Sustainable Development Goals (SDG) to end poverty in all its forms. As in the case of the SPI it offers a valuable complement to income-based poverty measures. The index identifies multiple deprivations at the household and individual level in health, education and standard of living. Employs micro data from household surveys, and—unlike the inequality-adjusted Human Development Index—all the comprising indicators are extracted from the same

understanding poverty determinants directly in households and individuals- narrowly pursues poverty reduction and people's well-being improvement, as it only focuses on the assessment and improvement of public policies and social programs. Hence, as per MIDES, MEF & INEC (2019), especially for emerging/transitional economies, MPI is complemented by SPI as it theoretically targets that poverty reduction leads to well-being improvements.

SPI is not critique-free. By being an objective-based measure, it is expected that it has been questioned for its incapacity to gauge subjective well-being. Additionally, it has been critiqued as being a '*composite index*' which comprises a mix of several unrelated factors. Via the examination of SPI construction, Boonlert (2017) has additionally argued the existence of solid statistical associations and related causality among its comprising variables, suggesting a lack of independence and the non-applicability of equal weights for constructing its dimensions. Questionings concerning the pondering approach have also been addressed by Norlén & Caperna (2018) and Land & Michalos (2018), who, in general terms, recommend using statistical methods to more accurately allocate weights to the structural variables which comprise a social development measure. Furthermore, measures emerging from governmental institutions have higher survival chances than the ones emerging from NGOs, somehow putting SPI in a statistically survival disadvantageous position in the short/medium term as SPI is run by an NGO (Social Progress Imperative).

Nevertheless, and even in the light of these contrasting argumentations, SPI is considered an actionable, solid, and integral tool to measure social and environmental performance, among other social development indicators (Porter *et al.*, 2013; Porter *et al.*, 2017; Fehder *et al.* 2018). Being a composite measure provides the foundations to potentially become an 'adoptable' gauging system in

---

survey. Per given household, each person is sorted as poor or non-poor depending on the weighted number of deprivations / experiences faced. Data is then aggregated into a nationwide poverty measurement. The index reflects both multidimensional deprivation incidence (headcount of the population in multidimensional poverty) and its intensity (average deprivation score experienced by poor population). It could be employed to create a comprehensive picture of populations living in poverty, besides of allowing comparisons across countries, regions and the world and within countries by ethnic group, urban or rural location, in addition to other key household and community characteristics. In 2018, the MPI was calculated for 105 developing countries (other countries due to data constraints). with a combined population of 5.7 billion (77% of the world total). About 1.3 billion people in the countries covered—23.3% of their entire population—lived in multidimensional poverty between 2006 and 2016-17.

the long run, as per the arguments provided in the previous subsection when referring to the trends followed by successful preceding measures still in production. SPI adoption worldwide is thereby suggested to be spreading instead of losing momentum, complying with the reported pattern of 'success' suggested in Land & Michalos (2018) and Barrington-Leigh & Escande (2018). As more countries and partners join the Social Progress Imperative movement, indicators refinement and data availability grow at country and industry levels (per improvements in National Statistics Agencies in countries that have adopted it or are in the process of doing so). Furthermore, as contended by Stern & Epner (2019), per every annual update and new release, the SPI methodology is reported to improve and include alternative/complementary calculation techniques to -for instance- overcome issues related to the weighing/pondering methodology. The use of geometrical averages instead of arithmetic averages has been lately used, as reported in MEF & CLACDS (2019) and Garcia (2019)

2.2 The context of FDI and Social Development in the Republic of Panama

In the following subsection, FDI figures for 2020 and 2021 are omitted, as worldwide influx disruptions caused by the COVID-19 pandemic make them not representative of this research. Panama's FDI reached $1648,8M during the first quarter of 2019, representing an 18,2% growth compared to the same quarter in 2018 and accounting for 10,1% of the entire country's GDP (MEF, 2019). Non-finance companies received investments for $1.389,9M; meanwhile, banks with general licenses[25] received $111,8M, Colon Free Trade Zone[26] (Colon FTZ)

[25] More than 120 banks from diverse countries throughout the world comprise the Panamanian International Financial.

[26] Commercial showcase established in 1948 to solve two basic needs at both the national and international levels: 1) Modernization of the economic service sector, 2) Streamline mechanism for regional commerce on a large scale. It has been in operation since then, becoming one of the pillars of the Panamanian economy. Imports (main ones from China, Singapore and the United States) and Exports (mainly to South America, Central America and the Caribbean) surpass annually $5 billion servicing a market of more than 525 million consumers. It captures services and centers for importation, storage, packaging and re-export of products from all parts of the world, especially electrical appliances, pharmaceutical products, liquors, among others. It contributes with almost 8 % of the GDP. Colon ZRF is first commercial free zone in the western hemisphere and the second in the world, after Hong Kong. Commercial activities are supported by transportation companies, 6 airports, 5 ocean ports equipped with up-to-date cargo handling facilities, spacious container terminals, a trans-isthmus railway and the Panama Canal annually handling 12,000 merchant vessels from 75 different countries. More than 20 banks participate have offices and branches located Colon ZFT.

$97,3M and banks with international licenses $49,3M. Furthermore, as per Contraloría General de la República (2019), reinvested profits increased (mostly international license banks and Colon FTZ companies), reaching $938M and accounting for 56,9% of the total FDI during this first quarter. As per MEF (2019), between 2014 and 2018, FDI totalled $23.998,2M, where finance and insurance activities, wholesale and retail trade, transportation, storage and courier, and mining and quarries exports were the highest-impact industries. The absolute difference amounted to an additional $10.085,2M compared to the previous quinquennium.

As per CEPAL (2020), in 2019, Central America attracted $11.507M, representing 7,2% of the total FDI stock allocation of the total $160.721M allocated to Latin America and the Caribbean (influxes from the USA and Europe majorly). As per CEPAL (2020), Panama also attracted the highest FDI within the Central American region, accounting for $5.981M in 2019 (+7.3% compared to 2018), representing 51% of the total FDI stock of Central America. In contrast (figures in parenthesis inform about percentual increasements/reductions compared to the previous year), Costa Rica amounted to $2.506M (-9.4%), El Salvador $662M (-19.9%), Guatemala $998M (1.0%), Honduras $947M (-31.4%) and Nicaragua $503M (-40.0%). In Chart 5, Panama depicts a clear FDI growth trend in the last years compared to the other Central American countries.

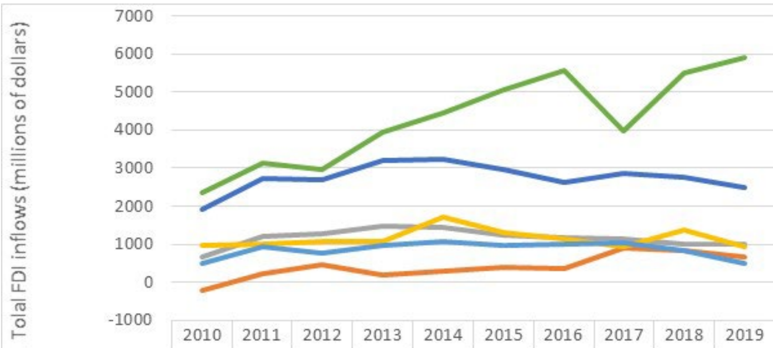
Although Panama dropped in 2019 to position 6th in Latin America concerning FDI attraction, it was the only country in the Latin American region that, between 2010 and 2018, attracted investments in a growing fashion, stepping up from position 9th to 5th[27] in FDI inflow; receiving higher amounts than Chile, one of the most outstanding markets for MNEs deciding to invest in Latin America and the Caribbean (CEPAL, 2020 pp76). As also quoted from CEPAL (2019, pp29): "*the expansion of the Panama Canal and its development as a logistic and transportation pole, in addition to a sustained strategic definition of pointing at service schemes attraction, has given impulse to FDI growth and is positioning the country as an access platform in the region.*" (See Chart 5.A.)

[27] CEPAL (2019) reports that within Latin America and the Caribbean, Panama the 5th country (4%) attracting FDI between 2017-2018, where Brazil (leader with 48%) followed by México (20%), Argentina (6%) y Colombia (6%) ranked above.

On average, FDI in Panama has represented an 8.9% figure of its nominal GDP, fluctuating within 6,56% and 12,70% values between 2010 and 2019. It is worth noting that MNEs rarely issue stock on the local market and, when they do, often issue shares without voting rights; local legal schemes allow them to regularly issue bonds and other instruments in the local securities market. Interestingly, the latter fact justifies FPI values surpassing FDI figures as a percentage of nominal GDP for a 2.41-fold factor. As depicted in Chart 5.B, FPI figures (as a percentage of nominal GDP) average a 21.5% figure during 10 years, ranging between the lowest value of 19.9% in 2019 and the highest value of 23.9% in 2010 (IMF, 2020). Furthermore, when FDI is broken down into comprising components, it is worth noting that most of the contribution to FPI is due to the effect of Long Term Debts Securities, which in general terms has represented on average a 19.1% value of the nominal GDP (2.14-fold factor) during the decade between 2010 and 2019, with its highest 21.4% value in 2015 and its lowest of 17.7% in 2019. (See Chart 5.C.)

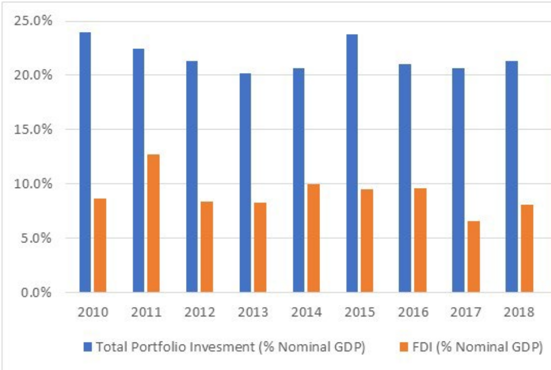
Chart 5. FDI total figures for Central American countries and FDI and FPI as a percentage for FDI in Panama (years 2010 to 2019).

A. FDI total figures for Central American countries

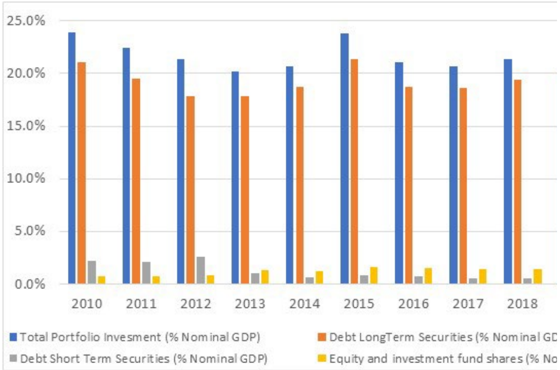


	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Costa Rica	1907	2733	2696	3205	3242	2956	2620	2856	2764	2506
El Salvador	-226	218	466	179	306	396	348	889	826	662
Guatemala	658	1219	1270	1479	1442	1231	1174	1130	994	998
Honduras	969	1014	1059	1069	1704	1317	1147	941	1380	947
Nicaragua	490	936	776	965	1077	967	989	1035	838	503
Panama	2363	3132	2980	3943	4459	5058	5585	3977	5487	5891

B. Comparison of FDI and FPI as a percentage of GDP (Panama only)



C. Main components of FPI as a percentage of GDP (Panama only)



Source: Author with data extracted from CEPAL (2020, pp90) and IMF (2020)

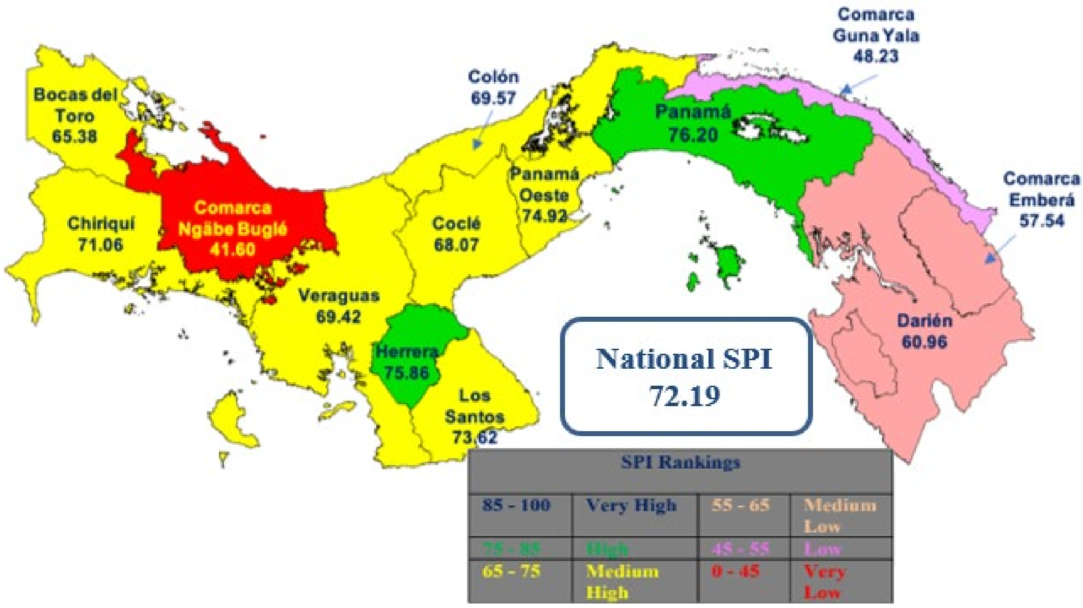
Although alternative figures of social development proxies, such as the Human Development Index, are available for Panama and its provinces, only SPI figures are used in the following exploration due to their role as the dependent proxy variable for this research. MEF & CLACDS (2019, pp12) reported that Panama launched its first 2019 SPI version, mainly structured with a gender approach (as per Garcia, 2019 with a worldwide pioneer focus) as disaggregated factors are calculated by sex at sub-national levels of provinces and indigenous regions[28]. Although SPI comprises 54 indicators (Porter *et al*., 2013; Porter *et al.*, 2017; Fehder *et al.,* 2018), in Panama, only 49 were estimated after data was sorted per SPI methodology guidelines (Stern & Epner, 2019). As reported in MEF & CLACDS (2019, pp25), out of the 49 estimated indicators[29], 35 stemmed

[28] SPI is already being used at subnational levels around the world. In Brazil, SPI is used in 776 municipalities of the Brazilian Amazon, to generate policies that increase the standard of living of its inhabitants, but without destroying the Amazonian forest ecosystem. For instance, in a small rural community, called Carauari, two multinational companies, used the SPI to generate, together with the community's population, a business responsibility program according to the real people needs. In Paraguay, the national government has decided to use the SPI as the official performance measure for the national development plan until 2030, both to identify an agenda of priorities, and also to measure the efficiency and impact of the next social policies in the coming 15 years. European Union is using SPI at the regional level as a tool to allocate and manage the resources of the Regional Cohesion Fund and improve the lives of millions of Europeans. In the United States, the state of California is adopting the SPI for its most important urban centers, encouraging and designing specific social interventions that help improve the standard of living in cities like San José.

[29] 33 exerted from the Multipurpose Survey (march 2018) from INEC: Instituto Nacional de Estadistica y Censo (National Institute from Statistics and Census), 2) 10 exerted from the Estadísticas Vitales e Indicadores Sociales del INEC (Vital Statistics and Social Indicators from the INEC), 3) 3 exerted from the MEDUCA: Ministerio de Educación (Education Ministry), 4) 1 exerted from the Tribunal Electoral (Electoral Tribunal), 5) 1 exerted from Centro de Estadística del Ministerio Público (Statistical Center of the Public Ministry), and 6) 1 exerted from the MINSA: Ministerio de Salud (Health Ministry).

from 2018 sources, 12 from 2017 and only 2 were obtained from data older than 2017. For Panama's SPI, the factors totalling method -simple arithmetic mean as per Stern & Epner (2019)- was replaced by geometric mean[30] as suggested in Norlén & Caperna (2018), seeking to reduce biases per dealing with extreme values (higher performance factors can compensate for lower performance). Thus, more balanced measurements are obtained, primarily due to the substantial gaps in the SPI comprising factors between the provinces and indigenous regions. Chart 6 depicts SPI figures for 10 provinces and 3 indigenous regions.

Chart 6. Panama's SPI per province and indigenous region (Comarca)



Source: Extracted from MEF & CLACDS (2019, pp43)

Two provinces score the highest, Panama and Herrera, with 76.20 and 75.86 points, respectively. The worst performance is shown by Guna Yala and Ngäble Buglé indigenous regions, with a low: 48.23 and very low: 41.60 scores, respectively. As shown in Table 3, Panama's Basic Human Needs dimension is considered 'high' as the country scored 78.91 points, whereas the province of Herrera exhibits the highest average score: 87.47 (very high). In the Foundations of Wellbeing dimension, the country's average score decreases to 75.17, and sort it does the highest score of 81.34 pointed out by the Province of Panama.

[30] The statistical properties of the geometric mean consider all the values of the distribution and so it is less sensitive than the arithmetic mean to the extreme values.

However, the Opportunities dimension shows concerning figures, as the highest score is nearly 68.47, reached by the Panama province.

Table 3. SPI scores per dimension and province/indigenous region (Comarca).

Provinces and indigenous regions.	Basic Human Needs	Fundamentals of Well-being	Opportunities	SPI
Total	78.91	75.17	63.42	72.19
Bocas del Toro	74.62	68.03	55.05	65.38
Coclé	78.60	65.14	61.60	68.07
Colón	73.80	76.74	59.46	69.57
Chiriquí	79.53	73.57	61.33	71.06
Darién	70.98	65.32	48.85	60.96
Herrera	87.47	75.66	65.97	75.86
Los Santos	87.04	70.53	65.00	73.62
Panamá	79.44	81.34	68.47	76.20
Panamá Oeste	83.46	78.37	64.30	74.92
Veraguas	76.94	67.27	64.64	69.42
Comarca Guna Yala	55.57	46.57	43.34	48.23
Comarca Emberá	74.04	55.34	46.50	57.54
Comarca Ngäbe Buglé	52.04	39.40	35.11	41.60

Source: MEF & CLACDS (2019, pp47)

Disaggregating the 3 most populated and more economically dynamic provinces in the Republic of Panama (highlighted in dotted rectangles in Table 3), scores are as follows[31]: Panama Metro (79,44; 81,34; 68.47; 76,20), Panama West (83,46; 78,37; 64,30; 74,92) and Colon (73,80; 76,74; 59,46; 69,57). As per the shown figures, the 3 provinces exhibit 'high' social development scores regarding the Basic Human Needs and Foundations of Well-being dimensions. Unfortunately, concerning the Opportunities dimension, scores are considered 'medium low' for the 3 provinces. Nonetheless, even when Basic Human Needs and Foundations of Well-being are suggested to be 'high', general challenges include universal access to electricity, internet, improved sanitation and access and availability of water and health services, and facing violence and corruption issues. Additionally, concerning the score of Opportunities, findings suggest that provinces face challenges and must focus resources on factors that can generate conditions for individuals to develop their capacities fully. Hence, as vehemently stated in the Introduction section, although the Republic of Panama has been one of the fastest-growing economies worldwide (CEPAL, 2020), it appears that it has

[31] Figures in parenthesis are respectively Basic Human Needs, Foundations of Wellbeing, Opportunities and total SPI scores.

failed to translate economic success into social development for its society, mainly in rural areas and to a greater extent in indigenous regions (MEF & CLACDS, 2019, pp12). The MPI figures show significant differences between income levels and fundamental aspects such as education, health[32] and housing in urban, rural, and indigenous regions[33].

2.3 Review of contemporary empirical studies directly linking FDI - Social Development

Shedding some light on the association between FDI and social development primarily requires searching the welfare economics literature strand for a framework -*theoretical* in nature- linking both dimensions directly, which could also be explanatory of the *reverse causal association and related path dependencies.* Nevertheless, the literature perusal mostly rendered an account of *empirical* studies instead. Furthermore, although those empirical studies undoubtedly enhanced the understanding of the link between the two dimensions, they majorly employed economic growth as an intermediate variable, leaving, in general terms, a void for this direct association sought. As follows, an overview of those empirical research works is provided. Subsequently, a summary of research studies chosen for their high relevance to link FDI and social development proxies specifically is provided: a) literature review sections and b) quantitive works.

2.3.1 Overview of the association between both dimensions

Research generally concentrates on the positive effects of FDI on social development (Arcelus *et al.*, 2005; Lehnert *et al.*, 2013; Reiter & Steensma, 2010;

[32] Panama, with a GDP PPP similar to Chile and Uruguay, lags behind these countries in social performance achievements, such as education and health. Economic development is not efficiently promoting investment in education (number of children and youth in secondary education and improve access to advanced education).

[33] Investments to energize the economy must also be made in rural and indigenous regions in order to achieve growth and inclusive development. Thus, SPI becomes paramount tool to generate a multisectoral roadmap that allows focusing resources, coordinating strategies and aligning messages around the priorities indicated by the index. Hence, alliances and innovations that accelerate economic growth can be articulated; in the meantime, that instruments that ensure economic prosperity is converted efficiently, sustainably and effectively into social performance are created.

Stiglitz, 2006; Sharma & Gani, 2004;), overlooking its potential negative side. Additionally, some of these research works also attempted to understand better the relevant mediators and moderators in the association of those two dimensions (Lehnert *et al*., 2013; Reiter & Steensma, 2010).

FDI inflows are reported to potentiate boosting economic growth and income in host nations via 1) Higher revenue amounts received by national and local governments, 2) MNE's technological and knowledge spillovers, and 3) Higher employment rate and income. In an aggregated fashion, these growth drivers increase host nations' competitiveness levels and social development (Ranis *et al.*, 2000; Borensztein *et al.*, 1998). This first potential impact of FDI pertains to tax collection revenues increase from MNEs, allowing host nations' national and local governments to augment public spending. Hence, resources become available for allocation to local and national social development-related projects: social infrastructure focused on education, health, basic needs and unemployment support (Ranis *et al.*, 2000). The second potential benefit focuses on how technology and knowledge transfer spillovers created by FDI may raise social development levels. MNEs with ample subsidiaries networks worldwide frequently have a range of international business areas as part of their company-specific advantages scheme: corporate strategy, innovation, technology and other applied managerial and technological practices. Many of those practices may induce productive spillovers in local companies creating efficiency, technology and knowledge enhancement effects (Blomström & Kokko, 1998; Liu, 2008; Kemeny, 2010). Those technological and knowledge spillovers may also potentiate economic growth and contribute to improvements in access to healthcare and education (Borensztein *et al.*, 1998), which in turn induce social development improvements for the host country's society (Ranis *et al.*, 2000). The third impact relates to FDI's potential to raise workers' demand by expanding workforce participation in host nations (Feenstra & Hanson, 1997). Higher labour demand, in turn, derives into higher wages for workers. Even when workers could potentially allocate those wages to a range of different products and services, much of a higher purchasing power would indeed be channelled to social development-related factors such as health and education (Ranis *et al.*, 2000; Bloom & Canning, 2000) as workers are more inclined to spend more significant amounts in improving their living standards. In this sense, higher income is also positively related to a higher number of years of education and a higher average education threshold for workers and their families (Brückner & Gradstein, 2013). Thereby, workers in a host nation are better positioned to climb to higher levels of skilled jobs or even become entrepreneurs by launching their own companies (Spender, 2013).

Nevertheless, although FDI may induce positive impacts, preceding research suggests that benefits may not always be evenly distributed in host nations. Some members of society might benefit more than others (Figini & Gorg, 2011). Although MNEs may require workers of all sorts, excessive demand for high-skilled workers (advanced technical and/or managerial capabilities) could potentially cause them to be paid disproportionately more than low-skilled or unskilled workers. For instance, high-skilled workers and highly educated professionals may become scarce resources and take the most benefits out of FDI inflows. Hence, the skilled–unskilled wage gap may potentially widen, therefore deepening income inequality (Chen *et al.*, 2011; Herzer *et al.*, 2014; Lee & Wie, 2015), which in turn is suggested to create job insecurity (Scheve & Slaughter, 2004; Bachmann *et al.*, 2014; Dill & Jirjahn, 2016) and related issues: 1) increase volatility of local labour markets, 2) foster a job-hopping environment, and 3) rise trend in turnovers rates. The rationale is that MNEs' presence in host nations is correlated to higher labour demand elasticities (Fabbri *et al.,* 2003). If the supply of local skilled or unskilled workers remains stable, but wages rise, the host nation may lose its competitive advantage against other host nations. MNEs may decide to move operations or production to other host nations as a secondary effect of this wage volatility, creating a job insecurity environment for the host nation workers (Bachmann et al., 2014; Dill & Jirjahn, 2016; Scheve & Slaughter, 2004). Volatility in labour markets usually reflects on higher job turnover rates amongst MNEs (Fabbri *et al.*, 2003), on higher substitution of irregular jobs comparatively to regular ones (Kim & Lee, 2015) and additionally on drops in productivity rates (Aitken & Harrison, 1999). In this same line of thought, welfare economics scholars have traditionally and often raised concerns about this income inequality issue (Lee & Wie, 2015; Chen *et al*., 2011; Herzer *et al*., 2014) and its close relation to job insecurity since both factors are paramount in what social development pertains. For instance, as mentioned earlier, concerning income inequality, better-paid workers have better access to healthcare and education, while those with lower wages are more constrained to access healthcare (Wilkinson & Pickett, 2006) and education services (Mayer, 2000; OECD, 2014b). The gaps between low-wage and high-wage workers cause variations in their children's access to education, as high-wage earners have a higher capacity to invest in it (Haveman & Smeeding, 2006). Additionally, income inequality seems to negatively impact the educational results of low-wage workers' children and the rate of higher education degree attainment (Haveman & Smeeding, 2006). Job insecurity, in turn, has similar impacts on social development. Workers facing job insecurity usually experience significantly minor psychiatric disorders, anxiety and high-stress levels (Rugulies *et al*., 2008), resulting in poor well-being and life satisfaction (Silla *et al.*, 2009). Additionally, the association between job insecurity and education is suggested as negative, as parents losing their jobs during their children's high school years appear to have a significant detrimental impact on subsequent higher education enrolment (Coelli, 2011). Job insecurity may also lead to poorer mental health, lower teenage academic performance and class attendance failing, particularly for low-income families (Ananat *et al*., 2017).

Additionally, as per the preceding works of Haans et al. (2016), Lind & Mehlum (2010), Baiashvili & Gattini (2020), Zhang *et al.* (2010) and Orbes *et al.* (2019), it appears reasonable to understand social development negative impacts as a function that increases at an accelerating rate per the influence of FDI. At higher FDI inflow levels, competition amongst MNEs increases within the host nation, pressuring labour markets -especially- for high-skilled workers. Hence, income inequality for low-skilled workers is bound to increase as income rises for higher-skilled workers. Higher competition between MNEs in host nations also increases job insecurity, raising the risks of job substitution/relocation as MNEs may consider moving to other locations as a direct response to rising wages. The negative impacts on social development above exposed may eventually strengthen by a higher multiplying factor when FDI inflow levels rise within a host nation. Hence, FDI's negative impacts on social performance increase at a rate moving along the FDI inflow rate.

As follows, a majorly dating from the past two decades, a summary of an in-depth analysis of the most relevant pieces of research, linking FDI and social development proxies in general and then funnelling into FDI and SPI associations in particular, is provided. Out of the plethora of research studies reviewed, 7 Literature Review works, and Literature Review sections of specific quantitative studies were considered relevant for inclusion in this subsection. Additionally, due to its quantitative nature, which targets identifying a rigorous and statistically sound conceptual/structural framework, analysis of methodological findings, conclusions and further research sections of 8 relevant contemporary quantitative works are also provided. Table 4 summarises the research works to be explored.

Table 4. Summary of research works explored directly exploring the association between FDI and social development.

Summary of analyses of Literature Review works and/or Literature Review Sections in given papers						
Research study	**Type of Study**	**Research focus summary**	**Proposes a theoretical model**	**Social performance variables associated with FDI?**	**Statistical rigour?**	**Is reverse causality tested?**
Dunning (1977)	Qualitative study	Although dated, its OLI Model is considered seminal in the FDI research. However, its factors are unrelated to social performance	No	No	No	No
Faeth (2009)	Literature review study	Reports 8 theoretical models/theories. Nonetheless, factors are unrelated to social performance	Yes	No	No	No
Idrees & Bakar (2019)	Qualitative Study	Explores the relationship of FDI and HDI factors in Pakistan.	No	Yes (HDI)	No	No
Gökmenoğlu *et al.* (2018)	Quantitative study	Explores the works of Arcelus, Sharma, & Srinivasan (2005); Srinivasan (2005); Gohoun & Soumare (2012) and Osenwengie & Sede (2013) linking FDI and HDI as explanatory factors	No	Yes (HDI)	No	No
Orbes *et al.* (2019)	Quantitative Study	Analyses the works of Anand & Sen (2000); Akhter (2004); Stiglitz (2006); Reiter & Steensma (2010) and Lehnert, Benmamoun, & Zhao (2013), which have explored the FDI and HDI relationships	No	Yes (HDI)	No	Relatively
Kolstad & Tøndel (2002)	Quantitative Study	13 works are explored linking FDI and social performance proxies. Only 2 out of the 13 studies examined employed social performance variables.	No	Relatively (2 out of 13 studies)	No	No
Tocar (2018)	Literature review study	It provides an exhaustive, up-to-date account of factors related to FDI researched in 32 preceding studies. Nonetheless, it does not directly offer quantitative findings regarding FDI and social performance associations and/or theoretical models. Several hypotheses - encouraged to further extend the knowledge in welfare economics (4 are directly related to SPI factors)	No	Relatively Many factors identified are intrinsically SPI related, while others are social performance proxies.	No	No

Summary of analyses of Methodology, Findings, Conclusions and Further Research Sections						
Research study	**Type of Study**	**Research focus summary**	**Proposes a theoretical model**	**Social performance variables associated with FDI?**	**Elaborated Statistical Approach?**	**Is reverse causality tested?**
Larrain *et al.* (2000)	Working paper	A quantitative time-series study researching FDI and the social nature spillovers induced by economic growth factors; in the specific case of Intel Company in Costa Rica (Central America)	No	No	No	No
Kolstad & Tøndel (2002)	Quantitative Study	Only researched one impact direction of FDI explained via 14 social performance proxies as regressors and 3 control variables. It uses multivariate regressions on longitudinal data. The authors acknowledged that data availability and limited variables constrain findings, encouraging further improvement of current models and their association/causality explanatory power.	No	Yes (HDI)	No	No
Sharma & Gani (2004)	Quantitative Study	Restrictively explored the directionality of the relationships through multivariate regressions with only 4 social performance proxies using the HDI and a low number of data points employing cross-sectional data.	No	Yes (HDI)	No	No
Feriyanto (2016)	Quantitative Study	Employs panel data (2006 to 2013) for 33 provinces in Indonesia. Analyses partial and simultaneous effects HDI caused by: a) Number of Working People (Employment), b) Economic Growth Rate and c) Domestic Investment / FDI. Findings comply with the characteristics of classic economic factor-based studies.	No	Yes (HDI)	Relatively	No
Gökmenoğlu *et al.* (2018)	Quantitative Study	Employs panel data for more than 40 years concentrating on Nigerian figures, linking FDI and HDI using several robust statistical techniques to test reverse causality.	No	Yes (HDI)	Yes	Relatively
Dechprom & Jermsittiparsert (2018)	Practitioner Study Quantitative	Explores one direction of a bulk SPI figure intended to be explained by 6 other variables (including FDI) using a multivariate regression on cross-sectional data.	No	Yes (SPI)	No	No
Deloitte (2014)	Practitioner Report Quantitative	Explores 54 SPI factors associated with FDI PPP and vice-versa (directionality) via correlations with cross-sectional data. Although no evidence of multivariate regression of affine methodologies is provided, the provision of R^2 figures suggests that somehow statistical methods were used.	Yes	Yes (SPI)	No	No
Orbes *et al.* (2019)	Quantitative Study	Using panel data from 139 countries and covering 15 years, explores directionality according to an inverted U-shaped association pattern. The 3 comprising HDI variables are employed to explain the unidirectional association with the net effect of FDI (benefits minus its costs), moderated by institutional quality variables (Business Sophistication Index and the Transparency Index).	Yes	Yes (HDI)	Yes	No

Source: the author

2.3.2 Summary of relevant literature reviews sections´ exploration

In general terms, the FDI phenomena associated with other factors have been academically studied by descriptive analysis until the 1960s and through econometrics since the early 70s. The literature survey work of Faeth (2009) accounts for 9 classical conceptual/structural frameworks concerning FDI: 1) Early studies of determinants of FDI; 2) Determinants of FDI based on the neoclassical trade theory; 3) Ownership advantages; 4) Aggregate variables; 5) Ownership, location and internalisation advantage (OLI-Model) framework; 6) Horizontal and vertical FDI models; 7) Knowledge capital model; 8) Diversified FDI/risk diversification models; 9) Policy variables models. Out of those 9 conceptual/structural frameworks, the ownership, location and internalisation (OLI-Model) proposed by Dunning (1977, 1993) has been traditionally used to explain FDI and its constituent factors[34]. The OLI eclectic paradigm is a three-tiered assessment framework[35] proposed to MNEs to follow when determining the benefits of pursuing FDI: 1) Ownership advantage (unique of production/management mode, patents, or trademarks/brand names) to be competitive in the host country. 2) Location advantage (less expensive supplies in home countries and/or a large domestic market) as a decision to invest in one place instead of another. 3) Internalization advantage, where owning facilities in a host country becomes a better choice than license agreements with a firm already based and operating in the host country. In addition, a fourth advantage has been frequently mentioned regarding control over technology or reduced transaction costs. Unfortunately, the OLI model does not provide a solid conceptual/structural framework associating FDI with the social development dimension, as is the case of the remaining 8 frameworks reported in Faeth (2009).

The literature review of Kolstad & Tøndel (2002) reports 13 relevant, diverse research papers whose findings are conflicting due to methodological differences, data and explanatory factors. Only 2 out of 13 studies analysed

---

[34] Classically and under the assumptions of market imperfections, as per Dunning & Pitelis (2008) when quoting Hymher (1960), 3 determinants to FDI have been proposed since the 1960´s: 1) Firm-specific advantages: once domestic investment is exhausted, companies could exploit its advantages to gain market power and competitive advantages. Several studies have attempted to explain how companies could monetize these advantages in the form of licenses. 2) Conflicts' removal: conflict arises when companies are already operating in foreign market or looking to expand operations within the same market. A proposed solution has been collusion, which means sharing the market with rivals or attempting to acquire direct production control (which further increases market imperfections). 3) Propensity to formulate an internationalization strategy to mitigate risk: companies' ability to formulate such a strategy depend on how well they manage 3 decision-making levels: a) Day-to-day supervision, b) Management decision coordination and c) Long-term strategy planning/decision making. Additionally, and in accordance with Wei (2000), studies suggest that cultural distance favors FDI as corroborated in significant flows between countries sharing a common language.

[35] After answering these three questions decision makers should be able to at least exclude some entry-mode strategies. If the MNE finds its assessments to be positive, engaging in FDI and control production activities may appear to be a good option. Additional strategic analyses may be required when doubt emerges between acquisition of an existing foreign company or partnering with a local company via a strategic alliance.

(aggregated econometric works based on empirical evidence) refer to social development factors influencing FDI in emerging/transitional economies: human capital and labour costs. Unfortunately, they do not exhibit any statistical explanatory power about FDI flows and their factors and/or causality directions. Therefore, no robust conceptual/structural framework could be identified in its literature review section. Furthermore, as acknowledged by the authors, data availability and a limited set of variables constrained their findings, encouraging further research to be carried out to improve current models and their association/causality explanatory power.

Out of the existing related literature, 3 relevant papers were found researching FDI and HDI. The papers they explored in their literature reviews are mentioned as follows: a) The qualitative work of Idrees & Bakar (2019) in Pakistan reviews several pieces of research intending to find an association between health & education -as constituent factors of the HDI- and welfare gains induced by FDI. b) The quantitative study of Gökmenoğlu *et al.* (2018) reports on the works of Arcelus, Sharma, & Srinivasan (2005); Srinivasan (2005); Gohoun & Soumare (2012) and Osenwengie & Sede (2013) and c) The quantitative research of Orbes *et al.* (2019) informs about the previous works of Anand & Sen (2000); Akhter (2004); Stiglitz (2006); Reiter & Steensma (2010) and Lehnert, Benmamoun, & Zhao (2013). Unfortunately, neither of the 3 papers proposes or provides a robust conceptual/structural framework explanatory of the direct association between FDI and social development.

Tocar (2018) exhaustively reviews 32 pieces of literature linking FDI and 76 different factors (comprising 11 categories). It informs neither positive, negative, non-significant or other effects of several factors[36] on FDI. Of those 76 factors, 58 are claimed to be non-economic factors (10 categories). This work is valuable because it identifies several up-to-date hypotheses to further extend the knowledge in welfare economics if researched. Out of the 18 proposed hypotheses, 14 are contented to be non-economic and intrinsically social development related (See Appendix 3. Summary of hypotheses to be researched regarding FDI and different categories of factors. SPI-affine factors are identified:

[36] Generally, those studies do not propose a large set of non-economic is proposed as the number is usually constrained, among which some appear to predominate meanwhile others are avoided.

italicised and bolded). Unfortunately, no robust conceptual/structural framework explaining causal linkages with statistical robustness stems from this work.

2.3.3 Summary of relevant quantitative research works

The overview of the Methodology, Findings, Conclusions and Further Research sections in the quantitative pieces of literature is found as follows. The working paper of Larrain *et al.* (2000), focused on the case of Intel Company spillover effects in Costa Rica, was the only study found in the literature review for a Central American country in which research somehow focuses on the 'social spillovers' induced by economic growth factors triggered by FDI. To the best of my knowledge, no specific welfare economics studies were found for Panama.

The econometric work of Kolstad & Tøndel (2002), although one may consider it dated, is suggested an early 'educated' attempt to relate FDI and social development proxies in the field of welfare economics, almost a decade before the 'worldwide wake-up call' of the Stiglitz Commission Report (Stiglitz, 2009) to extend the knowledge on the well-being and societal welfare topics. It is one of the few quantitative pieces of research found in the literature associating FDI and proxy variables for social development. The study sets FDI PPP[37] as a dependent variable, employs 3 control factors and 14 standard social development indicators and proxies composed into 3 categories: 1) Distributive outcomes:[38] illiteracy, socio-economic conditions and corruption, 2) Rights and liberties:[39] political rights, civil liberties, democratic accountability, religious tensions, 3) Security[40]: government stability, ethnic tensions, internal conflict,

---

[37] In accordance to World Bank (2008), FDI ppp "*does not suffer from the high volatility that characterizes FDI flow measure, and also accounts for the size and FDI capacity of the host country*".

[38]Address the extent to which economic/social progress improves the lives of societal members, including income distribution and reduction in absolute poverty, public services access to health care and/or education. Corruption is relevant since it entails the less resourceful potential discrimination which is opposite of inclusion.

[39] Through which individuals and social entities expand their opportunities pursuing their objectives/goals. Employs democracy/democratic accountability as proxies for standard indices of political rights/civil liberties. Areligious tensions index is also used as an imperfect proxy of the extent to which democratic rights can be asserted and exercised. UNDP's Human Development Gender Empowerment Index may be used to further expand this matter.

[40] Enhancement of social stability (measure the extent to which members of society are allowed to plan ahead, pursuing their goals minimum disruptions) and human security (integrity of society

external conflict. It employs panel data (from 1989-2000) from 61 developing (low- and middle-income) countries. Through correlations and multiple regressions, findings show positive, negative and non-significant relationships, where long-term political stability and reduced internal conflict and ethnic tensions are the most substantial social development factors. As quoted from Kolstad & Tøndel (2002, pp23), findings "*confirm the theoretical presupposition that social development issues play a relatively marginal role in influencing investment climates and investment decisions*". However, no robust conceptual/structural framework derives from this study as it only explores social development impacts on FDI without researching causality, as clearly stated in their work.

The work of Sharma & Gani (2004), although it may also be suggested as a dated piece of research, is also a considerable early attempt to link FDI and social development proxies. Its relevancy revolves around exploring HDI, which, as per Greve (2017), is the most frequent social development variable currently employed worldwide in welfare economics studies. HDI and the other 4 variables (economic growth, unproductive government expenditure, misery, conflicts) are used as social development proxies to explain FDI (as GDP percentage) as an independent variable. Conversely, FDI is explained by HDI and the other 4 variables. Variables related to political, social, and institutional factors are ignored. 90 observations for 15 low-income countries (GNP PPP of $785 or less according to World Bank's classification) and 114 observations for 19 lower and higher middle-income countries (GNP PPP between $785 and $9,655) are researched based on published cross-sectional data available from 1975 to 1999. R^2 figures for HDI as the dependent variable are 0.87 and 0.79 for middle-income and low-income, respectively, which are considered highly satisfactory figures in cross-sectional data studies. However, when FDI is employed as a dependent variable, R^2 figures are 0.22 (low-income) and 0.09 (middle-income). Although weak, empirical results confirm that FDI positively affects social development in low and middle-income countries' categories. For low-income countries, the

---

members and their property). Includes direct measures of government stability, bureaucracy's quality/independence of the, military role in politics, internal and external conflicts/ethnic tensions incidences. Workers' situation is indirectly perceived by the World Bank as a determinant of social stability, and so there is a focus on labor standards, job security and social security. Crime incidence and conversely the rule of law are considered key elements of human security.

other influence direction (social development exerts a significant positive effect on FDI) is also valid. Even when directionality is researched, reverse causality is not explored, as multivariate regressions and correlations support the study. Therefore, not a robust conceptual/structural framework stems from this research.

The quantitative work of Feriyanto (2016), based on panel data from 2006 to 2013 for 33 provinces of Indonesia, analyses the partial and simultaneous effects on the Human Development Index (HDI) induced by: a) the Number of Working People (Employment), b) Economic Growth Rate and c) Domestic Investment / FDI. As per their results, findings appear to comply with the results of a plethora of traditional economic factor-based studies with a specific focus on Indonesia: a) employment variables have a positive and significant impact on HDI, b) Economic Growth Rate does not affect HDI, and c) Domestic Investment / FDI partially have a positive and significant effect on HDI. The 3 variables have a simultaneously significant effect on the HDI. Nonetheless, although based on a Pooled OLS (POLS) Regression Analysis approach (from a Fixed and Random Effect perspective) suited for longitudinal studies, no path dependencies and/or reverse causal explanations are provided.

The study from Gökmenoğlu *et al.* (2018) employs FDI inflow figures (as a percentage of GDP) and HDI (per capita) comprising variables from 1972–2013 (Collected from World Bank development indicators, 2015). Three main equations as dependent variables are proposed: 1) Life expectancy at birth: $lnLEt$ = $\beta 0$ + $\beta 1 lnFDIt$ + εt, 2) School enrollment: $lnSEt$ = $\beta 0$ + $\beta 1 lnFDIt$ + εt and 3) Gross national income per capita: $lnGNIt$ = $\beta 0$ + $\beta 1 lnFDIt$ + εt, where FDI is the independent variable. For comparison purposes, logarithmic forms are used pursuing to estimate elasticity. The research sheds some light on the relationships between school enrollment (expecting a positive relationship) and life expectancy (expecting a negligent effect) because of the absence of empirical studies. The Augmented Dickey-Fuller (ADF)[41] and the Phillips-Perron (PP)[42] Unit Root[43] test are employed to confirm the existence of variables' integration. Additionally, the Johansen Cointegration Test[44] is performed to investigate long-run equilibrium relationships among variables based on the assumption that they are in the same order of integration, provided they are not stationary at their level forms. Long-Run Coefficients are estimated through DOLS (Dynamic Ordinary Least Squares)[45], a superior technique for small samples compared to alternative methods based on Monte Carlo simulations. The Toda-Yamamoto causality test[46] is used in pursuing to estimate the existence and direction of causality between variables. DOLS estimates suggest FDI has a positive, inelastic, and statistically significant impact on school enrollment (a 1% increase in FDI causes a 0.829% change in school enrollment in the long run) and GNI (a 1% increase in FDI leads to an 0.851% increase in GNI). Thus, FDI is suggested to contribute to educational development and income growth. Contrarily, FDI is

---

[41] It tests the null hypothesis that a unit root is present in a time series sample, eliminating the possibility of incorrectly rejecting a correct null hypothesis. The alternative hypothesis is usually stationarity or trend-stationarity.

[42] Unit root test to prove the null hypothesis that a time series is integrated of order. It builds on the Dickey–Fuller test and in a similar way addresses the issue that the process generating data may have a higher order of autocorrelation than is admitted in the test equation is endogenous and thus invalidating the Dickey–Fuller test. The test is robust with respect to unspecified autocorrelation and heteroscedasticity. It computes that residual variance is robust to autocorrelation.

[43] Feature of some stochastic processes that could potentially cause problems in statistical inference for time series models. Linear stochastic processes are said to have unit root, when 1 is a root of the process' characteristic equation which is non-stationary, although however it does not always have a trend. Roots of the characteristic equation are inside the unit circle (a modulus -absolute value- is less than 1) so that, process' first difference is stationary. Contrarily the process will have to be differenced several times to become stationary. Hence, unit root processes are called difference stationary.

[44] Test the cointegration of several time series. Cointegration existence among variables eliminates the possibility of spurious correlation, so that before estimating long-run coefficients, cointegration existence among variables should be identified. More than one cointegrating relationship is allowed to be tested, so that is applicable than the Engle–Granger test based on the Dickey–Fuller or Augmented Dickey–Fuller test. It is one of the most reliable techniques when compared to alternative ones for small samples. The null hypothesis test for the number of cointegrating vectors to be less than or equal to zero, one and two, respectively.

[45] The Stock and Watson Dynamic OLS (DOLS) provides evidence based on Monte Carlo simulations as a superior estimator for small samples compared to a number of alternative estimators. It eliminates internal and autocorrelation issues (dependent variable should be stationary at its first difference regardless of the levels of integration of the independent variables).

[46] This technique requires the calculation of an augmented VAR in order to ensure asymptotic distribution of Wald statistics. It employs a Modified Wald stat (MWALD) to estimate the causal relationship among series. VAR (k + dmax) is calculated where k is the optimal order of VAR model and dmax is the maximum order of integration. One of the major advantages of the test is that it could be applied regardless of the variables' integration order and model' cointegration properties. The optimal endogenous lag length must first be determined for which the Hacker and Hatemi-J information criteria could be used. Then, the level of maximum integration order of variables is calculated.

reported to have an inelastic and negative statistically significant impact on life expectancy at birth in the long run (a 1% increase in FDI decreases life expectancy at birth -a proxy for public health- by 0.059%) so that increases competitiveness is suggested to lead to economic insecurity and work stress which in turn causes public health deterioration. In addition, findings point to a bidirectional causal relationship between FDI and life expectancy at birth exists, used as a proxy of public health. FDI is suggested to cause public health deterioration as an induced effect of FDI increasing competitiveness and insecurity, negatively impacting public health, and causing FDI inflows to drop. By being public health a human capital component, changes in it cause productivity increases, ultimately attracting FDI. Additionally, FDI changes unidirectionally lead to Gross National Income per capita changes, suggesting that Gross National Income is FDI-driven causality-wise. Results were reported based on the Toda-Yamamoto Test; causality directions could not be thoroughly tested for all variables employed. This work of Gökmenoğlu *et al.* (2018) ends by stating that the explanatory effects of FDI on HDI are complicated, as the pros and cons of FDI should be considered if policymakers seek optimum results on human development. Remedies channelled to protect public health (negatively impacted due to FDI-induced competitiveness and insecurity) are encouraged, for example, by government spending on social healthcare systems and incrementing workers' compensation to reduce economic insecurity. The paper recognizes that even when the study is centred on Nigerian data, findings could guide policymakers in other developing countries to improve FDI attraction policies, avoiding possible negative consequences.

The recent empirical work of Orbes *et al.* (2019) explores cross-country variations (139 countries) in HDI attributable to differences in FDI based on unbalanced country-year panel data (from 2000–2014). The study examines the ‘Net’ effect (benefits and the related costs) of FDI over HDI and its comprising components (education, health, and income per capita) used as a dependent variable. As independent variables, the study employs FDI figures from UNCTAD 2016 and institutional quality measures (business sophistication and transparency index) from the World Economic Forum 2016 and the World Bank’s World Development Indicators 2016. All independent variables are lagged by one year, pursuing to reduce potential endogeneity and improve testing of the causal relationships. It additionally uses other control variables such as foreign aid, trade openness, government savings, government expenditure and GDP obtained from the International Monetary Fund 2016 figures and World Development Indicators. The study is based on the OLS-FE, accounting for time-invariant factors displaying systematic variations and unobserved heterogeneity across countries. Robustness checks -performed by testing the relationships of FDI and each HDI component and omitting multicollinear control variables- provide evidence for an inverted U-shape effect. Although restrictively based on the few indicators that comprised HDI, this empirical analysis primarily finds a positive and significant effect of FDI on HDI and an additional negative and significant squared effect.

On the one hand, also according to Orbes *et al.* (2019), countries with low business sophistication exhibit a steeper inverted U-shaped curve between FDI and human development, while those with high business sophistication show a flatter curve. On the other hand, low-transparency countries exhibit a steeper inverted U-shaped relationship between FDI and human development and vice versa for countries with high transparency. Findings by Orbes *et al.* (2019) suggest that FDI can boost social development in host countries. Nonetheless, policymakers are urged to be cautious when approaching FDI issues, alert to monitoring the benefits and social development-related costs -such as inequality- stemming from large amounts of FDI inflows since expecting FDI to deliver positive gains continually is not realistic. Although this research explores directionally only in one way (HDI variables being impacted by FDI), engaging in proving causality with statistical rigour is not compatible with the inverted U-shape found, as per a series of arguments explained in their work. Hence, the model cannot prove a reverse causality effect even when their work proposes a statistically stringent empirical framework that adds a new perspective to welfare economics.

The working paper of Dechprom & Jermsittiparsert (2018), stemming from the practitioner-research side, directly proposes SPI as the dependent variable to be explained by the following independent variables: FDI (pos, sig)[47], remittances (pos, sig.), governmental health expenditure (pos, sig), foreign aid (neg, insig.), international trade (pos, insig.), and countries' population (neg, insig.). Results from multivariate regressions employing a 5% confidence level exhibit an adjusted R^2 value of 0.569, meaning that 57% of variation on SPI is explained by the variation of variables employed. The regression model is tested for normality of its residuals, heteroskedasticity, model specification and serial correlation using CUSUM[48] and CUSUMSQ[49] under a 5% significance level. Results showed statistics along critical boundaries so that the null hypothesis of regression correctness cannot be rejected, statistically validating the model. SPI variable is treated as an aggregated 'bulk' figure for 120 countries, preventing the study from further examining the effects of their comprising factors on SPI. Additionally, results on directionality or, furthermore, on causality are not provided as the study is based on cross-sectional data. Therefore, no robust conceptual/structural framework derives from this study.

Although also deriving from a practitioner environment, the work of Deloitte (2014) may prove itself useful as an 'academic teaser' to further extend scholarly research in welfare economics. This study -directly linking FDI and SPI- may be considered an up-to-date reference in some research centres[50] partnering with the Social Progress Imperative NGO (See Appendix 2. Figure 2) in charge of measuring, monitoring, and further strengthening the SPI methodology and data availability (Garcia, 2020). Country-basis FDI (FDI PPP proxy figures) is matched to SPI figures (used as a social development proxy). Based on the classic

[47] pos=positive effect (regression coefficient is positive), neg= negative effect (regression coefficient is negative) sig=Significant (p-value is under 0.05), insig (p-value is equal of higher than 0.05)
[48] Cumulative Sum is a type of control chart employ in monitoring small changes in the process mean, by employing the cumulative sum of deviations from a target. Cumulative sum of deviations from the target are plotted for individual measures or subgroup means.
[49] Cumulative Sum of Squares, as in the case of CUSUM it could be used to test the constancy of the coefficients in a model.
[50]CLACDS (Centro Latinoamericano para la Competitividad y el Desarrollo Sostenible -Latin American Center for Competitiveness and Sustainable Development) is an applied research center part of the INCAE Business School. Its mission is to promote sustainable development in the Central American region through research, capacity development and dialogue. Its work methodology unites competitiveness, social progress, environmental performance and governance. It has works closely with different international organizations such as the World Bank, the IDB, GIZ, Social Progress Imperative, the US embassy and other partners in research and training programs for public and private sectors.

Rostow Economic Growth Stages Model[51], 132 countries are classified by GDP PPP data from the World Bank under one of 5 categories.[52] Findings suggest that GDP PPP and FDI PPP be positively associated. FDI PPP and SPI are reported to be positively associated with a correlation value of 0.57 across the 132 countries researched. This positive relationship also holds valid for the disaggregated dimensions: Basic Human Needs (0,49), Foundations of Well-being (0.51) and Opportunities (0.6). Therefore, the general relationship between FDI PPP and social development is suggested to develop and strengthen as GDP PPP grows (Increases in GDP PPP cause FDI PPP to increase, subsequently improving social development).

As per Deloitte (2014, pp2) and as reported in Kolstad & Tøndel (2002, pp10), FDI is suggested to vary at each stage of economic development, enabling nations to reach different stages. Although education is associated with FDI PPP and economic growth for countries at any development stage, other factors change more notably depending on the stage. For instance, factors such as infrastructure are fundamental to enabling under-developed countries to climb up the ladder, while political institutions, stability/security, skills, and quality of life change notably as countries grow. As nations climb the ladder, economic activities divert to different industries and sectors, causing FDI to be channelled to higher economic growth, higher-skilled and higher-technology industries and sectors. The latter favours spillovers, linkages, and the creation of clusters (primarily when private and public governmental support is provided to industries and sectors within the host country). Ultimately, those sectors and industries benefit from those spillovers created. This study also suggests that the change

---

[51] The Rostow Economic Growth Stages Model, published by American economist Walt Whitman Rostow in 1960, is one of the main historical models of economic growth. The model postulates that economic growth occurs in five basic stages, of variable duration: 1) Traditional society, 2) Transitional society, 3) Takeoff, 4) Path to technological maturity and 5) High mass consumption. Rostow argued that economic takeoff should initially be directed by a few individual economic sectors. This belief echoes the thesis of the comparative advantage of David Ricardo and criticizes the effort of Marxist revolutionaries for economic self-sufficiency, as it drives the "initial" development of only one or two sectors. This became one of the important concepts in the theory of modernization in social evolutionism. It is one of the most structuralist models of economic growth, particularly in comparison to the "backwardness" model developed by Alexander Gerschenkron, although the two models are not mutually exclusive.

[52] Within the parenthesis, the dollar ($) figures refers to the GDP per capita bracket for sorting out the countries. The second figure refers to the number of countries included in that particular group): Underdeveloped ($0-$1000, 21), Developing ($1001-$4000, 34), Emerging ($4001-$12.500, 34), Developed ($12.501-$30.000, 20), Highly Developed ($30.001-$100.000, 22).

magnitude for the different SPI factors differs as countries grow economically. As SPI factors evolve from one country group to another, some change with FDI more notably (deviating from the average score) than others[53]. By studying the average score for each SPI factor across country groups, one could identify 1) which SPI components are most developed within each group and 2) how SPI components change across the five groups identified, indicating a development path for the country groups.

Relationships between FDI and SPI are reported in the work of Deloitte (2014, pp2) to work in both directions. Factors such as infrastructure, education and personal and political security are suggested to be crucial when attracting FDI, which is a determinant for the movement direction. Nonetheless, although FDI could potentially create social development, both directly by supporting areas like healthcare and education or indirectly by providing employment, increasing local wages, and creating demand for services for local companies via de 'productive linkages' created, the potential positive outcomes may be interrupted under some circumstances. It is also worth mentioning in the work of Deloitte (2014, pp5) that 5 barriers are suggested to be interruptive of the 'virtuous' relationships between FDI and social development: 1) nations are constrained to receive 'start-up' FDI seeds that are required to be transformed into social development, known as Poverty Traps, 2) when FDI is natural resource-driven so no incentives for MNEs and country governments to create social development conditions exist, 3) nations with persistent conflicts deterring FDI attraction, depriving the host country of resources inflows which subsequently be transformed into social progress, 4) nations experiencing rapid economic growth rates with which the social development growth rate can not keep up the pace, 5) and nation attracting FDI via tax exception incentives which prevent resources to be transformed into social development, known as Tax Havens. This practitioner-inclined work of Deloitte (2014, pp2), although it states the existence

[53] Average score for each SPI component across the group show that: 1) All SPI components, but Health and Wellbeing and Ecosystem Sustainability increase from one group to the next one. 2) Increase is not homogeneous as SPI components change significantly between specific groups, suggesting that different aspects develop at different stages. 3) SPI components such as Nutrition and Basic Medical Care and Access to Basic Knowledge are high across all groups, suggesting that these aspects develop first (They reach a relatively high level across developing countries) and 5) Other SPI components, such as Access to Advance Education, start at relatively low levels and increase steep pace across all groups.

of reverse causality effects between FDI and SPI factors suggesting the existence of a *'virtuous' circle* matching the Ranis *et al*. (2000) empirical findings for the association between economic growth and social performance, unfortunately, lacks statistical robustness to adequately prove this claim, mainly because of its cross-sectional nature. Although the proposed model is considerably elaborated, it does not provide a robust and statistically sound conceptual/structural framework.

2.4 Underlying Theoretical Frameworks

Unfortunately, the review of the empirical literature in the previous subsection has been hampered by the lack of a clear theoretical framework that explains the potential bidirectional and related path dependencies and reversed causal mechanisms for a direct association between FDI and social development. This absence of theoretical foundations constraints -from an empirical standpoint- to execute tests of this relationship, seeking at least to find internal consistency within a set conceptual/structural framework. Alternatively, following most of the empirical works explored above, one may propose a supportive explanatory framework via an intermediate variable. Such a proposition, however, is not free of limitations as it also requires finding the appropriate underpinnings to choose the connecting theoretical models linking the two dimensions of interest (See Appendix 4. for an overview of the philosophy of social sciences, ontology and epistemology concerning theoretical models in economics).

Theoretically, the literature is well established to account for the possible impacts of *FDI on economic growth* in host countries. From an empirical standpoint, as explained in the previous subsection, a large body of research also explains those impacts, which are not consensual as they depend on the host country. However, although pointing to negative and neutral effects, literature informs about positive outcomes in general terms. As per the same token, a less extensive but less controversial body of knowledge regarding the association between economic growth and social development appears to exist, given that different growth scenarios are suggested to have different impacts on social development. Nonetheless, in general terms, the literature reports a positive relationship between the 2 variables exhibiting a bidirectional causation pattern. Under the latter perspective, interactions between FDI, economic growth and social development are suggested to be location-time specific. The effects of FDI on economic growth on the one hand and of economic growth on social development on the other are likely to differ in timelines and host countries (location). This perspective opens the possibility that in the case of Panama, FDI particularly interacts with economic growth, causing their impacts on social development to be potentially different from its neighbouring countries or other host countries considered comparable peers.

This interaction between FDI and social development via the economic growth dimension appears complex. The theoretical foundations that follow are rooted in 2 different strands of literature. One relates to the interaction of FDI and economic growth, and the other to the interaction of economic growth and social development. Those 2 theoretical literature venues are considered individually and subsequently become 'inspirational' in the proposition of the conceptual/structural framework explained in the research design section, suggested capturing the direct bidirectional linkage between FDI and social development and which one may empirically corroborate via employing the panel data analysis.

2.4.1 FDI and Economic Growth

Although the literature reviews of Angelopoulou & Liargovas (2014), Kolstad & Tøndel (2002), Tocar (2018) and Gökmenoğlu *et al.* (2018), when citing Alfaro *et al.* (2004) inform about mixed (positive, negative[54] and neutral), most empirical time-series research generally points at FDI positively stimulating economic growth (Suliman & Elian, 2014 and Gökmenoğlu *et al.*, 2018 when citing Amighini, & Sanfilippo, 2014 and Lall & Narula, 2004), in alignment with the

[54] Nevertheless, there have been concerns over environmental impacts of unregulated FDI and natural resources depletion, for example, water overconsumption in largescale commercial projects (Mabey & McNally, 1999). Additionally, host countries may cede vital industries control to MNEs unless protective measures are deployed. Although FDI is generally seen as a longer-term investment there also exist volatility risks related to liberalizing domestic industries and increased exposure to global markets. Local businesses may suffer due to pressure exerted by larger MNE competitors with significant competitive advantages (Blomström & Kokko, 1997).

previous subsection. Additionally, empirical studies suggest that depending on the type of investment, the effects on economic growth differ. This latter difference, buttressed by the different theoretical conceptualisations primarily extending from the Solow-Swan (1956), had led to several empirical studies attempting to identify and characterise the diverse categories/industries of MNEs immersed in the different host countries' economies. Endogenous growth theoretical models[55] stemming from the seminal work of Romer (1986), however, as reported in Mankiw *et al*. (1992), are alternatively suggested to offer a more sound theoretical background than exogenous neoclassical ones. In passing, as Barro's (1997, pp2) quote: "*it is surely an irony that one of the lasting contributions of endogenous growth theory is that it stimulated empirical work that demonstrated the explanatory power of the neoclassical model*". In this sense, although economic growth theory may be considered antagonistic, models are just partial, complementary and evolutionary, providing certain leeward for intelligibility when proposing explanatory arguments in the complexity of the economics discipline.

The theoretical framework herein proposed, linking FDI and economic growth, does not receive inspiration from exogenous neoclassical theories but from endogenous growth theory. The explanatory rationale precisely lies in neoclassical exogenous growth models theoretically avoiding technological change, in the long run, predicting economic growth to eventually converge to a steady state with zero per capita growth (diminishing return of capital). Conversely, in the endogenous growth models, the diminishing returns to capital[56] assumption do not hold, thereby better matching the contemporary economic reality of the Republic of Panama, which has exhibited a steady increase in GDP PPP in recent years. Accordance to Garcimartin (2020), the FDI inflows in Panama have majorly derived from MNEs reinvesting the previous year's net revenues, contrary to 'green field' investment. From this perspective, if FDI

[55] Endogenous growth models are characterised for laying stress on several inputs in addition to physical capital (technology, human capital, intermediate new goods, organizational capital, social capital and institutional design).

[56] Early endogenous growth models like Romer (1987) were explained via linear relationships between output and physical capital. However, such models were subsequently discarded inclusively by Romer (1993). From an empirical standpoint, the underlying reason is that many cross-section regressions exhibited a statistically significant linear relationship between investment and economic growth which unfortunately does not hold at shorter periods (Easterly, 1999).

inflows impact economic growth in Panama, the lasting effect is majorly explained by endogenous factors rather than external forces, according to Romer (1994). Furthermore, endogenous growth theory attempts to overcome the shortcoming of exogenous neoclassical theory by building macroeconomic models out of microeconomic foundations (Rebelo, 1991). As later explained, the nature of the data employed in this dissertation is inclined on the microeconomics side as it employs figures of individual MNEs in Panama, thereby turning endogenous growth models into better theoretical choices than neoclassical ones.

FDI has been contended to provide host nations with direct capital financing and contribute to positive externalities via advanced technology transfer, know-how, and knowledge diffusion. These externalities materialise through linkages derived from MNEs with local suppliers and via competition, imitation, and training (Liu *et al.*, 2021). As per a meta-analysis of Bhattacharyya (2012), greater competition from new companies can also lead to productivity gains and greater efficiency in host countries. Furthermore, FDI can additionally result in soft skills transfer as a secondary gain from job creation, training and access to R&D resources and technology (Baskaran & Muchie, 2008). It has also been suggested that policies enforced by MNE in the host country's subsidiary may, in turn, improve corporate governance standards, as implied from the work of Liu *et al.* (2021). Those latter effects align with the endogenous growth theory, which holds that investment in human capital, innovation, and knowledge are significant determinants of economic growth. Endogenous models engage in explaining 'spillover effects' for knowledge-based economies, suggested to be triggered by FDI inflows within the Panamanian economy (Vergara & Ellis, 2021), an assertion up-to-date empirically unproven in the literature or even in working papers from the governmental agencies in Panama, particularly PROPANAMA as the nation's institution in charge of FDI attraction. In this sense, the endogenous growth theory provides a more suitable ground for the 'spillovers' explorations proposed, as explained in detail in the research design section.

Endogenous growth theory also holds that the long-run growth rate of an economy depends on policy measures, which is an ongoing topic of debate in Panama, especially as regards FDI, as pointed out by Vergara & Ellis (2021), Fernandez (2021) and Garcimartin (2021). In general terms, FDI in Panama has been contented to lack a clear policy for strategic FDI attraction. PROPANAMA, as an appointed governmental institution in charge of FDI attraction, was until recently designated as a National Secretary, with enough workforce and financial resources to perform its duties. Nevertheless, it is still considered to face strategic and organizational issues. One of those core issues revolves around the absence of a proper intelligence department in charge of identifying key industries, a long-term plan for FDI attraction and an agenda of cooperation with key national and international stakeholders, among some other drawbacks (Vergara & Ellis, 2021; Fernandez, 2021 and Garcimartin, 2021). Besides, Panama has historically faced severe structural issues regarding what the public education system concerns, derived from the absence of key strategic government policies focused on assuring a continuity track in the long run (Fernandez, 2021; Garcimartin, 2021). Besides, although Foreign Portfolio Investment has historically been a significant component of Panama's economy, commerce (importing manufactured goods, storing them and exporting them) has also played an economic role that does not provide much leeward for value-adding activities. As contented in the work of Hausmann *et al.* (2017), government policies have failed to structurally steer the economy away from this model, under which value added to reexported goods in the Free Zones' system only accounts for an average of 1% of GDP. This latter macroeconomic feature is suggested to be explanatory of low local R&D and knowledge-based activity, considered the determinant factors to trigger sustained (long-run) technological progress in an economy (Hausmann *et al.* 2016a, Hausmann *et al.* 2016b)

The theoretical linkage between FDI and economic growth for this dissertation further extends to a widely cited model proposed by Borensztein *et al.* (1998), which empirically assesses the effect of FDI on economic growth. This model is supported by the preceding works of Romer (1990), Grossman & Helpman (1991) and Barro & Sala-i-Martin (1995), which considers technological progress in host countries' economies deriving from different forms of capital (infrastructure, equipment, other physical capital, human capital, know-how, etc.) to additionally include technological know-how -'blueprints for production processes and new products as defined by Nonneman & Vanhoudt (1996)- as another form of capital and just as any other input in production. See Equation 1.

Equation 1

$$g = c_0 + c_1 FDI + c_2\,(FDI\ x\ H) + c_3\,H + c_4\,Y_0 + c_5\,A + \ \varepsilon$$

Where g represents economic growth as a percentage rate of GDP, FDI is measured as a ratio to GDP, which is conceptually analogous to the fraction of goods produced by MNEs in the model, H stands for the *stock of human capital* as a proxy for social development, Y_0 stands for the initial figure of GDP per capita (Income), c_0 is the intercept o the equation, c_j (j = 1, 2, 3…) are the coefficients for different independent and interaction variables and ε is the error term accounting for all other excluded factors that may likely impact economic growth. A represents a set of control and policy variables which are frequently included as determinants of economic growth in cross-country studies: government consumption, the black market premium on foreign exchange, a measure of political instability (political assassinations and wars), a measure of political rights, a proxy for financial development, the inflation rate, and a measure of the quality of institutions. As one may expect, such a theoretical framework is not free of criticism as it presents the drawback of excluding domestic capital investment, which, as reported by Jalilian & Weiss (2002), is an assumption not closely conforming to conventional growth accounting procedures. Nonetheless, the framework is considered appropriate to be theoretically supportive and 'inspirational' for the research design proposed, seeking the direct association between the FDI and social development dimensions via economic growth from an empirical standpoint

Regarding the causation directionality, although Blomström & Kokko (1997) suggest that economic growth positively induces FDI, different types of FDI, depending on the MNE industry, may influence economic growth in different fashions and different host countries, in turn inducing variations in the causation directions. Nevertheless, as reported by Jalilian & Weiss (2002), empirical literature in general terms buttresses FDI flowing to economic growth to the point of exhibiting 'path dependencies' (lagged values of FDI are explanatory of economic growth) as per the work of Lipsey (2000).

2.4.2 *Economic Growth and Social Development*

Social development is a process intrinsically related to economic and political dimensions in a society, where human beings become its object and instruments, and at the same time, they are also its objective. Mukherjee & Chakraborty (2010) contends that social development is linearly and positively related to both income level and democracy, suggesting that nations characterised by higher levels of income and more robust democratic set-ups are likely to witness more elevated levels of social development. Complementary, higher initial levels of social development may positively affect the institutional quality and indirectly affect economic growth (Costantini & Salvatore, 2008). As reported by Ranis *et al.* (2000), Ranis & Steward (2001), Ranis (2004), and Boozer *et al.* (2003), a strong connection between economic growth and social development exists as high correlations between the two dimensions are reported in numerous studies (Omar, 2020; Ramirez *at al.,*1998; Ranis *et al.*, 2000; Ranis & Steward; 2001; Ranis; 2004; Ghosh, 2006; and Joshi, 2007). Economic growth provides the resource inflows that allow sustained improvements in social development, among which labour force quality, education or healthcare may outstand as its most significant comprising factors. At the same time, achievements in social development can make a critical contribution to economic growth. Under this perspective, two different causal chains could be distinguished: one flowing from economic growth to social development, as resources from GPD PPP (as an alternative measure of economic growth) are allocated to activities contributing to social development and another flowing from social development to economic growth, pointing at how social development aids in increasing GDP PPP.

As quoted from Ranis *et al.* (2000, pp208), the bidirectional causal association between those two dimensions is "*strongly supported by micro and macro studies in the literature. This means that an economy may be on a mutually reinforcing upward spiral, with high levels of social development leading to high growth and high growth, in turn, further promoting social development. Conversely, weak social development may result in low growth and, consequently poor progress toward social development improvement. The strength of links in the two chains influences the extent of mutual reinforcement* *between social development and economic growth, in either direction."* Those bidirectional chains are further reported to be associated with a reverse causality pattern in the research works of Omar (2020), Ramirez *et al.* (1998), Ranis *et al.* (2000), Ranis & Steward (2001), Ranis (2004), Ghosh (2006) and Joshi (2007).

Although applicable, postulates of economic growth and social development focus on the national, regional or global levels, for which they are considered 'very broad' from theoretical and empirical standpoints as they leave aside local spheres (Reyes, 2009). Nonetheless, the work of Ranis *et al.* (2000) systematically reports to narrow down this two-way association to a gamut of more specific factors. Such factors include the structure of the host nation's economy, the assets' distribution and policy choices made. The *human capital stock* is addressed as a factor that presumably impacts the policy choices and the strength of the associations at each stage of development. For instance, if members of a particular society work together in well-being promotion, if public morality is high, and if the community monitors malfeasance and participates in public life, all linking factors associated with economic growth and social development are likely to strengthen.

As contended by Ranis *et al.* (2000), Ranis & Steward (2001), Ranis (2004) and Boozer *et al.* (2003), the *theoretical underpinnings* for the relationship running from economic growth to social development precisely find its foundations on the capabilities approach based on the work of Sen (1984) and the World Bank and ILO's initial basic needs approach, earlier explained in the conceptualisations section. The HDI is considered the first significant attempt to translate the theory behind the capabilities approach into a gauging instrument for ranking nations (UNDP, 1990) and subsequently for empirical analysis.[57] However, this transformation from the normative theory into a quantitative

---

[57] Although capabilities are a applealing target for social development arena, measuring them is quite a cumbersome task, since the full set of potential human functionings is practically unobservable by definition. As per Streeten *et al.* (1981) an Streeten (1999) the capabilities approach shifts the analysis of social development to a vector of not mere attributes (a more traditional utilitarian or even the original basic needs view of human welfare) but also to a vector of the opportunities available to individuals (income, education, health). Opportunities are impacted by certain attributes as for instance a starving or uneducated individual would have fewer choices than a healthy, educated person. Nevetheles, the capabilities approach extends far beyond the attributes' approach in the sense that it analyses the social environment's role on human choice and agency: a member of a open, free society would have a higher chances of potential functionings in comparison to a member of an close dan oprresed society.

measure, which, although considered by Srinivasan (1994) a rough proxy[58] and simplification of the original capabilities theory, "*have had a strong influence on development thinking, causing developing countries to publish their own national-level human development reports and indices and modifying their policies*" as quoted by Ranis (2004, pp3). This relationship from economic growth to social development was additionally explored in Section 2.3 since the search for empirical research works directly linking FDI and social development mostly rendered literature reviews exploring this association via the intermediate link of economic growth-social development.

Concerning the relationship flowing from social development to economic growth, as also reported by Ranis *et al.* (2000), Ranis & Steward (2001), Ranis (2004) and Boozer *et al.* (2003), the previous-mentioned endogenous growth models become helpful from a foundational theory macro-perspective. Those models endogenise technical progress incorporating social development-related effects, stressing education, learning and R&D. Such endogenous growth theoretical models have incorporated skills/learning as critical determinants of comparative advantage, inducing simple two-factor approaches like the classical Heckscher-Ohlin model to be modified to the extent of aiding in explaining the Leontief Paradox or the dramatic success of the manufactured export growth of some developing countries as contented by Ranis & Stewart (2001). The association between social development to economic growth appears to be heavily impacted by income and asset distribution, with higher equality in distribution inducing higher economic growth rates (Boozer *et al.*, 2003). The underlying rationale is that the higher distribution equality, the higher the opportunities for better nutrition and a more robust demand for education, favouring productivity improvements. Additionally, equal income distribution may induce greater political and economic stability, positively influencing economic growth. Further, according to Lucas (1988), higher educational levels in the workforce increase capital's overall productivity as more educated people are more likely to innovate. Perotti (1993) similarly suggests the generation of such externalities: as societal members' education rises, the productivity levels with

[58] By centering on only 3 foundational variables (life expectancy, literacy, and GDP per capita), it notably ignores other paramount measures such as political freedom and income inequality, which are crucial for social development (Ranis, 2004).

whom they interact also rise, thereby increasing the aggregated productivity function. At a macro level, this positive impact of education on economic growth, with its size varying according to the measure of education and the particular growth model adopted, has been reported by Barro & Sala-i-Martin (1995) and Barro (1997). Complementary, regarding economic growth theoretical models, technical progress depends on the R&D levels in the host country. Via investment in labour and R&D capital, MNEs improve their profitability and the productivity of the MNEs which consume their outputs. Education plays a key role again by contributing to R&D and interactive learning, creating a spillover effect (Romer, 1990; Grossman & Helpman, 1991). Education is suggested to affect the nature and growth of exports, impacting the aggregated growth rate, thus becoming another way social development influences a host nation's macroeconomic performance. The education and skills of a host country's workforce affect its factor endowment and, consequently, its trade composition. For instance, following Wood (1994), even 'unskilled' workers are typically required to possess literacy, numeracy and discipline skills acquired in primary and lower secondary education at any contemporary manufacturing facility.

Omar (2020) proposes a set of simultaneous causal equations associating economic growth and social development (employing HDI as a proxy variable) based on the economic theory explanation of social development’s determinants. If HDI is substituted by the *stock of human capital* (H) as a more ample proxy variable for social development, the theoretical proposition reported in the work of Omar (2020) is shown as follows in **Equation 2** and **Equation 3.**

Equation 2

$$g = c_0 + c_1 H + c_2 \frac{E}{GDP} + c_3 \frac{S}{GDP} + c_4 A + \varepsilon$$

Equation 3

$$H = c_0 + c_1 GDP + c_2 g + c_3 O + c_4 I + c_5 \frac{E}{GDP} + c_6 \frac{GE}{GDP} + c_7 \frac{S}{GDP} + c_8 A + \varepsilon$$

Where g represents economic growth as a percentage rate of GDP, H stands for the stock of human capital, E / GPD is the ratio of exports in the host country to its GDP, S / GPD is the ratio of national savings in the host country to its GDP, O stands for the degree of commercial / trade openness, GE / GPD is the ratio of national government expenditure in the host country to its GDP, I stands for the inflation rate c_0 is the intercept of the equation, c_j (j = 1, 2, 3…) are the coefficients for different independent variables, ε is the error term accounting for all other excluded factors that may likely impact the dependent variable (g or H, depending on the equation), and A represents a set of control and policy variables.

At this point, it is worth mentioning that social development considers economic growth as a necessary condition but not a sufficient one. Under this perspective, social development becomes the central objective of human activity and economic growth, a potentially essential instrument for advancing it. Unfortunately, as per OECD/DAC (1995), there is no automatic link between economic growth and social development since it has to be constructed via social policies within a host country. The main issue revolves not around enacting a social policy bill but putting it into action. In this execution/reinforcement task, the role of the host country's government becomes paramount in a quest to improve the structure and quality of economic growth and increase its pace in a quest to effectively and quickly enhance social development. Advancements in social development require the involvement of all levels of institutions, from national governments to diverse civil society organizations, targeting the construction of an equitable societal fabric via de creation of economic opportunities and social services in the meantime that power imbalance is addressed (UNDP, 2015). Social development employs and/or changes the societal institutions and systems' processes via policies and programs, seeking to strengthen the capabilities/capacities of individuals, families, and communities (Drolet *et al.*, 2014).

One must acknowledge that reaching initial positive impacts on social development within a host nation is much easier than obtaining subsequent ones. If economic growth positively impacts social development in host nations, impact magnitudes are bound to be higher if pre-existing social development levels are low (e.g. primary education and healthcare systems). Comparatively, improvements are still likely to occur at high levels of pre-existing social development. However, their impacts are bound to be marginal since reaching an equal change magnitude in comparison to a low level of pre-existing social development may require a much higher level of economic growth (e.g. specialised healthcare and world-class education), as implied from the preceding works of Baiashvili & Gattini (2020), Zhang *et al.* (2010) and Orbes *et al*. (2019).

2.5 Identified Literature Gaps

In the following section, the literature gaps proposed to be filled by this dissertation are presented based upon the empirical research exploration for FDI and social development as per section 2.3, in addition to theoretical underpinnings explored in section 2.4 concerning the FDI-economic growth-social development relationship.

Section 2.3 concentrated on identifying a robust and statistically sound conceptual/structural framework, either empirical or preferably theoretical, directly associating FDI and social development, which could be foundational for the research design construction. Such a conceptual/structural framework was initially hypothesised to exist in the literature, explanatory of a vicious or virtuous two-way (reverse causality) circle/cycle pattern and exhibiting path dependencies for FDI and social development (via a proxy variable). Unfortunately, as earlier stated, the Literature Review studies and/or Literature Review sections of the pieces of research explored did not render such a conceptual/structural model. To a lesser extent, some of the analysis of the methodology, findings, conclusions and further research sections of quantitative-based studies examined in section 2.3, although incapable of fully proving reverse causality and path dependencies patterns with the statistical rigour sought, did become an 'academic teaser', providing important individual findings for constructing the research design's hypotheses. In passing, being unsuccessful in finding such a conceptual/structural framework may be justifiable since although rigorous statistical techniques and panel data [59] are available to examine different variables' associations, such techniques are rarely employed in social development-related studies (Land & Michalos, 2018). The extent to which the panel data employed for some of those studies explored in section 2.3 could have

[59] As per Wooldridge (2018), bound to improve the mathematical efficiency estimates when exploring causality with statistical rigour depending on the research model chosen

potentially resulted in more rigorous statistical findings, analysed under more advanced econometric techniques, is, of course, out of the scope of this dissertation and, instead a void that future researchers could engage. The main underlying reasons for the examined studies not complying with this 'hypothesised existing' conceptual/structural framework are summarised as follows.

The explanatory power of Larrain *et al.* (2000) is feeble as the analysis is majorly based on time series that employ stringent statistical quality indicators. As per the same token, Kolstad & Tøndel (2002, pp11) is inconclusive and even contradictory as various factors show different relationships[60] to FDI flows (positive, especially those concerning long-term political stability and reduced internal conflict and ethnic conflict tensions, negative or neutral). Sharma & Gani (2004) find positive relationships between FDI and social development proxies and vice-versa, but unfortunately, their study lacks statistical explanatory power, as stated by its authors in its findings section. Deloitte (2014) discusses significant relationships through correlations and R2 figures to explain the positive, negative or neutral associations, which unfortunately fails to provide more stringent statistical quality indicators as it employs crossectional data. This latter work is in contrast with Dechprom & Jermsittiparsert (2018), which employs CUSUM and CUSUMSQ tests to buttress findings of a positive association between FDI and SPI as an explanatory variable; or even in the case of Feriyanto (2016), which employs Pooled OLS (POLS) under a Fixed Effects and Random Effects approach as their foundational methodology. Orbes *et al.* (2019) engage in statistically rigorous demonstrations (e.g. Hausman Test, OLS-FE and GMM) or Gökmenoğlu *et al.* (2019), which employs a series of tests[61] to statistically and robustly support its claims.

Most research has concentrated on employing social development proxies, HDI being the primary index used as directly reported in the works of

[60] Kolstad & Tøndel (2002, pp8) study suggest that although "*FDI is attracted to countries with large domestic markets, open trade regimes, and substantial past inflows of FDI, the impact of growth rates, wages, human capital levels, taxes, infrastructure and macroeconomic conditions is more of a mixed bag*"

[61] As earlier mentioned, the Augmented Dickey-Fuller -ADF- and Phillips-Perron -PP- Unit Root Tests, Johansen Cointegration Test, Dynamic Ordinary Least Squares (DOLS) and Toda-Yamamoto causality test

Sharma & Gani (2004), Gökmenoğlu *et al.* (2018) and Orbes *et al.* (2019) and as per the literature review in those works (the work of Kolstad & Tøndel (2002) is the only one not using it). As mentioned in the Introduction section, only 2 studies relating to FDI and SPI have been specifically identified: the studies of Deloitte (2014) and Dechprom & Jermsittiparsert (2018). Moreover, as per Tocar (2018), studies in general only explore a few social factors related to FDI; thereby, the only research exploring up to 54 social development factors is the study of Deloitte (2014), as the rest only analyse 14 variables (work of Kolstad & Tøndel, 2002) or less (related to either to SPI or HDI). Nonetheless, although Deloitte (2014) employs this extensive number of indicators related to social development, its virtuous circle empirical framework proposed is unsupported by reverse causality and path dependency tests, thereby not complying with the requirements of the 'hypothesised framework' sought. Thus, the only 2 pieces of literature robustly engaging -statistically speaking- into causality tests so that they can be considered robust empirical frameworks are the works of Orbes *et al.* (2019) and Gökmenoğlu *et al.* (2018), which, unfortunately, neither test for reverse causality nor path dependencies.

Results of section 2.3, failing to identify the 'hypothesised existing' robust and statistically sound framework associating FDI and social development, should not be discouraging as this may frequently be the case of other explorations in the broad field of economics research. One may realise that a single economic theory may have its limitations when seeking plausible explanations of FDI inflows and their comprising/explanatory factors, since as quoted from Faeth (2009, pp165): "*FDI should be explained more broadly by a combination of factors from a variety of theoretical models such as ownership advantages or agglomeration economics, market size and characteristics, cost factors, transport costs, protection, risk factors and policy variables*". Although UNDP (2015) informs about studying mechanisms to enhance and advance social development, classically pointing at employment as critical social development advancement, factors like environmental sustainability, human rights, promoting equality and social justice, and participation in political and community life have also been identified to create better conditions for social development as they permit people to broaden their choices and opportunities. Thereby, social development-related variables are more pressingly suggested to require a much more complex examination, identified as a phenomenon not yet profoundly explored in association with FDI. According to Kolstad & Tøndel (2002, pp4), "*the main theories of how FDI is attracted to a host country focus on economic factors, and social development variables are at best of derivative importance*". Furthermore, although the scientific theory concept is still somewhat contested, as stated by Land & Michalos (2018, pp861), in comparison to "*other research fields, social indicators researchers have shown little interest in theory building*." Given this theoretical void, exploring the existing theory linking FDI and economic growth on the one hand, and economic growth and social development on the other, was required to adequately hypothesise about the relationship between FDI and social development upon sound economic foundations via economic growth as an intermediate variable. Most of the arguments for the 2 separated associations were presented in section 2.4. As follows, the hypothesised associations' causal directions based upon the theoretical underpinnings from section 2.4 and complemented by empirical findings from section 2.3 are presented from a deductive standpoint.

Although there is no consensus on the final effects of FDI on economic growth as amply contested previously, common conventional wisdom and the empirical and theoretical literature suggest in general terms that FDI is highly likely to raise economic growth via a productive spillover effect. The endogenous growth theoretical framework supportive for the FDI-economic growth association proposed upon the work of Borensztein *et al.* (1998) -as earlier stated- argues that productive spillover effects are created in host countries via technological progress (technology and knowledge transfer), deriving from different forms of capital: infrastructure, equipment, other physical capital, human capital, know-how, technical know-how (Nonneman & Vanhoudt, 1996), among others. In this venue, empirical literature suggests that these *transfer mechanisms* manifest, for instance, when MNEs spread their corporate schemes in local firms in host countries. Local firms adopt such a strategy, innovation, technology, and other applied managerial and technological advantages as '*best practices*', naturally inducing them to evolve, improve and sophisticate. Thereby, *productive linkages* triggered the host country's local firms to raise their efficiency, technology and knowledge baselines (Blomström & Kokko, 1998; Liu, 2008; Kemeny, 2010). Another way in which these mechanisms manifest, according to the empirical literature, is by rising market labour demand via workforce participation expansion (Feenstra & Hanson, 1997). The rationale is that in a scenario of higher market labour demand in the host country, MNEs are bound to raise higher wages for their workforce, increasing *household income*. Additionally, from a macroeconomics perspective, although dependent on the type of FDI as earlier contented, tax collection revenues from MNEs may be bound to increase, allowing the national and local governments in the host nations to augment their public budgets and spending power. Lastly, regarding endogenous growth models, Blomström *et al.* (1997) argue that longer-term association flowing from FDI to economic growth may reflect a reverse causality pattern.

The association of economic growth and social development is reported to exhibit a bidirectional pattern as per section 2.4.2 examination (Omar, 2020; Ramirez *et al.*, 1998; Ranis *et al.*, 2000; Ranis & Steward, 2001; Ranis, 2004; Ghosh, 2006 and Joshi, 2007). Theoretically, as abovementioned, this relationship is reported to be founded on the work of Sen's (1984) capabilities approach and the World Bank and ILO's initial basic needs approach (Ranis *et al.*, 2000; Ranis & Steward, 2001; Ranis, 2004 and Boozer *et al.,* 2003). From a macroeconomics perspective, the higher the magnitude of economic growth, the higher the opportunities for members of a society to access healthcare and education (Borensztein *et al.*, 1998), which in turn induce social development improvements (Ranis *et al.*, 2000). When higher local and governmental economic resources become available, chances for those resources to be allocated to social development-related projects, such as social infrastructure, education, health, basic needs and unemployment support, increase (Ranis *et al.*, 2000). From a microeconomics perspective, an increase in wages, a positive economic growth effect reported as higher purchasing power, potentially increases the chances of workers allocating higher household income amounts to a broader gamut of products and services, which may include social development-related factors such as health and education (Ranis et al., 2000; Bloom & Canning, 2000), pursuing improvements in their standards of living. Higher household income, as reported in the empirical literature, is also positively related to a higher number of years of education and higher average education levels for workers and their families (Brückner & Gradstein, 2013). Hence, they have a more solid foundation to access better-skilled job positions or even become entrepreneurs by founding domestic firms (Spender, 2013).

On the other hand, the association running from social development to economic growth, as explained in section 2.4.2, also has its theoretical underpinnings in the endogenous growth models, suggested to be heavily impacted by income/asset distribution, where the higher distribution equality, the higher the opportunities for better nutrition and health (Boozer *et al.*, 2003) but particularly for better access to education which induces improvements in labour productivity (Perotti, 1993) and raises the likelihood of innovation (Lucas, 1988). From a macroeconomics perspective, education is suggested to be a determinant factor (Wood, 1994) positively impacting economic growth, depending on the model and measure of education employed (Barro & Sala-i-Martin, 1995, Barro, 1997). The higher the education levels, the higher the contribution to R&D and interactive learning (Romer, 1990; Grossman & Helpman, 1991), impacting economic growth. The education and skills of the host country workforce are also argued to have effects on the factor endowment and consequently on its trade composition, impacting the nature and the export growth pattern, which is intrinsically related to the host country's aggregated economic growth rate. Furthermore, this bidirectional two-way relationship is argued to exhibit a reverse causality pattern, since as quoted from Ranis *et al.* (2000, pp208): a *"country performance can there be classified into four categories, virtuous, vicious and two types of lop-sidedness: social development lopsided (strong social development/weak economic growth) and economic growth lopsided (weak social development/strong economic growth)".* Furthermore, cyclic societal theory suggests that vicious ones generally influence social phenomena (Joll, 1985).

The initial 'hypothesised existing' framework sought but not found in the literature in section 2.3 may be posed at this point in the light of the empirical but mainly the theoretical argumentations stemming from the analysis of the latter linkages. Hence, targeting to fill the void of such a model in the welfare economics literature, this dissertation concretely focuses on the proposition of a 'conceptual/structural framework' exhibiting a two-way association between FDI (mainly using aggregated income figures of FDI industries in Panama) and social development (assuming SPI as an appropriate proxy measure), primarily focusing on one emerging/transitional economy where figures are further broken down into province levels. In this sense, via economic growth and as derived from the productive spillover effects above argued, FDI is expected to positively impact social development, as buttressed by the empirical work of Feriyanto (2016) and Orbes *et al.* (2019) finding. Complementary social development improvements in a host country may subsequently become foundational in FDI attraction, particularly from an education development perspective (Basu & Guariglia, 2007; Blomström, Kokko, & Mucchielli, 2003). As per Ranis *et al.* (2000, pp203), when citing OECD/DAC (1995), "*both domestic and direct foreign investment is influenced by a country's social development level -particularly the education and skills levels of the workforce*".

The proposed conceptual/structural framework ultimately targets to: 1) by studying reverse causality (bidirectional causal effects were not concretely found in the literature as already stated), matching similar *virtuous, vicious or lop-sided* circles patterns for the association between FDI and social development, as the ones reported by Ranis *et al.* (2000) to exist between economic growth and social development and which were explicitly exhibited by Panama to be *virtuous* and *social development lop-sided* since 1960 as exposed in the introduction section. The existence of such a reverse causality pattern is theoretically underpinned by all previous argumentations and suggested to exist and be further explored in the empirical works of (Blomström *et al.,* 2003 and Sharma & Gani, 2004). The conceptual/structural framework proposed would adequately test the general claim made by Deloitte (2014) about an existing *virtuous circle* between FDI and social development, which is also suggested, although yet unproven in the work of Gökmenoğlu *et al.* (2018). 2) confirming 'path dependencies' effects of FDI on social development or vice-versa, as empirical studies suggest a self-reinforcing impact of large past FDI inflows encouraging contemporary inflows (Kolstad & Tøndel (2002, pp21) when citing UNCTAD (1998) and Lipsey (1999)) [62].

As explained above, 2 productive spillovers effects are argued to be triggered by MNEs on economic growth: 1) *productive linkages* creation on local

[62] Countries attracting above average FDI inflows in one period may continue to do so in the next period.

firms in Panama and 2) increases in *household income* as local workers in MNEs receive higher and better salaries and compensation packages, thereby increasing their families global purchasing power. The effects of both productive spillovers are proposed to potentially be moderating variables of the two-way relationship between FDI and social development. One may notice that for *productive linkages* and *household income* to become moderating variables, they must be primarily ignited by FDI as an economic growth effect. Hence, both *productive linkages* and *household income*, besides their moderating effect, are also argued to affect social development directly. In this sense, a secondary gain emerging from this dissertation may also be to extend the existing knowledge of classic economic spillover effects (knowledge transfer, technology transfer, skills transfer, among the significant related gains) to subsequently transform into potential 'social spillovers', inducing improvements in the standards of living of members of the Panamanian society.

It is worth noting that 3 additional voids in the literature could be identified, which this dissertation intends to fill. First, under Land & Michalos (2018, pp861), there are "*relatively few multilevel studies"* even when it is recognized that *"most individuals grow up in families, communities, states, regions, countries with different social, economic, political and environmental features that have a variety of impacts on each other and the quality of people's lives*." Additionally, Kolstad & Tøndel (2002, pp13) recognize that "*further in-depth studies, for instance in the form of individual country case studies, will be required to establish these causal relationships with greater certainty."* Sharma & Gani (2004, pp.15) also encourage further research on a country basis. Out of the 6 relevant works mentioned, 3 of them engage in-country depth analysis: Larrain *et al.* (2000), which unfortunately lack statistical rigour (study in Costa Rica), and Feriyanto (2016) and Gökmenoğlu *et al.* (2018), respectively researching Indonesia and Nigeria, and which findings, although relatively well supported from a methodological robustness perspective, do not live up to the hypothesised existing conceptual/structural framework sought. In turn, the work of Orbes *et al.* (2019), although lacking this country-based analysis, calls for further reaching the field from a country-year, region-year and city-year level analysis. Dechprom & Jermsittiparsert's (2018) and Deloitte's (2014) studies also lack this country-disaggregated deepness analysis, representing a knowledge void for this dissertation to explore.

Second, regarding FDI comprising industries, studies' results depend on data disaggregation. Most of the research works in section 2.3 employed aggregated figures for the FDI inflows, implying that all industries accounting for FDI in a country are 'packed' into one 'bulk' FDI figure. This 'pack figure' implies a 'conflation issue'[63] and assumes that the same factors drive all sectors and industries, contrarily to a more reasonable investment decision scenario of different industries/sectors getting influenced by different factors. For instance, FDI in Nigeria is majorly driven by the oil industry. However, Panama is driven by international trading (Colon FTZ), non-finance companies and banking services (general and international licenses). Thus, although Deloitte (2014) examines industries/sectors, it lacks studying them in a country-basis fashion as explicitly extracted from Orbes *et al.* (2019) or other studies. Therefore, by employing MNEs' disaggregated figures, this dissertation proposes to add to the existing body of knowledge in the welfare economics arena.

Third, since panel data for SPI is still scarce as a consequence of the indicator's novelty since its recent production deployment in 2014, contributions to the body of knowledge are proposed to be added in light of a scant stock of studies (supported upon stringent methodologies capable of assuring statistical robustness) directly researching FDI and SPI as a social development proxy. Properly researching this social science phenomenon may fulfil several knowledge gaps in alignment with the growing trend and explicit requirements of academic research in welfare economics that emerged in the last decade (Stiglitz, 2019; Fleurbaey, 2009; Atkinson, 2011).

In summary, several exploratory features contribute to making this research singular, as stemmed from the empirical and theoretical literature review: 1) intends avoidance of the 'conflation' related issues by employing FDI

[63] Refers to treating 2 or more different concepts as one, often by merging information, texts, ideas, opinions' sets. This fusion of different subjects induces misunderstandings or errors which in turn make introduces difficulties in the analysis of the related relationships which tend to be emphasized by contrasts. Nevertheless, if the differences among the 2 or more concepts seems to be simply superficial, what is referred as "intentional conflation" may be desirable.

figures disaggregated into industries/sectors, 2) explores social development (SPI figures) to a province level, 3) is specific for one country (Panama), and 4) the country studied is an emerging/transitional economy for which welfare economics studies are practically inexistent.

3 CHAPTER THREE: PANEL DATA AND RESEARCH DESIGN

One foundation of the scientific method is experimentation. Although natural sciences settings are known for allowing to better control for experimental designs, the fact is that research in ‘experimental’ economics has evolved into finding ways also to develop experiments or quasi-experiments which pursue replicating those desired ‘experimental lab’ settings (Samuelson & Nordhaus, 2010) in controlled ‘economic’ environments (Friedman & Cassar, 2004). Nonetheless, as per Ferraro & Miranda (2017), those ‘experimental’ economics designs are rare. Instead, economic research usually focuses on observational designs[64] which rely upon panel data, considered capable of replicating results from ‘experimental’ economics-controlled trials’ designs (Ferraro & Miranda, 2017) due to 2 essential characteristics: 1) sample randomization and 2) control for observable and unobservable variables that may impact the economic system.

Although rational/deductive epistemological approaches appear to be preponderant concerning conceptual/structural frameworks and/or theory development, empiricist/inductive approaches -as herein followed- are also generally well-pondered. It is worth noting that this dissertation's conceptual/structural framework does not derive from a new knowledge field, as it is firmly rooted in the thorough review of +290 relevant theoretical, empirical and methodological literature.

This chapter is structured as follows: subsection 3.1 refers to panel data and related topics such as the level of analysis and the panel data settings, and subsection 3.2 describes the structure of this dissertation’s research design

[64] The absence of a comparison group and repeated pretest/posttest observations for a ‘before-and-after multiple group design’ are generally the primary constraints faced when performing economic experiments/quasi-experiments (Chambliss & Schutt, 2006, pp1114). The empirical research design herein employed is a longitudinal observational study fully quantitative in nature. This sort of design -where each MNEs per industry type is allocated in a less randomised fashion and exposed to less controlled experimental conditions- is advantageous when facing implicit ‘internal/causal’ and ‘external/generalisable’ trade-offs. According to Chambliss & Schutt (2006), results derived from longitudinal observational studies are usually high concerning external validity, therefore exhibiting higher generalisability than experiments/quasi-experiments (more prone to high internal validity but less generalizable).

regarding the research problem and questions, hypotheses posed, and variables employed.

3.1 Panel Data

3.1.1 Level of analysis

The primary dataset (PNISCa, 2020) used comprises a longitudinal record of MNEs classified per industry type in accordance to the activity they carry out, using the International Standard Industrial Classification of All Economic Activities code, abbreviated ISIC[65] and which is the standard economic activities classification code employed by the United Nations Statistics Division (UNSD). Hence, as per Bryman & Bell's (2011) SOGI (Societies, Organizations, Groups and Individuals) model structure, the primary unit of analysis is industry types in a given year. Following Garcia (2020) and Garcimartin (2022), there is a void of studies researching individual industries/sectors since the sort of panel data required to perform such research is generally subjected to confidentiality restrictions, protected by national government institutions in charge of tracking firms (MNEs) performance and FDI figures in different countries. Therefore, having access to this sort of disaggregated industry data poses a significant opportunity for researching and contributing to the body of knowledge in this field as the abovementioned ‘conflation’ issue -reported in preceding studies- becomes a subject of exploration. Nonetheless, it is paramount highlighting that banking services are directly excluded from this original database (PNISCa, 2020), so the Foreign Portfolio Investment (FPI) effect, which may be heavily associated with this industry (earlier reported to have been strongly fluctuated between 19,9% and 23.9% of the nominal GPD between 2010 and 2019 (IMF, 2022)) is suggested to be excluded or somehow restricted in this research.

[65] ISIC is widely used nationally and internationally to classify economic activity data (population, production, employment, gross domestic product, and other economic activities. It is considered a basic instrument to study economic phenomena as it fosters data comparability and promotes national statistical systems’ development.

3.1.2 Panel Data Setting

The different variables' sources explained below were merged into an industry-year unbalanced panel database comprising T = 6 years (2012 to 2017) and N= 168 industry types. Each industry type includes from 1 up to 36 MNEs, out of the sample of 965 MNEs (located throughout Panama's ten provinces), totalling 3728 data points: 1) Each data point for the independent and moderating variables comprises 48 aggregated Income fields (columns) and 32 aggregated Cost & Expenses fields (columns). Those figures are yearly recorded via a structured 'Non-Financial Firms Survey' from the pool of 965 operating MNEs, classified as FDI inflow recipients per the Panamanian National Institute from Statistics and Census taxonomy (PNISCa, 2020). 2) Data points for control variables directly derive from compiled databases between 2012 and 2017 (Panamanian National and Government Authorities, Institutes, Agencies and Departments), publicly retrievable from the Panamanian National Institute from Statistics and Census (PNISCb, 2020). 3) Dependent variable data points are the average SPI figures per industry type. Each SPI figure per industry is calculated as the average SPI value associated with a given MNE, depending on its province of location. SPI figures per industry type employed range between 2012 to 2017. Subsection 3.2.4. delves into detail in this SPI figures calculations. As the number of data points for all variables used was small, it is worth mentioning that running Principal Component Analysis (PCA), Factor Analysis or Cluster Analysis to shorten to smaller variables sets was unnecessary. It is paramount to highlight that the limited number of years of longitudinal data may be restrictive concerning the 'strength' of the associations for the frameworks proposed and their related patterns. Although all the methodologies employed are argued to be chosen for their suitability in circumventing the existing misspecification's detailed in Chapter 4, thereby being statistically robust, patterns resulting may be regarded as 'conservative' o 'possible suggestions' in the light of categorical statements finding no supportive grounds.

3.2 *Research Design*

3.2.1 Research problem

As per the exhaustive literature review performed in the welfare economics arena and affine research fields, the main problem encountered was the absence of a conceptual/structural framework to guide the proposition of hypothesised association patterns. As reported in the literature review, no robust conceptual/structural frameworks were found to explain the underlying dynamics between the direct association between FDI and social development, to the extent that the theoretical underpinnings had to be posed via economic growth as an intermediate variable as earlier exposed. In this sense, and from this dissertation's particular stance, the core problem gravitates around the inexistence of an up-to-date welfare economics *framework incapable of fully explaining the statistically significant causal associations between FDI and social development.* Hence, the interest in researching this field in welfare economics was primarily triggered to fulfil this void via the conceptualisation of a 'conceptual/structural framework' that may be foundational to explain the underlying mechanisms of social development associated with FDI and vice versa in the specific case of the Republic of Panama. Empirical data from the 10 provinces of the Republic of Panama is employed. It is worth noting that due to the nation's demographics and social-political distribution features, the majority of the of MNEs concentrate on the provinces of Panama Metro, Panama West and Colon, as they comprise 60% of the country´s total population, produce 87% of the entire country´s GDP and concentrate 82% of its total FDI (MIDES, MEF & INEC, 2019).

3.2.2 Research questions

As per Creswell (2009), in the light of the quantitative nature of this research, no research question is required, contrarily to qualitative or mixed methods studies cases. Nonetheless, as a conceptual/structural framework is sought, one main research question is posed to aid in developing hypotheses as paramount conditions for this sort of research.

RQ1: Do FDI and social development co-evolve, positively or negatively, impacting each other, so a 'vicious circle' or a 'virtuous circle' for social development exists?

Regarding RQ1, it is paramount to state that the existence of such 'virtuous' or 'vicious' circles can only be established as *potentially possible* from a conservative standpoint since, in light of the limited longitudinal panel data coverage of only 6 years, a statistically rigourous categorical affirmation is restricted. This exploration would identify such a pattern, categorically stating its existence will require a larger data set of perhaps 30+ years or this study being performed with panel data for several countries and 20+ years. The rationale is that studying economic circles/cycles requires large panel data sets seeking variability in the data points from a longitudinal perspective, seeking estimators to be as unbiased as possible.

Additionally, two secondary questions (RQ2 and RQ3) are posed seeking to specify RQ1 (Creswell, 2009) further:

RQ2: If existent, could the reverse causality association between FDI and social development be proven long-term patterns?

RQ3: Could FDI and social development variables exhibit causal path dependencies patterns in their evolution for the case of Panama?

3.2.3 Hypotheses

In the absence of a solid supporting theoretical background concerning welfare economics, as explained above, the central hypothesis (H1) and the two related secondary hypotheses (H2 and H3) herein presented were heavily structured from the suggested knowledge voids reported in the work of Tocar (2019). According to the literature, FDI is suggested to exert positive, negative, and even neutral pressures on social development, mainly in a linear, unidirectional fashion. In that sense, a 'theoretical void' explaining the causal associations between FDI and social development exists. This research poses hypotheses that particularly seek to shed some light regarding the interwoven underlying bidirectional mechanisms between FDI and social development and vice versa in the specific case of the Republic of Panama. As earlier argued, SPI is a priori chosen as a reliable, suitable, and robust proxy measure to gauge, understand and explain social development for societies, in contrast to other instruments and/or proxy measures such as the spread-out and well-known HDI. H1 is posed as follows:

H1: It exists a bidirectional causal association between FDI and social development in Panama

Under the assumption that FDI impacts social development and vice versa, several conditions or factors could probably strengthen or weaken this association. Hence, additional hypotheses (H2 and H3) are posed as part of a research design strategy to empirically support the core thesis (H1) and raise confidence levels about the association between FDI and social development. H2 and H3 concern two moderating variables: 1) aggregated average amounts per industry spent by MNE on compensation benefits offered to their employees employed as a proxy for ‘household income’, and 2) aggregated average amounts per industry locally invested by MNEs subcontracting services from other local firms, employed as a proxy for ‘productive linkages’. In the Literature Review, ‘household income’ and ‘productive linkages’ were explored as reported derived effects of ‘economic spillovers’. A more ample explanation of each moderating variable is given below and subsequently in section 3.2.4. H2 and H3 are posed as follows

H2: The bidirectional causal association between FDI and social development is stronger for industries investing higher amounts in total compensation benefits for their employees and weaker when lesser amounts are spent.

H3: The bidirectional causal association between FDI and social development is stronger for industries investing higher amounts in subcontracting services from other local firms in Panama and weaker when lesser amounts are spent.

The moderating effect of Total Compensation as regards H2 is very straightforward since, as per CEPAL (2018), MNEs in Central America are associated with ‘job creation spillover effects’ as they generate job figures per million dollars invested: 1) 4 jobs in the food and beverage industry, 2) 14 jobs in the medical devices manufacturing industry, 3) 80 jobs in the apparel manufacturing industry and up to 100 jobs in the company shared services industry. One may hypothesise that social development improves with more robust compensation packages spent by MNEs on their employees (proposed as a proxy for ‘household income’), especially when comparing those amounts to average ‘classic economic’ figures of ‘income per capita purchasing power parity’. In this sense, following the empirical and theoretical-based studies explored above in the Literature Review, one may expect social development to be higher for industries tending to spend higher amounts in employee compensation packages and lower for industries spending fewer amounts.[66]

Regarding H3, the latter explained ‘job creation spillover effect’ has also been suggested to extend when hiring services from other local firms. Hence, the underlying argument is that besides the known ‘multiplying effect’ or ‘inclusive business effect’ triggered in the economy by MNEs when subcontracting services from third parties (traditionally suggested in the literature as ‘economic spillovers’), the associations between FDI and social development are also potentially impacted at the moment of hiring those very same local. In other words, the traditional ‘economic spillovers’ or ‘productive linkages’ argued to be unleashed in an economy by MNEs when operating in the host country are considered a moderating variable that enhances/detriments ‘social spillovers’ creation. In this sense, one may hypothesise that the total amounts spent by MNEs when hiring the services they required for their core operation, local businesses directly hired, received the benefits of those ‘productive linkages’ created. With a lagged effect, however, those spent amounts by MNEs further ‘lubricate’ the economy downstream and create a multiplying effect that may allow

[66] The geographic location of the employees working for an MNE, may potentially have higher explanatory power for testing H2, as the social performance of individuals and their families is more related to the location where they live. Nevertheless, this sort of data was not available in the panel data employed.

social development indicators to improve, potentiating ‘social spillovers’ creation. Contrarily, when MNEs spend less on subcontracting services from other local firms, the ‘productive linkages multiplying effect’ is reduced and, in turn, the potential associated ‘social spillovers’.

3.2.4 Variables

The independent, dependent, moderating and control variables associated with this research design conceptual/structural framework are explained as follows. Appendix 6.A and 6.C shows a summary of the variables' descriptive statistics in addition to the ‘Non-Financial Firms Survey’ database (PNISCa, 2020). breakdown comprising fields used for the independent, dependent and moderating variables (all figures are in US dollars at the year of realisation).

3.2.4.1 Dependent variable

Average SPI figures per industry type - stemming from averaging SPI individual MNE figures- are employed as proxies of social development. Each SPI figure is allocated to a given MNE, depending on the province they are located in. Besides recorded aggregated SPI figures per each of the 10 Panamanian provinces, it is worth noting that panel data also record figures for its 3 dimensions and 12 components (Stern & Epner, 2019). In this sense, average figures per industry type may also be estimated for the 3 SPI dimensions and 12 comprising components. Nonetheless, this dissertation only employs the 3 individual dimensions figures for the Robustness Test 1 purposes, as later explained: 1) Basic Human Needs, 2) Foundations of Wellbeing and 3) Opportunity.

As earlier explained in the literature review, although aggregated SPI figures for Panama have been tracked since 2014 following the Social Progress Imperative’s estimations, they had not been calculated in a disaggregated fashion -per province and indigenous regions- until 2019 (MEF & CLACDS, 2019). In passing, after that year, no government institution in Panama has continued estimating disaggregated SPI figures to the best of my knowledge. Nonetheless, SPI data points for the pertaining years (2012-2017) per province and indigenous regions were subjected to projections supported by the availability of methodological literature, particularly the one involving SPI, secondary sources and statistical techniques. An in-depth analysis of the projections' rationale is found in Appendix 5 (Methodology employed for SPI components estimation). This Appendix 5 could be summarised as follows: a) In the light of empirically finding an adjusted R-Square figure correlation of 0.90 between SPI and HDI (corroborating findings reported in Social Progress Imperative 2018, 2019), 12 backwards-step multivariable regression models (with adjusted R-Squares ranging between 0.86 and 0.99) were performed per each SPI component dimension. Each backwards-step multivariable regressions employed derived/transformed HDI comprising variables figures per province between 2012 to 2017 (PNUD, 2020) as regressors to project the SPI figures; b) Neural networks buttressed by latter PNUD (2020) database; and c) Pondering ratios calculations obtained from Panama's 2019 SPI report dataset (MEF & CLACDS, 2019) following the methodology guidelines reported in Stern & Epner (2019).

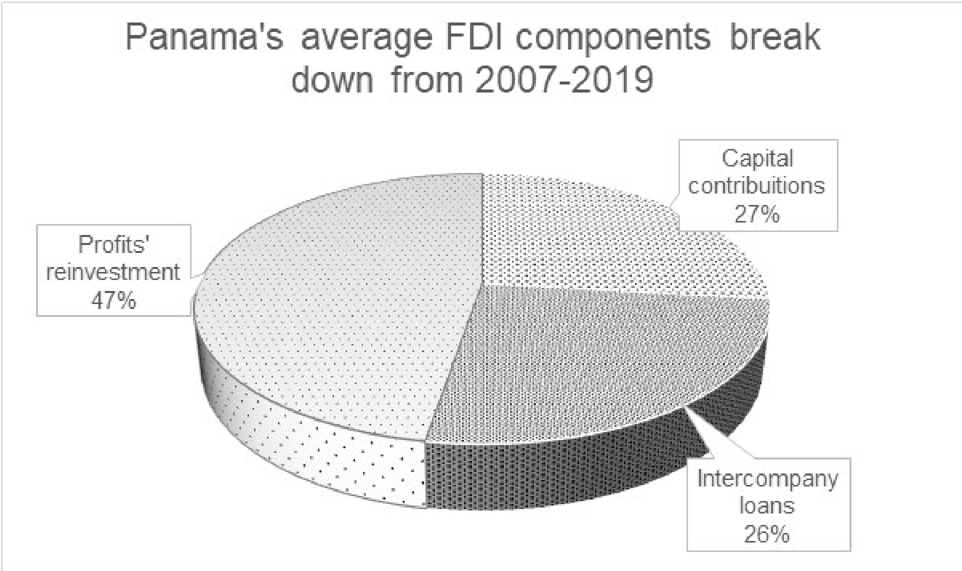
3.2.4.2 Independent variable

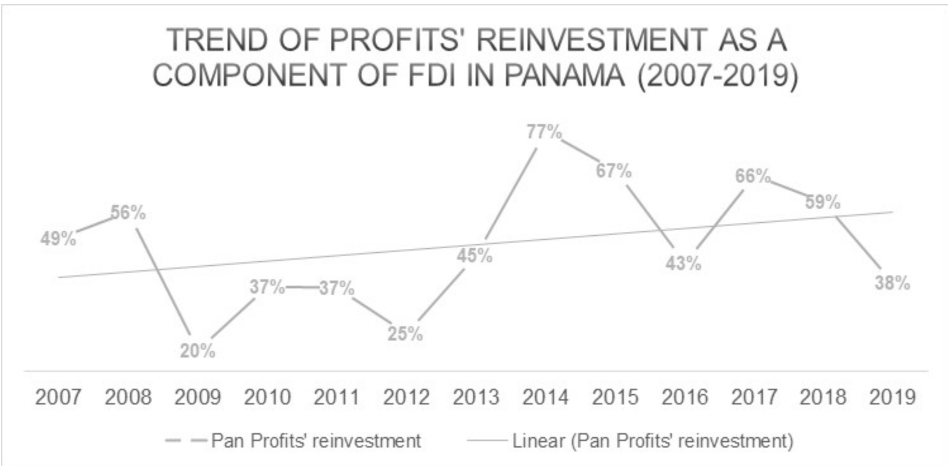
Financial flows capture direct investment amounts investors make in a specific period, unlike financial stocks, which account for direct investment cumulative value over time (OECD, 2008). Financial flows are useful to assess developments in FDI in a particular host country since changes in direction in these flows may indicate its investment climate status. Financial flows' components must be thereby understood and examined as they provide insights into the FDI nature. As per OECD (2014a) and OECD (2008) benchmark definitions for statistics accountability purposes, financial flows comprise 3 components: 1) Capital contributions, often associated with 'fresh' investments, such as '*greenfield*' or M&As, although they may additionally account for the extension of equity capital or financial restructuring. 2) Profits' reinvestment, conceptualised as the earnings portion that MNE's headquarters decides to reinvest in its MNE rather than receive as a dividend. Profits' reinvestment becomes a significant source of MNE financing. It is the least volatile of the 3 components. Profits' reinvestment ratio represents the share of earnings MNE headquarters decides to reinvest vs dividends distribution. MNE headquarters' perception of the investment climate in a host country may be reflected by reinvesting in profitable opportunities identified for its MNE. Nonetheless, MNE headquarters may contrarily request to pay higher dividends in case of facing pressures for financial resources. 3) Intercompany loans are often driven by short-term financing requirements within an MNE rather than more significant overall macroeconomic phenomena. It is the most volatile component and, from an FDI accounting perspective, the most difficult to explain due to direction-switching dynamics as large loans are received and paid off. From this perspective, due to the different nature of the 3 components, it is clear that FDI inward investments decreasing due to intercompany loan repayment must be interpreted differently from FDI inward investments dropping due to a decrease in capital contribution flows.

Those 3 latter components are conceptualised according to OECD (2014a) and OECD (2008) benchmark definitions for statistics accountability based upon the *directional principle*. Under this principle, FDI is recorded based on whether FDI transactions and positions represent investments abroad by MNE headquarters in the host country (outward FDI) or investments by foreign MNE headquarters in the host country (inward FDI). This differentiation is paramount to separate it from other types of investment, such as FPI (Foreign Portfolio Investment) above explained in the literature review and which accounting framework follows the *asset/liability principle* recording statistics based on whether they represent assets or liabilities to the host country (OECD, 2014a; OEDC, 2008).

MNE income flows may be debt-based or equity-based. Debt-based income derives from interest receipts and payments associated with intercompany loans, in contrast to equity-based income, which stems from the profits directly generated by the MNE (OECD, 2014a; OECD, 2008). Hence, equity-based generated profits may vary due to several different determinants; in general, differences between productivity -and profitability- directly reflect efficiency levels of capacity and specific assets usage of MNE in each host country (Rugman & Verbeke, 2001). From this standpoint, insofar as the profitability of a particular MNE directly derives from exploiting such advantages within a host country, the reinvesting profits decision each year is expectable to stem from the MNE headquarters (Clausing, 2001). Literature majorly points out the adverse effects of generated incomes of MNEs fleeing, presumably depriving host countries of reinvestment's potential economic spillover effects. Nonetheless, in the case of Panama, a time series analysis of FDI components from 2007 to 2019 (CEPAL, 2020) shows that a 47% average of yearly FDI inflow amounts has derived from MNEs reinvesting their previous years' profits. By choosing 2007 as the time series starting point, a rising trend for profits' reinvestment emerges, as shown in Chart 7.

Chart 7. Panama's historic average FDI components break down and trending growth of the profit's reinvestment component from 2012 to 2019





Source: Author analysis with data extracted from CEPAL (2020, pp87).

Aggregated average Main Income Sources figures -calculated as a percentage of Total Income per industry type- are chosen as a proxy for FDI and employed as the independent variable. As per the abovementioned argument, the underlying rationale is that next year's FDI inflow amounts for a given MNE may majorly depend on its potential to produce income in this current year. By only accounting for its Main Income Sources, this research concentrates on this MNEs' potential to take advantage of their capacity and assets to 'secure' their financing and operating sources for the next year, leaving aside other potential FDI income sources aligned to capital contributions and/or intercompany loans. This empirical 'path dependencies' phenomena, meaning figures of one period are related to figures of its previous one (lagged), priorly suggests employing Dynamic Panel Data (DPD) Models as later explained.

As explained above, one of the other 3 main components of FDI flows is Capital Contributions, which may account for either greenfied/M&As or/and equity capital extension /financial restructuring. Those amounts are what the Other Income Sources fields in the 'Non-Financial Firms Survey' account for (PNISCa, 2020). Hence, an aggregated average figure per industry type of Other Income Sources (all figures in the US dollar in the year of realization) is later employed as an alternative independent variable in section 5.2 for Robustness Test 2, seeking for the model's Structural Validity and Stability Tests.

3.2.4.3 Moderating variables

The Hypothesis subsection above, as per Baron & Kenny (1986), mentioned that moderating variables were chosen for determining the extent to which 'social spillovers' (SPI as a proxy for the dependent variable) are impacted (either strengthen/amplified, weaken/attenuated or even making the association disappear or change of direction) when directly inducing changes on the FDI (independent variable).

One chosen moderating variable is the aggregated average amounts spent per industry type in 'Total Compensation Packages' (estimated as a percentage of total Costs and Expenses with all figures in US dollars at the year of realisation). Following Senacyt (2019, pp107), between 2008 and 2018, the average income per capita of the Panamanian citizen has grown 150%, at a yearly 10% CAGR. Therefore, the underlying rationale revolves around exploring the potential of MNEs -within a given industry type- of moderating its effect on Main Income Sources (proxy of FDI) via the amounts invested in Total Compensation, which consequently would impact (either adjuvating or weakening) its potential for social development improvements creation. Total Compensation is suggested to benefit not only employees working for the MNEs but also their families, thereby becoming a proxy for 'household income'. The choice of this moderating variable priorly suggests employing a Dynamic Panel Data (DPD) Model approach, as lagged effects of 'Total Compensation Packages' in one period may be dependable on Main Income Sources (a proxy for FDI) amounts in a previous one. Hence, the moderating effect of FDI on social development is hypothesised to arise in the subsequent period.

The other moderating variable proposed intends to be a proxy for 'productive linkages'. The aggregated average figure of 'Services provided by third parties' per industry type (as a percentage of total Costs and Expenses with all figures in US dollars at the year of realisation) is employed. A secondary gain of researching this moderating variable may complement Senacyt's (2019) and Cajar's (2016) works, which have previously engaged in locally studying such traditional local 'economic spillovers'. The choice of this moderating variable also suggests priorly using a Dynamic Panel Data (DPD) approach as this 'Third Parties Expenditure' is also hypothesised to be a lagged variable. The underlying rationale coupled with the effects of 'Main Income Sources' (FDI proxy) as an independent variable: for 'productive linkages' to be created on local MNEs in one period, FDI must primarily be triggered (casual primary effect). After those 'productive linkages' have emerged, they may eventually moderate FDI in the next period, subsequently inducing a positive/negative impact on social development (dependent variable) during that very same period or/and on a subsequent one.

3.2.4.4 Control variables

As aforementioned, panel data used in this dissertation stems from the Panamanian national survey sources, which may be considered 'casual' or naturally occurring sources in a social science environment. Hence, unobserved variables are controllable via Ordinary Least Square Fixed Effect (OLS-FE) or more complex approaches, as later explained. Regarding the observed variables, developing a ‘ceteris paribus’ economic environment under a ‘conditional expectations’ perspective requires the introduction of control variables. Nonetheless, keeping control variables constant could potentially aggregate ‘noise research’ and affect its results, especially considering that they are not part of the study. Thus, as per Wooldridge (2018): *“deciding on the list of proper controls is not always straightforward and using different controls can lead to different conclusions about a causal relationship between the dependent and the independent variable. This is where establishing causality gets tricky: it is up to us to decide which factors need to be held fixed."*

It is worth noting that by ultimately seeking to develop an ‘empirical framework’ explanatory of potential ‘vicious’ or virtuous circles, the demonstration of reverse causality between the researched variables is crucial in this study. In this sense, choosing relevant control variables also becomes a significant endeavour as they aid in improving the -always partial- understanding of causal relationships. Hence, this research employs 5 observable control variables chosen for their identified potential to imprint high-magnitude effects on the association between the independent and dependent variables (Lenz & Sahn, 2020). Control variables are extracted from official publicly available sources of Panamanian National Institute from Statistics and Census between the years 2012 and 2017, which in most cases, compiled data from other different databases from Panamanian National and Government Authorities, Institutes, Agencies and Departments.

1. Masculinity Ratio: Human capital is considered a significant determinant of economic growth (Brummet, 2008), consequently impacting social development, as argued throughout this dissertation. In this sense, the masculinity ratio, as the proportion of the male population to its female counterpart, provides a gender-labour-inclined perspective of the human capital structure of a given society. This perspective appears to be particularly important for this research as it has traditionally been considered to have the potential to induce positive changes in social development or, on the contrary, create adverse effects. As contended by CEPAL (2018) regarding gender-labour differences, high ratios of the female workforce in MNEs for particular industries/sectors in Central America have become

critical drivers for social development improvements. Contrarily, as per Cecchini *et al.* (2020), gender-labour differences in Panama have been traditionally associated with unbalances in social development and disparities in access and exercise of social rights. Masculinity ratio is therefore chosen as a control variable due to the potential impact gender-labour proportions (human capital structure) may induce on social development. Figures were obtained by dividing the total population of men per province by the total feminine population per province.

2. The total population covered by social security services: The rationale supporting this choice as a control variable is that the larger a population gets coverage from a universal social security system, the higher the social development potential for those citizens to enjoy. As per ILO (2017), populations protected under welfare state-funded social security systems receive a series of social services such as healthcare, maternity leave, pensions, professional risks coverage and other related subsidies and benefits. In this sense, 'penetration' and 'coverage' of a nationalised social security system are expected. Figures per province ranging from 2012 to 2017 were obtained from the Panamanian National Institute of Statistics and Census. This control variable is estimated as a percentage of the total population registered under the Panamanian national social security system divided by the total population in the country.

3. Employment rate: It gauges the extent to which available labour resources (people available to work) are employed (OECD, 2020). As reported in MIDES, MEF & INEC (2019), and ECLAC / ILO (2020) employment rate in the Republic of Panama had been averaging 95% until 2019 (figures from 2020 and 2021 have been atypical due to the COVID-19 effect). As extracted for the definition provided by OECD (2020) for reporting statistics purposes, the employment rate is calculated as the ratio of the employed population to the working-age population, ranging from 16 to 64 years. The employed population includes those who reported having worked in gainful employment for at least 1 hour in the previous week or who had a job but were absent during the reference week. The employment rate is seasonally adjusted because of its sensitivity to economic circles. In the long term, however, they

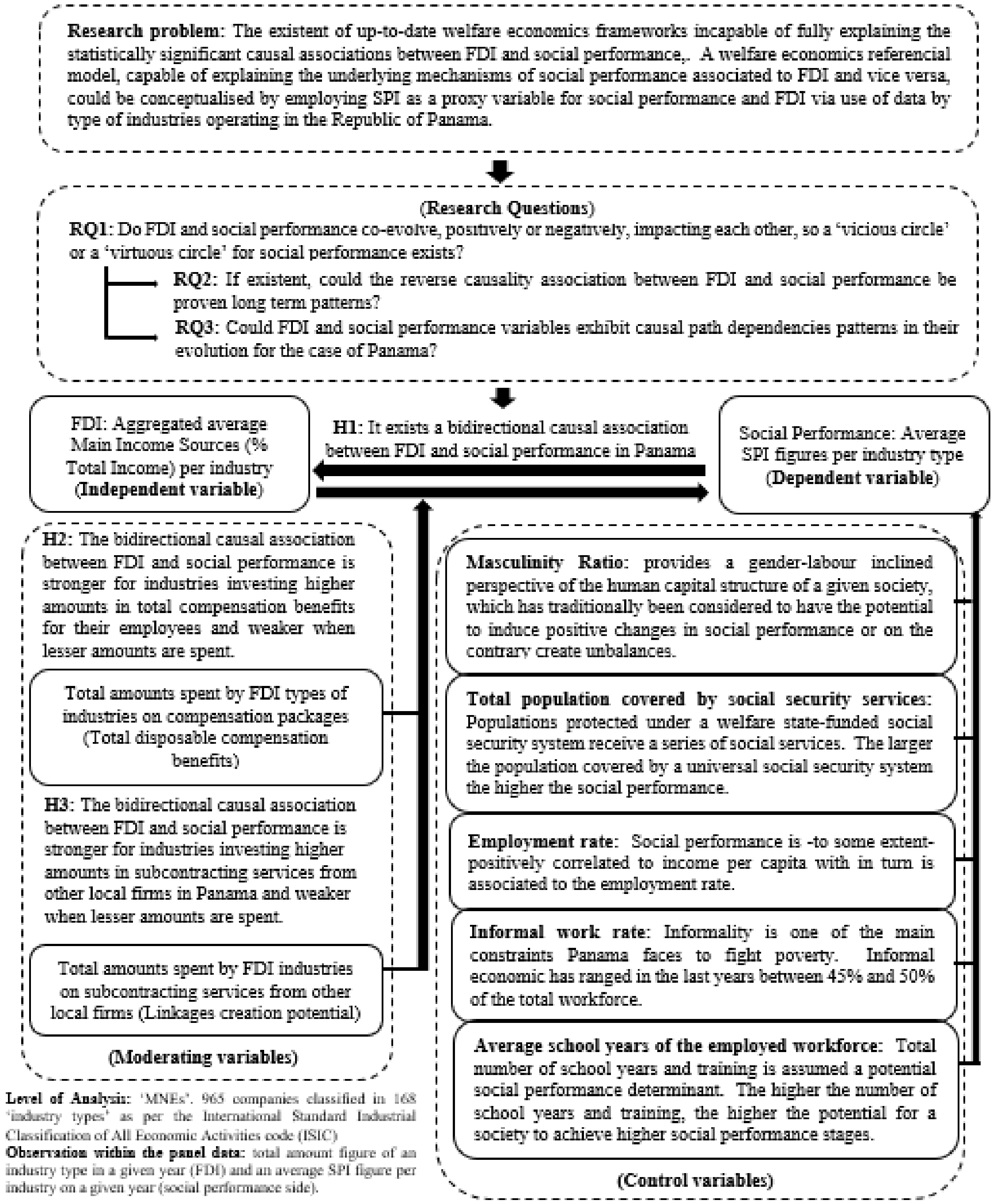
are affected significantly by higher education and government income support policies (e.g. for the female population and vulnerable groups). Employment rate figures were extracted from the sources mentioned above.

4. Informal work rate: As reported by CEPAL (2018), MNEs have been considered sources of formal employment in a scenario where informality has been traditionally the primary source of income for many households in Latin America and the Caribbean, averaging around 54% (ECLAC / ILO, 2020). As per CEPAL (2018), figures for Central America (except Costa Rica and Panama to a lesser extent) report employment under no-contract ranging between 44% to 51% for the male workforce and from 33% to 44% for female workers. In the case of Panama, as stated by MIDES, MEF & INEC (2019), the informal economy represents one of the main constraints faced by the country to fight poverty (and improve social development) which in the last years (previous to the atypical 2020 and 2021 figures due to the COVID-19 effect) has ranged between 45% and 50% of the total country workforce. Percentage figures of informal workers in relation to the entire available workforce were employed.

5. Average school years of the employed workforce: In general terms -although particularly referring to Latin America- the total number of school years and training of a country's population becomes a potential social development determinant (Reimers, 2006). The higher the number of school years and training, the higher the potential for a society to achieve higher social development stages. The average number of school years and training of the employed workforce population is used for this control variable.

See Chart 8 for the summary of this Research Design Model. Note that the bidirectional arrows between the independent variable (FDI) and dependent variable (SPI) imply directionality in both ways, as the research directly seeks bidirectional causation.

Chart 8. Research Design Model



Source: The author

4 CHAPTER FOUR: IDENTIFYING AND CIRCUMVENTING MISSPECIFICATIONS

Regarding its research design, panel data must be initially thoroughly analysed via different statistical tests to identify potential misspecification issues. Identifying those misspecifications is a previous crucial step in choosing the proper econometric approaches employed in Chapter 5 to tackle them subsequently. It is paramount to notice that although some subsections of Chapter 4 (and even Chapter 5) may eventually appear inclined toward econometrics concepts, the rationale for those explanations is to put the employed tests and their related arguments into context.

This chapter is structured as follows: subsection 4.1 refers to the identification of potential multicollinearity issues; subsection 4.2 engages in searching for endogeneity sources (omitted variables, measurement errors, simultaneity and selection bias); subsection 4.3 refers to the identification of heteroskedasticity and autocorrelation consistency (HAC), Cross-Sectional correlation and Autoregression misspecifications; and lastly subsection 4.4 proposes the methodological econometric–based frameworks to circumvent such misspecification.

4.1 Multicollinearity

As per Baltagi (2012), multicollinearity reduces the precision of the estimated coefficients by inflating their variance and type II error, turning p-values into untrustful figures to identify the model's statistically significant independent variables. Multicollinearity is not considered an important issue in panel data studies (Ismaeel *et al.*, 2021) mainly because the core units of analysis are industry types: MNEs comprising industries/sectors in aggregated fashion are considered heterogeneous entities (Orbes *et al.,* 2019). Nonetheless, Baltagi (2012) contends that observational studies are prone to multicollinearity issues directly induced by the data sources since, in general terms, the collection methods only sample over a limited range of values in the population. Hence, Gujarati & Porter (2009, pp337) stated that multicollinearity becomes *"a feature of the sample and not of the population …where there is no unique method of* *detecting it or measuring its strength…."* In the absence of an irrefutable multicollinearity test, however, a series of 'rules of thumb suggested by Gujarati (2003) and Gujarati & Porter (2009) as suitable means for its detection. A Correlation Matrix, a Variance Inflation Factors (VIF) Test, Auxiliary Regressions and a Condition Number Test using eigenvalues with standardised variables are performed as follows. Discarding or confirming the presence of multicollinearity becomes a paramount preliminary endeavour, as the series of follow-up post-estimation tests (intended to reveal the existence of several misspecification issues) are based upon pooled OLS calculations. See the Correlation Matrix in Table 5.

Table 5. Correlation matrix for the independent, moderating and control variables.

	FDI (Main Income Sources)	Total Compensation	Third parties expenditure	Masculinity Ratio	Population covered by SS	Average School Years	Employment rate	Informality rate
FDI (Main Income Sources)	1.0000							
Total Compensation	-0.1353*	1.0000						
	0.0001							
Third parties expenditure	0.0352	0.0005	1.0000					
	0.3053	0.989						
Masculinity Ratio	-0.0276	-0.1951*	0.0439	1.0000				
	0.4186	0.0000	0.2002					
Population covered by SS	-0.0263	0.0891*	-0.0759*	-0.4594*	1.0000			
	0.4412	0.0093	0.0266	0.0000				
Average School Years	-0.0341	0.1903*	0.0042	-0.8276*	0.4134*	1.0000		
	0.318	0.0000	0.9035	0.0000	0.0000			
Employment rate	-0.0632	0.1244*	-0.044	-0.3055*	0.2970*	0.2841*	1.0000	
	0.0638	0.0003	0.1997	0.0000	0.0000	0.0000		
Informality rate	0.0098	-0.1048*	-0.018	0.5693*	-0.3234*	-0.6781*	-0.3418*	1.0000
	0.7738	0.0022	0.5993	0.0000	0.0000	0.0000	0.0000	

Source: Author's estimates based on Stata17®

Note: * denotes p values < 0.05. Values above 0.7 suggest potential multicollinearity between two or more predictors (Baltagi, 2012). Pearson correlation figures above 0.7 are highlighted in light grey.

The 3 first variables in the table above correspond to the experimental variables (FDI -Main Income Sources as the main independent variable and Total Compensation and Third-Parties Expenditure as moderating variables), while the 5 remaining ones correspond to control variables. Out of the figures depicted in Table 5, only the correlation value of -0.8276 between the control variables Average School Years and Masculinity Ratio is above the 0.7 Pearson correlation coefficient threshold (with a statistically significant p-value below 0.05); therefore, a potential source of multicollinearity which -as reported by Gujarati & Porter (2009)- may stem from both control variables sharing a common trend (non-statistic behaviour) due to its cross-sectional time series nature.

As contented by Frost (2019, pp 2014), if high multicollinearity exists for control variables but not the experimental ones, one may interpret the coefficients of those experimental variables without exhibiting high variance issues. Hence, by adhering to the latter statement, one may preliminarily avoid resolving the multicollinearity issue found above, given only one pair of control variables exhibiting high correlation among themselves. Nonetheless, in pursuit of unveiling the true impact of those 2 control variables on the entire model (interaction with the remaining control variables and the core variables -experimental variables of interest-), further analysis is performed via a VIF Test and Auxiliary Regressions and the Condition Number Test as shown in Table 6.

Table 6. Multicollinearity Tests

a. Variance Inflation Factor (VIF) Test results.

Variable	VIF	1/VIF
Average School Years	4.04	0.2477
Masculinity Ratio	3.45	0.2895
Informality rate	1.94	0.5145
Population covered by SS	1.32	0.7568
Employment rate	1.2	0.8305
Total Compensation	1.07	0.9344
FDI (Main Income Sources)	1.04	0.9636
Third parties expenditure	1.02	0.9849
Mean VIF	**1.89**	

b. Auxiliary regressions R-squared Comparison Test

	R-square
Main Variables	
FDI (Main Income Sources)	0.036
Total Compensation (Modifying)	0.066
Third parties expenditure (Modifying)	0.015
Control Variables	
Masculinity Ratio	0.711
Population covered by SS	0.243
Average School Years	0.752
Employment rate	0.170
Informality rate	0.486

c. Condition Number Test using eigenvalues with standardised variables

	Eigenval	Condition Index
1	2.9281	1.0000
2	1.1251	1.6132
3	1.0234	1.6915
4	0.8542	1.8514
5	0.8105	1.9007
6	0.6926	2.0562
7	0.4150	2.6563
8	0.1511	4.4021

Condition Number: 4.4021

Eigenvalues & Cond Index computed from deviation sscp (no intercept)

Source: Author’s estimates based on Stata17®

VIF values[67] in Table 6a. are expected to be higher for the Average School Years and Masculinity Ratio variables, in alignment with the Correlation Matrix findings in Table 5. The VIF estimates how much the variance of a coefficient is inflated due to its dependence on other regressors. Following the ‘rule of thumb’ suggested by Neter *et al*. (1990), Gujarati (2003) and Gujarati & Porter (2009), by VIF values laying below the 5-figure threshold, a moderate/low correlation exist for both Average School Years (4.04) and Masculinity Ratio (3.45) and the remaining variables in the model (either control variables and core experimental variables). Similarly, the Mean VIF value of 1.89 (for all model variables), shown in Table 6a., additionally suggests a low aggregated correlation of all variables (either control or experimental/core variables) in the model.

As reported in Gujarati (2003) and Gujarati & Porter (2009), Klien’s ‘rule of thumb’ suggests that multicollinearity may be a troublesome issue if the R-square values obtained from single auxiliary regression are greater than the overall R-square of the regression of dependent variable on all the regressors. Under results in Table 5, R-square values of the auxiliary regressions in Table 6b. may be expected to be higher for Masculinity Ratio and Average School Years (0.71 and 0.75 respectively). Nonetheless, in neither case, those figures appear to be a potential source of multicollinearity issues since they do not surpass the 0.86 figure, which is the R-squared reference value for the overall regression (pooled OLS regression employing Social Progress Index as dependent variable).

Lastly, Table 6C. depicts the Condition Number Test using eigenvalues with standardised variables. Gujarati (2003) and Gujarati & Porter (2009) contend this test to be a more sophisticated ‘rule of thumb’; they also recognize that some authors consider it the “*best available multicollinearity diagnostic*” (Gujarati, 2003, pp362). Condition Number Test below the 10-figure threshold,

[67] VIF Test measures how much the behaviour (variance) of an independent variable is influenced, or inflated, by its interaction/correlation with the other independent variables (Neter *et al.*, 1990). Although heavily depending on the model nature, VIF figures of 1 indicates no correlation between a particular variable and the other variables; meanwhile, VIF values between 1 and 5 are a signal of a moderate correlation which in general is negligible from a multicollinearity perspective as it does not impact the model’s coefficients and standard errors estimates. Contrarly, although some literature sources point at values higher than 10, VIF values higher than 5 suggest a high correlation (Neter *et al.*, 1990). In such cases, avoidance of model’s estimate issues requires transforming/eliminating the variables exhibiting multicollinearity.

between 10 and 30 and exceeding the 30 figure, respectively, suggest a mild, moderate to strong and severe multicollinearity (Gujarati & Porter, 2009). Based upon the latter values as a reference to diagnose multicollinearity strength, a Condition Number of 4.40 suggests a mild impact of multicollinearity in the model's results if both experimental and control variables interact.

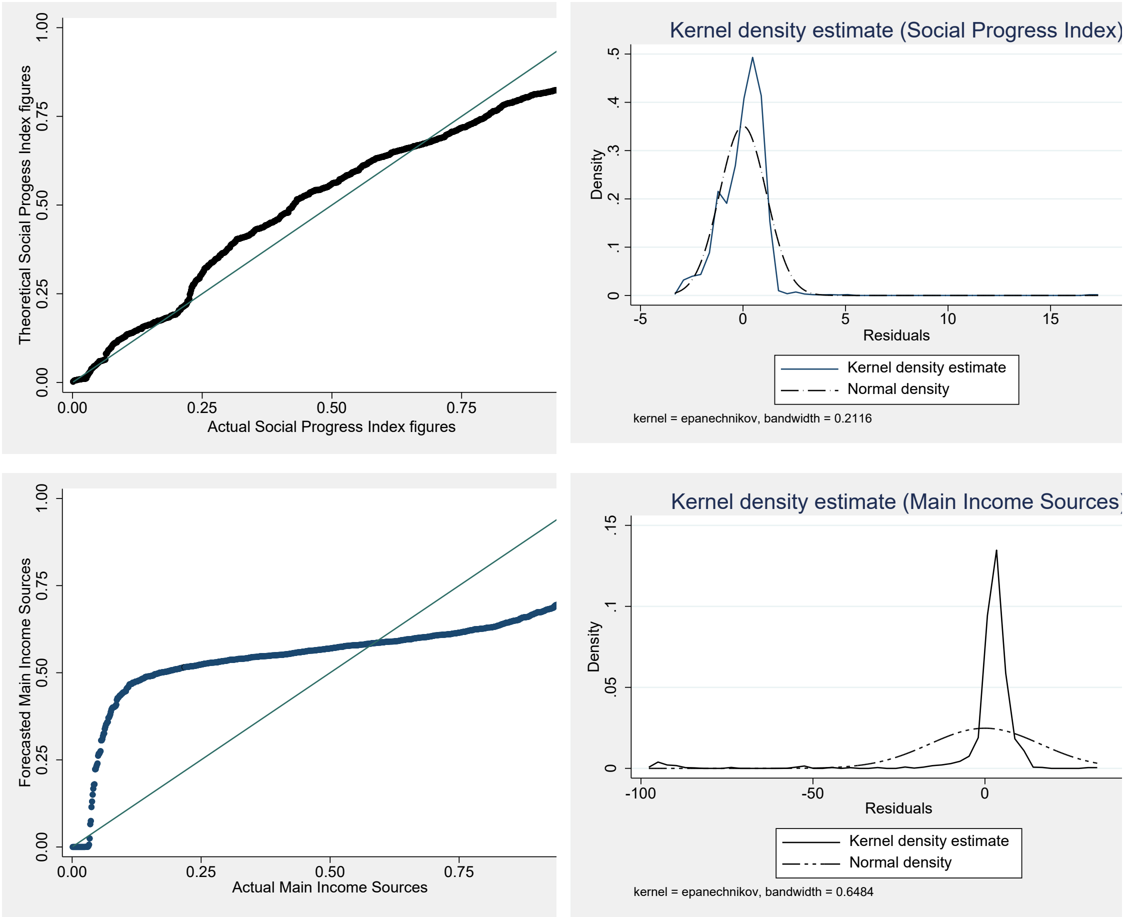
The findings of the 3 above-explained tests indicate that the multicollinearity issues potentially deriving from the 2 control variables could be considered negligible, even if interacting with the experimental and the remaining control variables that comprise the entire panel data. Coefficients and the estimates of their standard errors are suggested to remain unimpacted in their variance.

4.2 Endogeneity misspecifications

Non-correlation between explanatory variables and the error terms appears impossible to assume in econometric studies (Barros *et al.,* 2020). Hence, endogeneity-associated issues (in general terms, estimators' inconsistency leading to inappropriate inferences) must be identified and addressed, commonly via IV techniques (Greene, 2012). The problem generally faced is that variables that can be endogenous in one setting may be exogenous in another, even in the same data context. Hence, identifying endogeneity is a vital preliminary step for determining the estimation strategy in any empirical analysis. Nonetheless, the 'toolbox' for endogeneity testing is insufficient due to the statistical challenges that must be engaged (Greene, 2012; Barros *et al.,* 2020).

Endogeneity can be preliminarily identified via Q-Q graphs and Kernel Density Estimates graphs. Endogeneity may exist in some variables in a particular model by not complying with the normal distribution assumptions that OLS implies. As per Chart 9, where Social Progress Index and the Main Income Sources are plotted in Q-Q Actual vs Forecasted quantile graphs and Kernel Density graphs, both variables fail to fully comply with the assumption of samples being drawn from a population following a Normal Distribution approach, thereby suggesting that among other issues, endogeneity may exist.

Chart 9. Q-Q plots for Social Progress Index and Main Income Sources



Source: Author's estimates based on Stata17®

The existence of endogeneity in a system of equations can be confirmed or discarded by performing an Exogeneity Test under Gujarati & Porter (2009, pp705). This Exogeneity Test F-test is based upon a pooled OLS regression on simultaneous equations, as shown in Table 11. This F-test assumes a model that comprises 3 equations with 3 endogenous variables (y_1, y_2, and y_3) and 3 exogenous variables (x_1, x_2, and x_3.) as per the following equation: $y_{1i} = \beta_0 + \beta_2 y_{2i} + \beta_3 y_{3i} + \alpha_1 x_{1i} + u_{1i}$. A reduced form of y2 and y3 is formulated to assess the identifiability of a structural equation expressing an endogenous variable solely as a function of predetermined variables[68]. Subsequently, predicted values of y_{2i}

[68] Contemporary and lagged values of predetermined variables, but not necessarily future values, are uncorrelated with the error tems. In a more general acception, the value of predetermined variable is determined prior to the current period.

and y_{3i} are estimated ($\hat{y}_{2i}$ and $\hat{y}_{3i}$). Although the OLS estimator is neither consistent nor efficient in the presence of endogeneity, it can be employed to test its existence, as per the equation that follows: $y_{1i} = \beta_0 + \beta_2 y_{2i} + \beta_3 y_{3i} + \alpha_1 x_{1i} + \lambda_2 \hat{y}_{2i} + \lambda_3 \hat{y}_{3i} + u_{1i}$. Based on the latter equation, one can test the hypothesis that the coefficients of the predicted values are equal to 0 ($\lambda_2 = \lambda_3 = 0$). The rejection of this hypothesis implies that y_2 and y_3 are endogenous. Table 7 shows the results of an OLS employing the dependent, independent, and moderating variables proposed as the predetermined endogenous variables (4 instead of 3 as proposed Gujarati & Porter, 2009, pp705) and using the 5 control variables as predetermined exogenous variables. As per the test's p-value = 0.0000 results, the null hypothesis to favour exogeneity is rejected, confirming that the 4 core predetermined variables are endogenous. One must note that the test omits the Masculinity Ratio and Average School Years for exhibiting multicollinearity. Nonetheless, as per subsection 4.1, ample argumentations are provided based on a series of tests, and the potential multicollinearity issues both variables could introduce in the model are to be discarded, particularly because of their control variables' nature.

Table 7. Exogeneity Test

Source	SS	df	MS		
				Number of obs =	**852**
				F(9, 842) >	99999
Model	7846.75	9	871.86	Prob > F =	0
Residual	9.8E-09	842	1.2E-11	R-squared =	1
				Adj R-squared =	1
Total	7846.75	851	9.22	Root MSE =	3.4E-06

Social Progress Index	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
Main Variables						
FDI (Main Income Sources)	-0.0430	0.0000	-1.1E+06	0.0000	-0.0430	-0.0430
Total Compensation (Modifying)	0.1705	0.0000	3.6E+06	0.0000	0.1705	0.1705
Third parties expenditure (Modifying)	-0.0712	0.0000	-3.5E+06	0.0000	-0.0712	-0.0712
Main Variables (Forecasted)						
Main Income Sources (Forescast)	1.4867	0.0000	3.6E+06	0.0000	1.4867	1.4867
Total Compensation (Forescast)	0.4518	0.0000	6.0E+06	0.0000	0.4518	0.4518
Third parties expenditure (Forescast)	1.8301	0.0000	3.3E+06	0.0000	1.8301	1.8301
Control Variables						
Masculinity Ratio			omitted because of collinearity.			
Population covered by SS	0.1970	0.0000	3.0E+06	0.0000	0.1970	0.1970
Average School Years			omitted because of collinearity.			
Employment rate	1.0092	0.0000	2.3E+06	0.0000	1.0092	1.0092
Informality rate	0.3635	0.0000	1.7E+06	0.0000	0.3635	0.3635
Constant	-228.1289	0.0001	-2.3E+06	0.0000	-228.1291	-228.1287

(1) Main Income Sources Forecast = 0
(2) Total Compensation Forecast = 0
(3) Third parties expenditure Forecast = 0

F (3, 842) = 1.2e+14
Prob > F = 0.0000

Source: Author's estimates based on Stata17®

Once the general endogeneity issue has been identified, one must determine its sources[69]. For brevity purposes, Table 8 shows a summary of the results of the tests performed confirming the existence of Omitted Variables, Measurement Errors, Simultaneity and Non-random selection bias issues, which, as contended by Greene (2012) and Li *et al.* (2021)- are the 4 primary endogeneity sources in panel data research. A detailed explanation of each test and supportive arguments is provided in Appendix 7A.

Table 8. Summary of Test Results for Endogeneity misspecifications

Type of Test	Results' Test	Confirming / discarding outcome
Overall existence of endogeneity		
Exogeneity Test (Gujarati & Porter, 2009)	P-value = 0.0000	The null hypothesis that coefficients in the OLS regression are equal to 0 is not rejected. Hence, the 4 core predetermined variables are proven endogenous.
Omitted variables as a source of endogeneity		
Hausman Specification Test	Prov > chi 2 = 0.0000	The null hypothesis is that OLS-RE provides consistent estimates is strongly rejected. Hence OLS-FE is suggested to have a better statistical performance regarding coefficients' calculations than OLS-RE. Choosing the OLS-FE over the OLS-RE confirms the existence of an omitted variables issue and its related endogeneity issues
Measurement errors as a source of endogeneity		
Identification of Measurement errors sources	1) recoding errors (typos or rounding factors), 2) using proxies that diverge from the 'real' construct targeted to be observed, and 3) employing averages, ratios, indexes or percentages, among others as measures for the proxy variables.	The presence of those measurement error types in all variables employed in the model strongly suggests them as endogeneity sources in the panel data.
Simultaneity (Reverse Causality) as a source of endogeneity.		
Exogeneity Test (Gujarati & Porter, 2009)	P-value = 0.0000.	F-test renders the rejection of the null hypothesis suggesting both Main Income Sources (FDI) and social performance (SPI) to be endogenous variables.

[69] The rationale is choosing the statistical method that better tackles that particular endogeneity source. This method must be selected based on the type of estimator employed. Ideally, this estimator must be asymptotically consistent (unbiased) and efficient (small variance or mean square error as possible).

Non-random selection as a source of endogeneity.		
Qualitative identification of non-random selection (selection bias) sources.	Missing values for this unbalanced panel data are due to 1) non-responses in surveys and 2) survey records do not account for all 6 years. Individual decisions of officers designing the 'Non-Financial Firms Survey' (e.g. survey's structure, fields and wording employed). Personnel collecting the data may be a selection bias source (e.g. leaving out one particular MNE in one specific year for some unknown reason).	Endogeneity stemming from random selection is strongly suggested to exist.

Source: Author's estimates based on Stata17®

4.3 Heteroskedasticity and autocorrelation consistency (HAC), Cross-Sectional correlation and Autoregression misspecifications

To this stage, one has only confirmed the existence of 4 endogeneity misspecification sources. From a methodological standpoint, as per Hausmann Test reported in Table 8, Pooled OLS-FE[70] is suggested -up to this point- as a superior choice over Pooled OLS-RE[71] model to continue with the required misspecification tests. Hence, further seeking for Time Fixed Effects may also be required, for which a dummy variable (*D)* to the Pooled OLS-FE model, allowing the elimination of bias from unobserved heterogeneity (*ui*), which changes over time but is constant over the industry type while controlling for different factors across the panels, which are also constant over time (time-invariant). See Table 9[72].

[70] Pooled OLS-FE offers the advantage of eliminating the omitted variable effect and consistently calculating the observed explanatory variables (Wooldridge, 2018). Under this perspective, Pooled OLS-FE assumes that each industry type has different intercept figures (Ranjan & Agrawal, 2011). Thereby, by using Within Transformation on repeated observations for the Pooled OLS-FE, one could control for time-invariant factors displaying systematic variations and unobserved heterogeneity across industry types: industries do not only exhibit systematic structural differences but also differences in growth paths as regards their technological advancement (Binder & Georgiadis, 2010). This control of all time-invariant differences between industry types ultimately aims to prevent bias in the estimators (*β)* derived from the endogeneity induced by omitted variables / unobserved heterogeneity (*ui*).

[71] Pooled OLS-FE (*xtreg, fe* command in Stata17®) vs Pooled OLS-RE (*xtreg, re)*.

[72] The *testparm* command in Stata17® implements a post-estimation F-test for several joint coefficient variables. The Pooled OLS-FE regression besides including dummy variables (*i.Year* as per Stata17® notation), also includes the interaction of the moderating variables over the independent variables as per the research design.

Table 9. Fixed Effect regression (with dummy variables) and F-test

OLS-Fixed-Effects (Within) Regression			Number of obs	=	852	
Group variable: Industry/Sector			Number of groups	=	166	
R-squared:			Obs per group:			
Within	=	0.9449	min	=	1	
Between	=	0.8208	avg	=	5.1	
Overall	=	0.9094	max	=	6	
			F(15,671)	=	767.45	
corr(u_i, Xb) = 0.2160			Prob > F	=	0.0000	

Social Progress Index	**Coefficient**	**Std. err.**	**t**	**P>|t|**	**[95% conf. interval]**	
Main Variables						
FDI (Main Income Sources)	-0.0016	0.0027	-0.6100	0.5450	-0.0068	0.0036
Total Compensation (Moderating)	0.0004	0.0039	0.1100	0.9090	-0.0071	0.0080
Third parties expenditure (Moderating)	0.0081	0.0094	0.8700	0.3850	-0.0103	0.0265
Modifying Effects						
MainIncomeSources * TotalCompensation	0.0000	0.0000	1.1600	0.2450	0.0000	0.0001
MainIncomeSources * Thirdpartiesexpend	0.0000	0.0001	-0.4900	0.6240	-0.0002	0.0001
Control Variables						
Masculinity Ratio	-1.4825	0.0298	-49.7000	0.0000	-1.5411	-1.4240
Population covered by SS	-0.0452	0.0014	-31.7600	0.0000	-0.0480	-0.0424
Average School Years	-0.4762	0.0781	-6.1000	0.0000	-0.6296	-0.3229
Employment rate	0.0332	0.0140	2.3700	0.0180	0.0057	0.0607
Informality rate	-0.2135	0.0115	-18.5500	0.0000	-0.2361	-0.1909
Constant	239.2653	3.3198	72.0700	0.0000	232.7467	245.7838
Time Effects (Year)						
2013	-0.7359	0.0467	-15.7400	0.0000	-0.8277	-0.6441
2014	0.1389	0.0434	3.2000	0.0010	0.0537	0.2241
2015	-0.4819	0.0556	-8.6700	0.0000	-0.5911	-0.3727
2016	-1.0870	0.0556	-19.5400	0.0000	-1.1962	-0.9777
2017	-1.9845	0.0432	-45.9400	0.0000	-2.0693	-1.8997

sigma_u	1.4792	
sigma_e	0.2936	
rho	0.9620	(fraction of variance due to u_i)
F test that all u_i = 0 : F(165, 671) = 22.07		Prob > F = 0.0000

1	2013.Year = 0	
2	2014.Year = 1	F(5, 671) = 714.48
3	2015.Year = 2	Prob > F = 0.0000
4	2016.Year = 3	
5	2017.Year = 4	

Source: Author's estimates based on Stata17®

Results stemmed from the *testparm i.Year* test found at the bottom of Table 9 confirms the rejection of the null hypothesis that coefficients for all years dummy variables[73] are jointly equal to zero (each year dummy is, in effect, equal to zero). Hence, Time Fixed Effects must be included in the Pooled OLS-FE

[73] As per Kripfganz (2019), the advantage of using time dummies lies in their ability to be treated as strictly exogenous variables, which implies they are uncorrelated with the panel-specific effects (Fixed Effects). Moreover, as later explained, engaging Dynamic Panel Data Models allow using dummy variables as IVs without loss of generality.

regressions employed in the misspecification tests detailed in Appendix 7B, focused on confirming the existence of HAC (Heteroskedasticity and Autocorrelation Consistency), Cross-Sectional Correlation and Autoregression. Besides the Time Effects, the Pooled OLS-FE regressions include the interaction of the moderating variables over the independent variables. Table 10 shows the summary of the tests.

Table 10. Summary of Test Results for heteroskedasticity and autocorrelation consistency (HAC), Cross-Sectional correlation and Autoregression misspecifications

Type of Test	Results' Test	Confirming / discarding outcome
Groupwise heteroskedasticity.		
Modified Wald hypothesis test for FE model's residuals (Stata17® community-contributed xttest3 command)	Prov > chi 2 = 0.0000	The null hypothesis of homoskedasticity is rejected, confirming heteroskedasticity the error terms. Hence, the *'robust'* option from Stata17® is chosen to control for heteroskedasticity-robust SE (Huber/White Sandwich Estimator' standard errors).
Autocorrelation (serial correlation)		
Inoue & Solon (2006)'s LM portmanteau test statistic (*xtistest* command in Stata17®)	All 6 p-values are found below the 0.05 threshold (6 years in the panel data).	The null hypothesis poses the nonexistence of autocorrelation of any order. Hence, its rejection confirms serial correlation for every single time period (2012 – 2017).
C-H test (Cumby & Huizinga, 1990, 1992) Implemented in Stata17® by Baum & Schaffer (2013) via the *actest* post-estimation command	All p-values for both test blocks lay below the 0.05 threshold	The null hypothesis assumes that time-series exhibit a moving average (MA) of known order *q* (either zero or a positive value). Rejection of the null hypothesis of both test block sides confirms serial correlation existence exhibiting a moving average function up to the order of 6: MA(6).
A Stata17® abar post-estimation test (Arellano-Bond test) run after an equivalent non-dynamic pooled OLS FE panel data model.	All 5 possible z-values lay below the 0.05 threshold	Test assumes no autocorrelation under the null (q = 0) for a particular lag. As per the z-values for every lag (based on the Chi-Square hypothesis test), the null hypothesis is rejected, confirming serial correlation up to the 5 lagged order.

Cross-Sectional correlation		
Cross-sectional correlation test based on Pesaran (2004, 2015)	p-value = 0.0000 (SPI) p-value = 0.0000 (residuals)	The null hypothesis of cross-sectional independence / weak cross-sectional dependence is rejected. Hence, the existence of a strong correlation between panel units exists.
Autoregression.		
A Stata17® abar post-estimation test (Arellano-Bond test) run after an equivalent non-dynamic pooled OLS FE panel data model lagging the dependent variable (SPI) either 1 or 2 orders (years)	AR(1)'s z-value is above the 0.05 threshold while AR(2), AR(3) and AR(4) z-values lay below 0.05 for the 1-year lag of the dependent variable. All AR(1), AR(2) and AR(3) z-values lay below 0.05 for the 2-year lag of the dependent variable.	For 1-year lag: the null hypothesis is accepted for AR(1), confirming no autoregression. AR(2), AR(3) and AR(4) confirm autoregression. 2-year lag: the rejection of the null hypothesis for AR(1), AR(2) and AR(3) confirm the existence of autoregression.

Source: Author's estimates based on Stata17®

4.4 Overcoming the misspecification issues.

After identifying all the potential misspecification sources, identifying the best suitable method to tackle them becomes the next step, as shown below.

4.4.1 Tackling HAC, cross-sectional correlation and endogeneity for omitted variables and non-random selection.

Up to this point, the Pooled OLS-FE panel data model with Time Effects has been identified as the best suitable model for analysis. However, being susceptible to large SEs (Collischon & Eberl, 2020, pp295) is advantageous for controlling for omitted variables (unobserved heterogeneity) endogeneity. Unfortunately, when post-estimation tests are further performed based upon this Pooled OLS-FE and Time Effects model, they fall short in managing different misspecifications described above. Under Hoechle (2007, pp4), as shown in Table 11, a series of potential 'fixes' depending on the different misspecifications to overcome could be estimated via Stata17® in this quest for unbiased and efficient estimators.

Table 11. Suggested Fixed Effects panel data regressions depending on the misspecification type.

Command	Option	SE estimates are robust to disturbances being	Notes
`reg`, `xtreg`	`robust`	heteroscedastic	
`reg`, `xtreg`	`cluster()`	heteroscedastic and autocorrelated	
`xtregar`		autocorrelated with AR(1)[1]	
`newey`		heteroscedastic and autocorrelated of type MA(q)[2]	
`xtgls`	`panels()`, `corr()`	heteroscedastic, contemporaneously cross-sectionally correlated, and autocorrelated of type AR(1)	$N < T$ required for feasibility; tends to produce optimistic SE estimates
`xtpcse`	`correlation()`	heteroscedastic, contemporaneously cross-sectionally correlated, and autocorrelated of type AR(1)	large-scale panel regressions with `xtpcse` take a lot of time
`xtscc`		heteroscedastic, autocorrelated with MA(q), and cross-sectionally dependent	

[1] AR(1) refers to first-order autoregression

[2] MA(q) denotes autocorrelation of the moving average type with lag length q.

Source: Hoechle (2007, pp4)

As per the guidelines suggested in the latter table, by adding the *robust* and *cluster()* subcommand options on the *xtreg, fe* model with additional Time Effects, one may be able to control for both heteroskedasticity and serial correlation (autocorrelation) as shown on Model 2 in Table 12. Model 1 exhibits findings just by running the *xtreg, fe* model with additional Time Effects but without robust and cluster() subcommand options, allowing a comparison point. Nonetheless, since cross-sectional correlation issues were also found, the model's misspecifications are not only limited to being controlled for heteroskedasticity and serial correlation. Thus, although the *xtgls* and *xtpcse* models may seem appropriate to manage HAC, cross-sectional correlation, omitted variables, and non-random selection, only the *xtscc* becomes a suitable choice as serial correlation identified is not of 1-order (AR(1)) as required by *xtgls* and *xtpcse* (Greene, 2018), else exhibiting a Moving Average pattern reaching up a 6-order (MA(6)) as shown in Table 10 in subsection 4.3. The Driscoll-Kraay SE[74] (based upon the work of Driscoll & Kraay, 1998) may be employed via the

[74] The Driscoll-Kraay SEs are estimated following a nonparametric technique in which the covariance estimator works for balanced and unbalanced panels, and it is capable of handling

xtscc model, assuming an error structure heteroskedastic, autocorrelated up to some lag, and possibly correlated between groups (panels) as shown in Model 3[75].

Table 12. Comparison of models when controlling for heteroskedasticity, serial correlation and cross-sectional correlation.

		Model 1: Fixed Effects with Time effects WITHOUT controlling for heteroskedasticity and serial correlation	Model 2: Fixed Effects with Time effects WITH control for heteroskedasticity and serial correlation	Model 3: Fixed Effects / Discroll-Kraay SE / 5 lags	Model 1: Fixed Effects with Time effects WITHOUT controlling for heteroskedasticity and serial correlation	Model 2: Fixed Effects with Time effects WITH control for heteroskedasticity and serial correlation	Model 3: Fixed Effects / Discroll-Kraay SE / 5 lags
	Coeficient	SE			p - value		
Main Variables Effects							
FDI (Main Income Sources)	-0.0016	0.0027	0.0017	0.0004	0.5451	0.3396	0.0083
Total Compensation (Moderating)	0.0004	0.0039	0.0017	0.0004	0.9095	0.7927	0.3316
Third parties expenditure (Moderating)	0.0081	0.0094	0.0067	0.0031	0.3851	0.2289	0.0466
Moderating Variables Effects							
Main Income Sources*Total Compensation	0.0000	0.0000	0.0000	0.0000	0.2448	0.0649	0.0017
Main Income Sources*Third parties expenditure	0.0000	0.0001	0.0001	0.0000	0.6244	0.4460	0.1321
Control Variables Effects							
Masculinity Ratio	-1.4825	0.0298	0.1382	0.0391	0.0000	0.0000	0.0000
Population covered by SS	-0.0452	0.0014	0.0040	0.0013	0.0000	0.0000	0.0000
Average School Years	-0.4762	0.0781	0.2023	0.1889	0.0000	0.0197	0.0531
Employment rate	0.0332	0.0140	0.0283	0.0470	0.0182	0.2428	0.5116
Informality rate	-0.2135	0.0115	0.0384	0.0162	0.0000	0.0000	0.0000
Constant	239.2653	3.3198	13.1574	4.4234	0.0000	0.0000	0.0000
Time Variable Effects							
2012				(base year)			
2013	-0.7359	0.0467	0.0692	0.0689	0.0014	0.0043	0.0000
2014	0.1389	0.0434	0.0479	0.0658	0.0000	0.0000	0.0002
2015	-0.4819	0.0556	0.1061	0.0986	0.0000	0.0000	0.0051
2016	-1.0870	0.0556	0.0919	0.1236	0.0000	0.0000	0.0000
2017	-1.9845	0.0432	0.0767	0.0670	0.0000	0.0000	0.0000
N					852	852	852
F					767.45	605.94	8779.05
Prob > F					3.3140E-07	5.9754E-07	7.5198E-10
R square within					0.9449	0.9449	0.9449

Source: Author's estimates based on Stata17®

As per the latter table results, one could observe that SEs of Main Variables Effects (Main Income Sources, Total Compensation and Third-Parties Expenditure) drop their values when using the Driscoll-Kraay SE (Model 3) in comparison to employing the OLS-FE regression controlling for heteroskedasticity and serial correlation (Model 2). This SE value drop increases when comparing the Driscoll-Kraay SE regression (Model 3) to the traditional OLS-FE without controlling for heteroskedasticity and serial correlation (Model 1). Employing Driscoll-Kraay SE allows Main Income Sources and Third parties Expenditure and the interaction of Main Income Sources*Total Compensation to

missing values, thereby tackling non-random selection issues (selection bias). As the Driscoll-Kraay SE does not constrain the limiting behaviour of N, cross-sectional dimension size in finite samples does not restrict feasibility -even when N is larger than T-. Although SEs are robust to general cross-sectional and temporal dependence forms when T becomes large (Driscoll-Kraay estimator is based upon large T asymptotics), it is also applicable to panel datasets with a large N a small number of observations over time (T), provided that the due statistical precautions are taken.

[75] Results were obtained by employing the *ase* Stata17® sub option with 5-period lags (maximum lags permitted as per T=6), targeting SE figures adjustment since, as per Collischon & Eberl (2020, pp296), FE uses fewer cases for coefficients' estimation only representing within-panel changes over time.

be significant under a 0.05 p-value figure, suggesting this regression to be statistically more robust in comparison to Model 1 and Model 2, under which no explanatory variables and their interactions were significant. Although the F-statistic for the 3 models is also significant for forecasting purposes (laying below a 0.05 threshold), Model 3 is suggested to be slightly superior from a statistical perspective as its prob > F figure is on the e-10 magnitude (scientific notation), since Model 1 and Model 2 fall within the e-7 magnitude. The R-square-within value is a 0.9449 figure for the 3 models, somehow an expected finding as the same variables are used for comparison purposes. These results strongly suggest that employing this *xtscc* Stata17® command regression with Driscoll-Kraay SE may be a good fit for controlling for HAC, cross-sectional correlation and omitted variables' endogeneity and non-random selection misspecifications.

Although misspecification issues such as lagged variables effects and endogeneity for autoregression may still be tackled (controlled), developing a preliminary conceptual/structural framework is feasible. Searching for significant coefficients may appear to be the next step by following a coherent statistical analysis thread line. At this point also, it is worth noting that insofar as the conceptual/structural framework is developed, improvements in p-values significance for the coefficients (estimators) try to avoid as much as possible the spread-out tendency of 'p hacking', as pointed out in Verhulst (2016) and Hirschauer *et al.* (2018). Table 13 depicts 5 models employing the Pooled OLS-FE regression with Driscoll-Kraay SE. Improvements in the models target finding the best estimators possible, both from a statistical significance perspective and concerning their unbiasedness, efficiency, and predictive power.

Table 13. Comparison of models when controlling for heteroskedasticity, serial correlation and cross-sectional correlation through OLS-FE regressions with Driscoll-Kraay SE.

	Model 1	Model 2	Model 3	Model 4	Model 5
Main Variables Effects					
FDI (Main Income Sources)		-.00073257*	-.00228626*	-0.000561	
FDI (Main Income Sources) L2					.00252885***
Total Compensation (Moderating)			-.00219151*		
Third parties expenditure (Moderating)				0.006652	.01086896**
Moderating Variables Effects					
Main Income Sources*Total Compensation			.00005353**		
Main Income Sources*Third parties expenditure				0.0000	
Main Income Sources(L2)*Third parties expenditure					-.00008892**
Control Variables Effects					
Masculinity Ratio	-1.303814***	-1.4203011***	-1.4869682***	-1.4815648***	-1.4909932***
Population covered by SS	-.02528105***	-.04351231***	-.04536848***	-.0450612***	-.04550825***
Average School Years	-0.775806	-.51115516*	-0.487133	-0.479808	-0.459392
Employment rate	-.22655062*	0.038872	0.035040	0.035283	0.034144
Informality rate	-.30209331***	-.21649614***	-.2128989***	-.21207995***	-.21064584***
Constant	250.20***	232.96501***	239.8246***	238.97026***	239.4841***
Time Variable Effects					
2012		(empty)	(empty)	(empty)	(empty)
2013		-.74773092***	-.74850889***	-.73617866***	-.7260603***
2014		0.148215	0.140469	0.145119	0.133664
2015		-.45861007**	-.47698576**	-.47452593**	-.48705361**
2016		-1.0757377***	-1.0840295***	-1.0779611***	-1.0925774***
2017		-1.9960173***	-1.9844624***	-1.9767867***	-1.9837595***
N	860	860	860	852	850
F	934.22	10051.98	52476.02	38858.81	60505.44
Prob > F	2.03E-07	0.0000	0.0000	0.0000	0.0000
R square within	0.6696	0.9464	0.9442	0.9443	0.9445
					Legend: * p<.05; ** p<.01; *** p<.001

Source: Author’s estimates based on Stata17®

As per Hirschauer *et al.* (2018), one may remember that including control variables in a model aims to exclude alternative explanations while hypotheses with explanatory regressors are tested. Additionally, they are expected to maintain as much as possible a ‘ceteris paribus’ scenario (employing the same variables throughout all the research years intends to induce to the greatest extent, quasi-experimental-like controlling conditions to this observational study). Thus, although differences between explanatory or control variables are assumed unmeaningful from a statistical perspective, this premise does not hold from a conceptual standpoint, as earlier argued in subsection 3.2.3, since control variables’ inclusion and interpretation in a model becomes more theoretically motivated than a statistical decision.

Model 1 shows the OLS-FE regression with Driscoll-Kraay SE simply employing the control variables. The r-square-within value is 0.66, meaning that the control variables’ variation is explanatory of 66% of the variation in SPI, strongly suggesting being a good and effective fit for modelling purposes from a statistical power perspective. This value is expected to be lower than the other R-square-within figures for the remaining models (Model 2 to Model 5) since the rest of the variation (explanatory power) must be due to the other variables employed and their interactions, including the Time Effects, which as earlier explained function as additional control variables. Additionally, the model displays an F-statistic probability below 0.05, strongly suggesting that the chosen control variables -alone- account for an explanatory power that makes them suitable for SPI's prediction purposes, further buttressing their suitability as control variables. In effect, the remaining models (Model 2 to Model 5) that follow also exhibit similar F-statistic probability figures, also confirming their predictive statistical power.

As per Hirschauer *et al.* (2018), control variables are subjected to be removed from the model (pursuing parsimonious models) when they are not statistically significant or, more importantly, when their inclusion does not change the explanatory power of the regressors' estimates. From this perspective, one may preliminarily exclude the Average School Years as a control variable for not being statistically significant (p-value above the expected 0.05 threshold). Nonetheless, when considering the high explanatory power of control variables aggregately (R-square-within of 66%) and its increase of 95% when adding the other regressors (Model 2 to Model 5 as below explained) in addition to the above-provided argumentation of control variables being more a theoretical rather than a statistical choice, this out of range p-value discrepancy is to be considered a negligible.

Model 2 depicts the OLS-FE regression with Driscoll-Kraay SE, including the independent variable (Main Income Sources). Findings show the independent variable being statistically significant. Time variables' effects are significant for all possible years (the regression model automatically eliminates year base 2012 to avoid falling into the 'dummy variable trap') except for the year 2014. This pattern is also exhibited in the following models (Model 3 to Model 5). The r-square-within figure suffers a significant increase of almost 30%. Becoming 0.95 implies that 95% of the model's explanatory power is now due to the Independent Variable, in conjunction with the Time Effects variables and the Control Variables, which are supportive of the argumentations afore-provided for Model 1 concerning control variables, especially considering that 1 out of the 5 control variables (Employment Rate is now not complying with the 0.05 statistical p-value threshold) is statistically insignificant. This exact R-square-within figure is maintained for Model 3, Model 4, and Model 5. By suffering a substantial increase, methodologically speaking, control variables are strongly suggested as suitable for the different models.

Model 3 shows the OLS-FE regression findings with Driscoll-Kraay SE of the independent variable (Main Income Sources) and Total Compensation as a moderating variable. Both variables are statistically significant by themselves. Additionally, its moderating effect is corroborated as statistically significant, where the interaction of Total Compensation over the Main Income Sources variable causes a negligible amplifying effect as the related estimator is positive (0.00005353). Of the 5 control variables, 3 are statistically significant, again considered a minor statistical issue per the above argumentations.

Model 4 exhibits the results for the independent variable (Main Income Sources) and the other moderating variable (Third parties expenditure) by themselves and the moderating effect of the latter over the former. Unfortunately, the findings are not statistically significant. The same pattern of statistical significance for Control Variables and Time Effect variables remains as in Model 3.

As per the serial correlation findings in subsection 4.3 shown in Table 10, lagged effects for the independent variable (FDI) are corroborated in the data. Although a test to find out the most suitable time lag was not run (typically a Bayesian Information Criterion -BIC Test- or Akaike Information Criterion -AIC Test-), several regressions were estimated using lags 1 to 5 for the independent variable (FDI) targeting to test the coefficients' p-values behaviour. Model 5 shows the independent variable (FDI) with a 2-year lagged effect targeting to test its effect on the statistical significance of a regression employing Third parties' expenditure as a moderating variable. This lagged effect implies the existence of a 'path dependency' pattern since amounts spent by MNEs in Third Parties in a given industry would not induce a productive linkage effect in the same period but some periods later, preliminarily answering RQ3. The rationale is that productive linkages (Third Parties) impacting back into the Main Income Sources (FDI) would eventually be expected to manifest a moderating effect in subsequent years. As per Model 5, the Main Income Sources has a statistically significant 2-

lagged period effect on Social Progress (dependent variable) as per its 0.00252885 coefficient magnitude. Third Parties Expenditure also has a statistically significant effect on Social Progress as its coefficient value is 0.018689. Moreover, the combined (moderating effect) of Third Parties over the 2-lagged period of Main Income Sources (FDI) also has a statistically significant slight moderating negative (attenuating) effect on Social Progress as per its -0.00008892 coefficient figure. It is worth noting that this negative moderating effect is indeed counter-intuitive as productive linkages (Third parties' expenditure) over FDI (Main Income Sources) may be expected to impact social development positively.

4.4.2 Tackling measurement errors and simultaneity (reverse causality) endogeneity sources and autoregression issues.

OLS-FE models are advantageous because they limit the bias sources to time-varying variables (Leszczensky & Wolbring, 2019). In this sense, Pooled OLS-FE models are generally a great choice when tackling issues derived from models' variables not complying with the classic exogeneity assumptions. Furthermore, depending on the panel data characteristics and phenomena being researched, they are considered superior to similar models such as Pooled OLS-RE, Logit, Probit, and Poisson, among others, regarding their estimation consistency (unbiasedness) and robustness. Therefore, even when facing issues related to a partly unobserved time-varying heterogeneity (omitted variables endogeneity source), issues could even be potentially tackled through Fixed Effects Individual Slopes (FEIS) models.

Nonetheless, despite its suitability for eliminating time-invariant variables, the FE approach is not free of limitations, considered in general terms to be incapable (as it generally occurs with panel data methods) of solving the time-varying omitted variables problem (Collischon & Eberl, 2020). Several arguments support the latter statement, within which the last two may be considered the most relevant ones (Collischon & Eberl (2020, pp293:297): 1) Measurement errors are captured by an individual FE panel when they vary systematically between panels. However, time-varying variables measured with error induce all variance required for FE estimations to be error-measured based. 2) Information captured and misspecification sources (bias) eliminated are usually unknown or unclear; hence it is referred to as a ‘black box’. 3) Bounded to potentially exhibit validity issues (estimation results generalizability) by being solely estimated upon the within-panel variance. 4) Incapable of managing simultaneity (reverse causality) and lagged dependent variables (autoregression) issues., and 5) Estimations do not truly identify causal effects in most cases (if not all).

The *OLS-first-differences (FD) model* (a close relative of the OLS-FE) controls for time-invariant unobserved heterogeneity by demeaning the data, hence eliminating the panel-specific error term may then be considered. Like OLS-FE, the OLS-FD model assumes strict exogeneity for unbiased estimation of regressors’ effects. Nonetheless, this exogeneity assumption is weaker: OLS-FD only employs previous period figures for differencing, contrary to the OLS-FE model, which uses all past and future figures when calculating panel deviations. The *Lagged First Difference (LFD) Model* is precisely supported by this latter calculation principle, considered to perform better than OLS-FE, OLS-RE, Logit or Probit, and Poisson models. This improved performance concerns avoiding the bias derived from unobserved time-invariant heterogeneity (causal feedback of regressors on the dependent variable occurs by allowing correlation of regressors with future values of the idiosyncratic error term) and simultaneity (elimination of panel-specific error term by taking differences). As per Vaisey and Miles (2017), when cited in Leszczensky and Wolbring (2019), LFD model estimates may, unfortunately, be severely biased when the true timing of causal effects are not adequately depicted. The latter stems from not satisfying the assumption that changes in the dependent variable between two-time points are a function of the specified difference of a regressor between two preceding time points. If the true causal effect of a regressor on a dependent variable is contemporaneous instead of a lagged effect, the LFD model is prone to a specification error, underestimating the true effect size and providing estimates in the opposite direction. Hence, LFD model suitability depends on the proper theorisation of the actual lag structure: whether or not panel data lags match real-world causal lags of researched phenomena. Although conceptually, the classic theoretical direction for this research points to FDI causing social development to manifest, as earlier exposed, there is a void regarding the lag structure of this relationship. Hence, the LFD model may not simply be appropriate for this research since, as quoted in Leszczensky & Wolbring (2019, pp8), it "*can do more harm than good if it is applied either without precise theoretical knowledge about the underlying data generating process or if the temporal lags in the available data simply do not match the actual causal process.*"

In addition to the use of lagged regressors, one may also evaluate adding lagged values of the dependent variable (y_{t-1}, y_{t-2}, y_{t-3}…) as regressors on the right-hand side (RHS) of the equation, targeting to map the interplay between regressors (x_{1t}, x_{2t}, x_{3t} …) and the dependent variable over time. As per Bond (2002), Roodman (2009b) and Arellano & Bover (1995), those schemes are generally referred to as Autoregressive Distributed Lag (ARDL) for Panel Data methods or simply as Dynamic Panel Data (DPD) models as in the case of this dissertation. Nonetheless, the two different modelling schemes must be differentiated from a methodological testing standpoint, although panel data sets are in nature time-series, including cross-sections -panels- (ARDL time-series models[76] become foundational for DPD schemes). It is worth noting that even when ARDL time-series models have been employed in econometrics for decades, they have recently gained popularity in examining cointegrating relationships[77] between variables through the work of Pesaran & Shin (1998) and Pesaran *et al*. (2001).

As stated in the second paragraph of this subsection and as further confirmed by Nickell (1981), as cited in Leszczensky & Wolbring (2019, pp9), OLS-FE models (and OLS-RE also) are unsuitable for delivering unbiased and efficient estimates when dealing with lagged regressor of the dependent variable.

[76] ARDL time series models include: 1) Fully Modified OLS (Phillips and Hansen, 1992), 2) Canonical Cointegrating Regression (Park 1992), and 3) Dynamic OLS (Saikkonen 1992, Stock and Watson 1993).

[77] Related ARDL time-series cointegration analysis and testing procedures included: 1) Engle and Granger (1987) 2) Phillips and Ouliaris (1990) residual-based tests, 3) Hansen's (1992b) instability test, 4) Park's (1992) added variables to test, and 5) Johansen's (1991, 1995) system maximum likelihood approach. As per Baltagi (2011, pp143) the simplest form of an ARDL model occurs when both y_t and x_t are lagged once (ARDL (1,1)). Higher p order lags on y_t, and q order lag on x_t, (ARDL (p, q)) is also possible. As a general rule, this sort of model is initially tested to determine whether the specification is general enough to ensure noise disturbances. Subsequently, testing to unveil whether some restrictions can be imposed on this general model is performed: 1) reducing the lags order to arrive at a simpler ARDL model, or 2) estimating a simpler static *Error Correction (EC) Model* to test for *cointegration* of variables by reducing a typical vector autoregression framework to its corresponding conditional error correction form.

Correlation between the idiosyncratic error (εis) and the lagged dependent variable (Nickell bias) is induced, violating the strict exogeneity assumption and leading to biased estimates. Furthermore, the lagged dependent variable may correlate with the regressors, additionally biasing those regressors' estimates. Under Nickell (1981), this problem tends to have a higher effect on panel data with small T and larger N (micro panels as in this research).

In addition to causality testing, issues of lagged dependent variables and their related autoregressive error term have been suggested to generally find a solution by implementing IVs on DPD models (Baltagi, 2011). IVs fix correlation issues between y_{t-1} and the error term by replacing y_{t-1} with its predicted value $\hat{y}_{t-1}$, obtained through the regression of y_{t-1} over some exogenous variables or a set of z's of IVs for y_{t-1}. The fact that IVs are exogenous and uncorrelated with u_t, prevents $\hat{y}_{t-1}$ to be correlated with u_t. Based on the latter, Anderson & Hsiao (1981) suggest a solution to the Nickel bias issue by taking the first differences targeting to remove time-invariant unobserved heterogeneity, as further extended and popularized in the work Arellano & Bond (1991). Subsequently, as per Anderson & Hsiao (1981) also, the second-order lagged dependent variable figure (y_{it-2}) is employed as an IV for $\Delta y_{it-1\text{j}}$, under the following equation $\Delta y_{it} = \beta_1\, \Delta y_{it-1\text{j}} + \beta_2\, \Delta x_{it\text{j}} + \Delta \varepsilon_{it\text{j}}$.

This earlier implemented solution based upon a *standard IV* estimator (usually calculated via a 2SLS -2 Step Least Square- approach) only employs one IV for each panel (a small proportion of all available IVs). However, the up-to-date parameters can commonly be calculated via the Generalized Method of Moments IV estimator (*difference gmm IV*) (Hansen, 1982), which advantageously augments efficiency by estimating an equation' set with a varying number of IVs which depend on the available number of previous panels. The initial proposition of Arellano & Bond (1991) of employing all preceding levels of lagged dependent variables (y_{it-2}, y_{it-3},…) as IVs (either *standard IVs* or *difference gmm IVs*) was further strengthened by Arellano & Bover (1995) and Blundell & Bond (1998). They also suggested employing the first differences of the lagged dependent variables (Δy_{it-2}, Δy_{it-3},…) or combinations of both variables' sets as IVs to broaden IVs availability for the *gmm system estimator* calculation purposes (upon which GMM-System method is based as later explained). Hence, as per the latter fact, in addition to the already proven existence of heteroskedasticity and endogeneity, the *gmm estimator* appears to be a superior estimator over the *standard IV estimator*, since as per the quote of Baum *et al*. (2003, pp11): "*when heteroskedasticity is present, the GMM estimator is more efficient than the simple IV estimator, whereas if heteroskedasticity is not present, the GMM estimator is no worse asymptotically than the IV estimator.*"

Having reached this point of analysis, and after identifying the *gmm* estimator appropriateness, one must determine the more suitable method to comply with the research design goals. Even in the presence of the growing tendency of Bayesian-based estimation methods (Hinne *et al.*, 2020 and Leon-Gonzalez & Vinayagathasan, 2015) and the availability of different DPD approaches (Schaffer, 2005), which could easily use *gmm* as an estimator for calculation purposes (e.g., *ivregress* or the community-contributed *ivreg2* Stata17® commands), General Methods of Moments System (GMM-System) scheme (Arellano & Bond, 1991; Blundell & Bond, 1998) comes in handy. As per Leszczensky & Wolbring (2019, pp9), when referring to the *gmm estimator* and related DPD models, the GMM-System method "*offers a powerful toolbox to tackle endogeneity problems caused by both reverse causality and unobserved heterogeneity.*" Furthermore, under Kripfganz (2019), when referring to DPD methods, the GMM-System method is "*the predominant estimation technique for models with endogenous variables, particularly lagged dependent variables, when the time horizon is short*." In addition, Li (2021, pp335) argues that models employing IVs are generally constrained because exogenous IVs are often rare and difficult to find. Besides, proving exogeneity becomes a difficult task. In contrast, GMM-System has the advantage that IVs are easy to obtain as internal variables may serve that purpose, providing a suitable ground for estimating and testing without fully specifying a model. This latter characteristic becomes paramount in economic theory, in which the probabilistic structure of data is not always fully described.

Following Roodman (2009a, 2000b) and Drukker (2008), the 'GMM-System' or simply 'GMM' is a generic method to estimate parameters in statistical and econometrics models. It is considered a semiparametric technique with a finite-dimensional parameter of interest, implemented in the absence of information about the full shape of data's distribution function so that the Maximum Likelihood (ML) estimator, which is, in general, more efficient -statistically speaking- could not be applied (Li *et al.*, 2021, pp335). The rationale is that a *gmm estimator* is calculated via the minimization of the gmm criterion function J = N * g' * W * g, where N is the sample size, g are orthogonal moment conditions (specifying that all the exogenous variables, or IVs, in the equation, are uncorrelated with the error term) and W is a weighting matrix. In cases when the equation is exactly identified (meaning L = K, or the number of IVs is equal to the number of regressor/coefficients), the *gmm estimator* coincides with the *standard IV estimator*. Nonetheless, in cases of overidentification (L > K), the one-step gmm estimator is implemented via the choice of an initial L x L weighting matrix (W) -which, without updating, is employed in constructing a quadratic form at the moment conditions required to calculate the parameters. However, as this initial selection of a L x L weighting matrix (W) becomes a random process, there are as many gmm estimators as choices of Ws. Hence, a two-step estimator could be calculated by employing the initial W residuals for the one-step estimator, creating a new W, and then re-estimating the parameters based on this new optimal weighting matrix (OWM). A *gmm estimator* employing an OWM (inverse covariance matrix complying with orthogonal conditions that minimise the estimator's asymptotic variance) and where the independent and identically distributed (i.i.d) assumption is relaxed, referred to as an e*fficient gmm estimator*. Furthermore, when this *efficient gmm estimator* implements a covariance matrix of the disturbance error terms via the IVs residuals, a *feasible efficient two-step gmm estimator* could be calculated.

The methodological explanation above could be further extended concerning the two estimators distinctly instrumented for the GMM-System technique: 1) '*difference gmm*' under which estimations are made after first-differencing the panel data targeting the elimination of the Fixed Effects (Arellano & Bond, 1991). 2) '*gmm system'* under which the '*difference gmm*' efficiency increases by simultaneously calculating differences and levels (Arellano & Bover, 1995). GMM-System is designed to control Fixed Effects in short and wide panel datasets that fit linear models with dynamic dependent variables. Although GMM-

System allows testing the statistical robustness in the presence of missing values and unbalanced panel data sets, the method is susceptible to IVs proliferation (Blundell & Bond, 1998), which, as argued by Kripfganz (2019), can lead to substantial under rejection or overidentification of IVs, so that incorrectly signalling that the model is correctly specified when it is not. Under this perspective, estimators derived from GMM-System, compared to OLS-FE regression with Driscoll-Kraay SE, can manage significant concerns regarding modelling and controlling more restrictive and efficiently Fixed Effects, Time Effects and multiple regressors' endogeneity; while also avoiding bias (Drukker, 2008). In passing, assuming that errors and variables (regressors) are not serially correlated, GMM-System becomes an extension of the OLS-FE approach by including dependent variable lagged data points (Orbes *et al.*, 2019).

As per Kripfganz (2019), Stata 17® offers a series of commands which enable running *difference gmm* and *gmm system* estimators, depending on the assumptions and the model's complexity: *xtbond* and *xtdpdsys,* which are wrapped in the *xtdpd* command, similarly working as *xtabond2* (Roodman, 2009a). Moreover, Stata17®' *gmm* command can also fit single- and multiple-equation models with cross-sectional, time-series, and longitudinal (panel) data. Developed by Kripfganz (2019), the *xtdpdgmm* (a Stata community-contributed command as *xtabond2*) is the latest known implementation for DPD models employing the *gmm estimator* technique. The *xtdpdgmm* command, besides implementing linear gmm estimators as the latter commands (Arellano & Bond,1991; Arellano & Bover, 1995; Blundell & Bond, 1998; and Hayakawa *et al.* 2019), additionally incorporates non-linear moment conditions as suggested by the work of Ahn & Schmidt. (1995), which are argued to yield efficiency gains and more robust results for highly persistent data. Both the one-step or two-step GMM-System estimators (as in the cases of the other Stata® commands) are enabled. Additionally, an *iterated gmm estimator* that further updates the weighting matrix until convergence could also be run, as suggested by Hansen *et al.* (1996). In addition, and as in the case of other DPD models capable of running two-step estimators (based on the work of Windmeijer, 2005), a finite-sample SE correction is implemented for estimators with and without nonlinear moment conditions. Furthermore, it enables model transformations to include first differences, within-group means deviations, and forward-orthogonal deviations (FOD) and backwards-orthogonal deviations (BOD) of IVs. IVs for different model transformations could be combined to form the different configurations of the GMM-System.

GMM-System, of course, is not free of criticism, especially in what concerns causal inference, since as per Leszczensky & Wolbring (2019), when respectively citing Hsiao (2007:90) and Bun & Windmeijer (2010), it suffers from 1) downward bias when facing a large number of moment conditions, 2) weak IVs problems (as above exposed), and 3) requires multiple statistical tests to validate results (Li *et al.*, 2021). Furthermore, as per Leszczensky & Wolbring (2019) also, when respectively citing Newey & Windmeijer (2009) and Moral-Benito *et al.* (2018)*, gmm estimators* have also been criticised for exhibiting poor finite-sample performance and requiring a large number of sampled units.

Therefore, because of the latter methodological drawbacks, particularly concerning the *gmm estimator*, Leszczensky & Wolbring (2019) suggest employing the Cross-Lagged Panel Model with the FE approach (CLPM-FE). CLPM-FE stems from the work of Moral-Benito (2013), which shows that a DPD with lagged independent variables and FE can be calculated via a Maximum Likelihood (ML) estimator without the need to take first differences (FD) or without assumptions related to the initial observations of regressors and dependent variables. This last demonstration was the foundation for the work of Allison *et al.* (2019), which further showed that the Maximum Likelihood (ML) method could be implemented in a Structural Equation Modeling (SEM) scheme, also known as the ML-SEM method. In passing, in recent years, econometricians have explored this ML-SEM estimation as an alternative way to overcome some of the GMM-System method's limitations, making it a potentially suitable choice after being proven as a particular case of the general linear SEM (Allison, 2014).

Leszczensky & Wolbring (2019) state that regardless of whether or not time-invariant unobserved heterogeneity exists, both GMM-System and ML-SEM yield unbiased estimates in the presence of simultaneity (by a sequential rather than a strict exogeneity assumption). Nevertheless, Allison et al. (2019) report that ML-SEM outperforms GMM-System as regards bias and efficiency under most conditions when simulated data is employed: ML-SEM appears to be advantageous by not exhibiting serial correlation issues, also suggested providing better estimates than GMM-System when contemporaneous and lagged effects of regressors on the dependent variable are included, even in cases of reverse causality (Leszczensky & Wolbring, 2019). Nonetheless, if this contemporaneous effect is negligible (assumed negligible in some cases), GMM-System or a Lagged First Difference approach may render similar estimation results. Nevertheless, Bollen *et al.* (2014), the ML estimator -a mainstay for SEM models- is consistent, asymptotically efficient, and asymptotically normal with both correct asymptotic SE and a chi-square (likelihood ratio) test in the presence of ideal model characteristics: 1) Model structure is exactly correct, 2) observed variables stem from multinormal distributions, 3) Disturbances are homoskedastic, 4) Samples are large, and 5) Iterative estimators always converge. Nonetheless, the latter characteristics are rarely met in practice, hence becoming major drawbacks in employing ML-SEM as a suitable method. Moreover, although ML-SEM is implemented in Stata17® via the *xtdpdml* for which Moral-Benito *et al.* (2018) and Williams *et al.* (2018) when cited by Leszczensky & Wolbring (2019), the method capable of handling unbalanced panels (missing data) issues, nonnormally distributed variables and interaction effects, the simulation work of Leszczensky & Wolbring (2019) does not provide supportive concrete evidence in this regard, besides of advising about serial correlation issues.

Thereby, the *Model-Implied Instrumental Variable - Generalized Method of Moments (MIIV-GMM) estimator for Latent Variable Models,* which stems from the work of Bollen *et al.* (2014, pp.42), becomes another challenging proposed method. In effect, the *MIIV-GMM estimator* has been argued by Bollen *et al.* (2014) to surpass the classic ML estimator and Model-Implied Instrumental Variable Two-Stage Least Squares (MIIV-2SLS) -proposed in Bollen's previous work- in a series of characteristics: 1) Scalable estimation, 2) Scalable test statistics, 3) Heteroskedastic robustness, 4) Distributional robustness, 5) Local structural misspecification robustness and 6) Being a noniterative estimator. Nonetheless, the absence of a suitable Stata 17® command to repeatedly run this proposed estimator prevents it from being employed in this research.

In summary, although from an estimator's robust statistical perspective, ML-SEM appears best suited for this research's purposes, the absence of guiding structural equations (supporting theoretical welfare economics foundations for the associations sought in this research), presence of the misspecifications above cited by Bollen *et al.* (2014) which have been proven existent as per the content of this chapter, and its argued inability to handle unbalanced panel data, points at ML-SEM as an unsuitable method choice. Thus, GMM-System becomes the 'above ground' contender for tackling all the misspecification issues this Chapter 4 addresses. In this sense, the potential results that could have been obtained by employing the *MIIV-GMM estimator* and the ML-SEM methods, targeting to corroborate the assertions made respectively in the works of Bollen *et al.* (2014) and Moral-Benito *et al.* (2018), would indeed become future research endeavours, provided that the proper conditions for deploying both methods (panel data and algorithms wise) are met.

5 CHAPTER FIVE: BASIC MODELS

Once all potential influencing misspecifications have been adequately identified and tackled by choosing the more suitable econometric method, the targeted conceptual/structural framework development could be engaged. The chapter is structured as follows: subsection 5.1 fully delves into choosing between GMM-Difference and GMM-System approaches, the statistical significance criteria sought, the model selection tests, the final proposed models and the specifications test related, and subsection 5.2, which engages into the specification tests required to statistically buttress the final proposed models.

5.1 Model Development

5.1.1 GMM-Difference vs GMM-System

Arellano & Bond (1991) propose a rule to test the potential existence of efficiency estimation gains in the presence or absence of weak IVs for choosing between the GMM-System or the GMM-Difference approach. For decision purposes, the simplest form of DPD is estimated using the Pooled OLS[78] and the FE approach[79] are run using 1-order lag for the dependent variable (L1). The L1 coefficient for the former regression is set as the upper bound, and the L1 coefficient for the latter regression becomes the lower bound. Then, the GMM-Difference estimator (coefficient) is calculated in one-step and two-step regression for L1. If the L1 coefficient figure for the one-step and two-step estimation is lower or near the L1 Fixed Effects coefficient, the GMM-Difference method is biased because of weak IVs, so that the GMM-System would offer more statistical significance estimation benefits. This rationale appears very straightforward since GMM-Difference method estimation keeps many similarities to a Fixed Effects regression as both aim to eliminate the Fixed Effects. Table 14 shows the different L1 coefficients for the regressions mentioned above. As the moderating variables affect the regressions' output differently, two sets of regressions were estimated in the presence of the 2 moderating variables.

[78] Stata17®'s *regress* command
[79] the OLS-FE regression with Driscoll-Kraay SE using Stata17®'s *xtscc* command.

Table 14. Lagged dependent variable coefficient comparison for choosing between the GMM-difference and GMM-system methodologies.

Moderating (Total Compensation)	Moderating (Third Parties Expend)	
0.071240	0.073590	Pooled OLS
0.002000	0.001290	OLS-FE regression with Driscoll-Kraay SE
-0.0171 (a) / -0.0394 (b)	- 0.0263 (a) / -0.0407 (b)	One Step Difference GMM (No curtailed and collapse option)
-0.0003 (a) / -0.0600 (b)	-0.0218 (a) / -0.0560 (b)	Two Step Difference GMM (No curtailed and collapse option)
Coefficients (a) were calculated thorugh the xtdpdgmm command		
Coefficients (b) were calculated thorugh the xtabond2 command		

Source: Author's estimates based on Stata17®

Figures highlighted in grey show that the GMM-Difference coefficients calculated (with the respective Stata commands (a) *xtdpdgmm* (b) with *xtabond2*) are close to the L1 coefficient estimation for OLS-FE regression with Driscoll-Kraay SE, hence pointing out at GMM-System as a more suitable approach for research analysis (Arellano & Bond, 1991).

5.1.2 Statistical significance criteria

Generally and historically speaking, as earlier mentioned, statistical significance in research has been driven by targeting a p-value threshold of 0.05, which in some cases has led researchers to fall into a 'p-value hacking trap'[80] (Verhulst, 2016; Hirschauer *et al.,* 2018). DPD models are complex as their estimation stem from several interactions of variables and statistical tests that influence their outcomes, for which rugosity in 'hitting' a 0.05 p-value threshold target may eventually lead to possible statistical inaccuracies, especially when working with asymptotic p-values instead of exact p-values. When referring to the DPD model's specification tests Kiviet (2019, pp15) contends that "*the calculated p-values involve asymptotic approximations because the probability*

[80] As per the quote by Kiviet (2019, pp15): *"even a p-value of 1 does not imply the truth of the null hypothesis; it just means that the estimated values of the parameters correspond to their hypothesised values, but this does not imply that their true values correspond to the hypothesised values as well."* Two possible consequences arise when determining a p-value threshold to either reject or accept a null hypothesis: gaining efficiency or losing consistency. Choosing the habitual significance level of 0.05 as the borderline between reject and accept would constrain the probability of incorrectly rejecting the null hypothesis so that committing a Type I error, and potential efficiency gains losses. On the other hand, not rejecting a false null hypothesis would derive in a Type II error, which has a more severe consequence -statistically speaking- as it leads to inconsistent estimates and misguided inferences. Hence, limiting the probability of Type II errors to some low threshold appears more crucial than doing the same for Type I errors.

distribution by which they have been calculated is the relevant probability distribution for the test statistic concerned only if the sample were infinitely large in the cross-section dimension". Furthermore, Li *et al.* (2021, pp352) add that "*if the key regression coefficient in a GMM model is not significant, the results must be interpreted with caution… Insignificant results may be due to a small sample".* Table 15 provides p-values ranges depending on the specification tests to be carried out for GMM models as proposed by Kiviet (2019, pp19).

Table 15. Suggested p-values range for GMM models' specification tests.

Type of Test	Suggested p-value threshold	Observation
First-order serial correlation coefficient of the disturbances	0.01 - 0.05	The test should have substantial power when the actual coefficient is -0.5 instead of 0.
Second-order serial correlation coefficient of the disturbances	0.05 - 0.15	The test is expected to have only modest power and avoid type II errors.
Overall Hansen tests with a large number of degrees of freedom.	0.10 - 0.20	
Incremental Hansen tests with less than 10 degrees of freedom.	0.05 - 0.15 0.30 - 0.50 (a)	(a) When deciding if a regressor initially treated as endogenous appears to be predetermined or if a predetermined treated regressor is exogenous.
Omitting single regressors from models with satisfactory Hansen tests	0.4 - 0.6	Equivalent to 0.5 - 1.0 (t or z statistic)
Joint tests on the significance of substantial groups of regressors (interaction variables)	0.5 - 0.7	Balance improvements in efficiency while avoiding inconsistency.
Note: samples where N is small (smaller than 150) or reasonably large (over 2500) may motivate modifications of these tentative threshold ranges.		

Source: adapted from Kiviet (2019, pp19).

5.1.3 Model and Moment Selection Criteria (MMSC)

The general model specification followed an iterative process of different specifications where all models comply with the following structure: Dependent variables and independent variables were lagged for 2 periods[81] and individually

[81] When dealing with short panel data Kripfganz (2019) and Kiviet (2019) recommend not using lags higher than 2-periods (as in this case) even if the Andrews & Lu (2001) 3 model selection criteria (MBIC, MAIC and MQIC) suggests otherwise.

used with the moderating variable and the control variables as part of the RHS of the equation. For the GMM-Difference initial calculation, the lagged variables of the dependent and independent variables, in addition to the moderating variable and its interaction with the independent variable (characterised as endogenous variables), were used as IVs and curtailed within different lag ranges. Two periods of lagged interaction terms of the independent and moderating variables are also used as predetermined IVs within a lag range (curtailed).[82] Several models were calculated using different lag configurations for the exogenous and

---

[82] The *collapse* suboption is also employed to reduce the IV proliferation number as much as possible by transforming the GMM-type IVs into standard IVs. The *model(fodev)* suboption - instead of the *model(difference)* one- is also employed within the *gmmiv()* bracket. The rationale behind this is that since the first-difference transformation creates first-order serial correlation, implementation of forward-orthogonal deviations (FOD) transformed model creates IVs that remain serially uncorrelated (by subtracting the forward mean, the panel-specific effects and all other time-invariant variables are again eliminated) as proposed by Arellano & Bover (1995). For unbalanced panel data with interior gaps, the FOD-GMM estimator is employed as it is bound to retain more information in comparison to the diff-GMM estimator (Diff-GMM estimator and FOD-GMM estimators are identical when the default weighting matrix and all available GMM-type IVs -non-curtailed and non-collapsed- are used with balanced panel data). Control variables were treated as exogenous using the *model (mdev)* suboption within the *gmmiv()* bracket.

Regarding the level model equation, the complementary moderating variable, its interaction with the independent variable and additional interaction with the contemporary moderating variable are employed as extra IVs utilising the *model(level)* sub-option within the *gmmiv()* bracket. The *difference* sub-option is also used as the first-difference transformation of the IVs (and not the model itself) is required. Theoretical and empirical literature concerning panel data has traditionally pointed at slope coefficients explained via homogeneous relationships, which excludes the interaction of variables to potentially be helpful in detecting and modelling the slope's heterogeneity (Kiviet, 2019). Thus, predetermined variables were chosen as IVs and additional IVs for the level equation targeting for them to interact. Additionally, as per Kiviet (2019), theorists have lately attempted to improve the already existing but poorly specified panel models by supplementing the unobserved individual and Time Effects with further unobserved stochastic factors and observed explanatory-like interactions.

Regarding time dummies, by being a 6-year range study and in the absence of a rationale to remove them (Kripfganz, 2019), 5-year-dummy variables are included as regressors (Arellano & Bond, 1991) as required by GMM-Sys estimations (Coinciding with the Time Effect variables previously included in the OLS-FE with Driscoll-Kraay SE model). Nonetheless, as estimations stem from an unbalanced panel, IVs for time dummies are not specified for either the level or the difference model since one of them is asymptotically redundant. Therefore, *teffects* suboption is implemented to automatically add the correct number of time dummies and corresponding IVs. Although in some cases and even when asymptotically inefficient, the one-step estimator might have better finite-sample properties than the two-step or the iterated GMM estimator (*igmm suboption*), the *two step* option is used upon a cluster-robust optimal weighting matrix (in turn based on the initial weighting matrix calculated by the *one-step* GMM), so that allowing for intragroup correlation (industry clustered panels). The *vce (cluster panelvar)* suboption is also used (WC robust errors) for the model's SE to be HAC corrected (Anderson & Hsiao,1981 and Gørgens *et al.,* 2020). As the sample number employed in this research is considered small, the t-distribution and/or the F-distribution is implemented for p-values estimation via the *small* option (by default *xtdpdgmm* reports asymptotically standard-normally distributed z-statistics, and the post-estimation test command for linear hypotheses reports the asymptotically Chi-square-distributed Wald statistic).

Besides the above general structure, models employing Third-Parties Expenditure as a moderating variable also used the Stata17® *bodev* subcommand for the predetermined variables. By the work of Hayakawa *et al.* (2019), this backwards-orthogonal deviation (*bodev*) transformation of the IVs, in combination with the *model(fodev)* option of the error term, adds a '*double filter'* to the GMM estimator.

predetermined variables. All models included the *constant estimation*, as no significant difference was found in the coefficients and p-values when ignoring it in the regression models. Again, upon the argumentations provided in subsection 5.1.2 regarding statistical thresholds for GMM-Systems[83] estimations, it would be unreal to fully expect the construction of a trustworthy model with 95% confidence intervals based upon values of the unknown structural parameters.[84]

Models were ranked as per the Andrews & Lu (2001) Model and Moment Selection Criteria (MMSC)[85]. The MMSC removes 'a bonus term' from the overidentification test (further explained in subsection 5.1.5) that rewards fewer coefficients for a given number of moment conditions (or more overidentifying restrictions for a given number of coefficients). Table 16 shows the Akaike (AIC), Bayesian (BIC), and Hannan-Quinn (HQIC) ranking results for the test under which models with lower figures are preferred (Kripfganz, 2019).

Table 16. Model and Moment Selection Criteria (MMSC) tests outputs for both GMM system model estimations.

Ranking for GMM system models employing Total Compensation as a moderating variable

	N	J	nmom	npar	MMSC-AIC	MMSC-BIC	MMSC-HQIC
Model1A	149	38.355	67	18	-59.645	-206.838	-121.025
Model2A	149	38.086	66	18	-57.914	-202.104	-118.042
Model3A	149	37.551	64	18	-54.449	-192.631	-112.071
Model4A	149	49.592	45	14	-12.408	-105.531	-51.241

Ranking for GMM system models employing Third-Parties Expenditure as a moderating variable

	N	J	nmom	npar	MMSC-AIC	MMSC-BIC	MMSC-HQIC
Model1B	149	31.117	54	18	-40.883	-149.025	-85.979
Model2B	149	36.780	52	18	-31.220	-133.354	-73.810
Model3B	149	36.781	50	18	-27.219	-123.345	-67.304
Model4B	149	36.866	51	18	-29.134	-128.264	-70.472
Model5B	149	40.416	52	18	-27.584	-129.718	-70.175
Model6B	149	36.780	52	18	-31.220	-133.354	-73.810
Model7B	149	36.780	52	18	-31.220	-133.354	-73.810
Model8B	149	36.780	52	18	-31.220	-133.354	-73.810

Source: Author's estimates based on Stata17®

[83] The 'two-step GMM-System' via the Stata17®'s xtdpdgmm command is the chosen method to develop the conceptual/structural framework pursued.
[84] When referring to DPD, Kiviet (2019, pp32) argues that *"it is in general not clear yet which of the many alternative implementation options one should prefer in practice for testing procedures and for estimators of coefficients and of their variance*".
[85] Employing the *mmsc* post-estimation command in Stata17®.

Model 1 choice for both types of models (A and B) is ranked the lowest within the models' selection explored.

5.1.4 GMM-Sys regressions

Both Model 1 (A and B) choices are further explored. In the absence of two better contending models or unless one decides to neglect results due to unsatisfactory infinite sample behaviour, those frameworks may be referred to as the MSMs (Maintained Statistical Model)[86]. Table 17 depicts the variables' structure employed in the GMM system estimation and its related findings employing Total Compensation as a moderating variable. See the list of IVs[87] used in Appendix 8.

[86] As per Kiviet (2019, pp 33): "*MSM should ideally be such that the true underlying data generating process of the structural relationship can ultimately be represented and accurately estimated after imposing the right coefficient restrictions and finding and exploiting any additional valid and effective moment conditions*" as it has been proven in this case.

[87] Despite its capabilities to treat *causal effects*, IVs have unfortunately been traditionally considered incapable of directly identifying *causal mechanisms*, which is often referred to as a causal inference 'black box' approach precisely because of this blind application tendency in economic research (Imai *et al.*, 2011). Imai *et al.* (2011) have suggested that IVs could be used as moderators under the proper conditions to potentially provide a solution to their incapability of identifying *causal mechanisms*. Nonetheless, Holland (1988) contends that the suggested methodological approaches are of limited use since they a priori require to rule out the existence of *causal mechanisms* other than the hypothesised ones by assuming the direct effect of the treatment to be zero (i.e., an exclusion restriction). Hence, *causal mechanisms* exploration and testing are engaged via a parsimonious model in Chapter 6 based upon the PVAR methodology from which a dynamic structural model is proposed to stem.

Table 17. DPD Model structure using two steps GMM-System estimator (Total Compensation as a moderating variable)

Main Equation		
Type of variable	**Variable name**	**Lag range**
Dependent Varaibles	Social Progress Index	N/A
Independent Variable	Social Progress Index (Lagged 2 period)	N/A
Independent Variable	Main Income Sources (Lagged 2 periods)	N/A
Moderating Variable	Total Compensation	N/A
Interaction Effect (Moderating)	Main Income Sources * **Total Compensation**	N/A
Control Variable	Masculinity Ratio	N/A
	Population covered by SS	N/A
	Average School Years	N/A
	Employment rate	N/A
	Informality rate	N/A
Time Effect Variable	2012	Omitted
	2013	Omitted
	2014	Omitted
	2015	N/A
	2016	N/A
	2017	N/A
Difference Equation gmmiv (collapse, model (fodev))		
Type of variable	**Variable name**	**Lag range**
Endogenous	Social Progress Index	1 2
	Main Income Sources	1 2
	Total Compensation	1 2
	Main Income Sources * **Total Compensation**	1 4
Predetermined	L(0/2).Main Income Sources * L(0/2).Main Income Sources	0 4
	Total Compensation * **Total Compensation**	0 4
	L(0/2).Main Income Sources * **Total Compensation**	0 4
Exogenous	Masculinity Ratio	0 0
	Population covered by SS	0 0
	Average School Years	0 0
	Employment rate	0 0
	Informality rate	0 0
Level Equation gmmiv (difference, model (level))		
Type of variable	**Variable name**	**Lag range**
Additional Ivs	Third parties expend	0 0
	L(0/2).Main Income Sources * *Third parties expend*	0 0
	L(0/2).Main Income Sources * **Total Compensation** * *Third parties expend*	0 0
Note: Moderating variable is bold. Complementary Moderating Variable in italics		

Generalised Method of Moment Estimation						
Group variable: Industry/Sector			Number of obs	=	523	
Time variable: Year			Number of grou	=	149	
Moment conditions:			Obs per group: min			
linear =	67		min	=	1	
nonlinear =	0		avg	=	3.510067	
total =	67		max	=	4	
			(Std. err. adjusted for 149 clusters in Industry / Sector)			

Social Progress Index	Coefficient	WC-Robust Std. err.	t	P>|t|	[95% conf. interval]	
Main Variables						
Social Progress Index						
L1.	0.09418	0.07044	1.34000	0.18300	-0.04501	0.23337
L2.	-0.07335	0.03790	-1.94000	0.05500	-0.14824	0.00153
FDI (Main Income Sources)						
-.	0.00028	0.00153	0.18000	0.85400	-0.00274	0.00330
L1.	-0.00244	0.00270	-0.90000	0.36800	-0.00777	0.00289
L2.	0.00375	0.00359	1.04000	0.29900	-0.00335	0.01084
TotalCompensation	0.00651	0.00666	0.98000	0.33000	-0.00665	0.01966
Moderating Effects						
Main Income Sources * Total Compensation	-0.00004	0.00002	-1.62000	0.10800	-0.00008	0.00001
L1.Main Income Sources * Total Compensation	0.00005	0.00004	1.20000	0.23000	-0.00003	0.00014
L2.Main Income Sources * Total Compensation	-0.00010	0.00009	-1.17000	0.24600	-0.00027	0.00007
Control Variables						
Masculinity Ratio	-1.93079	0.16794	-11.50000	0.00000	-2.26265	-1.59893
Population covered by SS	-0.05441	0.00548	-9.93000	0.00000	-0.06524	-0.04358
Average School Years	-0.11675	0.47154	-0.25000	0.80500	-1.04856	0.81507
Employment rate	-0.06770	0.02717	-2.49000	0.01400	-0.12140	-0.01400
Informality rate	-0.11947	0.04389	-2.72000	0.00700	-0.20620	-0.03274
Constant	285.30460	21.79416	13.09000	0.00000	242.23670	328.37250
Time Effects (Year)						
2015	-0.83300	0.15578	-5.35000	0.00000	-1.14084	-0.52516
2016	-1.35612	0.05498	-24.66000	0.00000	-1.46477	-1.24747
2017	-1.61409	0.05957	-27.10000	0.00000	-1.73181	-1.49637

Source: Author's estimates based on Stata17®

As shown in Table 17, 3 times dummies variables are excluded from the model. One observation is lost from the effective estimation sample to avoid the 'dummy trap' (2012 as base-year). The other 2 time-effects variables are lost as 2-order lags are included for the dependent and independent variables. Although choosing which years to omit could have been done manually, dropping 2013 and 2014 was calculated internally by the *xtdpdgmm* function, which, as mentioned above, was run with the *teffects* suboption[88] to automatically add the correct number of time dummies and corresponding IVs, so that avoiding the collinearity/convergence associated to dummy time variables.

Following the latter, it is worth noting that GMM estimators are designed for events where N is typically much larger than T (Roodman, 2009a; Kiviet, 2019;

[88] The option teffects adds dummy variables, after removing collinear dummies, to inpedendent and standard variables and as standard instruments for the untransformed model.

Kiviet, 2020; Kripfganz, 2019), which justifies the suitability of GMM-Sys for this dissertation. It thereby may be counter-intuitive that given such a small number of periods (T=6), one may decide to further reduce the number of degrees of freedom by employing 2-order lags (not only 1-order) for the dependent variable and additionally for the independent one. However, Kripfganz (2019) recommends otherwise, arguing that higher-order lags of the dependent variable and/or the independent variables may have predictive power when added as regressors, aiding in dealing with serial correlation (and thus with the overidentification tests), given that the model is not dynamically misspecified. Under Flannery & Hankins (2013), empirical research employing GMM regressions has not traditionally reported estimations with higher order lags (second and onward) for the dependent variable as regressors since their use as IVs is argued to be invalidated in the presence of second-order serial correlation. Contrarily, Kripfganz (2019) and Kiviet (2020) contend that this invalidity issue may be due to the omission of those lag variables as regressors. If excluded, they might impact the error term if exhibiting nonzero coefficients, preventing them from being used as IVs. Adding lags of existing variables as regressors removes the possibility of becoming part of the error term, further potentiating them to improve the IVs' validity. Moreover, as per Kiviet (2020), if they aid in improving the post specifications tests such as AR() and Hansen Tests -which is the case of this dissertation as explained below- it may be worth including them even if it is statistically insignificant.

Given the restrictions in the degrees of freedom, one may confuse about lag ranges for the predetermined variables (0 4) and the endogenous variable Main Income Sources * Total Compensation (1 4) exceeding the length of the total panel data employed in the model's estimations. However, one may highlight that those curtailed lag ranges refer to the specification of lags of the IVs employed concerning the predetermined variables and the endogenous variable. As per Kripfganz (2019), using deep lags for the variables employed as IVs does not represent an issue in the model's estimations other than simply potentially becoming weak IVs. As shown in the Specification Tests (Section 5.1.5), weak IVs are not suggested to be present in this regression.

Although Kiviet (2019) recommends p-values to accept/reject a coefficient statistical significance in a GMM-System estimation to lay within a 0.4 – 0.6 range (provided that the Sargan-Hansen Tests are satisfactory), this value of reference could be broadened. Quoting Kiviet (2019, pp35): "*coefficients for the longest lag of a regressor or dependent variable lag must have a t-value above 0.5 or a p-value below 0.6 or 0.7 in order to be kept*". Thus, one may imply that statistical insignificance per se is not a sufficient reason to exclude a variable, particularly if its effect is on a variable of interest. In this sense, p-values above 0.7 will be carefully considered in this analysis, as the figures exhibited may be simply the result of small samples. In effect, the statistical behaviour of this same data may be consistent with the real-life characteristics of the variables they represent, provided that this data stems from bigger sample sizes or a different model is chosen.

Both lagged dependent variables (1-period lag and 2-period lag) become significant as their p-values are 0.0183 and 0.055 for L1 and L2. Hence, RQ2 is confirmed for social development as path dependencies of SPI are strongly suggested to exist since previous years of Social Progress figures have a significant statistical explanatory effect on Social Progress in a particular year: a positive effect of 0.094 as per the coefficient figure for L1 and a negative effect for -0.073 for L2. Although the 2 lagged coefficients for Main Income Sources are confirmed as statistically significant as their values are 0.36 and 0.29 for L1 and L2, respectively, the 'contemporary value' of the independent variable (FDI) becomes the only regressor in the entire GMM-System estimation to be 'questionably' confirmed as statistically significant as its p-value laying above 0.7. Nonetheless, as per Kiviet's (2019) argumentations above, because of its crucial effect on the model, its statistical effect is not to be considered negligible, especially in the light of the specification tests and robustness tests explained below. Coefficient values for the Main Income Sources and their L1 and L2 lagged effect are 0.0002, -0.0024 and 0.0037, respectively, confirming a path dependency effect for Main Income Sources as posed in RQ2. Additionally, H1 is preliminarily confirmed as the unidirectional association (FDI impacting social development) statistically significant for the contemporaneous and 2 lag figures of FDI. It could also be confirmed causal, per extended argumentations in subsection 6.1. Unfortunately, it could not yet be proven to exhibit bidirectionality. From this perspective, the R3 could not be explicated, implying neither R1 can.

Total Compensation is also confirmed statistically significant as a moderating variable with an individual effect of 0.0065. The moderating effect of Total Compensation over Main Income Sources has 3 different values -the 3 of them statistically significant- depending on the lagged variable for the Main Income Sources and the coefficient sign: slight attenuation of -0.000035 (no lag), slight amplification of 0.00005 (for L1) and slight attenuation of -0.0001 (for L2). Those latter findings partially confirmed H2 since although the modifying effect is statistically significant, it is not proven to be amplifying but instead attenuating for the contemporaneous value of Main Income Sources and its second-order lag. Nonetheless is fully confirmed when employing the 1-order lag of Main Income Sources.

Furthermore, regarding the Time Effects, the 3 possible time variables (the other 3 are omitted to avoid dummy trap and lagged variables as afore explained) are statistically significant. Regarding control variables, besides the Average School Years of Employed Population, which exhibits a p-value higher than 0.7 under Kiviet (2019, pp19) criteria, the remaining 4 control variables show p-values within a 95% confidence level. As shown in Appendix 8, 67 IVs were employed for this GMM-System estimation model.

Using the same command sub-options abovementioned and following a similar lagged and variable classification, Table 18 depicts the model’s variable structure employed in the GMM-System regression and related findings when employing Third-Parties Expenditure as a moderating variable. See the list of IVs used in Appendix 8.

Table 18. DPD Model structure using two steps GMM-System estimator (Third-Parties Expenditure as a moderating variable)

Type of variable	Variable name	Lag range
Main Equation		
Type of variable	**Variable name**	**Lag range**
Dependent Varaibles	Social Progress Index	N/A
Independent Variable	Social Progress Index (Lagged 2 period)	N/A
Independent Variable	Main Income Sources (Lagged 2 periods)	N/A
Moderating Variable	Total Compensation	N/A
Interaction Effect (Moderating)	Main Income Sources * **Total Compensation**	N/A
Control Variable	Masculinity Ratio	N/A
	Population covered by SS	N/A
	Average School Years	N/A
	Employment rate	N/A
	Informality rate	N/A
Time Effect Variable	2012	Omitted
	2013	Omitted
	2014	Omitted
	2015	N/A
	2016	N/A
	2017	N/A
Difference Equation gmmiv (collapse, model (fodev))		
Type of variable	**Variable name**	**Lag range**
Endogenous	Social Progress Index	1 2
	Main Income Sources	1 2
	Third parties expend	1 4
	Main Income Sources * **Third parties expend**	1 4
Predetermined	L(0/2).Main Income Sources * L(0/2).Main Income Sources	0 0
	Total Compensation * **Third parties expend**	0 4
	L(0/2).Main Income Sources * **Third parties expend**	0 0
Exogenous	Masculinity Ratio	0 0
	Population covered by SS	0 0
	Average School Years	0 0
	Employment rate	0 0
	Informality rate	0 0
Level Equation gmmiv (difference, model (level))		
Type of variable	**Variable name**	**Lag range**
Additional Ivs	*Total Compensation*	0 0
	L(0/2).Main Income Sources * *Total Compensation*	0 0
	L(0/2).Main Income Sources * *Total Compensation* * **Third parties expend**	0 0

Note: Moderating variable is bold. Complementary Moderating Variable in italics

Generalised Method of Moment Estimation							
Group variable: Industry/Sector				Number of obs	=	523	
Time variable: Year				Number of grou	=	149	
Moment conditions:				Obs per group: min			
linear =	54			min	=	1	
nonlinear =	0			avg	=	3.510067	
total =	54			max	=	4	
				(Std. err. adjusted for 149 clusters in Industry / Sector)			

Social Progress Index	Coefficient	WC-Robust Std. err.	t	P>|t|	[95% conf. interval]	
Main Variables						
Social Progress Index						
L1.	0.09560	0.06916	1.38000	0.16900	-0.04107	0.23227
L2.	-0.05596	0.03961	-1.41000	0.16000	-0.13424	0.02232
FDI (Main Income Sources)						
-.	-0.00028	0.00128	-0.22000	0.82500	-0.00282	0.00225
L1.	-0.00082	0.00155	-0.53000	0.59800	-0.00388	0.00224
L2.	0.00145	0.00199	0.73000	0.46600	-0.00247	0.00537
Third Parties Expenditure	0.00224	0.00309	0.72000	0.47000	-0.00387	0.00835
Moderating Effects						
Main Income Sources * Third Parties Expenditure	0.00001	0.00005	0.16000	0.87100	-0.00010	0.00012
L1.Main Income Sources * Third Parties Expenditure	0.00002	0.00010	0.16000	0.87000	-0.00019	0.00022
L2.Main Income Sources * Third Parties Expenditure	-0.00003	0.00009	-0.39000	0.69400	-0.00020	0.00014
Control Variables						
Masculinity Ratio	-2.01741	0.15923	-12.67000	0.00000	-2.33208	-1.70275
Population covered by SS	-0.05640	0.00449	-12.55000	0.00000	-0.06528	-0.04751
Average School Years	-0.30763	0.63120	-0.49000	0.62700	-1.55496	0.93970
Employment rate	-0.07334	0.02407	-3.05000	0.00300	-0.12089	-0.02578
Informality rate	-0.14028	0.04987	-2.81000	0.00600	-0.23883	-0.04173
Constant	296.09970	24.04108	12.32000	0.00000	248.59160	343.60780
Time Effects (Year)						
2015	-0.80270	0.13732	-5.85000	0.00000	-1.07407	-0.53133
2016	-1.32175	0.06022	-21.95000	0.00000	-1.44076	-1.20274
2017	-1.58403	0.06223	-25.45000	0.00000	-1.70701	-1.46105

Source: Author's estimates based on Stata17®

Both lagged dependent variables (1 -period lag and 2-period lag) become significant (L1 p-value is 0.16 and L2 p-value is 0.16), additionally confirming the existence of path dependencies as per the RQ2. In this sense, previous Social Progress figures are suggested to have a significant statistical explanatory effect on Social Progress in a particular year: a positive impact of 0.095 as per in coefficient figure for lag 1 and a negative impact of -0.055 for lag 2. As it occurred with the contemporaneous value of the independent variable in the previous model, Main Income Sources (FDI) is 'questionably' confirmed statistically significant as per its p-value = 0.825. Nevertheless, its effect is considered negligible due to its crucial impact on the model, in alignment with the abovementioned argumentations (the entire model complies with the specification and robustness tests, as argued by Kiviet (2019)). The lagged effects of Main Income Sources (FDI) as regressors are both confirmed statistically significant (L1 p-value is 0.59 and L2 is 0.46), respectively exhibiting a negative effect of -0.0008 and a positive one of 0.0014, thereby confirming a path dependency effect for FDI as sought in RQ2. Thus, as per the same token in the previous model, H1 is also preliminarily confirmed in the presence of a causal (subsection 6.1) unidirectional association (FDI impacting social development) statistically significant for the contemporaneous and 2 lag figures of FDI, which could neither be proven bidirectional, in turn, implying that neither R3 nor R1 can yet be explicated.

Third Parties Expenditure is confirmed as a moderating variable (p-value = 0.47) with an individual negative impact of 0.0022. The moderating effect of Third Parties Expenditure over Main Income Sources is also 'questionably' confirmed statistically significant (p-value = 0.87), exhibiting a negligent amplification effect as per its 8.77E-06 coefficient figure. Moderating effects of Third-Parties Expenditure over 1-lagged and 2-lagged values of Main Income Sources suggest amplifying and attenuating impacts as per their 0.000016 and -0.000038 coefficient magnitudes. Nonetheless, the 1-lagged regressor effect is statistically 'questionable' as per its p-value = 0.87, contrary to the 2-lagged effect, which is confirmed by its p-value = 0.69. The effects of those variables' interactions are to be considered significant, thus confirming H3 for the contemporaneous value of Main Incomes Sources and its effect on social development as positive (amplifying). The same H3 confirmation holds for the 1-order lag of Main Income Sources, although it is partially confirmed for its 2-order lagged attenuating effect suggested.

As in the case of the GMM-system model calculation shown in Table 17, as regards Time Effects, the 3 possible time variables (3 of them are omitted due to the lagged variables employed in the regression) are also statistically significant. Regarding control variables, all are found statistically significant as per Kiviet's (2019, pp19) criteria, where the Average School Years of Employed population is the only variable under the 0.7 p-value threshold, as the rest of the control variables exhibit p-values under the classic 0.05 figure criteria. 54 IVs employed for the GMM System estimations were used, as seen in Appendix 8.

It is important to stress that the regressors 'questionable' statistical significance-related coefficients shown in Table 17 and Table 18 are to be considered negligible, as per the results of the Robustness Tests subsection below. In addition, buttressed by the specification tests in the following subsection, the validity and relevance of the IVs based on the regressors and their interactions, besides the absence of second-order serial correlation -AR(2)- in the model's structure, is considered to surpass the importance of each of the regressors' statistical significance (Kiviet, 2019).

5.1.5 Specification Tests

Since the development of models which employ IVs assumes that model parameters are identified through apriori restrictions on the coefficients, testing under-identification validity and over-identifying restrictions become paramount. The 2 GMM-Sys regression models are tested via 4 post-specification tests[89]: 1) Kleibergen-Paap Langrange Multiplier (LM) under-identification robust test, 2) The overall Sargan-Hansen, 3) The Incremental Sargan-Hansen test, and 4) The Arellano-Bond Test for first-order [AR(1)] and second-order correlation [AR(2)].

---

[89] The 4 tests are mentioned as follows: 1) Kleibergen-Paap Langrange Multiplier (LM) under-identification robust test run utilising the *underid, underid kp* Stata17® post-estimation command. This J-statistic test is based on the Limited Information Maximum Likelihood (LIML) estimator as per the work of Kleibergen & Paap (2006) and informs about IVs having insufficient explanatory power to predict endogenous variables in the model for identification of the parameters (Windmeijer, 2018); 2) The overall Sargan-Hansen Test implemented through Stata17® *estat overid* post-estimation command employing a two-step weighting matrix following the GMM-System two-step estimation. This test seeks the model's over-identifying restrictions to determine if IVs used were correctly specified (as a group of IVs are exogenous), since a high ratio of IVs vs cross-sectional sample size can induce bias in the coefficient and SE estimates, in turn weakening the specification tests (Roodman, 2009a). The test is computed from IVs regression residuals by constructing a quadratic form based on residuals and exogenous variables cross-products. Under the null hypothesis that the over-identifying restrictions are valid, the statistic is asymptotically distributed as a chi-square variable; 3) The Incremental Sargan-Hansen test run via the Stata17® *estat overid, difference* post-estimation command for reporting statistics of the IVs validity for both the difference and level equation models. Removing subsets of moment conditions (IVs) -one at a time- without estimating the weighting matrix, the validity of the additional moment conditions for the level model is rejected. The corresponding Sargan-Hansen difference statistics are calculated to determine the validity of the omitted subset of overidentifying restrictions (Following the work of Newey (1985) and Eichenbaum *et al.* (1988) as cited in Kripfganz (2019)), and 4) The Arellano-Bond Test (Arellano & Bond, 1991) for first-order [AR(1)] and second-order correlation [AR(2)] implemented via the *estat serial, ar(1/2)* post-estimation command. The AR(1) and AR(2) tests, conducted for the first-differenced errors, check whether the idiosyncratic error term is serially correlated. An error term in the level equation being serially uncorrelated implies that the error term in the first differences equation exhibits a negative first-order serial correlation (correlation coefficient of -0.5) but no second-order or higher-order serial correlation. Hence, rejection of the null hypothesis of no first-order serial correlation is expected in first differences (AR(1) test), but the null hypothesis of no higher-order serial correlation in first differences (AR(2) or higher) must be accepted. No rejecting the AR(1) test null hypothesis then may suggest a high serial correlation of the idiosyncratic error term in the levels equation (In extreme cases, the error term in the level equation follows a random walk, so that in invalidating the model due to first-differenced errors being serially uncorrelated).

Although several versions based on the original Hansen test (Sargan–Hansen test or Sargan's J test as per the work of Sargan, 1958 and Hansen, 1982 as cited in Roodman, 2009a) exist for the first 3 post-estimation tests (targeting to detect face validity issues -under-identification and over-identification- concerning the IVs chosen), the versions herein employed are the ones recommended in Roodman (2009a), Kiviet (2019) and Kripfganz (2019). Additionally, as ignoring second-order serial correlation in the first-differenced error term may cast doubt regarding the assumption satisfaction required when estimating the difference equation, the Arellano-Bond Test (Arellano & Bond, 1991) for first-order [AR(1)] and second-order correlation [AR(2)] are employed. Table 19 shows the results of the 4 specification tests' findings for both GMM-System models.

Table 19. Hansen Specification tests output for both GMM-System model estimations.

Model 1: GMM-System employing Total Compensation as a moderating variable

Underidentification test: Kleibergen-Paap robust LIML-based (LM version)

Test statistic robust to heteroskedasticity and clustering on COD_CIIU

j = 69.84 Chi-sq(50) p-value = 0.0333

Sargan-Hansen test of the overidentifying restrictions

H0: overidentifying restrictions are valid

2-step moment functions, 2-step weighting matrix

chi2(49) = 38.3554 Prob > chi2 = 0.8635

Sargan-Hansen (difference) test of the overidentifying restrictions

H0: (additional) overidentifying restrictions are valid

2-step weighting matrix from full model

	Excluding			**Difference**		
Moment conditions	**chi2**	**df**	**p**	**chi2**	**df**	**p**
1, model(fodev)	38.263	47	0.814	0.093	2	0.955
3, model(fodev)	37.724	48	0.857	0.632	1	0.427
4, model(fodev)	35.488	43	0.785	2.867	6	0.825
5, model(fodev)	26.932	32	0.721	11.423	17	0.834
6, model(fodev)	36.252	43	0.757	2.103	6	0.910
7, model(fodev)	30.449	38	0.803	7.906	11	0.722
8, model(mdev)	37.011	44	0.763	1.345	5	0.930
9, model(level)	32.386	34	0.547	5.969	15	0.980
10, model(level)	36.319	46	0.846	2.036	3	0.565
model(fodev)	5.045	6	0.538	33.311	43	0.856
model(level)	28.355	31	0.603	10.000	18	0.932

Arellano-Bond test for autocorrelation of the first-differenced residuals

H0: no autocorrelation of order 1: z = -2.6640 Prob > |z| = 0.0077

H0: no autocorrelation of order 2: z = 0.1277 Prob > |z| = 0.8984

Model 2: GMM-System employing Third-Parties Expenditure as a moderating variable

Underidentification test: Kleibergen-Paap robust LIML-based (LM version)
Test statistic robust to heteroskedasticity and clustering on COD_CIIU
j = 50.08 Chi-sq(37) p-value = 0.074

Sargan-Hansen test of the overidentifying restrictions
H0: overidentifying restrictions are valid
2-step moment functions, 2-step weighting matrix
chi2(36) = 31.11 Prob > chi2 = 0.6999

Sargan-Hansen (difference) test of the overidentifying restrictions
H0: (additional) overidentifying restrictions are valid
2-step weighting matrix from full model

	Excluding			Difference		
Moment conditions	**chi2**	**df**	**p**	**chi2**	**df**	**p**
1, model(fodev)	27.141	34	0.792	3.976	2	0.137
3, model(fodev)	31.108	35	0.657	0.009	1	0.925
4, model(fodev)	23.845	29	0.737	7.271	7	0.401
5, model(fodev)	25.661	28	0.592	5.455	8	0.708
6, model(fodev)	22.817	28	0.742	8.300	8	0.405
7, model(fodev)	30.179	32	0.559	0.938	4	0.919
8, model(mdev)	21.798	31	0.889	9.319	5	0.097
9, model(level)	16.974	21	0.713	14.143	15	0.515
10, model(level)	28.678	33	0.682	2.439	3	0.487
model(fodev)	7.372	6	0.288	23.745	30	0.784
model(level)	14.751	18	0.679	16.365	18	0.567

Arellano-Bond test for autocorrelation of the first-differenced residuals
H0: no autocorrelation of order 1: z = -2.8144 Prob > |z| = 0.0049
H0: no autocorrelation of order 2: z = -0.3325 Prob > |z| = 0.7395

Source: Author’s estimates based on Stata17®

As per the Kiviet (2019) recommended p-values, all tests confirmed the statistical suitability of the proposed models: 1) Kleibergen and Paap Langrange Multiplier (LM) under-identification test determines whether the minimal canonical correlation between the endogenous variables and the IVs is statistically different from zero. In other words, after separating the exogenous variables and cross-correlations from the other endogenous variables and IVs, the test determines if the weakest correlation between an IV and one endogenous variable contributes enough to the independent variation by adding to the empirical rank of the IVs matrix. Kleibergen-Paap test’s p-value for Model 1 is below 0.05 and marginally above (p-value = 0.074 is considered a negligible statistical out-of-range magnitude as per argumentations later provided in subsection 5.2 when referring to the conjoint analysis of specifications tests) for Model 2; hence, one can reject the null hypothesis that the models are under-identified. Hence, the chosen IVs are confirmed relevant, meaning they are uncorrelated with the endogenous regressors. 2) Although Roodman (2009a) recommends a p-value higher than 0.25 for the overall Sargan-Hansen Test, Kiviet (2019 pp34) recommends this value to be p-value above 0.20. The null hypothesis that the over-identification restrictions are valid, meaning that IVs are uncorrelated with the error term (orthogonal to the errors to avoid heteroskedasticity issues) as a general exogeneity requirement, is accepted for both models (the null hypothesis that IVs used for the difference equation are exogenous cannot be rejected, supporting IVs being exogenous). Model 1's p-value could be rounded up to 0.86 (strong confirmation), and for Model 2, the p-value reaches almost a 0.70 figure (moderately strong confirmation). Hence, even in the presence of a higher number of IVs than endogenous regressors -and the restrictions induced by them- IVs remain valid (over-identification restrictions usually lead to misspecified models when the number of IVs is substantially larger than the number of estimated coefficients). 3) Incremental Sargan-Hansen overidentification tests are only meaningful if the reduced model has already passed the overall overidentification test, as it is in this case. Under the assumption that the *difference gmm* estimator is correctly specified, the test confirms the validity of the additional moment conditions chosen for the level model (for instance, p-values below 0.10 may indicate that the model and/or IVs require to be reformulated by including extra lags of variable as regressor). Since correlation with endogenous regressors can be assessed by examining the significance of the IVs excluded in the first–stage, IVs that satisfy orthogonal conditions for an overidentified model may be considered valid. In other words, high p-values indicate that the null hypothesis (posing that IVs in the level equation are exogenous) cannot be rejected, so the additional subsets of IVs employed for the level equation are suggested exogenous, making the results of the GMM-System model more reliable. Since all sub-models for difference and the level equation for Model 1 depict p-values ranging between 0.53 and 0.98, all IVs can be confirmed as valid, in concordance with the Overall Sargan-Hansen Test findings. Regarding Model 2, all sub-models for both difference and level equations lay above the 0.10 threshold (model 8 in the level equation is rounded up to 0.1 from its 0.097 figure), also corroborating the Overall Sargan-Hansen Test findings and

Model 2's statistical suitability as a whole. 4) Regarding the Arellano Bond Test, the second-order serial correlation coefficient of the disturbances -AR(2)- is expected to exhibit a p-value above 0.20, as it is the case for both models: as p-value= 0.89 for Model 1 and 0.73 for Model 2, acceptance of the null hypothesis that there is no second-order serial correlation is strongly confirmed. On the contrary, the test for first-order serial correlation coefficient -AR(1)- is expected to render a p-value below 0.05, as also occurs for both models: p-value= 0.007 for Model 1 and p-value= 0.0049 for Model 2, so that strongly failing to accept the null hypothesis of the non-existence of first-order serial correlation, which is a statistical condition for both models suitability and statistical validity.

5.2 Robustness Tests

Under Neumayer & Plümper (2017), Robustness Tests are up-to-date standard tests run on empirical studies to examine the 'core' regression coefficients 'behaviour' by moderating the regression structure via the addition or extraction of regressors. A model possesses structural validity if its coefficients are robust and plausible. Structurally speaking, core and non-core variables must be appropriately specified and chosen to ensure that Robustness Tests are, in effect, informative. In cases when Robustness Tests are not adequately estimated, model results might be misleading and/or misinformative.

2 Robustness Tests are proposed: 1) Since SPI comprises scores for 3 different dimensions: Basic Human Needs, Foundations of Wellbeing and Opportunities, the first Robustness Test focuses on testing whether the FDI and social development association suffer changes in the presence of each of these individual components, and 2) Second Robustness Test concentrates on testing findings' sensitivity using 1 alternative FDI measure as an independent variable. As explained in section 3.2.4, Other Income Sources is used as a proxy for FDI flows' Capital Contributions components as it comprises de greenfied/M&As or/and for equity capital extension /financial restructuring amounts (PNISCa, 2020). Both models' statistical power improvements and structural validity testing are pursued by contrasting findings to the original regression. Table 20 shows

the structural changes proposed in the two original equations and the resulting p-values in the specification tests.

Table 20. Equation parameters for Robustness Test 1.

Model 1: GMM-System employing Total Compensation as a moderating variable

Difference Equation gmmiv(collapse, model (fodev))					
	Dependent Variable Employed in the model	**Social Progress Index**	**Basic Human Needs**	**Foundations of Wellbeing**	**Oportunity**
	Type of gmm estimator	**2-step gmm**	**2-step gmm**	**iterative gmm**	**2-step gmm**
Type of variable		**Lag range**	**Lag range**	**Lag range**	**Lag range**
Endogenous	**Dependent Variable**	1 2	1 2	1 2	1 2
	Main Income Sources	1 2	1 2	1 2	1 2
	Total Compensation	1 2	1 2	1 2	1 2
	Main Income Sources * **Total Compensation**	1 4	1 4	1 4	1 4
Predetermined	L(0/2).Main Income Sources * L(0/2).Main Income Sources	0 4	0 1	(0 0) bodev	0 4
	Total Compensation * **Total Compensation**	0 4	0 0	(0 2)	0 4
	L(0/2).Main Income Sources * **Total Compensation**	0 4	0 3	(0 0) bodev	0 4
Exogenous	Masculinity Ratio	0 0	0 0	0 0	0 0
	Population covered by SS	0 0	0 0	0 0	0 0
	Average School Years	0 0	0 0	0 0	0 0
	Employment rate	0 0	0 0	0 0	0 0
	Informality rate	0 0	0 0	0 0	0 0

Model 2: GMM-System employing Third-Parties Expenditure as a moderating variable

Difference Equation gmmiv(collapse, model (fodev))					
	Dependent Variable Employed in the model	**Social Progress Index**	**Basic Human Needs**	**Foundations of Wellbeing**	**Oportunity**
	Type of gmm estimator	**2-step gmm**	**2-step gmm**	**iterative gmm**	**2-step gmm**
Type of variable		**Lag range**	**Lag range**	**Lag range**	**Lag range**
Endogenous	**Dependent Variable**	1 2	1 2	1 2	1 4
	Main Income Sources	1 2	1 2	1 2	1 2
	Third parties expend	1 2	1 2	1 2	1 2
	Main Income Sources * **Third parties expend**	1 4	1 4	1 4	1 4
Predetermined	L(0/2).Main Income Sources * L(0/2).Main Income Sources	0 4	(0 3)	(0 1) bodev	(0 0) bodev
	Total Compensation * **Third parties expend**	0 4	(0 1) bodev	(0 3)	(0 0) bodev
	L(0/2).Main Income Sources * **Third parties expend**	0 4	(0 3)	(0 1) bodev	(0 0) bodev
Exogenous	Masculinity Ratio	0 0	0 0	0 0	0 0
	Population covered by SS	0 0	0 0	0 0	0 0
	Average School Years	0 0	0 0	0 0	0 0
	Employment rate	0 0	0 0	0 0	0 0
	Informality rate	0 0	0 0	0 0	0 0

Source: Author's estimates based on Stata17®

One may observe that the proposed changes are minimal and are only applied to the original Difference Equation of the GMM-System model. By only including the backward orthogonal deviation (*bodev*) function and changing the lags number in some cases, the original structure of the model remains when substituting the dependent variable by any of the 3 main SPI comprising dimensions. The two-step gmm estimator remains in the case of Basic Human Needs and Opportunity, changing it to iterative gmm for the equation that employs Foundations of Wellbeing. The p-values and the specification tests for each model equation are exhibited as follows in Table 21.

Table 21. P-values and specification tests models' comparison for Robustness Test 1

Model 1: GMM-System employing Total Compensation as a moderating variable

Model Structure												
	SocialProgressIndex (Original)			Basic Human Needs			FoundationsofWellbeing			Opportunity		
	Coefficient	WC Robust SE	p-value	Coefficient	WC Robust SE	p-value	Coefficient	WC Robust SE	p-value	Coefficient	WC Robust SE	p-va
Dependant Variable												
L1.	0.0942	0.0704	0.1830	0.0474	0.0986	0.6310	0.1360	0.3844	0.7240	0.1362	0.1389	0.3
L2.	-0.0734	0.0379	0.0550	-0.0208	0.0367	0.5720	0.0052	0.0371	0.8880	-0.0315	0.0313	0.3
MainIncomeSources												
-.	0.0003	0.0015	0.8540	-0.0019	0.0017	0.2690	0.0001	0.0028	0.9720	0.0011	0.0020	0.6
L1.	-0.0024	0.0027	0.3680	-0.0016	0.0019	0.4030	0.0000	0.0003	0.9570	0.0005	0.0032	0.8
L2.	0.0037	0.0036	0.2990	0.0062	0.0043	0.1530	0.0004	0.0014	0.7720	0.0031	0.0062	0.6
TotalCompensation	0.0065	0.0067	0.3300	0.0069	0.0052	0.1830	0.0006	0.0014	0.6370	0.0067	0.0145	0.6
MainIncomeSources * TotalCompensation	0.0000	0.0000	0.1080	0.0000	0.0000	0.2550	0.0000	0.0001	0.9830	0.0000	0.0000	0.5
L1.MainIncomeSources * TotalCompensation	0.0001	0.0000	0.2300	0.0000	0.0000	0.3630	0.0000	0.0000	0.9700	0.0000	0.0001	0.9
L2.MainIncomeSources * TotalCompensation	-0.0001	0.0001	0.2460	-0.0001	0.0001	0.1970	0.0000	0.0000	0.7620	0.0000	0.0001	0.8
MasculinityRatio	-1.9308	0.1679	0.0000	-1.8648	0.2167	0.0000	-1.5459	4.0171	0.7010	-2.1700	0.3917	0.0
PopcoveredbySS	-0.0544	0.0055	0.0000	-0.0997	0.0062	0.0000	-0.0241	0.0863	0.7800	-0.0351	0.0117	0.0
Averageschoolyearsofemployed	-0.1167	0.4715	0.8050	-0.4545	0.6813	0.5060	-0.5630	17.0375	0.9740	0.0005	0.7650	0.9
Employmentrate	-0.0677	0.0272	0.0140	0.1083	0.0511	0.0360	-0.1929	1.2187	0.8740	-0.0467	0.0557	0.4
Informalworkrate	-0.1195	0.0439	0.0070	0.0726	0.0354	0.0420	-0.2351	1.3085	0.8580	-0.1485	0.0724	0.0
Year												
2015	-0.8330	0.1558	0.0000	-0.9091	0.0539	0.0000	-1.5109	3.4108	0.6580	-0.0593	0.2277	0.7
2016	-1.3561	0.0550	0.0000	-1.2681	0.1295	0.0000	-2.4567	2.7251	0.3690	-0.4329	0.1653	0.0
2017	-1.6141	0.0596	0.0000	-1.8735	0.1131	0.0000	-1.7685	1.2382	0.1550	-1.0170	0.2221	0.0
Const	285.3046	21.7942	0.0000	265.8691	29.1569	0.0000	262.2377	473.1223	0.5800	289.6487	48.9500	0.0

Specification Tests								
		p-value		p-value		p-value		p-va
Kleibergen-Paap LM under-identification Test		0.0333		0.0400		0.1200		0.0
AR(1)		0.0077		0.0002		0.0520		0.0
AR(2)		0.8980		0.9100		0.9450		0.3
Overall Sargan-Hansen Test		0.8630		0.6600		0.4370		0.6
Difference Sargan-Hansen Test	Excluding **p-value**	Difference **p-value**	Excluding **p-value**	Difference **p-value**	Excluding **p-value**	Difference **p-value**	Excluding **p-value**	Differ **p-va**
1, model(fodev)	0.8144	0.9546	0.8622	0.0289	0.4793	0.2149	0.8528	0.0
2, model(fodev)							0.5753	0.8
3, model(fodev)	0.8566	0.4268	0.6327	0.6803	0.4767	0.2219		
4, model(fodev)	0.7851	0.8253	0.6376	0.5376	0.3828	0.5538	0.7045	0.2
5, model(fodev)	0.3282	0.9526	0.5519	0.6947	0.3489	0.6335	0.971	0.2
6, model(fodev)	0.7632	0.9302	0.6449	0.5045	0.4389	0.407	0.8559	0.0
7, model(fodev)	0.5468	0.9803	0.7685	0.3363	0.3579	0.5902	0.8021	0.2
8, model(mdev)	0.846	0.5649	0.5034	0.9374	0.4085	0.4951	0.5912	0.5
9, model(level)			0.3503	0.9103	0.5489	0.2862		
10, model(level)			0.6431	0.5082	0.5503	0.1235		
model(fodev)	0.5381	0.8559	0.0000	1.0000	0.003	0.9847	0.6416	0.5
model(level)	0.6028	0.9319	0.3822	0.842	0.4171	0.461	0.7803	0.2

Model 2: GMM-System employing Third-Parties Expenditure as a moderating variable

	SocialProgressIndex (Original)			Basic Human Needs			FoundationsofWellbeing			Opportunity		
	Coefficient	WC Robust SE	p-value	Coefficient	WC Robust SE	p-value	Coefficient	WC Robust SE	p-value	Coefficient	WC Robust SE	p-value
Dependant Variable												
L1.	0.0956	0.0692	0.1690	0.0417	0.0755	0.5810	0.2060	0.0356	0.0000	0.1869	0.1394	0.1820
L2.	-0.0560	0.0396	0.1600	-0.0022	0.0315	0.9450	-0.0255	0.0091	0.0060	-0.0401	0.0397	0.3140
MainIncomeSources												
-.	-0.0003	0.0013	0.8250	0.0004	0.0015	0.7800	0.0022	0.0012	0.0790	-0.0004	0.0025	0.8870
L1.	-0.0008	0.0015	0.5980	-0.0006	0.0017	0.7280	-0.0065	0.0018	0.0000	-0.0014	0.0022	0.5210
L2.	0.0015	0.0020	0.4660	-0.0009	0.0018	0.6310	0.0030	0.0011	0.0050	0.0018	0.0040	0.6500
Thirdpartiesexpend	0.0022	0.0031	0.4700	-0.0083	0.0096	0.3850	0.0028	0.0021	0.1920	-0.0107	0.0180	0.5530
MainIncomeSources * Thirdpartiesexpend	0.0000	0.0001	0.8710	0.0000	0.0001	0.6920	-0.0001	0.0000	0.1370	0.0001	0.0001	0.5200
L1.MainIncomeSources * Thirdpartiesexpend	0.0000	0.0001	0.8700	0.0000	0.0001	0.9940	0.0003	0.0001	0.0000	0.0000	0.0002	0.9950
L2.MainIncomeSources * Thirdpartiesexpend	0.0000	0.0001	0.6940	0.0001	0.0001	0.0650	-0.0002	0.0001	0.0000	0.0000	0.0001	0.7420
MasculinityRatio	-2.0174	0.1592	0.0000	-1.9933	0.1680	0.0000	-1.0088	0.1445	0.0000	-2.0955	0.4575	0.0000
PopcoveredbySS	-0.0564	0.0045	0.0000	-0.1003	0.0052	0.0000	-0.0038	0.0021	0.0720	-0.0285	0.0148	0.0560
Averageschoolyearsofemployed	-0.3076	0.6312	0.6270	-0.8819	0.5947	0.1400	1.0816	0.5364	0.0460	0.3458	0.7186	0.6310
Employmentrate	-0.0733	0.0241	0.0030	0.1164	0.0511	0.0240	-0.0253	0.0191	0.1870	-0.0386	0.0689	0.5760
Informalworkrate	-0.1403	0.0499	0.0060	0.0717	0.0385	0.0650	0.0743	0.0255	0.0040	-0.0399	0.1354	0.7690
Year												
2015	-0.8027	0.1373	0.0000	-0.9049	0.0631	0.0000	-2.2924	0.0575	0.0000	-0.3195	0.3986	0.4240
2016	-1.3217	0.0602	0.0000	-1.2603	0.1243	0.0000	-2.6690	0.0656	0.0000	-0.6241	0.2901	0.0330
2017	-1.5840	0.0622	0.0000	-1.8597	0.0957	0.0000	-1.7381	0.1160	0.0000	-0.8898	0.1617	0.0000
Const	296.0997	24.0411	0.0000	282.3116	23.5359	0.0000	158.7930	22.3849	0.0000	270.7963	64.0509	0.0000
Specification Tests												
			p-value			**p-value**			**p-value**			**p-value**
Kleibergen-Paap LM under-identification Test			0.0740			0.0880			0.0530			0.0686
AR(1)			0.0049			0.0025			0.0336			0.0531
AR(2)			0.7395			0.8373			0.4399			0.2752
Overall Sargan-Hansen Test			0.6900			0.5164			0.6235			0.4988
Difference Sargan-Hansen Test		Excluding	Difference		Excluding	Difference		Excluding	Difference		Excluding	Difference
		p-value	**p-value**		**p-value**	**p-value**		**p-value**	**p-value**		**p-value**	**p-value**
1, model(fodev)		0.7919	0.137		0.6503	0.0752		0.666	0.2215		0.8434	0.0231
2, model(fodev)								0.594	0.5475		0.6007	0.1313
3, model(fodev)		0.6566	0.9251		0.4779	0.7977		0.5861	0.8631		0.4689	0.5007
4, model(fodev)		0.7365	0.4012		0.3643	0.8826		0.6834	0.3138		0.85	0.0596
5, model(fodev)		0.5917	0.708		0.8586	0.1232		0.3229	0.9182		0.4888	0.4487
6, model(fodev)		0.7422	0.4047		0.3809	0.9486		0.5971	0.522		0.4758	0.4709
7, model(fodev)		0.5589	0.9191		0.5458	0.3966		0.417	0.8945		0.4868	0.4493
8, model(mdev)		0.8893	0.097		0.4358	0.6848		0.5804	0.578		0.9916	0.0012
9, model(level)		0.7127	0.5147		0.5556	0.4015		0.6253	0.4857		0.9093	0.0983
10, model(level)		0.6823	0.4865		0.6874	0.0707		0.6088	0.4677		0.5432	0.2739
model(fodev)		0.2878	0.7835		0.2543	0.5967		0.6169	0.5629		0.8278	0.344
model(level)		0.679	0.5671		0.4485	0.5507		0.5528	0.596		0.8402	0.1821

Source: Author's estimates based on Stata17®

Figures out of the statistical range proposed by Kiviet (2019) for GMM-System analysis are highlighted in grey. Although some p-values for the regressors are out of range when employing the 3 SPI dimensions as a dependent variable substitute for SPI, Kripfganz (2019) and Li *et al.* (2021) lay stress on the importance of the specification tests above coefficients' p-values statistical significance in the GMM-System regression. Except for the Kleibergen-Paap LM under-identification Test in the case of Foundations of Wellbeing being used as a dependent variable (p-value = 0.12) and the AR(1) Test in the case of Opportunity (with a p-value = 0.059 marginally out of range), the 3 models employing Total Compensation as a moderating variable depict statistical significant specification tests. Nonetheless, as stated by Kripfganz (2019), p-values are not to be used as a hard threshold, which somehow provides the researcher with some leeward to "*jump from one side*" of the threshold to the other, in particular when facing the 'statistical difficulties' of conjointly aligning not 1 but 5 specification tests when modelling via GMM-System (Li *et al.*, 2021).

Although some isolated p-value values lay below the 0.10 threshold for the Incremental Sargan-Hansen Test (0.0289 for the 1model(fodev) when employing Basic Human Needs and 0.0132 and 0.0435 respectively for the 1model(fodev) and 6model(fodev) when using Opportunities), the high p-values of the Overall Sargan-Hansen Test (0.66 and 0.61 respectively) may concede some leeward for those individual p-values to be considered as negligible figures, as the overall validity of IVs is confirmed. Based on a conjoint analysis of the specification tests, the 3 models are considered to retain their structural validity in the light of minor adjustments[90] as per Table 20 and relaxation of the statistical validity of the coefficients.

A similar analysis applies when employing Third-Parties Expenditure as a moderating variable. The Kleibergen-Paap LM under-identification Test is marginally out of range (0.088, 0.0530 and 0.0686, respectively) for the 3 models using the different dimensions as the dependent variable (in passing, as above exposed, the original model using SPI as the dependent variable was marginally out of range with p-value=0.0740). Nonetheless, IVs are considered relevant, especially if models are analysed from the conjoint perspective of remaining specifications tests (AR(1) Test, AR(2) Test and the Overall Sargan Test), which in all cases comply with the p-values threshold proposed by Kripfganz (2019). Individual Incremental Sargan-Hansen Tests (p-value = 0.0752 for 1model(fodev) of the Basic Human Needs dimension and 0,0231, 00596, 0.0012 and marginally 0.0983 for the 1model(fodev), 3model(fodev), 8model(fodev) and 9model(fodev) respectively for the Opportunity model) are considered negligible in the light of the overall IVs validity of the Overall Sargan-Hansen Test. Hence, conjoint analysis of the specification tests points to the 3 models retaining their structural validity. As in the previous case, the latter is subjected to the minor adjustments[91] highlighted in Table 20 besides the coefficients' statistical validity relaxation.

---

[90] Lag range reduction of the predetermined variables in addition to double filter with the backward orthogonal deviation (bodev) and use iterative gmm estimator when employing Foundations of Wellbeing as dependent variable.

[91] Lag range reduction of the predetermined variables in addition to double filter with the backward orthogonal deviation (bodev), use *iterative gmm estimator* when employing Foundations of Wellbeing as the dependent variable and lag range change from (1 2) to (1 4) for the lagged value of the dependent variable when classified as an endogenous variable

Kripfganz (2019) contents that in the presence of a small T (as in this case where T=6), it becomes difficult to add variables/lags or start with deeper lags for the IVs intending to solve specification tests issues, in which circumstances one must accept imperfect results scenarios. Nonetheless, drawing tentative conclusions is still possible. The previous conjoint analysis for the 2 models, far from being considered imperfect, is suggested to be robust, where some of the p-values out of range are considered negligible from a more conservative statistical perspective.

Concerning Robustness Test 2, the equation parameters are shown in Table 22.

Table 22. Equation parameters for Robustness Test 2.

Model 1: GMM-System employing Total Compensation as a moderating variable

	Difference Equation gmmiv (collapse, model (fodev))		
	Independent Variable Employed in the model	**Main Income Sources (Original)**	**Other Income Sources**
Type of variable	**Type of gmm estimator**	**2-step gmm**	**2-step gmm**
		Lag range	**Lag range**
Endogenous	Social Progress Index	1 2	1 2
	Independent Variable	1 2	1 2
	Total Compensation	1 2	1 2
	Independent Variable * **Total Compensation**	1 4	1 4
Predetermined	L(0/2).Independent Variable * L(0/2).Independent Variable	0 4	0 4
	Total Compensation * **Total Compensation**	0 4	0 4
	L(0/2).Independent Variable * **Total Compensation**	0 4	0 4
Exogenous	Masculinity Ratio	0 0	0 0
	Population covered by SS	0 0	0 0
	Average School Years	0 0	0 0
	Employment rate	0 0	0 0
	Informality rate	0 0	0 0

Model 2: GMM-System employing Third-Parties Expenditure as a moderating variable

	Difference Equation gmmiv (collapse, model (fodev))		
	Independent Variable Employed in the model	**Main Income Sources (Original)**	**Other Income Sources**
Type of variable	**Type of gmm estimator**	**2-step gmm**	**2-step gmm**
		Lag range	**Lag range**
Endogenous	Social Progress Index	1 2	1 2
	Independent Variable	1 2	bodev (1 2)
	Third parties expend	1 4	bodev (1 3)
	Independent Variable * **Third parties expend**	1 4	bodev (1 3)
Predetermined	L(0/2).Independent Variable * L(0/2).Independent Variable	0 0	0 0
	Total Compensation * **Third parties expend**	0 4	0 4
	L(0/2).Independent Variable * **Third parties expend**	0 0	0 0
Exogenous	Masculinity Ratio	0 0	0 0
	Population covered by SS	0 0	0 0
	Average School Years	0 0	0 0
	Employment rate	0 0	0 0
	Informality rate	0 0	0 0

Source: Author's estimates based on Stata17®

In the case of the model employing Total Compensation as a moderating variable, it could be observed that no changes in the lag parameters are applied when substituting Main Income Sources for Other Income Sources as the independent variable. In the model using Third-Parties Expenditure as a moderating variable, the backward orthogonal deviation (bodev) function is employed for 3 of the 4 endogenous variables (highlighted in grey). Table 23 depicts the individual findings for the regressors' p-values and the specifications tests associated with the Robustness Test 2 equations and how they compared to the original model findings.

Table 23. P-values and specification tests models' comparison for Robustness Test 2

Model 1: GMM-System employing Total Compensation as a moderating variable

Model Structure						
	Main Income Sources (Original)			Other Income Sources		
	Coefficient	**WC Robust SE**	**p-value**	**Coefficient**	**WC Robust SE**	**p-value**
Social Progress Index						
L1.	0.0942	0.0704	0.1830	0.0941	0.0705	0.1840
L2.	-0.0734	0.0379	0.0550	-0.0733	0.0379	0.0550
Independent Variable						
-.	0.0003	0.0015	0.8540	-0.0003	0.0015	0.8560
L1.	-0.0024	0.0027	0.3680	0.0025	0.0027	0.3630
L2.	0.0037	0.0036	0.2990	-0.0037	0.0036	0.3000
TotalCompensation	0.0065	0.0067	0.3300	0.0064	0.0066	0.3340
Independent Variable * TotalCompensation	0.0000	0.0000	0.1080	0.0000	0.0000	0.1080
L1.Independent Variable * TotalCompensation	0.0001	0.0000	0.2300	-0.0001	0.0000	0.2260
L2.Independent Variable * TotalCompensation	-0.0001	0.0001	0.2460	0.0001	0.0001	0.2470
MasculinityRatio	-1.9308	0.1679	0.0000	-1.9316	0.1679	0.0000
PopcoveredbySS	-0.0544	0.0055	0.0000	-0.0544	0.0055	0.0000
Averageschoolyearsofemployed	-0.1167	0.4715	0.8050	-0.1182	0.4734	0.8030
Employmentrate	-0.0677	0.0272	0.0140	-0.0676	0.0272	0.0140
Informalworkrate	-0.1195	0.0439	0.0070	-0.1195	0.0437	0.0070
Year						
2015	-0.8330	0.1558	0.0000	-0.8330	0.1556	0.0000
2016	-1.3561	0.0550	0.0000	-1.3561	0.0547	0.0000
2017	-1.6141	0.0596	0.0000	-1.6143	0.0593	0.0000
Const	285.3046	21.7942	0.0000	285.4060	21.7997	0.0000
Specification Tests						
			p-value			**p-value**
Kleibergen-Paap LM under-identification Test			0.0333			0.0331
AR(1)			0.0077			0.0078
AR(2)			0.8980			0.8989
Overall Sargan-Hansen Test			0.8630			0.8620
Difference Sargan-Hansen Test		Excluding **p-value**	Difference **p-value**		Excluding **p-value**	Difference **p-value**
1, model(fodev)		0.8144	0.9546		0.8126	0.9531
2, model(fodev)						
3, model(fodev)		0.8566	0.4268			
4, model(fodev)		0.7851	0.8253		0.798	0.9063
5, model(fodev)		0.3282	0.9526		0.8138	0.692
6, model(fodev)		0.7632	0.9302		0.7759	0.8491
7, model(fodev)		0.5468	0.9803		0.6393	0.9113
8, model(mdev)		0.846	0.5649		0.7609	0.9305
9, model(level)					0.5458	0.9796
10, model(level)					0.8444	0.5643
model(fodev)		0.5381	0.8559		0.4835	0.8667
model(level)		0.6028	0.9319		0.6004	0.9315

Model 2: GMM-System employing Third-Parties Expenditure as a moderating variable

Model Structure						
	Main Income Sources (Original)			Other Income Sources		
	Coefficient	WC Robust SE	p-value	Coefficient	WC Robust SE	p-value
Social Progress Index						
L1.	0.0956	0.0692	0.1690	0.0788	0.0719	0.2740
L2.	-0.0560	0.0396	0.1600	-0.0486	0.0359	0.1770
Independent Variable						
-.	-0.0003	0.0013	0.8250	0.0007	0.0007	0.2950
L1.	-0.0008	0.0015	0.5980	0.0009	0.0006	0.1490
L2.	0.0015	0.0020	0.4660	-0.0029	0.0016	0.0780
ThirdPartiesExpend	0.0022	0.0031	0.4700	0.0030	0.0037	0.4060
c.Independent Variable#c.ThirdPartiesExpend	0.0000	0.0001	0.8710	0.0000	0.0001	0.3970
cL.Independent Variable#c.ThirdPartiesExpend	0.0000	0.0001	0.8700	0.0000	0.0001	0.7720
cL2.Independent Variable#c.ThirdPartiesExpend	0.0000	0.0001	0.6940	0.0001	0.0001	0.0960
MasculinityRatio	-2.0174	0.1592	0.0000	-2.0518	0.1605	0.0000
PopcoveredbySS	-0.0564	0.0045	0.0000	-0.0555	0.0046	0.0000
Averageschoolyearsofemployed	-0.3076	0.6312	0.6270	-0.3844	0.4717	0.4160
Employmentrate	-0.0733	0.0241	0.0030	-0.0645	0.0300	0.0330
Informalworkrate	-0.1403	0.0499	0.0060	-0.1197	0.0510	0.0200
Year						
2015	-0.8027	0.1373	0.0000	-0.8310	0.1309	0.0000
2016	-1.3217	0.0602	0.0000	-1.3547	0.0690	0.0000
2017	-1.5840	0.0622	0.0000	-1.5737	0.0464	0.0000
_cons	296.0997	24.0411	0.0000	299.4631	21.2729	0.0000
Specification Tests						
			p-value			p-value
Kleibergen-Paap LM under-identification Test			0.0740			0.1451
AR(1)			0.0049			0.0393
AR(2)			0.7395			0.9721
Overall Sargan-Hansen Test			0.6900			0.8658
Difference Sargan-Hansen Test		Excluding	Difference		Excluding	Difference
		p-value	p-value		p-value	p-value
1, model(fodev)		0.7919	0.137		0.8857	0.3117
2, model(fodev)					0.8373	0.8234
3, model(fodev)		0.6566	0.9251		0.8433	0.6432
4, model(fodev)		0.7365	0.4012		0.8455	0.5992
5, model(fodev)		0.5917	0.708		0.7825	0.7732
6, model(fodev)		0.7422	0.4047		0.8602	0.5935
7, model(fodev)		0.5589	0.9191		0.7641	0.8656
8, model(mdev)		0.8893	0.0970		0.8425	0.5983
9, model(level)		0.7127	0.5147		0.8742	0.6183
10, model(level)		0.6823	0.4865		0.9165	0.2363
model(fodev)		0.2878	0.7835		0.0000	1.0000
model(level)		0.679	0.5671		0.9	0.6136

Source: Author’s estimates based on Stata17®

As per the latter findings, the model employing Total Compensation as a moderating variable remains virtually the same when using Other Income Sources as an independent variable. Concerning the model employing Third-Parties Expenditure as a moderating variable, findings suggest structural improvements by following a similar rationale analysis as Robustness Test 1. The latter stems from 1) only 1 of the regressors’ p-value is above the 0.7 figure suggested by Kiviet (2019), 2) All IVs are significant as per the Incremental Hansen Test, which is effect suffers an overall improvement by increasing from 0.69 to 0.86, suggesting that IVs become even more valid. 3) AR(1) is kept under the 0.05 threshold; meanwhile, the AR(2) figures improve, rising from 0.73 to 0.97, virtually suggesting the non-existence of serial correlation. 4) The Kleibergen-Paap LM under-identification Test is the only figure that does not improve as it increases from 0.074 to 0.140, suggesting that IVs become less relevant. Nonetheless, in light of the other model statistical improvements, as based on the analysis ‘tips’ suggested by Kripfganz (2019) and Kiviet (2019), this figure is considered marginally out of range, so the overall structural model characteristics are considered from a statistically conservative perspective to be maintained.

Quoting Holland (1988): *"Statistical science does more good in the world when it concentrates on measuring the effect of causes than when it attempts to explicate the causes of effects. Well-founded measurements of causal effects are the building blocks of the successful identification of causes. Causal effects come first, not last, in the difficult process of causal inference.*" Nonetheless, Imai *et al. (*2011, pp765) contrarily argue that: *"researchers seek to study not only whether one variable affects another but also how such a causal relationship arises".* In general terms, the nature of mechanisms underlying social science has been debated in academic circles for decades and centuries in philosophic ones[92]. Although the Humean 'causation as regularities' theoretical stance[93] may still hold relevant up-to-date in social research, the realist theoretical standpoint of 'causation as a causal mechanism'[94] would be pursued in this study as per its research design. Causality testing via structural models is suggested as appropriate for this research, which, even when conceptualised differently in the literature, are pointed out as capable of identifying 3 main distinct but related objects: deep structural parameters, *underlying mechanisms*, and counterfactuals (Low & Costas, 2017; Blundell, 2017)

Structural models account for causal mechanisms, which require a robust underlying theoretical background in the field. As quoted from Reiss & Wolak (2007, pp4282) when referring to structural models: "*economic theory is used to develop mathematical statements about how a set of observable endogenous*

[92] In general terms, Chambliss & Schutt (2006, pp108) and Menard (2008) propose 5 criteria for causality testing. The first 3 criteria point at testing the causal relationship; meanwhile, the last 2 criteria seek to strengthen the causal explanations considerably: 1) empirical association, 2) temporal priority of the independent variable, 3) non-spuriousness, 4) identifying a causal mechanism, and 5) specifying the context in which the effect occurs. Nonetheless, in general terms, studies research may not meet all 5 criteria, potentially leaving voids about causal conclusions' validity or avoiding assertions about causal relationships (Chambliss & Schutt, 2006).

[93] Entirely constituted by facts about empirical regularities among observable variables so that there is no underlying causal nature, causal power, or causal necessity.

[94] Notions of causal mechanisms and causal powers are fundamental, asserting that scientific research endevour seeks arriving at empirical justified theories and hypotheses about those causal mechanisms. Within this realist approach, 3 main models of influence (Cartwright, 1988) prevail: 1) Agent-based models, which aggregate results of individual-level choices into macro-level outcomes, 2) Structural models which attempt to demonstrate causal effects of social structures or institutions on social outcomes (levels of compliance), and 3) Social influence models which intend to identify factors working behind the agents' backs to influence their choices.

variables, y, are related to another set of observable explanatory variables, x". Moreover, Cartwright (1988) argues that causal effects identification requires substantive theoretical support to hypothesise about the causal powers or capacities governing the entities in question, meaning *causal mechanisms*. As afore explained, the literature review did not render a theoretical framework *directly* linking FDI and social development, especially from a bidirectional standpoint that poses the potential existence of either *vicious, virtuous or lop-sided circles*. Such a void, in passing, implied not counting with the related *structural equations*, which, as aforementioned, restricted this research to be performed via ML-SEM, for which the semiparametric GMM-Sys approach was chosen as a suitable robust alternative. Nevertheless, as it occurs in much economic scholarly research, the absence of supportive theory relating to different social constructs or variables could be approached via an intermediate variable, as in this research. A plethora of empirical economic research and supportive economic theory relating FDI and *economic growth* and *economic growth* and social development was 'inspirational', properly allowing hypothesising about the existence of such a sought relationship between FDI and social development via *economic growth*, their related moderating variables and associated *causal mechanisms* as described in the research design 3.2 section.

This chapter is structured as follows: subsection 6.1 proposes 'unidirectional structural models' based upon the causal effects derived from the GMM-Sys regressions; subsection 6.2 describes the 'bidirectional dynamic structural model' proposed, which stem from the detailed exploration and testing of causal mechanisms after stationarity testing, Panel Autoregression Reduced Forms, model stability, Grainger Causality tests, and Impulse-Response functions, and subsection 6.3 summarises all previous findings -comprising the variables and their interactions employed- by proposing the final conceptual/structural framework pursuit in this dissertation.

6.1 Unidirectional Static Structural Models (Causal Effects)

Out of the 3 features mentioned above for models to be considered structural (Low & Costas, 2017; Blundell, 2017), the *causal mechanisms* characteristic becomes paramount, heavily relying on causality testing methods, which subsequently lead to compliance with 2 remaining features: *structural parameters* and *counterfactuals*. Hence, although the GMM-System method falls short of identifying *causal mechanisms,* it is nonetheless suggested as capable of accounting for *causal effects* [95] by tackling endogeneity arising from simultaneity. From this standpoint, the coefficients of the GMM-Sys regressions shown in Table 17 and Table 18 in subsection 5.1.4 are considered statistically suitable for addressing *causal effects* from a unidirectional structural 'static' perspective, flowing from FDI to social development. Hence, the GMM-Sys specifications reported in subsection 5.1.4, written in a mathematical version as shown in Equations 4 and Equation 6, are proposed as static structural models (depending on the modifying variable employed). In passing, those two latter equations can be rewritten in a shorter version, extending into broader economic terms, thereby proposing them as *unidirectional structural equations*, as shown in Equations 5 and 7. One may notice then that the same analysis rationale regarding RQ1, RQ2, RQ3, H1, H2, and H3, afore explained in section 5.1.4., also apply to the following equations as they stem from the same results. Based upon the specifications in Table 17, Equation 4 proposes a Static Structural Model which employs Total Compensations as a modifying variable**.**

[95] As Imai *et al.* (2011) argue, IVs have been widely employed to identify *causal effects* of - typically- endogenous variables across social disciplines. Their capability for *causal effects* identification assumes that IVs: 1) have no direct effect on the dependent variable (implying an exclusion restriction feature), 2) have a unidirectional effect (monotonicity feature), 3) possess an ignorability feature and 4) assume a stable unit treat value. Thereby, if IVs are available and they are believed not to hold the ignorability of the mediator, their use to study *causal effects* may appear as a suitable alternative. In this sense, after the recognition of endogeneity issues, the underlying rationale to employ IVs to identify *causal effects* is supported by key assumptions: 1) IVs are essentially random (ignorability of IVs feature); 2) they influence the dependent variable only via the *causal mechanism* (exclusion restriction), and 3) higher magnitudes of IVs never lead to lower values of *causal mechanisms* (monotonicity).
As the same units (industry type) are observed over more than one period, SPI, as the dependent variable, is impacted by several observed and unobserved factors. Insofar as the unobserved effects (omitted variables) are correlated with the independent (treatment) variable FDI (Main Income Sources), endogeneity would be present in the model, invalidating the use of correlations for causal effect estimations. As per subsection 5.1.4 findings, heavily supported by the specifications tests in subsection 5.1.5 and Robustness Test and their related specifications test in subsection 5.2, the basic models proposed calculated via the GMM-Sys and corresponding *feasible efficient gmm estimator* are pointed at as an appropriate method for causal inference in the presence of misspecification issues, particularly the extreme case of endogeneity by simultaneity (Leszczensky & Wolbring, 2019).

Equation 4

$$\boldsymbol{SPI_{it}} =$$

$+ (0.094 * SPI_{it-1}) - (0.073 * SPI_{it-2})$	SPI Lagged effect
$- (0.00028 * MIS) - (0.0024 * MIS_{it-1}) + (0.0037 * MIS_{it-2})$	FDI contemporary and lagged effects
$+ (0.0065 * TC)$	Moderating variable contemporary effect
$- (0.00004 * MIS * TC) + (0.00005 * MIS_{it-1} * TC) - (0.0001 * MIS_{it-2} * TC)$	Moderating variable contemporary and lagged effects interactions
$- (1.93 * MR) - (0.054 * PCSS) - (0.116 * \mathrm{ASY}) - (0.067 * ER) - (0.119 * IR)$	Control variables
$- (0.83)_{t+4} - (1.35)_{t+5} - (1.61)_{t+6}$	Time (Year) Effects
$+ 285.30_{\mathrm{j}}$	Constant
$+ \varepsilon_{it\mathrm{j}}$	Error term

where,

SPI= Social Progress Index
MIS = Main Income Sources
TC = Total Compensation
MR= Masculinity Rate
PCSS = Population Covered by Social Services
AV = Average School Years
ER = Employment Rate
IR = Informality Rate

Instead of proxy variables, broader economic variables may be employed intending to propose a 'structural' equation. A simplified version of Equation 4 may be rewritten in more general terms, as shown in Equation 5.

Equation 5

$$\boldsymbol{SD_{it}} = \alpha_0 + \sum_{j=1}^{2}(\beta_j * SD_{it-j}) + \sum_{j=0}^{2}(\gamma_j * FDI_{it-j}) + (\delta_0 * HI)$$
$$+ \sum_{j=0}^{2}(\lambda_j * HI * FDI_{it-j}) + D + A + \varepsilon_{it\mathrm{j}}$$

Where SD_{it} represents the contemporary value for social development as the dependent variable. The coefficient α_o is the constant for the entire regression and the β_j, γ_j, δ_0 and λ_j values are the coefficients for the remaining independent and interaction variables. The term SD_{it-j} comprises the 2 lagged values for the social development employed as additional independent variables. As per the same token, the term FDI_{it-j} also comprises 2 lagged values of *FDI*, besides its contemporary value, as independent variables. *HI* represents the contemporary value of Household Income. In addition, as a moderating variable, this contemporary figure interacts with the contemporary value and 2 lagged values of *FDI*. *D* represents the set of dummy variables included for time effects purposes. A represents a set of control and policy variables that may be frequently included in empirical research as determinants of social development. ε_{itj} is the error term to encompass all the other variables that have not been accounted for and are likely to impact social development.

As per the same token, specifications reported in Table 18 are also foundational in constructing Equation 6, proposed as a Static Structural Model which employs Third Parties Expenditure as a modifying variable

Equation 6

$\boldsymbol{SPI_{it}} =$

$+ (0.095 * SPI_{it-1}) - (0.055 * SPI_{it-2})$	SPI Lagged effect
$- (0.00028 * MIS) - (0.00082 * MIS_{it-1}) + (0.00145 * MIS_{it-2})$	FDI contemporary and lagged effects
$+(0.0022 * TPE)$	Moderating variable contemporary effect
$+ (0.00001 * MIS * TPE) + (0.00002 * MIS_{it-1} * TPE) - (0.00003 * MIS_{it-2} * TPE)$	Moderating variable contemporary and lagged effects interactions
$- (2.01 * MR) - (0.056 * PCSS) - (0.307 * \mathrm{ASY}) - (0.073 * ER) - (0.14 * IR)$	Control variables
$- (0.80)_{t+4} - (1.32)_{t+5} - (1.58)_{t+6}$	Time (Year) Effects
$+ 296.09_{j}$	Constant
$+ \varepsilon_{itj}$	Error term

where,

SPI= Social Progress Index
MIS= Main Income Sources
TPE=Third-Parties Expenditure
MR= Masculinity Rate
PCSS = Population Covered by Social Services
AV = Average School Years
ER = Employment Rate
IR = Informality Rate

As in the case of Equation 4, Equation 6 may be rewritten employing broader economic variables also intending to propose a 'structural' equation. See Equation 7.

Equation 7

$$\boldsymbol{SD_{it}} = \alpha_0 + \sum_{j=1}^{2}(\beta_j * SD_{it-j}) + \sum_{j=0}^{2}(\gamma_j * FDI_{it-j}) + (\delta_0 * PL)$$
$$+ \sum_{j=0}^{2}(\lambda_j * PL * FDI_{it-j}) + D + A + \varepsilon_{it\mathrm{j}}$$

As in the case of Equation 5 SD_{it} represents the contemporary value for social development as the dependent variable. α_o is the regression's constant and the β_j, γ_j, δ_0 and λ_j values are the coefficients for the remaining independent and interaction variables. SD_{it-j} comprises the 2 lagged values for the social development employed as additional independent variables. FDI_{it-j} also comprises 2 lagged variables of *FDI*, besides its contemporary value, as independent variables. *PL* represents the contemporary value of Productive Linkages, which additionally interacts with the contemporary value and 2 lagged values of *FDI* as a moderating variable. *D* is the set of time dummy variables. A is a set of control and policy variables and $\varepsilon_{it\mathrm{j}}$ is the error term accounting for all other excluded factors that may likely impact social development.

6.1.1 Analysis by MNE Industrial Sector

Due to the complexity of the models employed to support the latter proposed equations, which considered a variety of interactions of variables, lagged effects of the dependent and independent variables, time effects (D) and control variables (A), another sort of dummy variable -seeking to enlarge the explanatory strength of the GMM-Sys further- was not introduced. However, adding dummy variables for Industry Type (I) could further explain how social development may differ depending on the type of MNEs industry, in other words, their Fixed Effects (FE) impacts. For brevity purposes, GMM-Sys regression and associated post-estimation tests are shown in Appendix 9 (GMM-Sys estimations with dummy variables for major industrial sectors), where the variable StructureDummy refers to industry dummies. The 189 industries employed in the previous analysis were collapsed into 16 structural sectors per the Standard Industrial Classification of All Economic Activities previously explained. (See also Appendix 6.B for the percentage contribution of every industry to the entire sample in millions of dollars). Table 24 summarises the coefficients of the GMM-Sys regressions depending on the moderating variable employed and their associated p-values per Industry Type.

Table 24. Industry effects

	Total Compensation as a moderating variable			Third-parties Expenditure as moderating varaible		
	Coefficient	P>|t|	% Diff	Coefficient	P>|t|	% Diff
Industries						
Agriculture, forestry and fishing		Base			Base	
Manufacturing	-54.8097	0.384	80%	-14.8465	0.718	95%
Electricity, gas, steam and air conditioning supply	-41.9637	0.41	85%	-8.075224	0.652	97%
Water supply, sewage, waste management and remediation activities	-59.0085	0.373	79%	-8.614795	0.552	97%
Wholesale and retail trade, repair of motor vehicule and motorcycles	-63.0753	0.38	77%	-16.52246	0.713	94%
Transportation and storage	-61.1219	0.383	78%	-17.50465	0.708	94%
Accommodation and food services activities	-99.8929	0.475	64%	-36.77154	0.866	87%
Information and communication	-58.3373	0.383	79%	-17.79469	0.703	94%
Real estate activities	-277.0886	0.408	0%	-50.497	0.876	82%
Professional, scientific and technical activities	-55.0681	0.403	80%	-13.39101	0.962	95%
Administrative and support service activities	-67.5731	0.374	76%	-14.32628	0.627	95%
Education	30.69601	0.62	111%	-11.23365	0.685	96%
Human health and social work activities	-213.4001	0.361	23%	-34.02122	0.696	88%
Arts, entertainment and recreation	-91.9614	0.37	67%	-23.99511	0.684	92%
Other services activities	-68.5387	0.381	75%	-19.91568	0.702	93%
Const	276.52	0.101	100%	287.4484	0.077	100%

Source: Author's estimates based on Stata17®

One must note that 1 industry out of the 16 classifications (Mining and Quarries) was not employed, as there was only 1 observation in the panel data. Despite the Accommodation and Food Services Activities p-value=0.866 and Real State Activities industries p-values=0.876 for the regression related to Third-Parties Expenditure, all other p-values were found statistically significant as per Kiviet's (2019) guidelines in section 5.1.4. Nonetheless, these effects are considered negligible per the rationale explained in section 5.1.5 (See Appendix 9). The field regarded as % Diff displays the percentual difference of the contribution of a given industry concerning the contribution to social development associated with the base coefficient (276.52 and 287.44 respectively per regression depending on the moderating variables), which in this case refers to the Agriculture, Forestry and Fishing industry.

Concerning the Total Compensation coefficient, if all other variables are maintained constant, the contribution factor (coefficient) of the Manufacturing industry to social development is, on average, 80% less when compared to the contribution (coefficient) of the Agriculture, Forestry and Fishing industries. For the Total Compensation regression, the contributing factors to the social development of all industries exhibit an arithmetic mean of 69%. They fluctuate between 0% in the case of the Real Estate Activities industry (meaning that Real

Estate Activities, on average, are not bound to contribute to social development) and 11% in the case of the Education industry (suggested bound to contribute 11% more to social development in comparison to the average contribution of Agriculture, Forestry and Fishing industry). Notably, this is the only industry surpassing Agriculture, Forestry and Fishing in contributing to social development. In passing, such a finding may be supported by certain theoretical and conceptual assertions in the literature, particularly because this regression concerns Total Compensation as a proxy for Household Income. In the way this equation is structured (lagged effects of social development and Main Income Sources as independent variables and interaction moderating effects), the higher contribution of the Education industry to social development is expected to follow a direct causal effect path and an interaction one. Education is one of the main comprising factors of the up-to-date existing social development measures reported in the literature; thereby, one may expect that MNEs in the Education industry may directly induce a positive effect on social development. On the interaction venue, one may expect FDI to trigger positive productive spillover, increasing Household Income derived from MNEs' employees accessing better-paid jobs. One may expect such an increase in disposable income to stimulate households to 'invest' in Education to augment their living standards and positively contribute to general social development. As per the same token, one would also expect a similar casual effect path regarding the Human Health and Social Work Activities industry, as healthcare, in general terms, is an important comprising factor of social development as supported by the literature. In this sense, it is counter-intuitive that the Human Health and Social Work Activities industry, on average (directly and by interaction), contributes only 23% to social development compared to the contribution of the Agriculture, Forestry and Fishing industries. Such contradictory findings, diverging from the classic theoretical conceptions, may be explicated by the limitations of the panel data set, suggested to affect the efficiency of the coefficient estimators. Initial calculations were based upon an already T-constrained panel data set (T=6), which becomes further restricted when adding industry dummies, as the same data points were broken down into 16 new samples per industry type.

Industry-type impact coefficient differences regarding Third-Parties Expenditures as a moderating variable are reported to fluctuate on average between 82% (Real Estate Activities) and 97% (for both the Electricity, gas, steam and air conditioning supply industry and the Water supply, sewage, waste management and remediation activities) when compared to the base figure of Agriculture, Forestry and Fishing industry. The arithmetic mean of the variation of all industries is 93%, where it is interesting that none of the industries' coefficients surpasses the average contribution to the social development of Agriculture, Forestry and Fishing as a base industry. By being Third-Parties Expenditure, the moderating variable in this case, as per the characteristics of the Panamanian economy, one would likely expect a higher contribution (direct and by interaction effects as per the above-provided rationale) to the social development of the Wholesale and Retail Trade, Repair of Motor Vehicle/Motorcycle industry and the Transportation and Storage industry. The Special Economic Zone (SEZ) regimes are designated economic areas where MNES are offered incentives to encourage investment, up-to-date totalling 5,400 SEZs across 147 nations UNCTAD (2021). Incentives may comprise free trade-related fees (duties and taxes) and various customs preferences for goods to be stored, handled, traded and exported. The MNEs in the panel data falling into this Wholesale category belong in general terms to this Free Trade scheme, where is worth noting that the Colon Free Trade Zone (established in 1948) is the largest in the Americas and the second largest in the world after Shanghai FTZ (established in 2013). Given the relative importance of this industry over Agriculture, Forestry and Fishing, one may expect that MNEs immersed in the SEZ scheme may create productive linkages with local companies by outsourcing and subcontracting their services and/or purchasing their products. Hence, a multiplying effect in the local and national economy would be potentially ignited, which would be expected to positively impact social development directly and by interaction with other factors. Similarly, MNEs in the Transportation and Storage industry are intrinsically related to Panama's economy's 'logistics machinery'. Such major infrastructure comprises the 2 locks sets of the Panama Canal, the ports both in Balboa (Panama City on the Pacific Ocean) and Colon (on the Caribbean side), the railroad system linking both oceans, the 4 major airports in Panama, where the Tocumen Airports is the largest hub in Central America and the Caribbean. The results herein exposed are counterintuitive by dimensioning the potential impact that MNEs that belong to this industry may have in an aggregated fashion on social development via productive linkages creation in the economy and iteration with other factors. In the same way, argued above, to what extent this may be due to the restriction of data points in the panel data set is subject to future research via either enlarging the current panel data set or employing a different one with the same or similar proxy variables.

6.2 Bidirectional Dynamic Structural Model (Causal Mechanisms)

The *casual effects* proposed in the static structural model explained in the previous subsection partially confirmed H1, as the relationship tested was unidirectional. Nonetheless, the causal relationship between FDI and Social Development has been hypothesised to be bidirectional, where the two directions may not necessarily be mutually exclusive. Hence, to assess the relative importance of forward causality of those two variables (FDI affecting Social Development) and reverse causality (Social Development affecting FDI) must be tested. The Panel-data Vector Autoregression (PVAR) Reduced-Form model is employed for those purposes. Reduced-Form models evaluate endogenous variables in terms of observable exogenous variables and identify relationships between the variables. The PVAR approach is a method that combines the classic VAR approach and the panel-data approach, deriving into estimations consistency improvements (Love & Zicchino, 2006). The traditional VAR side of the model treats all variables as endogenous and interdependent (both dynamic and static), including exogenous variables (Canova & Ciccarelli, 2013). Specifically, by following Canova & Ciccarelli (2013, pp45), PVARs are pointed at for being particularly suited to 1) Capture both static and dynamic interdependencies, 2) Unrestrictively treat links across units, 3) Incorporate time variation in coefficients and shocks' variance, and 4) account for cross-sectional dynamic heterogeneities. Complementary, its panel-data side allows controlling for cross-sectional unobserved individual heterogeneity. The core rationale for employing a PVAR at this point gravitates around that this type of model is reported in the literature as well suited for researching cycle/circle patterns (as required in RQ1), particularly in the absence of a detailed specification of the structure of the economic model (as per Canova & Ciccarelli (2013) when citing Canova *et al.* (2007), Canova & Ciccarelli (2012), Canova & Ciccarelli, 2009).

Moreover, as per Koop & Korobilis (2016), PVARs were proven to be robust methods for estimating spillovers and linkages.

6.2.1 Stationarity (Unit Root) testing

A common practice in a time series VAR approach is testing for Unit-Root ('Random walk' behaviour, meaning an unpredictable systematic pattern). Per the explanation in the paragraph above, PVAR is a VAR approach in nature, for which confirmation of *stationarity* for each variable using Unit-Root tests [96] becomes necessary before estimating a PVAR via a *gmm estimator* (Abrigo & Love, 2016). In univariate cases, if the modelled variable is near Unit-Root, the *gmm estimator* exhibit weak IVs issues (Blundell & Bond, 1998) as the idiosyncratic error is only left after both FD (First Differences) and FOD (Forward Orthogonal Deviations) transformations, making moment conditions to become completely irrelevant. In such cases, pre-transforming variables employing growth rates or differencing them may mitigate this issue.

The *xtunitroot fisher* command in Stata 17® both supports the ADF test (Augment Dickey-Fuller Test) and the Phillips-Perron test (a modification of the ADF test). The problem with the former test is its high Type I error rate, so the latter is left as the best option for Unit-Root testing purposes as autocorrelation and heteroskedasticity in the errors are corrected. The trend option is used to test for time trends. The *demean* option – which computes the series' mean across panels and subtracts it from the cross-sectional series- mitigates the cross-sectional dependence impact. Additionally, as the Fisher test assumes

[96] Various tests for Unit-Root (*stationarity testing*) are implemented in Stata17® via the *xtunitroot* command (Abrigo & Love, 2016): Levin–Lin–Chu (2002), Harris–Tzavalis (1999), Breitung (Breitung, 2000; Breitung & Das, 2005), Im–Pesaran–Shin (2003), Fisher-type (Choi 2001) tests and the Hadri (2000) Lagrange multiplier (LM) test. The last test is based on the null hypothesis that all the panels are (trend) stationary; meanwhile, the rest support the null hypothesis that all panels contain a Unit-Root. Nonetheless, out of those tests, the only two suitable for handling unbalanced panel data are the Im–Pesaran–Shin test and the Fisher-type test, where the latter unfortunately requires data not exhibiting gaps, leaving the former as the only option. This Fisher-type test operates from a meta-analysis perspective, in the sense that the Unit-Root test is conducted for each panel, subsequently combining the individual p-values into an overall test statistic. This estimate stems from an inverse chi-squared, inverse-normal, inverse-logit and a modified version of the inverse chi-squared transformation, which is proposed to be used when N is believed to tend to infinity, insofar the standard inverse chi-squared test statistic approaches infinity.

data being generated by an AR(1) process, for higher-order processes, first-differenced and lagged-level data are replaced by the residuals from regressions of those two series on the first number of lags of the first-differenced data. Hence, the *lag ( ) option,* which specifies the lags number employed to remove higher-order autoregressive components, is run from lags(1) until lag(5), rending in all cases the same results for both dependent and independent variables. See Table 25 for Unit-Root test results.

Table 25. Unit-Root (Stationary) test results using a Phillips-Perron approach a Fisher type test.

Fisher-type unit-root test
Based on Phillips–Perron tests

H0: All panels contain unit roots
Ha: At least one panel is stationary

AR parameter: Panel-specific
Panel means: Included
Time trend: Included
Newey–West lags: 3 lags
Asymptotics: T -> Infinity
Cross-sectional means removed

		Social Progress Index		Main Income Sources		Third Parties Expediture		Total Compensation	
		Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
Inverse chi-squared(300)	P	2854.27	0.0000	2293.330	0.0000	2410.356	0.0000	2301.142	0.0000
Inverse normal	Z	-39.63	0.0000	-27.709	0.0000	-25.764	0.0000	-26.041	0.0000
Inverse logit t(619)	L*	-69.13	0.0000	-53.608	0.0000	-55.237	0.0000	-54.636	0.0000
Modified inv. chi-squared	Pm	104.28	0.0000	81.377	0.0000	86.526	0.0000	82.052	0.0000
Number of panels		168		168		166		166	
Average number of period		5.12		5.12		5.13		5.13	

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

Source: Author's estimates based on Stata17®

The null hypothesis of this test considers all panels containing Unit-Root effects. Hence as per all the P, Z, L* and Pm individual tests p-values being statistically significant under a 1% level (All figures shown are 0.0000), the null hypothesis can be rejected, confirming the non-existence of Unit-Roots effects (and confirming a *stationary* pattern) in the panels under the given test conditions (included panel mean and time trend) for neither of the 4 main variables. This finding is expected to be derived from the models' specification tests since the IVs were previously proven valid and reliable when using the *gmm estimator* under some conditions.

6.2.2 Model Selection

The Stata17® *pvarsoc* command is employed for PVAR model selection purposes. Based on an estimation sample of the least restrictive PVAR model (e.g. with the highest lag order employed for all models to be estimated), *pvarsoc* reports model overall coefficient of determination, Hansen's (1982) J statistic and corresponding p-value, and Andrews & Lu (2001)' moment model selection criteria (based on the Hansen's J statistic) which require the number of moment conditions in the PVAR model to be greater than the number of endogenous variables. *pvarsoc* was run for first- to third-order (*maxlag(3)*) employing the contemporaneous values and the first 4 lag values of the endogenous variables (SPI, Main Income Sources, Total Compensation and Third-Parties Expenditure) as IVs (*instlags(0/4)*) as shown in Table 26.

Table 26. PVAR model selection criteria

Selection Order Criteria
Sample: 2016-2016

lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	1	65	0.44	-234.52	-62.86	-132.46
2	1	43	0.66	-181.33	-52.59	-104.79
3	1	35	0.33	-114.97	-29.14	-63.94

Source: Author's estimates based on Stata17®

Based on Andrews & Lu (2001)' s 3 model selection criteria (MBIC, MAIC and MQIC), the overall determination coefficient for the first-order PVAR becomes the preferred choice per their smallest MBIC, MAIC and MQIC values. It is worth noting that although Hansen's J statistic is sought to be minimised, this statistic does not correct the degrees of freedom compared to Andrews & Lu's (2001) model and moment selection criteria. In any case, the 3 models do not appear to exhibit misspecification issues, as IVs are suggested to be valid.

6.2.3 Panel Vector Autoregression Reduced-Form Model

After testing the non-existence Unit-Root effects (hence exhibiting stationarity), the PVAR-reduced form model emerges as a suitable candidate to fully answer RQ1, as the method allows testing the existence of cycle/circle associations between variables. See Table 27.

Table 27. PVAR Reduced-Form model

Panel Vector Autoregression	Number of obs	=	523		
GMM Estimation	Number of panels	=	149		
	Ave. no. of T	=	3.51		
Final GMM Criterion Q(b) = 0.172					
Initial weight matrix: Indentity					
GMM weight matrix: Robust					

	Coefficient	**Std. err.**	**z**	**P>|z|**	**[95% conf. interval]**	
Social Progress Index						
Social Progress Index (L.1)	0.0196	0.022	0.880	0.378	-0.024	0.063
Main Income Sources (L.1)	0.0106	0.004	2.440	0.015	0.002	0.019
Total Compensation (L.1)	0.0312	0.008	3.720	0.000	0.015	0.048
Third-Parties Expediture (L.1)	0.0367	0.008	4.320	0.000	0.020	0.053
Main Income Sources x Total Compensation (L.1)	-0.0004	0.000	-4.410	0.000	-0.001	0.000
Main Income Sources x Third-Parties Expenditure (L.1)	-0.0004	0.000	-4.450	0.000	-0.001	0.000
Masculinity Ratio	-1.7332	0.276	-6.270	0.000	-2.275	-1.192
Population covered by SS	-0.0303	0.005	-6.280	0.000	-0.040	-0.021
Average School Years	-0.9207	0.549	-1.680	0.094	-1.998	0.156
Employment rate	-0.0299	0.018	-1.650	0.099	-0.066	0.006
Informality rate	-0.0814	0.028	-2.880	0.004	-0.137	-0.026
Main Income Sources						
Social Progress Index (L.1)	-1.8671	0.766	-2.440	0.015	-3.368	-0.366
Main Income Sources (L.1)	0.0861	0.100	0.860	0.390	-0.110	0.283
Total Compensation (L.1)	-0.2042	0.181	-1.130	0.260	-0.560	0.151
Third-Parties Expediture (L.1)	0.3996	0.282	1.420	0.156	-0.153	0.952
Main Income Sources x Total Compensation (L.1)	0.0024	0.002	1.230	0.219	-0.001	0.006
Main Income Sources x Third-Parties Expenditure (L.1)	-0.0049	0.003	-1.930	0.054	-0.010	0.000
Masculinity Ratio	-28.5968	9.473	-3.020	0.003	-47.164	-10.030
Population covered by SS	-0.0377	0.164	-0.230	0.818	-0.359	0.283
Average School Years	-64.2320	18.981	-3.380	0.001	-101.435	-27.029
Employment rate	-0.0289	0.619	-0.050	0.963	-1.242	1.184
Informality rate	0.1447	0.883	0.160	0.870	-1.587	1.876
Total Compensation						
Social Progress Index (L.1)	-0.1020	0.883	-0.120	0.908	-1.833	1.629
Main Income Sources (L.1)	-1.0027	0.209	-4.810	0.000	-1.412	-0.594
Total Compensation (L.1)	-1.1284	0.419	-2.700	0.007	-1.949	-0.308
Third-Parties Expediture (L.1)	-3.1459	0.446	-7.050	0.000	-4.021	-2.271
Main Income Sources x Total Compensation (L.1)	0.0180	0.004	4.740	0.000	0.011	0.025
Main Income Sources x Third-Parties Expenditure (L.1)	0.0294	0.004	6.890	0.000	0.021	0.038
Masculinity Ratio	-37.0871	13.649	-2.720	0.007	-63.839	-10.335
Population covered by SS	0.2243	0.274	0.820	0.414	-0.313	0.762
Average School Years	-79.1238	28.541	-2.770	0.006	-135.063	-23.184
Employment rate	-3.0106	0.737	-4.080	0.000	-4.456	-1.565
Informality rate	-5.2853	1.089	-4.850	0.000	-7.419	-3.151
Third-Parties Expenditure						
Social Progress Index (L.1)	1.5377	0.861	1.790	0.074	-0.150	3.225
Main Income Sources (L.1)	0.0196	86.028	1.940	0.052	-0.325	0.364
Total Compensation (L.1)	0.0769	0.335	0.230	0.818	-0.579	0.733
Third-Parties Expediture (L.1)	1.1137	0.347	3.200	0.001	0.433	1.795
Main Income Sources x Total Compensation (L.1)	-0.0043	0.003	-1.420	0.156	-0.010	0.002
Main Income Sources x Third-Parties Expenditure (L.1)	-0.0077	0.003	-2.280	0.023	-0.014	-0.001
Masculinity Ratio	7.4229	12.158	0.610	0.541	-16.405	31.251
Population covered by SS	0.4611	0.199	2.320	0.020	0.071	0.851
Average School Years	14.0496	25.188	0.560	0.577	-35.318	63.417
Employment rate	0.4830	0.703	0.690	0.492	-0.896	1.862
Informality rate	4.9688	1.180	4.210	0.000	2.655	7.282
Main Incomes Sources x Total Compensation						
Social Progress Index (L.1)	-204.5642	100.259	-2.040	0.041	-401.069	-8.060
Main Income Sources (L.1)	-94.3308	23.362	-4.040	0.000	-140.119	-48.542
Total Compensation (L.1)	-124.2883	48.498	-2.560	0.010	-219.344	-29.233
Third-Parties Expediture (L.1)	-263.2541	46.826	-5.620	0.000	-355.032	-171.476
Main Income Sources x Total Compensation (L.1)	1.9610	0.456	4.310	0.000	1.068	2.854
Main Income Sources x Third-Parties Expenditure (L.1)	2.5151	0.446	5.640	0.000	1.641	3.389
Masculinity Ratio	-4132.3320	1542.834	-2.680	0.007	-7156.232	-1108.432
Population covered by SS	19.8242	32.874	0.600	0.546	-44.608	84.256
Average School Years	-8908.4870	3173.527	-2.810	0.005	-15128.490	-2688.489
Employment rate	-269.1760	84.792	-3.170	0.002	-435.366	-102.986
Informality rate	-552.5001	125.644	-4.400	0.000	-798.758	-306.243
Main Incomes Sources x Third-Parties Expenditure						
Social Progress Index (L.1)	167.3159	86.028	1.940	0.054	-1.297	335.929
Main Income Sources (L.1)	-23.9820	17.543	-1.370	0.172	-58.366	10.403
Total Compensation (L.1)	-27.8991	31.913	-0.870	0.382	-90.447	34.649
Third-Parties Expediture (L.1)	45.4799	31.078	1.460	0.143	-15.431	106.391
Main Income Sources x Total Compensation (L.1)	-0.0773	0.289	-0.270	0.789	-0.644	0.489
Main Income Sources x Third-Parties Expenditure (L.1)	-0.1349	0.293	-0.460	0.645	-0.709	0.439
Masculinity Ratio	387.5370	1254.555	0.310	0.757	-2071.346	2846.420
Population covered by SS	36.8769	20.575	1.790	0.073	-3.449	77.203
Average School Years	698.7480	2621.479	0.270	0.790	-4439.257	5836.753
Employment rate	68.6398	72.417	0.950	0.343	-73.295	210.575
Informality rate	526.6395	120.642	4.370	0.000	290.185	763.094

Instruments: (1/3).(SPI MIS TC TPE MISxTC MISxTPE) MasculinityRatio PopcoveredbySS Averageschoolyearsofemployed Employmentrate Informalworkrate
Test of overidentifying restriction:
Hansen's J chi2(32) = 25.38 (p = 0.212)

Source: Author's estimates based on Stata17®

In Table 27, the PVAR model employs the *gmm estimator* [97] for calculations. As per the results of model selection in subsection 6.2.2., 1-order lags (*lags(1) suboption*) for SPI, Main Income Sources, Total Compensation, Third-Parties Expenditure and the interaction effects of both moderating variables with Main Income Sources are employed as endogenous variables. Lags 1-3 of those same variables were additionally implemented as IVs via the *instlags(1/3)* sub-option. The forward orthogonal deviation option was employed to remove the Fixed Effects (fod) in light of unbalanced panel data[98]. Additionally, the *td* option, subtracting its cross-sectional mean before estimating each variable, was employed to remove time-fixed effects from all the variables before any other transformation. Control variables were treated as exogenous and employed as IVs. The *overid* option was also used to calculate the Hansen J estimator to test IVs' validity. Since dealing with unbalanced panel data, the *gmmstyle*[99] option was employed to arrive at valid and reliable IVs

The Hansen's J Test exhibits a p-value = 0.212, confirming that the IVs used in the PVAR model are relevant and valid. A PVAR model threshold p-value of 0.10, as proposed in the work of Abrigo & Love (2016), is employed. For the specifications in the block where Social Progress Index is the dependent variable, only the lagged value of Social Progress Index (L.1) exhibits a p=value which is not statistically significant (0.378), as the remaining endogenous variable and even the control variables in the regression lay above the 0.10 threshold figure. Given the complexity associated with a PVAR comprising many endogenous variables and their interactions, but particularly because of the Hansen's J Test corroborating reliability and validity of IVs, this Social Progress Index (L.1)

[97] The PVAR approach, stemming from the work of Holtz-Eakin *et al.* (1988) and implemented in Stata17® by Abrigo & Love (2016) through the *pvar* community contributed command, controls for autocorrelations and time trends, additionally allows handling unobserved heterogeneity (from a cross-sectional perspective) over the basis of a *gmm estimator* and GMM-System calculations. It fits multivariate panel regression of each dependent variable on lags of itself, lags of all other dependent variables and exogenous variables.

[98] Under Abrigo & Love (2016), theoretically speaking, employing FOD or FD should not make a diffentrece when dealing with balance panel data and a large number of cross-sectional panels. Nonetheless, unbalance panel data magnifies the problem when using FD, which generally speaking requires a longer time dimension than FOD, which may become a problem for short panels PVAR models.

[99] As per Holtz-Eakin *et al.* (1988), missing observations are replaced with zeroes to create IVs from observed realizations (upon the standard assumption that IVs are uncorrelated with the errors) to produce more efficient estimates (Observations with no valid IVs are excluded). Efficiency is improved by including a longer set of lags as IVs, which unfortunetally is unattractive as it reduces observations especially with unbalanced panels or with missing observations.

variable failing the statistical significance compliance requirement is to be considered negligible.

Regarding the block where Main Income Sources is the dependent variable, 3 variables lay below the p-value threshold: Main Income Sources (L.1), Third-Parties Expenditure (L.1) and the interaction variable of Main Income Sources x Total Compensation (L.1). Additionally, 3 out the 5 control variables fall above this 0.10 p-value threshold. One may question the suitability of those specifications in supporting a statistically sound and robust model. Nonetheless, as per the same token exposed in the previous paragraph, in the light of a complex PVAR employing many endogenous variables, their interactions and control variables, a Hansen's J Test corroborating the reliability and validity of IVs; but in special results shown below in section 6.2.5 (Granger Causality Test); specifications are considered for model development purposes. However, this proposition must be conservative, much in alignment with the restrictions associated with the panel data previously mentioned: before a *categorical* claim, the relationship existence is only posited as *possible.* Findings in Table 27 could be written in two mathematical expressions representing a set of bidirectional equations for the association between Main Income Sources as a proxy for FDI and the Social Progress Index as a proxy for social development, employing both moderating variables and their interactions, in addition to the Contro Variables. See Equation 8 and Equation 9.

Equation 8

$$\begin{aligned}\boldsymbol{SPI_{it-1}} = {} & (0.02 * SPI_{it-1}) + (0.011 * MIS_{it-1}) + (0.031 * TC_{it-1}) + (0.037 * TPE_{it-1}) \\ & - (0.0004 * (MIS * TC)_{it-1}) - (0.0004 * (MIS * TPE)_{it-1}) \\ & -(1.733 * MR) - (0.030 * PCSS) - (0.921 * \mathrm{ASY}) - (0.030 * ER) \\ & - (0.081 * IR) + \varepsilon_{it\mathrm{j}}\end{aligned}$$

Equation 9

$$\begin{aligned}\boldsymbol{MIS_{it-1}} = {} & -(1.867 * SPI_{it-1}) + (0.086 * MIS_{it-1}) - (0.204 * TC_{it-1}) + (0.040 * TPE_{it-1}) \\ & + (0.002 * (MIS * TC)_{it-1}) - (0.005 * (MIS * TPE)_{it-1}) \\ & -(28.59 * MR) - (0.038 * PCSS) - (64.23 * \mathrm{ASY}) - (0.029 * ER) \\ & + (0.145 * IR) + \varepsilon_{it\mathrm{j}}\end{aligned}$$

where,

Endogenous variables	Exogenous (Control Variables)	Error term
SPI= Social Progress Index MIS= Main Income Sources TC=Total Compensation TC * MIS = Total Compensation	MR= Masculinity Rate PCSS = Population Covered by Social Services AV = Average School Years ER = Employment Rate IR = Informality Rate	$\varepsilon_{it\mathrm{j}}$

In broader economic terms, by adding constant coefficients to Equations 8 and Equation 9 and extending both expressions to comprise a higher number of lags and industry effects, the following set of *bidirectional structural equations*, as proposed in Equation 10 and Equation 11.

Equation 10

$$\boldsymbol{SD_{it}} = \alpha_0 + \sum_{j=1}^{n} \beta_j * SD_{it-j} + \sum_{j=0}^{n} \gamma_j * FDI_{it-j} + \sum_{j=0}^{n} \delta_j * HI_{it-j} + \sum_{j=0}^{n} \lambda_j * PL_{it-j} + \sum_{j=0}^{n} \mu_j * (HI * FDI)_{it-j} + \sum_{j=0}^{n} \nu_j * (PL * FDI)_{it-j} + I + A + \varepsilon_{it\mathrm{j}}$$

Equation 11

$$\boldsymbol{FDI_{it}} = \alpha'_0 + \sum_{j=1}^{n} \beta'_j * SD_{it-j} + \sum_{j=0}^{n} \gamma'_j * FDI_{it-j} + \sum_{j=0}^{n} \delta'_j * HI_{it-j} + \sum_{j=0}^{n} \lambda'_j * PL_{it-j} + \sum_{j=0}^{n} \mu'_j * (HI * FDI)_{it-j} + \sum_{j=0}^{n} \nu'_j * (PL * FDI)_{it-j} + I + A + \varepsilon'_{it\mathrm{j}}$$

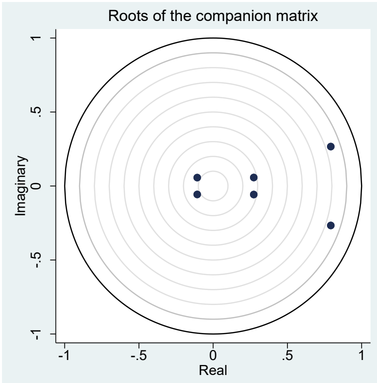
Where SD_{it} and FDI_{it} represent the contemporary values for Social Development (SD) and Foreign Direct Investment (FDI) as the dependent variables in either equation. The coefficients α_o and α'_o are the constants for the two entire regressions and the $\beta_j, \gamma_j, \delta_j, \lambda_j,\ \mu_j, \nu_j, \beta'_j, \gamma'_j, \delta'_j, \lambda'_j$ and μ'_j values are the coefficients for the remaining independent and interaction variables for both equations. The terms SD_{it-j} , FDI_{it-j} , HI_{it-j} PL_{it-j} , $(HI * FDI)_{it-j}$ and $(PL * FDI)_{it-j}$, comprise up to *n* lagged values of Social Development (SD), Foreign Direct Investment (*FDI*), Household Income (*HI),* Productive Linkages (*PL)* and the interaction moderating effect of Household Income and Foreign Direct Investment (*HI * FDI)* and Productive Linkages and Foreign Direct Investment (*PL * FDI*) as endogenous variables. I represents a set of dummy variables for the industry classification of MNEs. A represents a set of control and policy variables treated as exogenous, which may be frequently included in empirical research as determinants of Social Development (SD) and Foreign Direct Investment (FDI). $\varepsilon_{it\mathrm{j}}$ and $\varepsilon'_{it\mathrm{j}}$ are the error terms to encompass all the other variables that have not been accounted for and are likely to impact Social Development (SD) and Foreign Direct Investment (FDI).

6.2.4 Model stability testing

Reduced-form PVAR's coefficients cannot be interpreted as causal influences without priorly imposing identifying parameters' restrictions. Hence, the PVAR Reduce model was tested for stability, reformulating it as an infinite-order Vector Moving Average Model (VMAM) by imposing assumptions about the error covariance matrix (Abrigo & Love, 2016). Table 28 shows the stability test results.

Table 28. Eigenvalue stability condition for PVAR models

Eigenvalue stability condition		
Real	**Imaginary**	**Modulus**
0.792	-0.267	0.836
0.792	0.267	0.836
0.274	-0.058	0.279
0.274	0.058	0.279
-0.107	0.057	0.121
-0.107	-0.057	0.121
All the eigenvaues lie inside the unit circle PVAR satisfies stability condition		



Source: Author's estimates based on Stata17®

Latter findings corroborate the PVAR model stability since all moduli of the companion matrix figures -based on the estimated parameters- lay below 1. Besides, as all eigenvalues lie inside the unit circle PVAR, the stability condition is satisfied, indicating that the variables employed are stationary (Santiago *et al.,* 2019), in alignment with the findings from subsection 6.2.1. As follows, the existence of *bidirectional causality* for the model derived from the reported regression in Table 27 is sought via the Granger causality test and Impulse-Response Function (IRF) approaches.

6.2.5 Granger Causality Test

As quoted from Bayraktar-Sağlam & Sayek (2017, pp5): "*over the past decade, the notion of Granger causality tests are well accepted and widely used in the panel econometrics',* as predictive causality and feedback is an essential aspect of longitudinal analysis. The null hypothesis of the Grainger Causality Test[100] method (Granger, 1969) assumes that coefficients on all the lags of an endogenous variable are jointly equal to zero; thus, coefficients may be excluded in an equation of the PVAR model. Causal links among all the variables comprising the PVAR Reduced-Form model (Table 27) after performing the Granger Causality Test are shown in Table 29.

[100] The initial choice to perform the Granger Causality Test was via the implemented community-written *xtgcause* command (developed by Lopez & Weber (2017) upon the proposed work of Dumitrescu & Hurlin (2012)). Nonetheless, the procedure was found unsuitable for unbalanced panel data with gaps. Alternatively, the Granger Causality Test -developed for PVAR and implemented as a separate Wald test (Stata17® *pvargranger* command). From a broad perspective concerning causality testing, Shrestha & Batta (2018) state that if two variables, Y (dependent variable) and X (independent variable), are cointegrated, then there may exist any of the 3 relationships: a) X affects Y, b) Y affects X and c) X and Y affect each other. The first two show a unidirectional relationship, while the third depicts a bidirectional relationship. If two variables are not cointegrated, one does not affect the other and is independent. The causality test method developed by Granger (1969) determines the underlying pattern for such a relationship.

Table 29. Granger Causality Test for Regression employing Total Compensation as a moderating variable.

Equation / Excluded	chi2	df	Prob > chi2
Panel VAR-Granger causality Wald test			
Ho: Excluded variable does not Granger-cause Equation variable			
Ha: Excluded variable Granger-causes Equation variable			
Social Progress Index			
Main Income Sources	5.958	1.000	0.015
Total Compensation	13.867	1.000	0.000
Third-Parties Expenditure	18.652	1.000	0.000
Main Income Sources x Total Compensation	19.421	1.000	0.000
Main Income Sources x Third-Parties Expenditure	19.847	1.000	0.000
ALL	48.080	5.000	0.000
Main Income Sources			
Social Progress Index	5.946	1.000	0.015
Total Compensation	1.267	1.000	0.260
Third-Parties Expenditure	2.010	1.000	0.156
Main Income Sources x Total Compensation	1.511	1.000	**0.219**
Main Income Sources x Third-Parties Expenditure	3.722	1.000	0.054
ALL	15.707	5.000	0.008
Total Compensation			
Social Progress Index	0.013	1.000	0.908
Main Income Sources	23.097	1.000	0.000
Third-Parties Expenditure	49.646	1.000	0.000
Main Income Sources x Total Compensation	22.435	1.000	0.000
Main Income Sources x Third-Parties Expenditure	47.474	1.000	0.000
ALL	70.369	5.000	0.000
Third-Parties Expenditure			
Social Progress Index	3.189	1.000	0.074
Main Income Sources	0.012	1.000	0.054
Total Compensation	0.053	1.000	0.818
Main Income Sources x Total Compensation	2.014	1.000	0.156
Main Income Sources x Third-Parties Expenditure	5.179	1.000	0.023
ALL	44.820	5.000	0.000
Main Incomes Sources x Total Compensation			
Social Progress Index	4.163	1.000	0.041
Main Income Sources	16.304	1.000	0.000
Total Compensation	6.568	1.000	0.010
Third-Parties Expenditure	31.606	1.000	0.000
Main Income Sources x Third-Parties Expenditure	31.791	1.000	0.000
ALL	57.878	5.000	0.000
Main Incomes Sources x Third-Parties Expediture			
Social Progress Index	3.783	1.000	0.052
Main Income Sources	1.869	1.000	0.172
Total Compensation	0.764	1.000	0.382
Third-Parties Expenditure	2.142	1.000	0.143
Main Income Sources x Total Compensation	0.071	1.000	0.789
ALL	48.939	5.000	0.000

Source: Author's estimates based on Stata17®

Stemming from Table 29, one may notice that the 6 secondary tests labelled ALL, which refer to the coefficients of all the endogenous variables' lags in the PVAR model (other than those of the dependent variable) being jointly zero, report a p-value below 0.05 which corroborates that all comprising variables in the each of the 6 blocks are endogenous. The main interactions concerning hypotheses posed in the Research Design are highlighted in grey, where it is to be noticed that besides the interaction term of Main Income Sources x Total Compensation (p-value = 0.21), the remaining p-values are reported below the 0.05 threshold, thereby statistically corroborating the existence of causality links. One may notice from block 1 that Main Income Sources (proxy for FDI) 'grainger causes' SPI (a proxy for social development) or $(MIS \rightarrow SPI)$ as per Granger Causality Testing Notation (p-value = 0.0015). Conversely, as per block 2, SPI 'grainger causes' Main Income Sources or $(SPI \rightarrow MIS)$ as per Granger Causality Testing Notation (p-value = 0.015). In this sense, Equation 8 and Equation 9 not only suggest that the bidirectional structural link between FDI and social performance (and vice versa) is a statistically valid association but also a causal relationship, thereby corroborating H1.

As suggested in the literature review and hypothesised in the research design, FDI may induce 'economic spillovers', such as increasing Household Income (HI). This causal link is corroborated in block 3 by Main Income Sources (a proxy for FDI) 'grainger causing' Total Compensation (a proxy for Household Income) per the p-value of 0.000 reported. Once Household Income is induced, it may directly impact social development and become a moderating variable, as posed in H2. The first effect may be observed in block 1, in which Total Compensation (HI) 'grainger causes' SPI or in Granger Causality Testing Notation $(TC \rightarrow SPI)$ as per p-value = 0.000 in block 1. The second effect is also shown in block 1, where the interaction variable Main Income Sources x Total Compensation (a proxy for FDI x HI) 'grainger causes' SPI or in Granger Causality Testing Notation $(MIS\ x\ TC \rightarrow SPI)$ as per p-value = 0.000. Conversely, as per block 2 findings, Main Income Sources x Total Compensation as interaction variable does not 'grainger causes' MIS or in Granger Causality Testing Notation $(MIS\ x\ TC \rightarrow FDI)$ as per p-value = 0.210. The *causal impact* of this interaction variable on both SPI (the proxy for social development) and MIS (the proxy for FDI) partially corroborates H2, as only the $(MIS\ x\ TC \rightarrow SPI)$ is found statistically significant.

Similarly, according to the literature review and research design, another way in which FDI induces 'economic spillovers' is via Productive Linkages (PL) creation. This causal link is corroborated in block 4 by Main Income Sources (FDI proxy) 'grainger causing' Third-Parties Expenditure (Productive Linkages proxy) per the marginally out-of-range p-value of 0.054 reported. Once triggered in the economy, it has been hypothesised to directly impact social development and become a moderating variable, as posed in H3. Block 1 shows that the first impact as Third-Parties Expenditure (PL) 'grainger causes' SPI or in Granger Causality Testing Notation $(TPE \rightarrow SPI)$ as per p-value = 0.000. Block 1 also shows this second effect, where the interaction variable Main Income Sources x Third-Parties Expenditure (proxy for FDI x PL) 'grainger causes' SPI or in Granger Causality Testing Notation $(MIS\ x\ TPE \rightarrow SPI)$ as per p-value = 0.000. Conversely, block 2 shows the results for the interaction of Main Income Sources x Third-Parties Expenditure 'grainger causing' MIS or in Granger Causality Testing Notation $(MIS\ x\ TPE \rightarrow FDI)$ as per its marginal out of range p-value = 0.054. Hence, the *causal impact* of this interaction variable on both SPI (the proxy for social development) and MIS (the proxy for FDI) corroborates H3.

By confirming the existence of a reserve causality association between FDI and social development, H1 has been fully confirmed, which implies that RQ2 is partially answered as this reverse causality association has still to be corroborated/rejected to comply with a long-run pattern. As earlier discussed, it is paramount to note, however, that the latter corroborations, particularly the one pertaining to H1, could only be established as *potentially possible*, as the limited longitudinal panel data coverage of only 6 years, unfortunately, restricts a statistically rigourous categorical affirmation.

Causal association and causal directions derived from Table 29 only provide a short-term notion since the Grainger Causality Test fails to achieve long-run comprehension of the underlying *causal mechanisms,* so targeting to provide a full answer to RQ2, IRFs (Impulse–Response Functions) [101] are employed. As per the same token, although RQ3 was answered since subsection

[101] Impulse Response Functions (IRFs) are suggested to have a known interpretation in the light of complying with the eigenvalue stability condition (explained in subsection 6.2.4), implying that the PVAR model is invertible and has an infinite-order vector moving-average representation (Abrigo & Love, 2016).

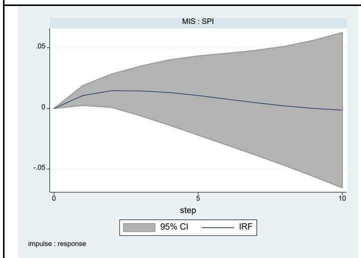
5.1.4 (re-engaged in subsection 6.1), a long-run pattern for path dependencies will also be fully explored via IRFs.

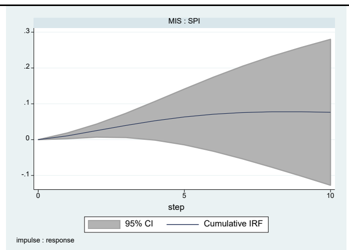
6.2.6 Impulse – Response Function (IRF)

Since the PVAR model is corroborated stable, one may calculate Impulse Response Functions (IRFs)[102] to assess the *long-run behaviours* of the 4 core endogenous variables in conjunction with their 2 moderating effects. IRFs combine the effect of multiple parameters into one summary (per period). IRFs summarise a given variable's temporal response pattern (behaviour) when it faces shocks in another variable. Additionally, IRFs reveal a variable's time to return to equilibrium after the shock or innovation occurs. It is essential to mention that the IRF plots' analysis, in general terms, aims to understand the nature of relationships between variables, where figures are set as mean coefficient factors or dynamic multipliers. Thereby, IRF[103] plots are usually interpreted in terms of standard deviation (StDev) measures instead of coefficient estimates per se. See Table 30.

Table 30. Impulse / Response Functions

A. Impulse: Main Incomes Sources / Response: Social Progress Index



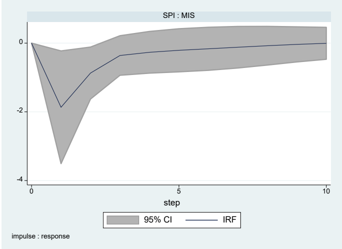


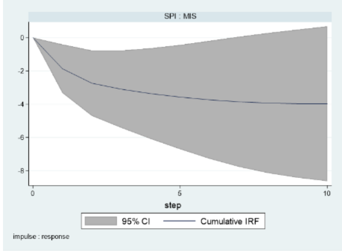
Response variable and Forecast Horizon	Impulse variable Main Income Sources (Individual Effect)	Impulse variable Main Income Sources (Cumulative Effect)
Social Progress Index		
0	0.0000	0.0000
1	0.0106	0.0106
2	0.0146	0.0253
3	0.0144	0.0396
4	0.0131	0.0528
5	0.0106	0.0634
6	0.0076	0.0710
7	0.0047	0.0757
8	0.0021	0.0778
9	0.0000	0.0778
10	-0.0014	0.0764

[102] IRFs are computed from the ‘exact’ posterior distribution of IRFs; hence relying on the asymptotic normality assumption is not required. An entire Markov Chain Monte Carlo (MCMC) sample of IRFs simulated from this posterior distribution is summarised into a single statistic: posterior mean / median IRF. In addition, IRFs provide more stable estimates for small datasets due to the prior incorporation of model parameters.

[103] The Stata17®’s *pvarirf* post-estimation command to calculate and plot IRFs at a 10 periods horizon with a Gaussian approximation based on 1000 Monte Carlo simulations (*mc(1000)*) for SE and confidence intervals purposes. It is crucial to notice that although the order of the variables does not affect PVAR estimates, it does affect IRFs calculations. So, the Stata17® *porder()* subcommand[103] is employed based on the predetermined causal order hypothesised in the Research Design and corroborated as per the findings in subsection 6.2.5

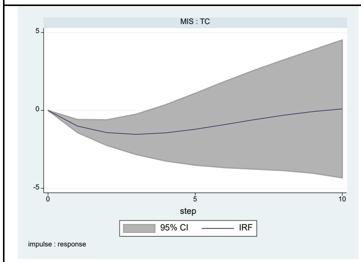
B. Impulse: Social Progress Index / Response: Main Income Sources

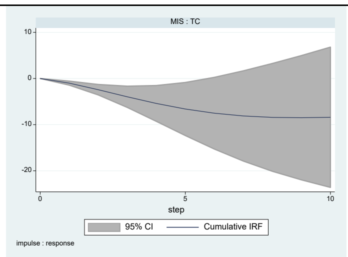




Response variable and Forecast Horizon	Impulse variable Social Progress Index (Individual Effect)	Impulse variable Social Progress Index (Cumulative Effect)
Main Income Sources		
0	0.0000	0.0000
1	-1.8671	-1.8671
2	-0.8713	-2.7384
3	-0.3600	-3.0984
4	-0.2667	-3.3651
5	-0.2088	-3.5739
6	-0.1646	-3.7385
7	-0.1194	-3.8579
8	-0.0756	-3.9335
9	-0.0366	-3.9701
10	-0.0053	-3.9755

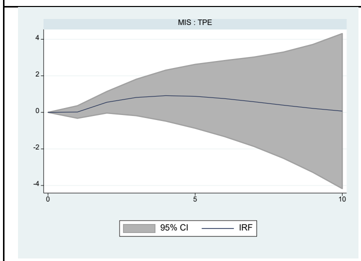
C. Impulse: Main Incomes Sources / Response: Total Compensation

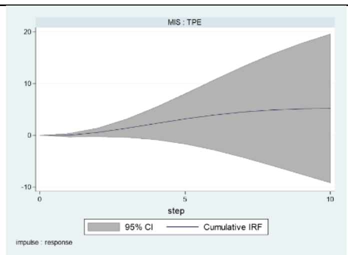




Response variable and Forecast Horizon	Impulse variable Main Income Sources (Individual Effect)	Impulse variable Main Income Sources (Cumulative Effect)
Total Compensation		
0	0.00000	0.00000
1	-1.00272	-1.00272
2	-1.42465	-2.42736
3	-1.53620	-3.96356
4	-1.43951	-5.40308
5	-1.20797	-6.61104
6	-0.90873	-7.51977
7	-0.59603	-8.11580
8	-0.30951	-8.42531
9	-0.07396	-8.49927
10	0.09909	-8.40018

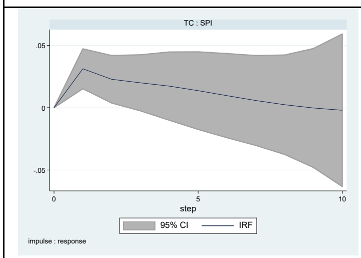
D. Impulse: Main Incomes Sources / Response: Third-Parties Expenditure

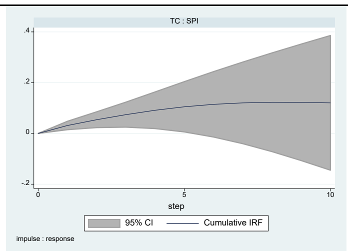




Response variable and Forecast Horizon	Impulse variable Main Income Sources (Individual Effect)	Impulse variable Main Income Sources (Cumulative Effect)
Third-Parties Expenditure		
0	0.00000	0.00000
1	0.01958	0.01958
2	0.55352	0.57311
3	0.81625	1.38935
4	0.91439	2.30374
5	0.87908	3.18282
6	0.75420	3.93702
7	0.58085	4.51787
8	0.39338	4.91125
9	0.21745	5.12871
10	0.06967	5.19838

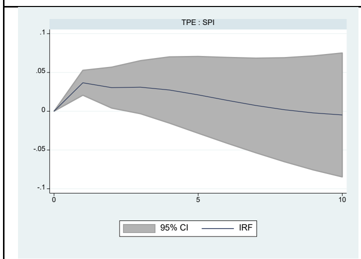
E. Impulse: Total Compensation / Response: Social Progress Index

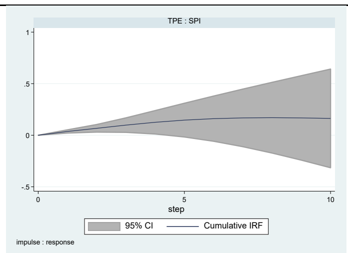




Response variable and Forecast Horizon	Impulse variable Total Compensation (Individual Effect)	Impulse variable Total Compensation (Cumulative Effect)
Social Progress Index		
0	0.0000	0.0000
1	0.0312	0.0312
2	0.0228	0.0540
3	0.0200	0.0740
4	0.0173	0.0913
5	0.0137	0.1049
6	0.0097	0.1146
7	0.0058	0.1204
8	0.0024	0.1227
9	-0.0002	0.1225
10	-0.0021	0.1204

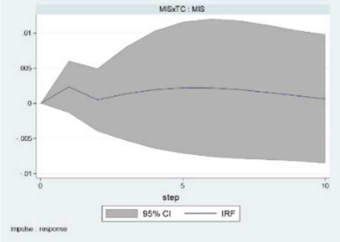
F. Impulse: Third-Parties Expenditure / Response: Social Progress Index

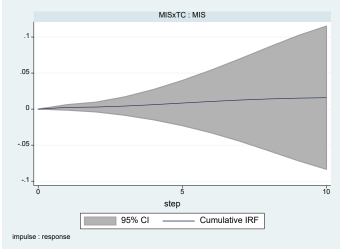




Response variable and Forecast Horizon	Impulse variable Third-Parties Expenditure (Individual Effect)	Impulse variable Third-Parties Expenditure (Cumulative Effect)
Social Progress Index		
0	0.0000	0.0000
1	0.0367	0.0367
2	0.0304	0.0671
3	0.0310	0.0981
4	0.0274	0.1255
5	0.0211	0.1467
6	0.0141	0.1607
7	0.0074	0.1682
8	0.0019	0.1701
9	-0.0022	0.1679
10	-0.0048	0.1631

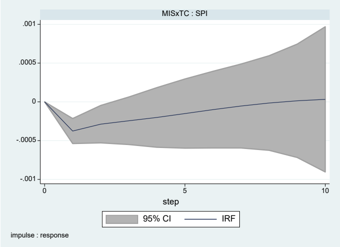
G. Impulse: Main Incomes Sources x Total Compensation / Response: Main Income Sources

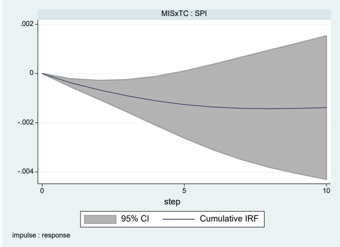




Response variable and Forecast Horizon	Main Income Sources and Total Compensation (Individual Effect)	Main Income Sources and Total Compensation (Cumulative Effect)
Main Income Sources		
0	0.00000	0.00000
1	0.00235	0.00235
2	0.00050	0.00286
3	0.00137	0.00422
4	0.00194	0.00616
5	0.00224	0.00840
6	0.00221	0.01061
7	0.00195	0.01256
8	0.00155	0.01411
9	0.00109	0.01520
10	0.00065	0.01585

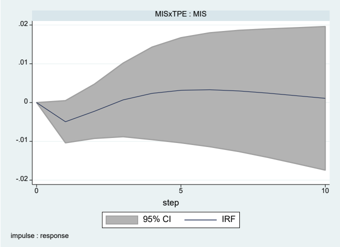
H. Impulse: Main Incomes Sources x Total Compensation / Response: Social Progress Index

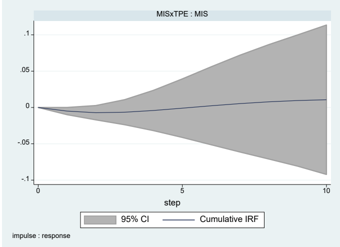




Response variable and Forecast Horizon	Main Income Sources and Total Compensation (Individual Effect)	Main Income Sources and Total Compensation (Cumulative Effect)
Social Progress Index		
0	0.00000	0.00000
1	-0.00038	-0.00038
2	-0.00029	-0.00066
3	-0.00024	-0.00091
4	-0.00020	-0.00111
5	-0.00015	-0.00126
6	-0.00010	-0.00136
7	-0.00005	-0.00141
8	-0.00002	-0.00143
9	0.00001	-0.00142
10	0.00003	-0.00138

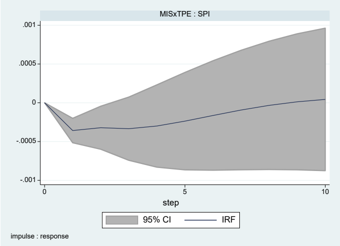
I. Impulse: Main Incomes Sources x Third-Parties Expenditure / Response: Main Income Sources

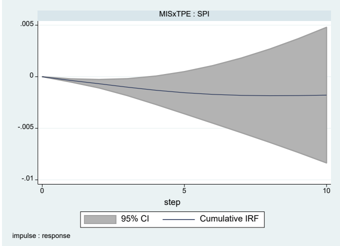




Response variable and Forecast Horizon	Impulse variable Main Income Sources and Third-Parties Expenditure (Individual Effect)	Impulse variable Main Income Sources and Third-Parties Expenditure (Cumulative Effect)
Main Income Sources		
0	0.00000	0.00000
1	-0.00495	-0.00495
2	-0.00226	-0.00720
3	0.00069	-0.00651
4	0.00238	-0.00413
5	0.00317	-0.00096
6	0.00331	0.00235
7	0.00300	0.00535
8	0.00244	0.00779
9	0.00177	0.00956
10	0.00110	0.01066

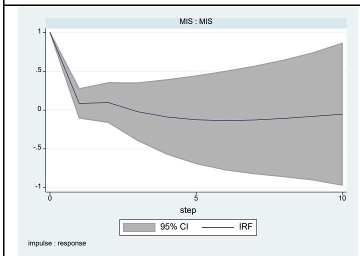
J. Impulse: Main Incomes Sources x Third-Parties Expenditure / Response: Social Progress Index

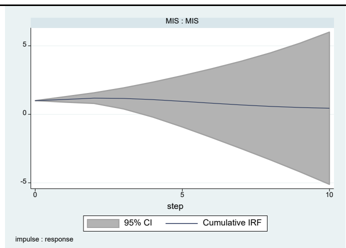




Response variable and Forecast Horizon	Impulse variable Main Income Sources and Third-Parties Expenditure (Individual Effect)	Impulse variable Main Income Sources and Third-Parties Expenditure (Cumulative Effect)
Social Progress Index		
0	0.00000	0.00000
1	-0.00036	-0.00036
2	-0.00032	-0.00068
3	-0.00033	-0.00101
4	-0.00030	-0.00131
5	-0.00024	-0.00155
6	-0.00016	-0.00171
7	-0.00009	-0.00181
8	-0.00003	-0.00184
9	0.00001	-0.00183
10	0.00004	-0.00178

K. Impulse: Main Incomes Sources / Response: Main Income Sources





Response variable and Forecast Horizon	Impulse variable Main Income Sources (Individual Effect)	Impulse variable Main Income Sources (Cumulative Effect)
Main Income Sources		
0	1.0000	1.0000
1	0.0861	1.0861
2	0.0967	1.1828
3	-0.0207	1.1621
4	-0.0880	1.0740
5	-0.1248	0.9493
6	-0.1356	0.8137
7	-0.1275	0.6862
8	-0.1071	0.5791
9	-0.0807	0.4984
10	-0.0530	0.4454

L. Impulse: Social Progress Index / Response: Social Progress Index

Source: Author's estimates based on Stata17® using 1000 Monte Carlo simulations

Although in Table 30, proxy variables names are employed for plots and individual/cumulative impact charts, the following analysis employs broader economic terms of those variables (e.g. Main Incomes Sources is referred to as FDI). IRFs were calculated upon 1000 Monte Carlo simulations following the impact order hypothesised in the Research Design: FDI triggers economic spillovers, Household Income (HI) and Productive Linkages (PL) in this case. Subsequently, Household Income (HI) and Productive Linkages (PL) may directly impact Social Development and interact with FDI to moderate the bidirectional association between FDI and Social Development. As extensively stated, it is paramount to note again that all findings below reported may be restricted to *potentially possible*, as, in the absence of a higher number of periods for this panel data, it would be rash to make *categorical claims.*

The association between FDI and Social Development was found to be *causal and bidirectional,* as per findings reported in Table 29*,* thereby corroborating H1. However, as posed in RQ2, this reverse causality association should be additionally explored for a long-run pattern. Findings reported in IRF Section A and IRF Section B respectively show the long-run impacts of FDI on Social Development and of Social Development on FDI. IRF Section A shows that a change in 1 StDev of FDI positively impacts Social Development in 0.0106 StDev in period 1, which is a *weak* effect consistent with findings of the statistically significant coefficient = 0.0106 reported in Equation 8, pertaining to the 1-period lagged value of Main Income Sources, as a proxy for FDI. Subsequent periods (until period 5) also exhibit weak positive effects. Then impact contributions from the 6-period to the 10-period are negligible and positive, except for the 10-period, which is negative. The cumulative chart exhibits a convergence value of 0.07 StDev from the 6-period, where the confidence levels (grey areas in the chart) are inclined to broaden on the positive area of the chart. In this sense, *FDI is strongly suggested to induce a growing and persistent (Santiago, 2019), although weak, long-term effect on Social Development.* Concerning IRF Section A, 1 StDev change in Social Development impacts in -1.867 StDev in period 1 (a finding congruent with the statistical significance coefficient reported in Equation 9) and -0.87 StDev in period 2. Subsequently, the individual impact StDev values keep being *negative* and *decreasing in* *magnitude* until the 10-period. Accumulation of those decreasing StDev magnitudes reaches a convergence figure of -3.97 StDev by period 9-period, as shown in the cumulative plot, in which confidence levels broaden within the negative area of the plot. Thus, *Social Development is strongly suggested to induce a growing long-term effect on FDI.*

Those two previous results answer RQ2: The reverse causal association of FDI on Social Development and of Social Development on FDI is strongly suggested to respectively exhibit *a positive but weak long-run stable and persistent pattern* concerning the former, and *a negative robust long-run persistent* pattern as regards to the latter. Such findings also answer RQ1, strongly suggesting the existence of a '*lop-sided circle'* regarding the bidirectional association between FDI and Social Development, as posited in the Research Design. Although both effects are suggested to be persistent and stable in the long run as per their StDev magnitudes, impacts are suggested to be *strong* for the link running from FDI to Social Development and *weak* for the link running from FDI to Social Development, suggesting a *lop-sidedness* pattern inclined on the former rather than on the latter link.

From a theoretical perspective, as derived from the Literature Review and as also hypothesised in the research design, FDI is argued to have the potential to trigger various economic spillovers, among which House Income increases, and Productive Linkages development are included. Once this effect has been unleashed, both variables are hypothesised to impact Social Development directly and act as moderating variables, so their interaction with FDI may potentially attenuate and/or amplify the bidirectional relationship between FDI and Social Development. Those latter impacts are explained as follows.

IRF Section C shows that the impact of FDI on Household Income is negative from the 1-period (-1.002 StDev) until the 9-period (-0.073 StDev) and positive in the 10-period (0.099 StDev). Negative StDev figures peak in the 3-period to decrease in magnitude depicting a U-shape pattern. The negative individual magnitudes of such impacts are far from negligible since, as shown in the cumulative plot, the long-run effects are suggested to grow negatively until converging to a -8.40 StDev value in the 8-period. Confidence levels mostly broaden up on the negative area of the plot. Thereby, *FDI is strongly suggested to induce a direct growing and persistent strong negative long-run effect on Household Income.* In passing, such a finding is counterintuitive, contrasting the literature from a theoretical perspective, as FDI has been extensively argued to mostly increase Household Income as the main gain of MNEs paying better salaries compared to local average jobs. As per the same token, IRF Section D shows that the impact of FDI on Productive Linkages exhibiting an inverted U-shape pattern: growth of individual StDev magnitude from 1-period (0.0195 StDev) to 4-period (0.914 StDev) and then exhibiting a declining trend of positive individual magnitudes until the 10-period (0.069 StDev). The cumulative effects are not negligible, as the cumulative plots show a growing pattern which is not suggested to converge, reaching a 5.19 StDev impact magnitude in the 10-period. Confidence levels mostly broaden up on the positive area of the plot. Hence, *FDI is strongly suggested to induce direct growth and persistent strong positive long-run effect on Productive Linkages.*

After exploring the long-run impacts of FDI on both Household Income and Productive Linkages, the direct impacts of those two variables are explored on Social Development. IRF Section E depicts the impact of Household Income on Social Development. Individual magnitudes are positive but weak from the 1-period (0.312 StDev) until the 8-period (0.0024 StDev) and then respectively exhibit negligible negative magnitudes of -0.0002 and -0.0021 in the 9-period and the 10-period. When exploring the total accumulative effect in the long-run, a weak positive cumulative impact is exhibited, suggesting to converge to a 0.12 StDev magnitude in the 7-period, where confidence levels are more inclined to be on the positive area of the cumulative plot. Thus, *Household Income is strongly suggested to induce a direct growing and persistent weak positive long-run effect on Social Development.* Such findings also appear counterintuitive in light of FDI inducing a negative impact on Household Income in the long run. Argumentations regarding this counterintuitive and contrary to the theoretical literature finding will be further engaged in section 6.3, which concerns the Proposed Framework. Similarly, IRF Section F shows the impact of Productive Linkages on Social Development. Individual magnitudes are positive but weak from the 1-period (0.0367 StDev) until the 8-period (0.0019 StDev) and respectively exhibit negligible negative magnitudes of -0.0022 and -0.0048 in the

9-period and the 10-period. When exploring the total accumulative effect, in the long run, a weak positive cumulative impact is suggested to exist, which reaches a 0.17 StDev magnitude in the 8-period and then slightly starts to decline in the 9-period and 10-period (0.1631 StDev). Confidence levels appear to similarly range between the negative and positive areas of the plot, although more inclined on the positive side. Thus, *Productive Linkages are suggested to induce a direct growing weak positive long-run effect on Social Development.*

The bidirectional casual association between FDI and Social Development, moderated by the interaction of FDI and Household Income as posed in H2, was fully confirmed by results of Equations 8 and 9 regarding the statistical significance of their coefficients and from a causality perspective by findings in Table 29. Long-run effects of this moderating impact (interaction of FDI and Household Income on FDI) are shown in IRF Section G. A negligible impact of 0.0023 StDev on FDI in period 1 is suggested. Afterwards, individual interaction effects are all positive but negligible, reaching a positive cumulative magnitude of around 0.015 StDev by 10-period. Thus, the moderating effect of Household Income and FDI on FDI *is strongly suggested to be negligible in the short and long run.* Similarly, the long-run effects of this moderating impact (interaction of FDI and Household Income on Social Development) are shown in IRF Section H. A negligible impact magnitude of -0.00038 StDev on Social Development in period 1 is reported. Afterwards, individual interaction effects are all negative but negligible until the 8-period (-0.00002 StDev) and positive but negligible in the 9-period (0.00001 StDev) and 10-period (0.00003 StDev). Magnitudes are suggested to converge to a negative but negligible cumulative value of around -0.0014 StDev by the 7-period. Thus, the moderating effect of Household Income and FDI on Social Development is *strongly suggested to be negligible in the short and long run.* This latter finding *statistically corroborates the causal impacts of the moderating effects hypothesise in H2. However, such impacts on the bidirectional associations between FDI and Social Development are negligible, so neither attenuating nor amplifying effects could be distinguished.*

In this same venue, H3 hypothesised that the bidirectional casual association between FDI and Social Development might be moderated by the interaction of FDI and Productive Linkages, which in passing was fully confirmed by results of Equation 8 and 9 regarding the statistical significance of their coefficients and from a causality perspective by findings in Table 29. Long-run effects of this moderating impact (interaction of FDI and Productive Linkages on FDI) are shown in IRF Section I. Negligible individual impacts of -0.0049 StDev on FDI in 1-period and of -0.0022 StDev in 2-period are reported, where the remaining individual magnitudes are shown as positive but negligible StDev figures. Negative but negligible cumulative magnitudes are reached until the 5-period, afterwards turning into positive but also negligible StDev magnitudes until the 10-period. So, the moderating effect of Productive Linkages and FDI on FDI *is strongly suggested to be negligible in the short and long run.* Similarly, the long-run effects of this moderating impact (interaction of FDI and Productive Linkages on Social Development) are shown in IRF Section J. A negligible impact magnitude of -0.00036 StDev on Social Development in period 1 is reported. Afterwards, individual interaction effects are all negative but negligible until the 8-period (-0.000003 StDev) and positive but negligible in the 9-period (0.00001 StDev) and 10-period (0.00004 StDev). Magnitudes are suggested to converge to a negative but negligible cumulative value of around -0.0018 StDev by the 7-period. Thus, the moderating effect of Productive Linkages and FDI on Social Development is *strongly suggested to be negligible in the short and long run.* This latter finding *statistically corroborates the causal impacts of the moderating effects hypothesise in H3. However, such impacts on the bidirectional associations between FDI and Social Development are negligible, so neither attenuating nor amplifying effects could be distinguished.*

Paths dependencies are conceptually explained by the current values of a given variable, being explained by past values of itself. The existence of path dependencies for Social Development and FDI were corroborated from a causality perspective per the results reported in Table 27, thereby answering RQ3. Nonetheless, the statistical significance of the 1-period lagged values coefficients of FDI and Social Development may only suggest the existence of path dependencies in the short run. Thus, to corroborate those path dependencies existing beyond the 1-period, IRF Section K and IRF Section are analysed in conjunction with its associated Forecast-Error Variance Decomposition (FEVD) shown in Table 31.

Table 31. Forecast-Error Variance Decomposition (FEVD)

Response variable and Forecast Horizon	Impulse Variable					
	Social Progress Index	Main Income Sources	Total Compensation	Third-Parties Expenditure	Main Income Sources x Third-Parties Expenditure	Main Income Sources x Total Compensation
Social Progress Index						
0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.6673	0.1365	0.0028	0.0043	0.1645	0.0247
3	0.5887	0.1324	0.0039	0.0038	0.2319	0.0394
4	0.5431	0.1227	0.0036	0.0036	0.2733	0.0537
5	0.5147	0.1163	0.0047	0.0037	0.2966	0.0639
6	0.4977	0.1149	0.0074	0.0041	0.3066	0.0693
7	0.4880	0.1168	0.0107	0.0047	0.3084	0.0714
8	0.4828	0.1199	0.0137	0.0053	0.3068	0.0716
9	0.4799	0.1228	0.0159	0.0057	0.3046	0.0711
10	0.4780	0.1248	0.0171	0.0060	0.3033	0.0708
Main Income Sources						
0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1	0.2326	0.7674	0.0000	0.0000	0.0000	0.0000
2	0.2222	0.7622	0.0035	0.0032	0.0040	0.0050
3	0.2185	0.7567	0.0120	0.0031	0.0039	0.0058
4	0.2158	0.7528	0.0163	0.0034	0.0059	0.0058
5	0.2134	0.7479	0.0179	0.0036	0.0103	0.0068
6	0.2113	0.7419	0.0181	0.0037	0.0164	0.0087
7	0.2097	0.7358	0.0179	0.0036	0.0223	0.0107
8	0.2085	0.7308	0.0179	0.0036	0.0268	0.0123
9	0.2078	0.7275	0.0181	0.0036	0.0296	0.0133
10	0.2075	0.7255	0.0184	0.0037	0.0310	0.0139

Source: Author's estimates based on Stata17®

Path dependencies are a phenomenon whereby history matters since what has occurred in the past may persist in the future. In this sense, if an IRF plot shows that a variable forecasts itself, it may imply a path dependency for that variable. Nonetheless, as per the way IRFs plots are calculated (shocks depend on all the exogenous variables that interact in the PVAR model), before making such a claim, one may first seek the percentual contribution of each of those exogenous variables to the entire StDev shock contribution via the Cholesky Forecast-Error Variance Decomposition (FEVD). As highlighted in grey in Table 31, FDI makes a *strong contribution* to itself, starting with 76% in the 2-period and ending with 72% when reaching the 10-period. Regarding Social Development, Social Development *significantly contributes* 66% on itself in the 2-period and ends with a 48% contribution in the 10-period.

By bearing the latter findings in mind, one may now observe the long-run pattern of FDI impacting its future values in IRF Section K. The individual magnitudes for 1-period and 2-period are respectively 0.086 StDev and 0.096 StDev and afterwards are negative, ranging between -0.02 StDev (3-period) and -0.13 StDev (6-period). The cumulative plot shows a stable pattern of 1 StDev, causing the next period to be around 1 STDev until the 5-period, which starts to decline until exhibiting a 0.44 StDev figure in the 10-period. This latter pattern *strongly suggests that current FDI magnitudes may impact future FDI magnitudes in alignment with FDI path dependencies posited in RQ3*. This *self-reinforcing mechanism is suggested to be a stable loop*, allowing a similar aggregated FDI inflow magnitudes until the 5-period (around 1 StDev of FDI impacts 1 StDev on FDI inflow in the next period). This finding aligns with the rationale behind proposing Main Income Sources as a proxy for FDI since industries classified as FDI recipients in Panama, not fully funded by 'green field' resources, on average, reinvesting 47% of their yearly incomes as previously shown in Chart 7.

Complementary, the long-run pattern of Social Development impacting its future values is observed in IRF Section L. The individual magnitudes are positive but weak from 1-period (0.0019 StDev) to 6-period (0.0028 StDev) and, afterwards, become negative but negligible. The cumulative plot shows a stable slight growth pattern of 1 StDev, causing the next period to also be around 1 STDev until the 10-period, reaching a 1.10 StDev magnitude. This latter pattern *strongly suggests that current Social Development magnitudes may impact future Social Development magnitudes in alignment with the path dependencies posited in RQ3*. This self-reinforcing mechanism suggests that Social Development remains in an unchanged stable state, where around 1 StDev of Social Development impacts 1 StDev on Social Development in the next period. This latter finding suggests the existence of a *lock-in loop,* as explained below. In this sense, Social Development appears to be a highly persistent variable as it induces long-lasting effects on itself (Santiago, 2019). Table 32 summarises the long-run impacts related to the IRFs.

Table 32. Average SD magnitudes and confidence level limits for the 1-period and 10-period order for each Impulse Response Function

IRF function Impulse / Response	**Long run effect**
A. Impulse: Main Incomes Sources / Response: Social Progress Index	FDI is strongly suggested to induce a growing and persistent, although weak, long-term effect on Social Development
B. Impulse: Social Progress Index / Response: Main Income Sources	Social Development is strongly suggested to induce a growing and persistent long-run effect on FDI.
C. Impulse: Main Incomes Sources / Response: Total Compensation	FDI is strongly suggested to induce a direct growing and persistent strong negative long-run effect on Household Income
D. Impulse: Main Incomes Sources / Response: Third-Parties Expenditure	FDI is strongly suggested to induce direct growth and persistent strong positive long-run effect on Productive Linkages
E. Impulse: Total Compensation / Response: Social Progress Index	Household Income is strongly suggested to induce a direct growing and persistent weak positive long-run effect on Social Development.
F. Impulse: Third-Parties Expenditure / Response: Social Progress Index	Productive Linkages are suggested to induce a direct growing weak positive long-run effect on Social Development.
G. Impulse: Main Incomes Sources x Total Compensation / Response: Main Income Sources	The moderating effect of Household Income and FDI on FDI is strongly suggested to be negligible in the short and long run
H. Impulse: Main Incomes Sources x Total Compensation / Response: Social Progress Index	The moderating effect of Household Income and FDI on Social Development is strongly suggested to be negligible in the short and long run.
I. Impulse: Main Incomes Sources x Third-Parties Expenditure / Response: Main Income Sources	The moderating effect of Productive Linkages and FDI on FDI is strongly suggested to be negligible in the short and long run.
J. Impulse: Main Incomes Sources x Third-Parties Expenditure / Response: Social Progress Index	The moderating effect of Productive Linkages and FDI on Social Development is strongly suggested to be negligible in the short and long run.
K. Impulse: Main Incomes Sources / Response: Main Income Sources	FDI magnitudes are strongly suggested to impact future FDI magnitudes, thereby exhibiting a path dependency pattern (Stable Loop)
L. Impulse: Social Progress Index / Response: Social Progress Index	Social Development magnitudes are strongly suggested to impact future Social Development magnitudes, thereby exhibiting a path dependency pattern (Stable Loop)

Source: Author's estimates based on Stata17®

It is worth noting that the same methodology previously applied was also run individually for the relationship of Household Income as a moderating variable and Productive Linkages as moderating variables. See Appendix 10 (Panel Vector Autoregression Reduced-Form Model and IRFs per Moderating Variable).

6.3 Proposed Framework

Theory and practice are connected under the concept that the former guides the latter. On the other hand, practice permits generating research questions and testing theory, contributing to theory-building and selecting practice guidelines (Imenda, 2014). At this stage, it would be presumptuous to claim that the proposed conceptual/structural framework may offer characteristics of a theoretical framework[104] (grand theory or even middle-range theory), especially as per Hawking's (1988 pp9) quote: "*a theory is a good theory if it satisfies two requirements: It must accurately describe a large class of observations based on a model which contains only a few arbitrary elements, and it must make definite predictions about the results of future observations*" The limited number of panel data, but especially the fact that it only refers to limited empirical findings, constrains this proposed conceptual/structural model to make *generalisable claims and predictions* about the relationship between FDI and social development under more ample conditions. Besides, the conceptual/structural model applicability from a *practical and conceptual* perspective is circumvented only to Panama, leaving aside cases of other countries and/or provinces.

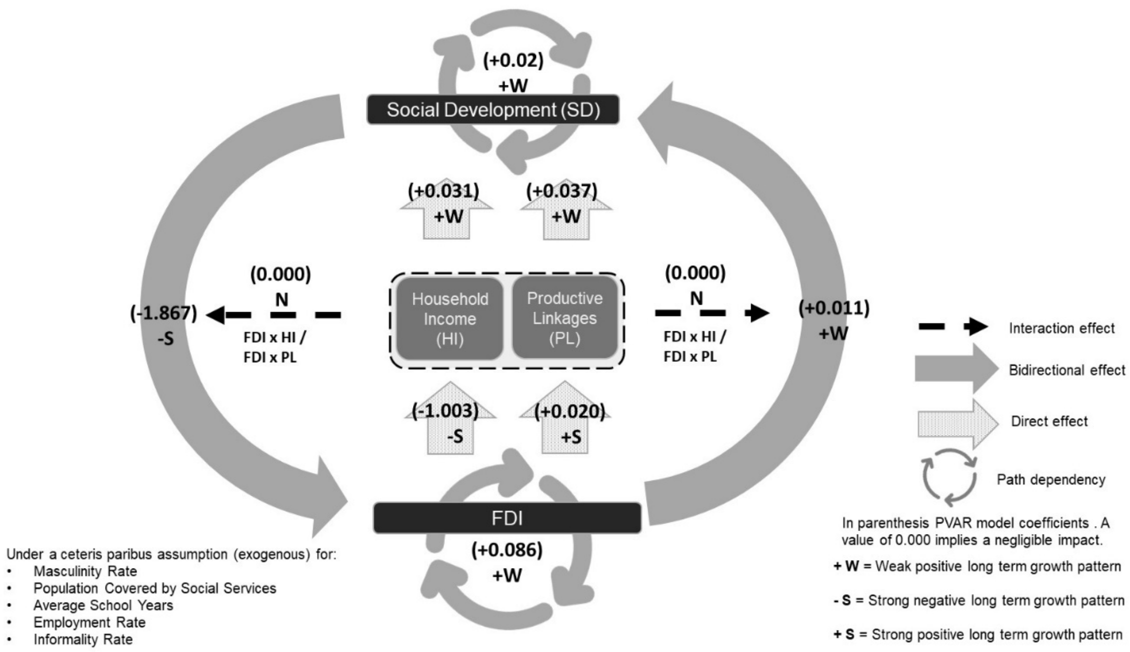
Nonetheless, carefully interweaving existing conceptual and theoretical frameworks[105] may potentially reinforce and strengthen the learning function via empirical research, further adding to the body of knowledge in a given discipline (Liehr & Smith, 1999, pp2). In passing, this is precisely the main goal of this

[104] As explained in the Introduction section, a theoretical framework directly relating FDI and Social Development could not be found after the Literature Review perusal, hence for which relationships posited in the Research Design found inspiration in affine economic-related frameworks. Such situations may frequently be encountered in research, particularly in social science disciplines, where research design may not stem only from one theory or concepts within one theory. In such cases, the researchers may 'synthesise' the existing views in the literature concerning a given situation –both theoretical and empirical findings. This synthesis may be called a conceptual model or structural framework, representing an 'integrated' view of the situation by bringing together several related concepts to explain or predict a given event or give a more ample comprehension of the phenomenon of interest (Liehr & Smith 1999). Hence, in the absence of a theoretical model, such a conceptual model or structural framework may be employed.

[105] The process of arriving at a conceptual framework is similar to an inductive process whereby small individual pieces (concepts in this case) are brought together to describe a larger relationship map. Hence, a conceptual/structural framework derives from concepts, just as a theoretical framework stems from theory. Although an entire theory may serve as one's theoretical framework, a conceptual/structural framework may typically be of limited scope and immediately applicable to a particular study. While in natural sciences, research is generally guided by one theory, in social sciences, no single theory can be meaningfully employed for research purposes.

dissertation: the proposition of a conceptual/structural framework that future researchers may adopt to advance further knowledge concerning the FDI and Social Development bidirectional association. From an *inductive standpoint*, particularly in the economic arena (if compared to natural sciences), the establishment of a conceptual/structural framework may serve as a springboard for researchers to 'sharpen it' by carrying out further research largely 'shaped up' from a synthesis of other existing literature in the field and freshly collected data. Cumulatively findings over time may lead to the articulation of theory, upon which a middle-range / grand theoretical framework may thus evolve. The proposed conceptual/structural framework depicted in Chart 11 targets to encourage further research in this field, allowing economists, practitioners and government-related agencies to steer policy-making towards improvements in Social Development mainly. Again, as exhaustively disclaimed earlier, in the presence of such a small set of periods (T=6) of panel data, this conceptual/structural framework is *conservatively* presented as a *possible explanatory association* of the explored variables without intending to make a *categorical claim*.

Chart 10. Proposed Conceptual/Structural Framework



Source: The author

Figures in the parenthesis are the coefficients from the PVAR Model in Table 27. Besides the moderating effect of *FDI x HI*, which does not 'grainger causes' FDI, the remaining depicted associations are found 'causal' as per Table 29 results. The long-run effects reported in Table 30 are classified as +W (weak positive long-term growth pattern), -S (Strong negative long-term growth pattern) and +S (Strong positive long-term growth pattern).

Although a 'mixed bag' of effects as reported in the literature review, theoretical and empirical studies generally suggest FDI positively impacting on economic growth by triggering economic spillovers in the host countries. These economic spillovers may include Productive Linkages and increases in Household Income as mechanisms of economic growth by inducing 'multiplying effects' in the economy. Besides soft skills, technological and knowledge transfers, productivity/efficiency gains, corporative learning and R&D, capital financing was pointed out in the literature as a crucial factor in economic growth stemming from FDI. Thus, via their headquarters' approved yearly budget allocation, MNEs are argued to 'inject' financial resources into the economy to subcontract and outsource services and buy products from local firms required to operate. Those financial resources are additionally allocated to pay salaries and other benefits (avoiding the informal economy) to their workers/employees in payroll, expected to maintain a regular and sustained income household flow which also benefits their families. In addition, theoretical and empirical research majorly argues about economic growth being bidirectionally linked to social development, inducing positive, negative or mixed effects that may create vicious, virtuous or lop-sided patterns, as reported in the literature review. From this standpoint, economic growth via Productive Linkages and Household Income may potentially positively impact social development, unleashing in turn 'social spillover' effects. As per the theoretical underpinning in the literature review, the transformation of economic growth into social development is, from a macroeconomics perspective, a function of policy measures, tax collection and income and assets distribution, as governments have the responsibility, ideally guided by their 'social contracts', to 'pulverise' financial resources to initiatives which reach the major benefits for society as possible: healthcare, education and nutrition programs, unemployment support schemes and construction of social-related infrastructure for water and power provision, among the most common social development factors. Furthermore, from a microeconomics perspective, households may make income allocation choices to improve their living standards by accessing better healthcare private programs or attaining higher education degrees, in turn impacting social development. In either case, micro or macro impacts, a bidirectional improvement effect appears to emerge under which social development also contends to favour economic growth. As exposed below, findings of the model depicted in Chart 11 are strongly suggested to be internally consistent with such empirical and theoretical arguments, particularly with the general postulates of endogenous growth models, as all variables (even FDI due to its path dependency effect) are strongly suggested to emerge, interact and derive secondary effects within the Panamanian economy.

The casual path from FDI to Productive Linkages fits the first relationship pattern as per its +0.020 coefficient, and its strong growth positive long-term effect (+S) reported, since as per IRF notation in Table 32, 1 StDev shock in FDI induces, in conjunction with other variables in the model, an aggregated average cumulative change figure of 5.19 StDev on the Productive Linkages variable by 10-period. For aggregated MNEs, this latter result corroborates this theoretical/empirical argued multiplying effect of FDI inducing an economic spillover via Productive Linkages, triggered by a weak effect that is subsequently suggested to amplify in the long term. In passing, this cumulative effect appears not to converge after the 10-period, a distinctive feature of endogenous model propositions, bounded to exhibit long-lasting contribution factors. In the case of Panama, due to the characteristics of its service-related economy with low levels of sophistication (Hausmann *et al.,* 2016a; Hausmann *et al.,* 2016b), such factors may be inclined to the soft skills, corporative learning and mainly on the tax collection, more than on the R&D, technology/knowledge transfer or the productive/efficiency side.

Additionally, the casual path from Productive Linkages to Social Development induces a weak positive short-term effect (coefficient = 0.037) and a weak but positive growth effect (+W) on Social Development in the long run, which reaches a 0.16 StDev impact on Social Development in the 10-period (Table 32). This latter result also aligns with the suggested positive effects that Productive Linkages may directly induce on Social Development. However, although the short-term impact is reported to be slightly higher than the FDI to Productive Linkages impact (0.037 vs 0.020), its long-lasting effect exhibits a weak amplification (0.16 StDev vs 5.19 StDev). Such a weaker long-term impact is, in passing, expectable. One must note that although this impact may stem from MNEs -for instance- implementing Social Responsibility programs, it is strongly suggested to be a direct reflection of the government's tax collection function. Such general public resources are to be subsequently invested in social-related development initiatives. Unfortunately, especially for developing nation like Panama, such long-term impact social projects are more difficult and complex to deploy as challenges related to red tape, corruption, malfeasance, lack of planning, policy-making, and policy-implementation issues must be overcome as a general rule (Hausmann *et al.*, 2017). From a scholarly perspective, this latter 'social spillover' effect triggered by Productive Linkages certainly adds to the body of knowledge of empirical findings in this welfare economics venue, potentially to be strongly exploited from a policy-making perspective.

On the other hand, the casual path from FDI to Household Income reports a short-term -1.003 coefficient finding and a strong amplifying cumulative negative growth long-term pattern (-S), which is suggested to converge to an average impact figure of -8.40 StDev by 8-period. This finding is counterintuitive as one may expect MNEs positively contribute to Household Income. Nevertheless, income inequality is reported in empirical research as a potential outcome induced by FDI, driven by high-skilled to low-skilled compensation disparities, accounting as one of the main labour-market distorting factors. Even when Panama's service-based economy is regarded as lacking complexity, filling top executive and managerial vacancies with high-skilled employees, especially for MNEs, becomes cumbersome. The fact and the matter is that many of those positions end up being covered by ex-pats who are offered larger compensation plans when recruited by international headhunting agencies if compared to local employees (Hausmann, 2016a). As higher amounts must be allocated to high-skilled positions, yearly compensation budgets for low-skilled employees are suggested to reduce, so their average compensation ends up being similar or lower compared to the workforce not employed by MNEs. As shown in Appendix 6.C, the main 3 aggregated industries as a percentage of their yearly revenue are Wholesale and Retail Trade (28.79%), Manufacturing (16.79%) and Transportation and Storage (12.50%), adding up a 58% of the panel data. Such industries require low-skilled employees compared to the Professional, Scientific and Technical Activities industry, which contributes only 1,47% of the aggregated revenue of the panel data and is suggested to be driven by high-skilled personnel. Thereby, a plausible alternative explanation for the latter effect is that the low-skilled / high-skilled workers ratio is high for the aggregated panel data (almost 60% driven by 3 low-skilled industries), suggesting that the Household Income related to an MNE employee may be lower than the average general employee not working for an MNE. Unfortunately, even when it was requested, the panel data employed did not account for the average compensation per employee per MNEs (or the number and position of employees per firm), so average figures and ratios could be compared to the income per capita ppp reported per province per year (PNUD, 2020). In any case, such contradictory findings may be left for future research.

Contrary to the previously reported finding, the causal path from Household Income to Social Development exhibits a positive 0.031 coefficient impact and a weak, positive long-term cumulative effect which converges to a 0.12StDev average impact figure by the 7-period. One may notice that even when such an effect aligns with empirical and theoretical findings reported in the literature, it may also appear counterintuitive. In light of FDI inducing a negative long-run persistent impact on Household Income, Household Income is suggested to be constrained in having the potential to impact Social Development positively. However, as extracted from the literature, Household Income allocation to Social Development activities is argued to derive from private family choices. Hence one may hypothesise that household resources may be channelled to raise familiar living standards even when such financial resources are restricted. For e.g., parents with limited income may decide to invest their budgets in moving to a better neighbourhood, providing better nutrition, accessing better healthcare programs and improving the education schemes for their children, among the classic Social Development factors. This positive casual relationship is also paramount to be understood from a policy-making and government perspective, as it additionally provides to 'social contract' in conjunction with Panamanian government responsibility. As in the previous case, however, further exploration is recommended, particularly in association with FDI: FDI-Household Income-Social Development linkage.

As hypothesised in H2 and H3, once Household Income and Productive Linkages have been ignited in the economy, they can be subsequently employed as moderating variables intending to understand their potential amplifying/attenuating effect on the bidirectional association between FDI and Social Development. As per the PVAR model and Equation 8 and Equation 9 results, the 4 moderating interaction effects $((FDI\ x\ HI\ \rightarrow SPI), (FDI\ x\ PL\ \rightarrow SPI), (FDI\ x\ HI\ \rightarrow FDI), (FDI\ x\ PL\ \rightarrow FDI))$ were found statistically significant, with only *FDI x HI,* not 'grainger causing' FDI as per the Grainger Causality Test results. Unfortunately, even under those sound statistical and robust conditions, the 4 potential interaction impacts are negligible in the short-run (coefficients = 0.000) and also in the long-run (convergence to -/+ 0.00 IRF values). Hence, without such moderating effects, FDI is suggested to only and directly receive the impact effects flowing from Social Development (below explained). Conversely, Social Development is suggested to be directly impacted by FDI (also below explained), although it also indirectly receives the effects triggered by FDI as afore explained. From this perspective, such impacts mostly remain in the 'economic spillover' domain (FDI transforming into Household Income despite the counterintuitive findings and Productive Linkages) and afterwards in a 'social spillover' domain by both Household Income and Productive Linkages directly and positively impacting on Social Development.

Path dependencies explain the continuous use of a practice based on historical preference or choice. From an economic perspective, path dependencies can result from the inability or reluctance of MNEs to commit to change because of the cost implications, as it is often easier and less cost-effective to follow the path of an already set practice than to develop a new alternative one even if more efficient. The FDI yearly inflows are strongly explained by the reinvesting income decisions of MNEs as indicated on Chart 11 by the path dependency circle shape over FDI . This self-funding causal mechanism is fully aligned with the fact that FDI in Panama has not been reported as being characterised by 'green field' investment in recent years but by an average 47% profit reinvesting effect, as explained in the Introduction and Research Design sections. The coefficient for the FDI loop is 0.086, reporting a weak growth pattern until period 2-period when it reaches a 1.18StDev impact value and starts declining, but without falling below the 1StDev value figure. In this sense, FDI's path dependency is suggested to exhibit a stable behaviour are hypothesised when proposing the independent variable, potentially reinforcing itself for the 5-period. Nonetheless, after the 6-period, although declining, cumulative StDev impact values are not negative, suggesting that the reinversion of FDI profits is maintained although without following the same initial investment pattern. Additionally, the Social Development path dependency is also suggested to follow a stable reinforcing loop, as per the 0.02 coefficient figure reported and as per its IRF pattern, which, although weak, exhibits a growth potential in the long run, where all IRF figures for the 10 periods range above a minimum value of 1.01 StDev (1-period) and a maximum of 1.1169 (6-period). Besides, it is paramount to note that the confidence figures (grey areas in IRF) never fall below 0.9StDev. It appears reasonable to consider the Social Development creation as a function driven by a stable mechanism that slightly increases its yearly magnitude. This cumulative effect is suggested to be explained by the direct effects of the 'social spillovers' induced by Household Income and Productive Linkages and the direct effect of FDI as per its coefficient of 0.011 (below explained). It is also crucial to notice that those causal mechanisms may likely continue in the long-run. By being the FDI economic drivers, they are yearly reinforced by the aggregated self-funding effect of MNEs in Panama. The same pattern applies to the Social Development path dependency, which appears to be in a lock-in loop, although marginally increasing over time. Lastly, one may compare path dependency loops in ratio-like estimation. If the short-run ratio of the FDI path dependency loop and Social Development loop is calculated (0.086 / 0.02), a 4.3 figure emerges. One may interpret that the FDI loop has 4.3 higher chances to grow upon its previous values than the Social Development loop, to some extent suggesting an evolutive pace. As reported in the literature, nations which experience high economic growth rates are reported to be highly restricted from properly transforming that economic growth into Social Development. FDI has the potential to induce economic growth. In light of FDI aiding in inducing economic growth, chances for Social Development to grow at the same pace appear to be limited.

When RQ1 was answered previously, the link flowing from FDI to Social Development was reported positive (coefficient = 0.011) in the short run. In the long-run, a weak (marginal) but positive amplifying effect was found, converging to a 0.07 StDev figure by the 6-period. As mentioned above, this association was not found to be moderated by the Productive Linkages and Household Income variables, so the impact is directly exerted. Concerning the link flowing from Social Development to FDI, the short-term effect was negative (coefficient = -1.867) and strongly and negatively cumulative in the long-run (negative amplification), to the point of reaching an impact value of -3.97StDev in the 10-period, suggested to maintain its negative momentum. This association is neither moderated by the Productive Linkages nor Household Income variables, so its negative impact is also directly exerted.

The findings of the FDI to Social Development linkage are consistent with previous empirical research, which generally point out that FDI positively impacts Social Development, as extensively argued in the literature review section. Such a weak impact of FDI on Social Development may be explained by the feeble intervention of the Panamanian government concerning FDI policies, as empirical research suggests policy-making and policy-intervention [106] as determinant factors driving the impact of FDI on Social Development (also suggested internally consistent with endogenous growth theory). This relationship is argued to strengthen when FDI policy limits foreign investments in certain economic sectors (Reiter & Steensma, 2010). As extracted from the work of Hausmann *et al.* (2017) and per Fernandez (2021) and Garcimartin (2021), Panama does not count with a structured '*strategic national roadmap'* regarding FDI attraction, meaning that there is no proper identification of which type of FDI that should be

[106] This literature in general terms points at FDI positively impacting on economic growth (Borensztein *et al.*, 1998), local productivity levels (Gorg & Strobl, 2001; Kakwani, 1981), human capital and education levels (Kottaridi & Stengos, 2010). Recent studies have engaged into examining whether FDI enhances/deters social development (Arcelus *et al.*, 2005; Lehnert *et al.*, 2013; De Schutter, Swinnen, & Wouters, 2013; Reiter & Steensma, 2010; Sharma & Gani, 2004) employing in some cases mediation and moderation impact variables. For instance, Lehnert *et al.* (2013) have concluded that the positive relationship between FDI and social development is mediated by the quality of national governance. Reiter & Steensma (2010) report this relationship to being moderated by FDI policy, strengthening when FDI policy limits foreign investments into certain economic sectors. Additionally, their research reports this relationship being moderated by host nation corruption levels, strengthening in presence of low levels of corruption. In similar way, Stiglitz (2006) reports a positive association between FDI and social development, which strengthens or weakens depending on the capability of host country government to regulate its balance between with the markets. Interestingly, welfare economics / development economics has rarely connected with significant research that may provide evidence for negative FDI spillovers (Orbes *et al,* 2016), rather than the work of Melamed & Samman (2013) which reports the inequality factor as negative FDI spillover adeversly impacting on social development.

lured to fit the nation's comparative advantages better. One may then speculate that 'naturally' a portion of the rapid economic growth experienced by the country, captured via taxation to MNEs, is transforming into Social Development. However, as afore-described, the rate of Social Development advancement is suggested to be behind the rate of this economic growth, thereby restraining Panama from unleashing its full potential of turning it into better living standards for Panamanian society. Although basic needs for the population have been historically fulfilled in general terms, there are still deficiencies in healthcare, basic, secondary and tertiary education, unemployment and child support and other social-related programs. As reported by the SPI, Panamanian citizens, in general, are still restricted from unfolding their full human capacities.

The association flowing from Social Development to FDI has been less explored, to the extent that research regarding this causal direction did not render conclusive findings as explained in the literature review. In general terms, the scant empirical research has been concentrated on the reverse causal link flowing from FDI to Social Performance. From this perspective, findings about this particular linkage may potentially add to the body of knowledge in this field. An explanatory rationale for the negative short-run impact and related amplifying the long-run negative effect may find ground in the very same nature of Panama's FDI. The major component of FDI is profits' reinvestment rather than 'green field' investment. The former does not necessarily require Social Development factors to function, but the latter certainly does. In this sense, the negative effect impact may strongly suggest that Panama is restricted from attracting 'fresh FDI capital', contrary to the ongoing effect of profits' reinvestments, in alignment with the FDI path dependency findings. Although Panama is not a sophisticated economy, the 'green field' FDI attraction, regardless of the industry type, requires, for instance, education, as probably one the most important 'transversal' factors as exhaustively reported in the literature. Other factors, such as IT and telecommunication services, transportation and electric power infrastructure, and access to well-established healthcare systems, may also be identified as FDI attraction drivers. The contributors to Social Development in this proposed model (direct effects of FDI, Household Income and Productive Linkages) feebly add to the aggregated Social Development function argued to be a stable locked-in loop. By not changing, neither education nor any other related Social Development factor appears to evolve, potentially keeping the FDI greenfield function attraction stagnated, which coincides with Panama not being considered a well-suited nation for FDI attractions concerning its Social Development limitations, mostly if compared to a neighbouring country like Costa Rica (Garcimartin, 2021; Hausmann, 2016a). Nonetheless, under those conditions, the model suggests that the 'FDI wheel mechanism' may be kept running without the impulse injected by 'green field' investment, heavily 'feeding' from the profits' reinvestment function.

In summary, although a vicious or virtuous circle/cycle pattern was initially hypothesised to stem from this research, the bidirectional causal pattern herein found may be more appropriately described as a *lop-sided circle, negatively inclined on the association running from Social Development to FDI.*

7 CHAPTER SEVEN: CONCLUSIONS, FUTURE RESEARCH AND PRACTICAL CONTRIBUTIONS

The following chapter is structured as follows: subsection 7.1 exposes the conclusions stemming from this dissertation, subsection 7.2 delves into the practical contributions, and subsection 7.3 engages in the proposed further research that could arise from this study.

7.1 Conclusions

The most common type of DPDs are based on large N and small T, as is the case of this dissertation (N>100 and T<10 data panel), which offers the advantage of facing fewer statistical drawbacks when testing structural validity (Roodman, 2009 when cited in Labra & Torrecillas, 2018). DPD models are also advantageous for controlling unobserved regressors and lagged simultaneity effects (reciprocal causality). Nonetheless, attempting to do both simultaneously leads to a series of estimation issues since finding IVs simultaneously correlated with regressors uncorrelated with the error term is usually challenging. However, despite its high degree of complexity and imposed constraints not always aligned with the data's statistical properties, especially when dealing with dynamic heterogeneity of many variables and their interactions, the GMM-System, via the use of lagged IVs, has been pointed at in the literature as the methodological solution to this issue mentioned above (Allison *et al*., 2019). Despite its statistical suitability, estimation of the basic MSM models proposed employing GMM-System, was not a priori choice but part of a funnelling methodological process that considered the different statistical characteristics of the panel data, for which a battery of tests was deployed to identify the existent misspecifications required to be controlled.

The Specification Tests results for the basic MSM proposed models and the Robustness Tests models calculated upon the GMM-System methodology rendered valid and relevant IVs, which allowed the proposition of *unidirectional static structural equations.* Nonetheless, this methodology fell short in testing dynamic relationships, which complementarily required using the PVAR model to explore the existence of ‘cycle/circle’ patterns and spillover effects, permitting the proposition of *bidirectional dynamic structural equations*.

RQs were answered, and H1, H2 and H3 were confirmed to arrive at the Research Design's ultimate goal of structuring a conceptual/structural framework. As afore explained, this very absence of an underlying theoretical background directly linking FDI and social development prevented posing those hypotheses under some 'educated guidelines' regarding magnitudes and directions of moderating variables' impacts (e.g. although lagged interactions were priorly expected in general terms for social development, literature was not supportive in this regard). In this sense, the ideal desired outcome would have probably been this proposed conceptual/structural framework describing a *virtuous circle/cycle* or *social development lop-sided circle/cycle*; results are bound to describe a lop-side circle/cycle better*, negatively inclined to the linkage from Social Development to FDI*. Thus, this pattern indicates that the association between FDI and social development could not be assumed as straightforward as expected or else undoubtedly complex.

The primary 'engine' keeping FDI running in Panama was not the circle/cycle itself but the path dependency's causal mechanism, which creates a positive subcircle (stable loop) on the FDI side. In this sense, path dependencies should not be considered isolated events but social phenomena that must be further and deeply researched. They may become major economic factors, pointed at as 'complex' phenomena driven by mutually interacting variables generating feedback loops and non-linear dynamics. When path dependencies exist, stakeholders are suggested to become 'locked in' by self-reinforcing mechanisms, where evolution is determined by contingencies (probabilistic events). In this sense, breaking out could not be achieved once locked in unless exogenous shocks occur (Vergne & Durand,2010). Panama is suggested to be immersed in such events, appearing in general terms to be locked in a loop capable of creating economic prosperity but incapable of transforming it into 'pulverised' social development for its society as suggested by the Social Development locked-in path dependency stable loop. Moreover, the spillover effects are also highly relevant, mainly because MNEs, sectors, industries, countries and regions can no longer be treated in isolation. A growing tendency of shocks and innovations appears to be swiftly propagating, and contagion effects, either positive o negative, are paramount to be studied to anticipate and control them, especially from a policymaker's perspective. In this sense, it is crucial to consider the dynamic responses to shocks and innovations, and their transmission across sectors, regions or countries may substantially differ. It would then become irrational to treat all of them symmetrically without disregarding them for their specific peculiarities.

In the literature review, Deloitte (2014) proposes 5 different mechanisms preventing a nation from reaching a virtuous circle between FDI and social development. Tax Havens are identified as one of those preventing mechanisms, which may provide a plausible alternative explanation for the pattern shown by the proposed conceptual/structural framework in alignment with the nature of Panama's economy. According to OEDC (2021), the criteria that define a jurisdiction as a Tax Havens include minimal or highly reduced tax liability to individuals and businesses, lack of transparency, and a legal scheme that prevents the exchange of information between nations. In this sense, Panama has been historically considered one of the most well-established Pure Tax Havens in the Caribbean, as no taxes are imposed at all due to its legislation strictly regulating the nation's offshore jurisdiction and financial services [107]. Besides, nations regarded as Tax Havens are also suggested for not showing much diversification in their economy comprising sectors, another highlighted feature that Panama exhibits (Hausmann *et al.* 2016a, Hausmann *et al.* 2016b). Low restrictions on capital movements across countries and low influence in government intervention in international trade are essential features of Tax Havens, which Panama features.

[107] Panama's offshore jurisdiction offers a wide range of financial services, such as offshore banking, offshore companies incorporation, vessel registration, and trusts and foundations inscriptions. Offshore companies that only engage in business outside of the jurisdiction are not required to pay taxes. Additionally, offshore companies' owners incorporated in Panama are exempt from corporate, withholding, income, capital gains, local, estate and inheritance taxes. Furthermore, one may also conduct business within the offshore jurisdiction without paying taxes, an additional benefit not available in many offshore tax havens (Business conducted within the jurisdiction is subject to local taxes). On the othe hand, strict confidentiality legal schemes and regulations protect corporate and individual financial privacy, which applies to offshore corporations' documentation, trusts, and foundations, with stringent civil/criminal penalties for confidentiality violations. Corporate shareholders' names must not mandatorily and publicly be registered. Additionally, strict banking secrecy laws prohibited Panamanian banks from sharing information concerning offshore banks and holders' accounts, only exempting the cases of a Panamanian court order in conjunction with a criminal investigation. Moreover, Panama has few tax treaties with nations with strong economic ties to it, further protecting foreign offshore banking customers. Lastly, the benefit of no exchange control laws exists, for which offshore business entities incorporated in Panama and individual offshore banking customers have no limits or reporting requirements for inbound and outbound wire transfers.

Common wisdom may consider nations with Tax Haven status capable of inducing rapid economic growth and raising their citizens' living standards. However, they are suggested to show lower levels of social development related to FDI, despite their ability to attract significant FDI PPP inflows (e.g. Lebanon or Trinidad and Tobago). As per OECD (2021) and OECD (2012) is rarely the case when a nation vastly improves its economic growth and its social development as a result of becoming a Tax Haven. Contrarily, this process is strongly referred to as a misguided development strategy, often leading to inequality increases (e.g. Panama's Gini index roughly doubles the level of Japan or Germany) and restriction of social development to occur. *Tax avoidance* has been proposed as the underlying constraining mechanism, considering taxation the most important, beneficial, and sustainable source to finance and maximise social development potential (Burgess & Stern, 1993). The core purpose of taxation is to raise resources for governments to deliver essential public services, such as social benefits, healthcare, education, employment, and better infrastructure, which are fundamental for societies to function. In this sense, taxation is more than revenue for a government but a tool for development, where IMF (2016) suggests that societies must allocate minimum tax revenue of at least 15% of their GDP to provide such basic services. In the case of Panama, Tax Revenue and Corporate Income Tax Revenue figures respectively fluctuated between 9.22% and 10.99% of its GDP[108] and 1.55% and 2.64% of its GDP during the comprising years of this study (IMF, 2020). In this venue, it is equally important how collected taxes are spent since, as WHR (2020) reports, a strong correlation exists between taxation and citizens' satisfaction and well-being. In the absence of corruption and irregular planning and spending, employing the Nordic countries as a reference, the mechanism is simple: the higher the taxes, the higher the chances for the nation's government to provide better living standards for its population. Unfortunately, in accordance to OEDC (2021), Tax Havens are estimated to deprive the world of about USD 200 billion per year in global tax revenue, where developing countries lose more than USD 50 billion each year, which is around the same yearly amount provided as international aid by developed nations to developing ones

[108] For those same years such figures fluctuated between 12.66 percent and 13.00 percent of GDP and between 2.24 percent and 2.76 percent of GDP in the case of Costa Rica (IMF, 2020).

Tax Havens are argued to legally encourage tax avoidance of MNEs by promoting FDI attraction. According to OECD (2021, pp4), "*assets held offshore, beyond the reach of effective taxation, are equal to about a third of total global assets."* In this sense, MNEs are suggested to actively avoid paying taxes both in the nations where their raw materials originate and in the host nations where they make most of their profits. As expected from any other Tax Haven, MNEs in Panama and their related headquarters offices are argued to employ *'tax professionals'* seeking legal ways to take advantage of tax legislation. The most common way to achieve so is via '*transfer mispricing*', which usually involves the MNE headquarters or another branch overcharging or undercharging the MNEs branch in the host nation for the use of goods and services, hence *artificially creating a low tax jurisdiction* for the MNE's profit[109]. In this sense, while many MNEs claim to practice '*corporate social responsibility,* this widespread use suggests otherwise. Furthermore, many MNEs claim to have '*green policies'* and '*charitable foundations'*, but few of those address those *pseudo-philanthropy* preferences for their use in cutting taxes. As extracted from OEDC (2021), the use of Tax Havens to legally avoid taxes hampers advancements in social development not only in Panama but throughout Latin America. To what extent Panama's Tax Haven scheme may be additionally used to facilitate tax evasion/money laundering is another subject of debate that may also contribute to constraining social development to be induced.

While using a Tax Haven jurisdiction like Panama is not illegal for MNEs, financial secrecy is generally appointed to constrain the ability to analyse the impact of financial flows on economic activities, as they make it very difficult to track international capital flows, limiting accountability. A very strong resistance concerning MNEs' annual accounts transparency is suggested to exist. Recent international debates propose that these issues may be easily faced in developing and developed countries ally politically, as both are losing money flows resulting from weak international tax rules. Cooperation in accounting and tax profit booking must be promoted in MNEs, and transparency in the financial

[109] e.g. Chiquita, Delmonte, and Dole fruit companies, all of which source bananas from plantations in Latin America, are argued to pay an effective tax rate of 14 percent despite their MNE headquarters being based in the USA where corporate tax rate reaches 35 percent.

information can be shared with the public domain seeking traceability of capital flows. This transparency issue also concerns the real ownership of shell companies, and trusts registered on behalf of Panamanian residents. As brought to light in the Panama Papers case in 2016, which involved the leak of information from the Mossack Fonseca Attorneys at Law firm, the legal structures in the country were found to have been routinely used to hide the identities of the final beneficiaries' accounts. Up-to-date, Panama's Legal system does not publicly require registering the final beneficiaries of limited liability entities, trusts and foundations, preventing tracking the routes of financial inflows/outflows of MNEs that are out of reach of any regulatory authorities in developing countries.

Specialisation and concentration of industries in host countries have been suggested in the literature as a feature that makes economies highly vulnerable to economic shocks. Nonetheless, despite the contended specialisation of Panama's economy in industries such as commercial services (FTZ regimes), transportation and logistical services and baking services, the country has not severely experienced such economic shocks throughout the years as other nations have. In passing, Panama's economy has been considered particularly resilient, not only in Latin America but worldwide. For instance, based upon IMF (2022) figures, while experiencing a CAGR of around 10% from 2000 to 2007, instead of plummeting during the 2008 financial crisis -as most countries around the world- GDP in Panama exhibited growth figures. GDP kept its momentum, growing 8.57% between 2008 and 2009 and 17.82% from 2009 to 2010, one of the only countries in the world, contrastingly exhibiting a 2-digit GDP growth during this global economic shock event (IMF, 2022). Additionally, even when FDI figures dropped worldwide in 2008, Panama exhibited an FDI inflow as a percentage of GDP figure of 34% (the average value for the years 2000 to 2007 was 31%, showing its peak value of 36% in this last year), and respectively 22% and 24% figures in 2009 and 2010. Furthermore, as per IMF (2022), the highly volatile FPI market instruments represented 33.9% of the nominal GDP (the average figure between 2000 and 2007 was 31% of GDP); and despite those figures respectively dropped to 22.2% and 24.5% in 2009 and 2010, Panama did not report significant money outflows in those years. In passing, the event of FPI not flowing out of Panama during economic crisis events is suggested to be explained by FPI being mostly represented by long-term debt securities, as mentioned above in the literature review section. Furthermore, although Panama´s GDP plummeted by almost 18% after the COVID-19 outbreak from 2019 to 2020, it has rebounded to a GDP percentage growth of 15.34%, representing a significant annual change of 33.28% between 2020 and 2021. Although FDI also plummeted from 6.65% of nominal GDP in 2019 to 1.12% in 2020, this figure has jumped to a 2.90% in 2021. A more interesting fact is that FPI, which again is pointed at as highly volatile and vulnerable to economic shocks, grew an actual 8.23% from 2019 to 2020, reaching a 26.80% figure as a percentage of GDP by 2020. Although, as afore explained, FPI inflows are completely separated from FDI amounts in the panel data employed, its 'resilience' behaviour indeed contributes to the global 'resilience' feature contended for characterising Panama's economy, which may be explicable of this 'locked-in' path dependency FDI loop described above.

This latter argument of resilience to economic shocks somehow aligns with another mechanism suggested in empirical and theoretical research to be restrictive of social development. WHR (2020) states that an association exists between being a top FDI recipient country and exhibiting lower social development levels than similar nations. Nations experiencing high FDI CAGRs are suggested to be prevented from transforming their economic growth rates into social development improvements for their societies, as the rate of evolution of the economy can not cope with the rate of evolution of social development. As mentioned in the Introduction section, Panama is up to date, the 1st FDI recipient in the Central American region and 5th in Latin America, depicting a 2-digit FDI PPP CAGR in the past years. In the conceptual/structural model, the ratio of the FDI self-reinforcement loop (in turn inducing economic growth) is suggested to grow faster than the SPI self-reinforcement loop, offering a complementary alternative plausible explanation for Panama being deprived of reaching a higher social development level more coherent with its economic advancement pace.

Panama's incapability of reaching its highest potential to transform economic advancement into social prosperity may be explained by the conjoint effects of those previously described barriers and likely other additional factors. The proposed conceptual/structural framework exhibiting economic spillovers and path dependencies dynamics may require further research on how shocks and innovations are transmitted across panels (countries, regions, industries, sectors, and MNEs). The main target then would be to characterise average and cross-sectional effects, aiming to understand all the potential sources they arise from, the analysis of past tendencies and how they had influenced current events and how they could potentially evolve in the future. Policymakers should be provided with facts and counterfactuals to construct alternative social policy-making and reformulating scenarios. Hence, the arising questions now revolve around how path dependency loops for FDI and social development could be dismantled and rearranged and how economic spillovers could be strengthened to favour social spillovers.

It would be rash to state that this proposed conceptual/structural model is a simplified version of the reality in welfare economics for the particular association between FDI and social development. The main underlying reason has been extensively explained earlier since the limited number of years (T=6) in the panel data excludes making *categorical claims but establishes the conservative possibility* of the sought bidirectional relationship. Besides, this research field's complexity and the gamut of possible patterns and plausible explanations that a cycle/circle–like relationship implies also turn this exploration into a cumbersome endeavour. Despite the latter, given the theoretical frameworks and voids directly linking FDI and social development, as extensively explained earlier, the *structural unidirectional and dynamic structural models* proposed may offer some potential to become a conceptual/structural framework to guide future research in welfare economics. Ideally, researchers would be encouraged to question the conceptual/structural framework full extent, ultimately seeking to complement and refine it, potentiating it to evolve into a theoretical framework applicable to a more ample scope of host countries' realities in the field of welfare economics. From this perspective, aggregated findings of this dissertation may be employed as ‘building blocks’, for instance, to support further claims regarding the Tax Haven and the differential FDI / social development growth rate conceptual arguments above explained. Other conceptual assertions could also be placed under the scrutiny of academic research.

As per the latter, the conceptual/structural framework proposed herein excludes many other host countries' economic patterns, and their potential explicability only applies to the economic reality in Panama. Hence, to what extent this proposed conceptual/structural framework may describe the FDI and social development association of other countries that exhibit similar features as Panama is another arising question which could potentially be answered in the medium/long run via scholarly research. However, from a policymaker and practitioner perspective, implications derived from the results should not be ignored in the short term. Under the ‘social contract’, the State's primary responsibility and commitment ought to procure and assure its citizens what is required to reach their highest status of well-being possible. Of course, this procurement and ensuring functions are to be operationalised to the extent that a State has economic resources to transform them into well-being, as could be implied from the differences in social development stemming from SPI reports when comparing developed nations (exhibiting higher GDP PPPs) and emerging/transitional economies. Upon this rationale, a country like Panama, with the highest GDP PPP in Latin America, should be in a ‘privileged’ position -from a mere economic stance- to procure their citizens better conditions to reach their most elevated well-being position in comparison to a country like Costa Rica, which GDP PPP is roughly up-to-date 50% less than Panama’s. However, interestingly Costa Rica’s SPI score in the past decade has ranked on average 6+ points above Panama’s, as mentioned in the Introductory section. The underlying explanatory reasons for a nation like Costa Rica being capable of achieving a higher social development status with fewer economic resources is complex as it is a function of many different interrelated factors. Studying such factors would probably require a case study approach, which is out of this dissertation's scope. Nonetheless, it is paramount mentioning that those reasons may not majorly be economic-related but more inclined on the policymaking side. The reason being it that as Costa Rica has been historically considered a ‘*welfare state’* in the region since it abolished its army in 1948, a date which marked the beginning of a series the governmental transformations in health, education, and public investment in social-related infrastructure (e.g. hydroelectric power plants, potable water supply). Those transformations were not arbitrary decisions but planned ones, where of course, a lagged effect of economic impact on social development and path dependencies in the social development evolution could be assumed to have existed.

Given the latter arguments, one may imply that it becomes imperative for a country like Panama to develop national policy mechanisms to unlock both the FDI and the social development loops, as further argued below concerning the potential practical contributions of this dissertation. Those dismantling mechanisms may be complex but are certainly inclined on the policymaking side. The Tax Haven conceptual framework above argued may be used to conceptualise a set of influencing factors to deconstruct and reconstruct the FDI and social development loops. It is essential to highlight that approving bills is not as critical as implementing them within a policymaking domain. For instance, much in line with this Tax Haven argumentation, Panama has been struggling with the adverse effects concerning the Panama Papers' effect since 2016, as the country has been included in influential international 'grey' and 'black' money laundry and tax evasion lists on several occasions. Although the Economics and Finance Ministry had conceptualised a bill comprising a series of requirements to exclude Panama from the lists and had managed its way through for its approval by the Parmailment, the bill has lacked a strategy to be appropriately deployed in reinforcing anti-money laundry and anti-evasion practices. Such an ineffectiveness in operationalising those bills has been detrimental to all the efforts made, as the country has not fully demonstrated the required compliance hence lately experiencing being in/out of the lists. Last but not least, it is also important to remember that the earlier those transformations are implemented, the better, as lagged effects could be expected in the long run, as implied from the IRFs results.

7.2 Practical Contributions

This dissertation fulfils the requirements for earning a Doctor of Business Administration (DBA) degree, characterised by being Action-Oriented Research (AOR) inclined[110]. Nevertheless, six concrete reasons make it more affine to a Doctor of Philosophy (PhD) stance: 1) research problem studied is not practical oriented for a specific organization but instead discipline-oriented into 'welfare

[110] As per Coghlan (2007, pp. 300), *"comprises the organizational project that the manager-researcher is working on with organizational colleagues with an intended outcome of problem resolution or a change successfully implemented".*

economics', and so the application of an integral research mix of several social sciences disciplines is not required, 2) the main target is creating a broad 'conceptual/structural framework' that could be foundational in further extending theoretical knowledge in the field, 3) the 'conceptual/structural framework' is not a specific case study for an organization but an empirical research-based approach heavily engaging 'theoretical minutia' as per requirements of a PhD stance, 4) I am not performing in a manager-researcher role, getting involved in interaction circles with other practitioners and managers in an organization, 5) data to be employed was obtained from publicly available sources and not directly from an organization, 6) employment of secondary sources (Panamanian government public databases), which does not require to create and validate data-gathering tools and then collect the data, further distancing myself from the characteristic AOR research-manager role.

Despite these crucial structural differences in the academic research perspective, the proposition of specific frameworks is one way for scholarly research to be successfully translated from academic work into managerial knowledge (McGahan (2007) since practitioner incline knowledge may stem from academia and vice-versa (Van de Ven, 2007)[111]. In this sense, rather than leaving the proposed conceptual/structural framework as a merely academic exercise or/and a foundation to encourage future research, one may also envision it becoming a source of 'actionable governmental policies' seeking to benefit Panama's society, especially in an up-to-date scenario marked by a growing number and larger MNEs interacting with the Panamanian economy. Hence, the contributions derived from the conceptual/structural framework[112] may be experienced not only by academics but also practitioners and policymakers' circles in Panama, provided that the proposed conceptual/structural framework finds grounded, practical orientation via 3 main outlets: social policies, economic policies and FDI attraction policies

[111] This latter assertion has, in effect, been proven to be the case of this dissertation, since in accordance with Sirgy (2012)'s quote when cited in Land & Michalos (2018, pp861): "*most of the theories employed were developed by scholars solving problems arising in standard disciplinary research*".

[112] As quoted by Kislov *et al.* (2019, pp1): a "*well-developed theory 'enables knowledge to emerge out of seeming chaos, providing a common language for studying implementation phenomena and guiding the actual practice of implementation."*

Although as per Van de Ven (2007, pp1), when quoting Tranfield *et al.* (2003) and Rousseau (2006), "*studies show that practitioners often fail to adopt the findings of research in fields such as…. management*", practitioner environments may become 'factories of ideas' where knowledge could be co-produced between academics and managers by approaching issues, testing ideas and sharing different perspectives on common problems. In this sense, developing and deploying those social, economic, and FDI attraction policies intrinsically requires this conjoint academia-practitioner cooperative role, ultimately aiming to construct a 'national multisectoral roadmap'. As one may imply from this dissertation's results that the primary short-term focus of this roadmap must, in effect, be decoupling the FDI and social development 'locked in' loops and subsequently rearranging them to induce social spillovers and 'greenfield' FDI attraction via mainly interrelated economic-social policy proposition, its reinforcement and implementation.

This roadmap, in general terms, must be employed for orchestrating the creation of synergies between academics, policymakers, practitioners in private businesses, multilateral entities and government agencies in Panama (Vergara & Ellis, 2021), which as per Orbes *et al.* (2019), is a complex but paramount requirement among all stakeholders (public and private institutions either national or international). Synergies' primary target should engage the industry/sectors within the Panamanian economy which account for the majority of FDI inflows: Wholesale and retail trade, Manufacturing and Transportation and Storage, which, if adequately supported by specific high-impact/priority initiatives, may favour higher countrywide social development spillovers and linkages' creation with local businesses. Of course, the Household Income construct must be studied further to understand the contradictory results derived from the conceptual/structural model proposed under which it receives a negative contribution from FDI. Additionally, Household Income appears to induce more variability in social development function by industry/sector from the *unidirectional static structural model approach*, where Education is the only industry/sector suggested to excel in its contribution over the other industries/sectors. As per the same token, and although not exhibiting much variability within different industries/sectors under the *unidirectional static structural model approach*, the Productive Linkages function should be strengthened as it is suggested to induce weak but positive contributions to social development directly.

The general benefits of creating synergies revolve around 1) strengthening public and private sectors alliances (government, private business, unions, civil society leaders), 2) focusing on channelling resources (especially public), 3) centralised strategy coordination, 4) centralised social marketing messages' alignment, and 5) coordinated efforts for international FDI attraction particularly for 'greenfield' inflows. The main stakeholders identified in Panama concerning social, economic and FDI attraction policies' development and deployment are listed below. This list is not exhaustive as there are eventually more stakeholders whose involvement may also be crucial for the creation of synergies and also for social, economic and FDI attraction policy deployment, depending on the alternative developing avenues chosen:

- Academics researching economics, welfare economics and social development fields.
- Academics working for government-funded institutions such as National Statistics Agencies (NSA) are responsible for developing data collection tools and tracking mechanisms for social development.
- Policymakers who may directly influence the development of social policies, economic policies and FDI attraction policies, just to mention the 3 main policy-oriented avenues.
- Practitioners in private businesses in different industries/sectors (mainly Wholesale and retail trade, Manufacturing, Transportation and Storage) with whom synergies -targeting social development spillovers and linkages' opportunities- could be created.
- Practitioners working for diverse Panamanian governmental institutions (National Health Ministry, National Education Ministry, the Small and Medium Enterprise Ministry and the Economics and Finance Ministry).
- Practitioners in governmental (public) institutions such as the Panamanian National Investment Promotion Agencies (NIPA), known as PROPANAMA, in charge of planning and deploying FDI attraction international marketing strategies.

- Practitioners in national and international economic aid agencies and multilateral entities.
- Decision-makers and CEOs in MNEs operating in Panama and/or potentially being attracted into Panama.
- Academics within the universities offering the most demanded careers per industries/sectors required by MNEs operating and attracted to in Panama.
- Civil society and union leaders, especially those involved in primary FDI industries and sectors.
- Philanthropists and impact investors searching for high-impact social projects.

Out of the stakeholders mentioned above, it is worth noting that the Economics and Finance Ministry and PROPANAMA are suggested to be the 2 main potential stakeholders benefiting from the proposed conceptual/structural framework. On the one hand, the Economics and Finance Ministry is officially responsible for planning, funding, coordinating (with other governmental institutions and private and public stakeholders) and deploying economic and social policies in the Republic of Panama. On the other hand, PROPANAMA specifically focuses on all affairs related to FDI in Panama. From an institutional strategic standpoint, as per Vergara & Ellis (2021), PROPANAMA is vested with the mission of "*attracting sustainable and social impact foreign direct investments, …. contributing…. to improvements in the quality of life of the Panamanian society.*" Thereby, the conceptual/structural framework proposed strategically fits PROPANAMA's goal from an AOR perspective in developing and deploying FDI inward attraction policies and launching associated international marketing campaigns for FDI attraction, particularly regarding 'greenfield' investment, seeking to aid in reversing the negative effect of social development over FDI suggested existing. Of course, this also requires improvements in social development conditions, particularly by solving the historic structural issues in its education system, which is a strong determinant factor restraining Panama from relatively complex and technologically inclined 'greenfield' FDI attraction, as argued in (Hausmann *et al.* 2016a, Hausmann *et al.* 2016b) and empirical research findings reported in the literature review.

Articulating PROPANAMA's mission involves channelling resources to specific FDI 'greenfield' initiatives with high countrywide social development potential, for which developing synergies between other governmental organizations (via policy interventions), private businesses and multilateral entities are required. For instance, direct funding for the operation of PROPANAMA is majorly provided by the Economics and Finance Ministry and, on a smaller scale, by PNUD, as a multilateral entity (Vergara & Ellis, 2021). Among the remaining stakeholders, some may also have high contribution potential to synergies' creation, e.g. the National Health Ministry and the National Education Ministry, which are considered vital institutions in coordinating efforts with the Economics and Finance Ministry for nationwide deployment of social-related initiatives and social marketing campaigns. National Statistics Agency (NSA), in charge of collecting and monitoring a broad range of indices, indicators and statistics countrywide, may concentrate on improving or extending their methodologies and tools for quantity and quality purposes (Land & Michalos, 2018), pursuing to ensure and gauge that economic prosperity is converted efficiently, sustainably and effectively into social development. The SME (Small and Medium Enterprise) Ministry, known as AMPYME, in charge of developing the Panamanian SME sector, should deploy inclusive initiatives to favour linkages' creation so local businesses -providing specialized services demanded by MNEs- obtain the appropriate support for their development and growth. Universities' role should concentrate on offering tailored careers for the most demanded industries/sectors, targeting to supply MNEs being attracted and/or already operating in Panama with the best skilled and trained personnel possible. Civil society and union leaders must also become agents supporting, rather than hindering, synergies' development efforts once convinced of the potential benefits of FDI to specific industries.

7.3 Future Research

First, contrarily to the GMM-System and PVAR approach choice, from an efficiency, consistency, SE and unbiasedness perspective, employing a DPD Model with a Maximum Likelihood (ML) estimator would have been more 'desirable', strongly suggested in the literature to be superior than the *gmm* *estimator* as per its asymptotic statistical properties. Nonetheless, due to the unbalanced panel data characteristics, the absence of prior knowledge of the model structure, the presence of homoskedastic SEs, and observed variables not complying with normal distribution assumptions prevented this dissertation from being estimated via the Cross-Lagged Panel Model with FE (CLPM-FE), the Model-Implied Instrumental Variable - Generalized Method of Moments or MIIV-GMM[113]or directly the Structural Equation Modelling (SEM)[114] methods. Hence, it is strongly encouraged to alternatively engage this research from those latter methods to corroborate the herein-derived findings and/or test the proposed *equations* and its *unidirectional static structural* and *bidirectional dynamic structural models*.

Second, additional research is encouraged on ruling causal mechanisms for lock-in path dependencies, since from a policy-making perspective regarding FDI and social development is crucial to structurally understand their behaviour, factual and counterfactuals.

Third, the data employed in this dissertation focused on one country only, which restrictively allowed the proposition of a framework conceptually aligned with the Tax Haven and high economic growth patterns reported in the literature. Further research is encouraged to confirm the validity of the other transformation barriers to social development related to FDI, stemming from using similar panel data for other countries exhibiting the features claimed to characterise every barrier type.

Forth, corroboration of the findings herein reported is also encouraged by using this very same data set but with a different aggregation structure which collapses into a different arrangement of sectors or subsectors or another type of classification (e.g. brackets of yearly profits)

---

[113] Unfortunately has not been implemented in Stata17® yet.

[114] Under which *latent variables* are conceptually parallel to unobserved heterogeneity in GMM-System and other econometric methods and where multiple estimations and interrelated dependence between endogenous (equivalent to dependent variables) and exogenous variables (equivalent to independent variables) exist.

Fifth, although this dissertation allowed research on a province-basis, as per Jaax (2020), when citing Beresford (2008) and Ishizuka (2009, 2011), differences across local political jurisdictions are suggested to be potential drivers of disparities. Therefore, further research on more disaggregated figures such as regional, county or city levels deepness is suggested to establish causal relationships with greater certainty.

Sixth, besides further research of the Household Income variable (via another proxy) as per its contradictory findings, a different array of variables must be explored as moderating variables with higher explanatory power and the potential to unlock the path dependency loops in FDI and social development, with the ultimate target of further inducing social development advancements and in turn 'greenfield' FDI attraction.

Seventh, given the results of the unidirectional exploration effects per industry type being feebly informative and even contradictory to the theoretical literature, further research is encouraged to deconstruct the driving forces for MNEs to invest in different industries/sectors in Panama. Employing more robust panel data for MNEs, particularly with an extended T of more than 20 years, may improve the estimator's efficiency[115] and the derived findings. This exploration is encouraged to be extended to other nations, seeking to enlarge the comprehension of the underlying mechanisms driving investment decisions for asset-oriented MNE (e.g. electronics or ICT) and which require better-educated and skilled workers, asset-exploiting MNEs (e.g. extractive industries) or labour-intensive MNEs (e.g. textile industries). Such suggested exploration must be maintained as a core research venue in welfare economics.

Eight, one may also hypothesise that firms' attitudes may change in response to the global emphasis on corporate social responsibilities, basing their investment decisions on industries, sectors and/or projects promising higher impacts on social development in host nations. However, this research does not engage in exploring this attitudinal effect, so it is further recommended.

[115] Panel data (T=6) employed in this dissertation is highly constrained. Although GMM-Sys regressions were statistically significant and IVs valid and reliable, splitting panel data into 16 subsamples for dummy variables calculation, constrained estimator's efficiency even higher.

8 REFERENCES

Abrigo, M. R. M., & Love, I. (2016). Estimation of Panel Vector Autoregression in Stata. The Stata Journal, 16(3), 778–804.

Allison, P. D. (2014) Maximum Likelihood for Dynamic Panel Models with Cross-Lagged Effects. Retrieved from http://statisticalhorizons.com/wpcontent/uploads/ML-DynamicPanel-1SP.pdf

Allison, P. D., Williams, R., Moral-Benito, E. (2019) Maximum Likelihood for Cross-lagged Panel Models with Fixed Effects. Sociological Research for a Dynamic World Volume (3) 1–17

Alkire, S.(2009) The human development and capability approach, in Deneulin, Séverine; Shahani, Lila (eds.), An introduction to the human development and capability approach freedom and agency, Sterling, Virginia Ottawa, Ontario: Earthscan International Development Research Centre, pp. 22–48

Ananat, E. O., Gassman-Pines, A., Francis, D. V, & Gibson-Davis, C. M. (2017). Linking job loss, inequality, mental health, and education. Science, 356(6343), 1127–1128.

Anand, S., Sen, A. (2000). Human development and economic sustainability. World Development, 28(12), 2029–2049.

Anand, P.; Santos, C.; Smith, R. (2009) The measurement of capabilities, in Basu, Kaushik; Kanbur, Ravi (eds.), Arguments for a better world: essays in honor of Amartya Sen, vol. 1, Oxford New York: Oxford University Press, pp.283–310.

Anderson, T. W., and C. Hsiao (1981) Estimation of dynamic models with error components. Journal of the American Statistical Association 76: 598-606.

Andrews, D. W. K, & Lu, B. (2001). Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. Journal of Econometrics 101 (1): 123–164.

Ahn, S. C., and P. Schmidt. (1995) Efficient estimation of models for dynamic panel data. Journal of Econometrics 68: 5-27.

Aitken, B. J., & Harrison, A. E. (1999). Do domestic firms benefit from direct foreign investment? Evidence from Venezuela. American Economic Review, 89(3), 605– 618

Angelopoulou, A and Liargovas, P. (2014) Foreign Direct Investment and Growth: EU, EMU and Transition Economies. Journal of Economic Integration. Center for Economic Integration, Sejong University 29(3), 470-495

Arcelus, F. J., Sharma, B., & Srinivasan, G. (2005). Foreign capital flows and the efficiency of the HDI dimensions. Global Economy Journal, 5(2), 1–12.

Arellano, M.; Bond, S. R (1991) Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations the Review of Economic Studies. 58(2), 277-297

Arellano, M.; Bover, O. (1995) Another look at the instrumental variable estimation of error-components models. Journal of Econometrics 68: 29-51.

Atkinson, A. (2011). The Restoration of Welfare Economics. *The American Economic Review 101*(3), 157-161.

Baiashvili T., Gattini L. (2020). Impact of FDI on economic growth: The role of country income levels and institutional strength. EIB Working Papers 2020/02, European Investment Bank (EIB).

Bachmann, R., Baumgarten, D., & Stiebale, J. (2014). Foreign direct investment, heterogeneous workers and employment security: Evidence from Germany. Canadian Journal of Economics, 47(3), 720–757.

Baltagi, B. H. (2011). Econometrics. Heidelberg: Springer.

Baltagi, B.H., Bresson, G., Pirotte, A. (2003) Fixed effects, random effects or Hausman–Taylor?. Economics Letters 79, 361–369.

Baron, R.M.; Kenny D.A. (1986) The Moderator-Mediator Variable distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations. Journal of Personality and Social Psychology. 51(6) 1173-1182

Barrington-Leigh, C. and Escande, A. (2018) Measuring Progress and Well-Being A Comparative Review of Indicators. Social Indicators Research. 135:893–925

Barro, R.J, Sala-i-Martin, X. (1995). Economic Growth, McGraw-Hill, Cambridge, MA.

Barro, R.J. (1997). Determinants of Economic Growth. A Cross-Country Empirical Study. Cambridge MIT Press.

Barros, L., Castro, F.H., Da Silveira, A., Bergmann, D. (2020) Endogeneity in panel data regressions: methodological guidance for corporate finance researchers. Review of Business Management 22, 437–461.

Bayraktar-Sağlam, B.; Sayek, S. (2017) Labor Costs and Foreign Direct Investment: A Panel VAR Approach, Economies, MDPI, Open Access Journal, vol. 5(4), pages 1-23, September.

Baskaran, A. & Muchie, M. (2008) Foreign Direct Investment and Internationalization of R&D: The Case of BRICS Economics Diiper Research Series Working Paper No. 7

Bhattacharyya, S (2012). Legal Regimes Governing Foreign Direct Investment (FDI) in Host Countries. Advocates for International Development

Baum, C.F., Schaffer, M.E., and Stillman., S. (2003). Instrumental variables and GMM: Estimation and testing. Stata Journal 3 (1): 1–31.

Baum, C.F., Schaffer, M.E. (2013) ACTEST: Stata module to perform Cumby-Huizinga general test for autocorrelation in time series. Statistical Software Components. S457668, Boston College Department of Economic

Binder, M., & Georgiadis, G. (2010). Determinants of human development: Insights from state-dependent panel models. UNDP-HDTO Occasional Papers No. 2010/24.

Blomström, M. and Kokko, A. (1997) The Impact of Foreign Investment on Host Countries: A Review of the Empirical Evidence World Bank Policy Research Working Paper.

Bloom, D. E., & Canning, D. (2000). The health and wealth of nations. Science, 287(5456), 1207–1209.

Bollen, K.A., Kolenikov, S. and Bauldry, S. (2014) Model-Implied Instrumental Variable—Generalized Method of Moments (MIIV-GMM) Estimators for Latent Variable Models. Psychometrika 79, 20–50

Bond, S.R. (2002) Dynamic panel data models: a guide to microdata methods and practice. Portuguese Economic Journal, 141–162

Boozer, M., G. Ranis, F. Stewart and T. Suri (2003), "Path to Success: The relationship between human development and economic growth", Discussion Paper No. 874, Economic Growth Center, Yale University.

Borensztein, E., De Gregorio, J., & Lee, J. W. (1998). How does foreign direct investment affect economic growth? Journal of International Economics, 45(1), 115-135.

Born, B.; Breitung, J. (2016) Testing for Serial Correlation in Fixed-Effects Panel Data Models, Econometric Reviews, 35:7, 1290-1316, DOI:10.1080/07474938.2014.976524

Boonlert, J. (2017) Beyond the equal-weight framework of the Social Progress Index International. Journal of Social Economics. 44(12), 2336-2350

Bruno, M., Ravallion, M., & Squire, L. (1996). Equity and growth in developing countries: Old and new perspectives on the policy issues. Income distribution and high-quality growth. World Bank. Policy Research Working Paper 156: 117-146.

Brückner, M., & Gradstein, M. (2013). Income and schooling. Retrieve from http://voxeu.org/sites/default/files/file/DP9365.pdf

Bryman, A. & Bell, E. (2011) Bussines Research Methods. 3rd Edition. Oxford University Press. New York. United States of America

Blundell, R. (2017). What Have We Learned from Structural Models? *The American Economic Review*, *107* (5), 287–292.

Burgess, R.; Stern, N. (1993) Taxation and Development. *Journal of Economic Literature*, vol. 31, no. 2, 1993, pp. 762–830

Burnham, K. P.; Anderson, D. R. (2002) Model Selection and Multimodel Inference: A practical information-theoretic approach (2nd ed.). Springer-Verlag.

Blundell, R.; Bond. S.R (1998) Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics* 87:115–143.

Brummet, Q. (2008) The effect of gender inequality on growth: A cross-country empirical study. Digital Commons Honors Project. 88

Cajar, R. (2016) Diversificación de la Matriz Productiva de Panama. Friedrich-Ebert-Stiftung. Análisis - ISSN 2413-6611

Canova, F.; Ciccarelli, M. (2013). Panel Vector Autoregressive Models: A Survey, CEPR Discussion Papers 9380, C.E.P.R. Discussion Papers.

Cartwright, N. (1989) Nature's Capacities and their Measurement. Book. Oxford: Oxford University Press.

CEPAL -Comisión Económica para América Latina y el Caribe- (2017). La Inversión Extranjera Directa en América Latina y el Caribe 2017. Naciones Unidas, Santiago. (LC/PUB.2017/18-P)

CEPAL -Comisión Económica para América Latina y el Caribe- (2018). La Inversión Extranjera Directa en América Latina y el Caribe 2018. Naciones Unidas, Santiago. (LC/PUB.2018/13-P)

CEPAL -Comisión Económica para América Latina y el Caribe- (2019). La Inversión Extranjera Directa en América Latina y el Caribe 2019. Naciones Unidas, Santiago. (LC/PUB.2019/16-P)

CEPAL -Comisión Económica para América Latina y el Caribe- (2020). La Inversión Extranjera Directa en América Latina y el Caribe 2020. Naciones Unidas, Santiago. (LC/PUB.2020/15-P)

Chambliss, D. and Schutt, R. K. (2006) Making Sense of the Social World: Methods of Investigation (Inglés) 2nd Edition. Sage Publications. Pine Forge Press. United States of America

Chandra R. (Ed.) (2016) Handbook of Research on Global Indicators of Economic and Political Convergence. Advances in Finance, Accounting and Economics (AFAE) Book Series. IGI Global. Hershey PA. USA

Cecchini, S.; Holz, R. and Rodríguez Mojica A. (2020) La matriz de la desigualdad social en Panamá. Serie Políticas Sociales, N° 236 (LC/TS.2020/121). Santiago, Comisión Económica para América Latina y el Caribe (CEPAL)

Chen, Z., Ge, Y., & Lai, H. (2011). Foreign direct investment and wage inequality: Evidence from China. World Development, 39(8), 1322–1332.

Clausing, K. (2001) The impact of transfer pricing on intrafirm trade, in J. Hines (ed.), International Taxation and Multinational Activity, University of Chicago Press.

Clegg, S.R. Schweitzer, J., Whittle, A., Pitelis, C. (2017) Strategy: Theory and Practice. Sage Publications Ldta 1 Oliver's Yard. 55 City Road. London EC1Y 1SP

Coelli, M. B. (2011). Parental job loss and the education enrollment of youth. Labour Economics, 18(1), 25–35.

Coghlan, D. (2007) Insider Action Research Doctorates Generating Actionable Knowledge. Higher Education Springer. 54(2), 293-306

Collischon, M.; Eberl, A. (2020). Let's Talk About Fixed Effects: Let's Talk About All the Good Things and the Bad Things. Köln Z Soziol 72, 289–299. https://doi.org/10.1007/s11577-020-00699-8

Costantini, V.; Salvatore, M. (2008) Environment, human development and economic growth. Ecological Economics, Vol. 64, No. 4, pp. 867-880.

Contraloría General de la Republica (2019) Comportamiento de la Economía a través de sus Principales Indicadores Económicos y Financieros del Sector Público Al 30 de junio de 2019. Published November 2019. Contraloría General de la Republica de Panama.

Coyle, D. (2014) GDP: A Brief but Affectionate History. Princeton, NJ: Princeton University Press.

Creswell, J. W. (2009). *Research design: Qualitative, quantitative, and mixed methods approaches.* Thousand Oaks, CA: Sage Publications. pp 131-133

Dechprom, S. & Jermsittiparsert, K. (2018) Foreign Aid, Foreign Direct Investment and Social Progress: A Cross Countries Analysis. Working Paper. Universidad del Zulia. Biblioteca Digital del Repositorio Académico. 34(86): 2086-2097

Deeming, C. (2013), Addressing the social determinants of subjective wellbeing: The latest challenge for social policy. Journal of Social Policy. 42(3), 541–565.

Deloitte. (2014) Foreign Direct Investment and Inclusive Growth. The Impacts on social progress.

De Hoyos. R., Sarafidis., V. (2006) Testing for cross-sectional dependence in panel–data models. The Strata Journal 6(4) 482-496

Diener, E., Suh, E.M., Lucas, R.E. and Smith, H.L. (1999). Subjective well-being: three decades of progress. Psychological Bulletin. 125, 276–302

Dill, V., & Jirjahn, U. (2016). Foreign owners and perceived job insecurity: Evidence from linked employer-employee data. International Journal of Manpower, 37(8), 1286–1303.

Dowding, K.; Van Hees, M.; Anand, P.; Graham, H.; Carter, I.; Guala, F. (2009). The development of capability indicators. Journal of Human Development and Capabilities.10(1): 125–152.

Driscoll, J. C.; Kraay, A. C. (1998) Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data, Review of Economics and Statistics 80, 549-560.

Drolet, J., Sampson, T., Jebaraj, D. P., & Richard, L. (2014). Social Work and Environmentally Induced Displacement: A Commentary. Refuge: Canada's Journal on Refugees, 29(2), 55–62.

Drukker, D.M. (2003) Testing for serial correlation in linear panel-data models. Stata Journal (3)2: 168-177.

Drukker, D.M. (2008) Econometric analysis of dynamic panel-data models using Stata. Summer North American Stata Users Group meeting

Dunning, J. and Pitelis, C. (2008) Stephen Hymer's contribution to international business scholarship: an assessment and extension. Journal of International Business Studies (39) 167-176

Dunning, J. H. (1977), "Trade, location of economic activity and MNE: A search for an eclectic approach" in B. Ohlin, P.O. Hesselborn and P.M. Wijkman (eds), The international allocation of economic activity, Macmillan, London

Dunning, J. H. (1993). Multinational enterprises and the global economy. Addison-Wesley, Wokingham

Dumitrescu, E.-I. and Hurlin, C. (2012) Testing for Granger non-causality in heterogeneous panels. Economic Modelling, 29(4):1450–1460.

Easterlin, R. A. (1974) Does economic growth improve the human lot? Some empirical evidence. In P. A. David & M.W. Reder (Eds.). Nations and households in economic growth. London: Academic Press. 89–125.

Easterlin, R. A. (2013) Happiness and Economic Growth: The Evidence. *IZA Discussion Papers 7187, Institute of Labor Economics (IZA)*.

Easterly, W. (1999) Life During Growth. Journal of Economic Growth 4, 239–276.

Echandi, R., Krajcovicova, J., and Qiang, Christine Z. (2015) Impacts of Investment Policy in the Global Modern Economy: A Review of Literature. Policy Research Working Paper 7437. World Bank, Washington, D.C.

ECLAC / ILO -Economic Commission for Latin America and the Caribbean / International Labour Organization - (2020) Work in times of pandemic: the challenges of the coronavirus disease (COVID-19) Employment Situation in Latin America and the Caribbean, No.22 (LC/TS.2020/46), Santiago, Chile

Fabbri, F., Haskel, J. E., & Slaughter, M. J. (2003). Does nationality of ownership matter for labor demands? Journal of the European Economic Association, 1(2–3), 698–707.

Faeth, I. (2009) Determinants of Foreign Direct Investment – A tale of nine models. Journal of Economic Surveys. 23(1): 165–196

Fehder D., Porter M., and Stern S. (2018) Empirics of Social Progress Interplay between Subjective Well-Being and Societal Performance. Conference Proceeding American Economic Association. AEA Papers and Proceedings, 108 (2018): 477-482.

Feenstra, R. C., & Hanson, G. H. (1997). Foreign direct investment and relative wages: Evidence from Mexico's maquiladoras. Journal of International Economics, 42(3), 371– 393.

Fei, J.C.H., Ranis, G., Stewart, F. (1985) Towards via balanced growth strategies: A locational perspective. Paper prepared by UNIDO.

Fernandez (2021, June 25th). Telephonic interview at INDESA firm in Panama.

Ferraro P. and Miranda J.J. (2017) Panel Data Designs and Estimators as Substitutes for Randomized Controlled Trials in the Evaluation of Public Programs. Journal of the Association of Environmental and Resource Economists 4(1):281-317

Feriyanto, N. (2016) The effect of employment, economic growth, and investment on HDI: In provinces in Indonesia. Journal of Economics, Business, and Accountancy Ventura 19(1), 1 – 12.

Figini, P., & Gorg, H. (2011). Does foreign direct investment affect wage inequality? An empirical investigation. The World Economy, 34(9), 1455-1475

Fisher, C. D. (2010) Happiness at Work. International Journal of Management Reviews. 12: 384–412

Flannery, M. and Hankins, K. (2013). Estimating dynamic panel models in corporate finance. Journal of Corporate Finance, 19, pp.1-19.

Fleurbaey, M. (2009) Beyond GDP: The Quest for a Measure of Social Welfare. Journal of Economic Literature. 47(4), 1029–1075.

Freedman, D. (2006) On the So-Called "Huber Sandwich Estimator" and "Robust Standard Errors". The American Statistician, 60(4), 299-302.

Friedman, D. and Cassar, A. (eds) (2004) Economics Lab– An intensive course in experimental economics, London, Routledge.

Frost, J (2019) Regression Analysis: An Intuitive Guide for Using and Interpreting Linear Models. Statistics by Jim Publishing State College, Pennsylvania USA

Garcia, J. (2019, October 1st). Personal interview at CLACDS.

Garcimartin, C (2020, May 25th). Telephonic interview at Interamerican Development Bank in Panama.

Garud, R.; Kumaraswamy, A.; & Karnøe, P. (2010) Path Dependence or Path Creation? Journal of Management Studies 47(4) 760-776

Gohou, G., & Soumaré, I. (2012). Does foreign direct investment reduce poverty in Africa and are there regional differences? World Development, 40(1), 75-95.

Ghosh, M. (2006) Economic growth and human development in the Indian States. Economic and Political Weekly, Vol. 41, No. 30, pp.3321–3329.

Gökmenoğlu, K.K; Apinran, M. O.; Taşpınar, N. (2018) Impact of Foreign Direct Investment on Human Development Index in Nigeria. Business and Economics Research Journal. 9(1): 1-13

Gørgens, T.; Chirok H. and Sen X., (2020) On the asymptotic distribution of the quadratic GMM estimator of a dynamic panel data model under a unit root, Economics Letters, 197, (C)

Granger, C.W.J (1969) Investigating causal relations by econometric models and cross-spectral methods. Econometrica, 37 (3), pp.424-438

Greene, W.H. (2011). Fixed Effects Vector Decomposition: A Magical Solution to the Problem of Time-Invariant Variables in Fixed Effects Models? Political Analysis, 19(2), 135-146.

Greene, W. H. (2012). Econometric Analysis (Sixth ed.). Upper Saddle River: Pearson.

Greve, B. (2017) How to measure social performance. Social Policy and Administration. 51(7), 1002–1022

Grossman, G., Helpman, E. (1991) Innovation and Growth in the Global Economy, MIT Press Cambridge, MA

Grömling, M. ; Klös, H-P (2019) Inclusive Growth - Institutions Matter! Intereconomics. 54(3) 184-192

Gujarati, D. (2003) Basic Econometrics, 4th Edition, McGraw-Hill, Boston, USA

Gujarati, D. N; Porter, D.C (2009) Basic Econometrics (Fifth ed.) New York: McGraw-Hill, USA

Hall, J., Hackmann, C., Van der Hoeven, R., & Heintz, J. (2013). Issues for a global human
development agenda. United Nations Development Programme Human Development Report Office Occasional Paper Series

Hagerty, M. et al. (2001) Quality of life indexes for national policy: Review and agenda for research. Social Indicators Research. 55(1), 1–96

Haans, R. F., Pieters, C., & He, Z. L. (2016). Thinking about U: Theorizing and testing U-and inverted U-shaped relationships in strategy research. Strategic Management Journal, 37(7), 1177–1195.

Hansen, L. P., J. Heaton, and A. Yaron (1996) Finite-sample properties of some alternative GMM estimators. Journal of Business & Economic Statistics 14: 262-280.

Hansen, L. P. (1982) Large Sample Properties of Generalized Method of Moments Estimators. Econometrica. 50(4): 1029–1054

Hausman, J. (1978). Specification Tests in Econometrics. *Econometrica, 46*(6), 1251-1271. doi:10.2307/1913827

Hausman, J. and McFadden, C. (1984) Specification test in econometrics. Econometrica, 52, 1219-1240

Hausmann, R, Obach J, Santos MA (2017) Special Economic Zones in Panama A critical assessment. Working Paper. Center for International Development (CID) at Harvard University.

Hausmann, R., Espinoza, L., Santos, M.A. (2016a). Shifting gears A growth Diagnostic of Panama. Working Paper 325. Center for International Development (CID) at Harvard University.

Hausmann, R., Morales, J., Santos, M.A. (2016b) Economic Complexity in Panama Assessing opportunities for productive diversification. Working Paper RWP16-046. Center for International Development (CID) at Harvard University.

Haveman, R., & Smeeding, T. (2006). The role of higher education in social mobility. The Future of Children, 16(2), 125-150.

Hawking S 1988. A Brief History of Time: The Updated and Expanded Tenth Anniversary Edition. New York: Bantam Press.

Hayakawa, K., Qi, M. and Breitung, J. (2019) Double filter instrumental variable estimation of panel data models with weakly exogenous variables. Econometric Reviews 38: 1055-1088.

Helliwell, J., Layard, R. and Sachs, J. (2012), World Happiness Report. Retrieved from http://www.earth.columbia.edu/sitefiles/file/Sachs%20Writing/2012/World%20Happiness-%20Report.pdf (accessed 20 Feb 2020).

Herzer, D., Hühne, P., & Nunnenkamp, P. (2014). FDI and income inequality—evidence from Latin American economies. Review of Development Economics, 18(4), 778–793.

Hicks, P. (2012). A framework for citizen-centred social statistics and analysis. Queen's University School of Public Policy, Working Paper 48.

Hinne, M., Gronau, Q.F., Van Den Bergh, D., Wagenmakers, E.-J. (2020) A Conceptual Introduction to Bayesian Model Averaging. Advances in Methods and Practices in Psychological Science 3, 200–215.

Hirschauer, N.; Grüner, S.; Mußhoff, O.; Becker, C. (2018) Pitfalls of significance testing and p-value variability: An econometrics perspective. Statist. Surv. 12, 136--172. doi:10.1214/18-SS122.

Holland, P. W. (1988). Comment: Causal Mechanism or Causal Effect: Which Is Best for Statistical Science? Statistical Science, 3(2), 186–188.

Hoechle D. (2007) Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence. The Stata Journal; 7(3):281-312

Holtz-Eakin, D., W. Newey, and H. S. Rosen. (1988). Estimating vector autoregressions with panel data. Econometrica 56: 1371–1395.

Idrees, S. & Bakar, A. (2019) Foreign Direct Investment and Social Sectors Development: A Review. Pakistan Journal of Humanities and Social Sciences. (7)1, 93 – 105.

ILO -International Labour Organization- (2017) World Social Protection Report 2017–19: Universal social protection to achieve the Sustainable Development Goals International Labour Office – Geneva: ILO, 2017

International Commission on Peace and Food (1994) Uncommon Opportunities: An Agenda for Peace and Equitable Development, Zed Books, UK.

Imai, K., Keele, L., Tingley, D., Yamato, T. (2011) Unpacking the Black Box of Causality: Learning about Causal Mechanisms from Experimental and Observational Studies. American Political Science Review, 105 (4): 765-789.

Imenda, S (2014) Is There a Conceptual Difference between Theoretical and Conceptual Frameworks? Journal of Social Sciences, 38:2, pp185-195

IMF (2016) Tax Capacity and Growth: Is there a Tipping Point? International Monetary Fund. Working Paper No. 2016/234

Ismaeel, S; Midi, H; Sani, M (2021) Malaysian Journal of Fundamental and Applied Sciences, Vol. 17 636-646

Jaax A. (2020) Private sector development and provincial patterns of poverty: Evidence from Vietnam. World Development. 127 104747

Jacobs, G & Asokan N. (1999) Towards a Comprehensive Theory of Social Development. In: Human Choice, World Academy of Art & Science, USA

Jalilian, H., & Weiss, J. (2002). Foreign Direct Investment and Poverty in the ASEAN Region. ASEAN Economic Bulletin, 19(3), 231–253

James, S; J Gubbins, P.; Murray, Ch JL; Gakidou, E (2012). Developing a comprehensive time series of GDP per capita for 210 countries from 1950 to 2015. Population Health Metrics. 10 (1)

Jones, Ch. I. and Klenow, P. J. (2016) Beyond GDP? Welfare across Countries and Time. The American Economic Review. 106(9): 2426-2457

Joshi, D. (2007) The Relative Unimportance of Economic Growth for Human Development in Developing Democracies: Cross-Sectional Evidence from the States of India. Paper presented at the 2007 Annual Meeting of the American Political Science Association, August 30th-September 2nd, 2007.

James Joll, J (1985) Two Prophets of the Twentieth Century: Spengler and Toynbee Review of International Studies. Cambridge University Press Vol. 11, No. 2 pp. 91-104

Kemeny, T. (2010). Does foreign direct investment drive technological upgrading? World Development, 38(11), 1543–1554.

King, G.; Roberts, M. E. (2015) How Robust Standard Errors Expose Methodological Problems They Do Not Fix, and What to Do About It. Political Analysis. 23(2): 159–179.

Kleibergen, F.; R. Paap (2006). Generalized reduced rank tests using the singular value decomposition. Journal of Econometrics 133 (1): 97–126.

Kislov, R., Pope, C., Martin, G.P., Wilson P.M. (2019) Harnessing the power of theorising in Implementation research. Implementation research, 14(103) 1-8. https://doi.org/10.1186/s13012-019-0957-4

Kiviet, J. F. (2019) Microeconometric dynamic panel data methods: Model specification and selection issues. MPRA Paper 95159, Munich Personal RePEc Archive.

Kiviet, J. (2020). Microeconometric dynamic panel data methods: Model specification and selection issues. Econometrics and Statistics 13, 16-45.

Kiviet, J.F., Pleus, M. & Poldermans, R. W. (2017) Accuracy and Efficiency of Various GMM Inference. Techniques in Dynamic Micro Panel Data Models Econometrics 2017, 5, 14; doi:10.3390/econometrics5010014

Kim, H.-H., & Lee, H. (2015). Different types of liberalization and jobs in South Korean firms. East Asian Economic Review, 19(1), 71–97.

Kohler., U.; Kreuter, F. (2009) Data Analysis using Stata, Third Edition, StataCorp LP

Kolstad, I. and Tøndel, L. (2002) Social performance and Foreign Direct Investments in Developing Countries. Chr. Michelsen Institute Development Studies and Human Rights Report R 2002: 11. Bergen, Norway

Koop, G. & Korobilis, D. (2016) Model uncertainty in panel vector autoregressive models. European Economic Review, 81, pp. 115-131.

Kripfganz, S. (2019) Generalized method of moments estimation of linear dynamic panel-data models. London Stata Conference 2019 17, Stata Users Group.

Land, K.C. (2014). History of social indicators and its evolution. In Encyclopedia of quality of life and well-being research. Edited by A.C. Michalos, 2,875–2,882. Dordrecht, The Netherlands: Springer.

Land, K. C., & Michalos, A. C. (2018). Fifty years after the social indicators movement. Has the promise been fulfilled? An Assessment Agenda for the Future. Social Indicators Research. 35:835–868

Labra, R. & Torrecillas, C. (2018) Estimating dynamic Panel data. A practical approach to perform long panels. Revista Colombiana de Estadística 41(1): 31-52

Larrain, F., Lopez-Calva, L. and Rodriguez-Clare, A. (2000) Intel: A Case Study of Foreign Direct Investment in Central America. CID Working Paper Series 2000.58, Harvard University, Cambridge, MA.

Lee, J.-W., & Wie, D. (2015). Technological change, skill demand, and wage inequality: Evidence from Indonesia. World Development, 67, 238–250.

Lehnert, K., Benmamoun, M., & Zhao, H. (2013). FDI Inflow and human development: Analysis of FDI's impact on host countries' social welfare and infrastructure. Thunderbird
International Business Review, 55(3), 285–298.

Lenz, G., & Sahn, A. (2020). Achieving Statistical Significance with Control Variables and Without Transparency. Political Analysis, Cambridge University Press. 1-14. doi:10.1017/pan.2020.31

Leszczensky, L., & Wolbring, T. (2019). How to Deal with Reverse Causality Using Panel Data? Recommendations for Researchers Based on a

Simulation Study. Sociological Methods & Research. https://dx.doi.org/10.1177/0049124119882473

Leon-Gonzalez. R.; Vinayagathasan. T. (2015) Robust Determinants of Growth in Asian Developing Economies: A Bayesian Panel Data Model Averaging Approach. National Graduate Institute for Policy Studies. Tokyo, Japan.

Li, J., Ding, H., Hu, Y. Wan and G. (2021) Dealing with dynamic endogeneity in international business research. Journal of International Business Studies 52, 339–362

Liehr P, Smith MJ 1999. Middle range theory: Spinning research and practice to create knowledge for the new millennium. Advances in Nursing Science, 21(4): 81-91.

Lind, J. T., & Mehlum, H. (2010). With or without U? The appropriate test for a U-shaped relationship. Oxford Bulletin of Economics and Statistics, 72(1), 109–118

Lipsey, R. (2000) Inward FDI and economic growth in developing countries. Transnational Corporations 9, no 1.

Liu, Z. (2008). Foreign direct investment and technology spillovers: Theory and evidence. Journal
of Development Economics, 85(1), 176–193.

Lopez, L., & Weber, S. (2017) Testing for Granger causality in panel data, IRENE Working Paper 17-03, Institute of Economic Research, University of Neuchâtel,

Love, I., & Zicchino, L. (2006). Financial development and dynamic investment behaviour: Evidence from panel VAR. The Quarterly Review of Economics and Finance, 46, 190–210.

Low, H. & Costas, M. (2017) The Use of Structural Models in Econometrics. Journal of Economic Perspectives 31(2): pp33–58

Liu, L., Henley, J., Mousavi, M.M. (2021) Foreign interfirm networks and internationalization: Evidence from sub-Saharan Africa. Journal of International Management 27, 100810.

Lucas, R (1988). On the Mechanism of Economic Development. Journal of Monetary Economics, 22, 3-42.

Mayer, S. E. (2000). Income inequality, economic segregation and children's educational attainment. Chicago, IL: Irving B. Harris Graduate School of Public Policy Studies, University of Chicago.

Mabey, N. & McNally, R. (1999) Foreign Direct Investment and the Environment: From Pollution Havens to Sustainable Development. World Wildlife Fund United Kingdom Report

Mankiw, N.G, David Romer, D.; David N. Weil, D.N (1992) A Contribution to the Empirics of Economic Growth, The Quarterly Journal of Economics, Oxford University Press, vol. 107(2), pages 407-437.

McGahan, A. (2007) Academic Research That Matters to Managers on zebras, dogs, lemmings, hammers and turnips. Academy of Management Journal. 50(4), 748-753

MEF -Ministerio de economía y Finanzas- and CLACDS -Centro Latinoamericano para la Competitividad y el Desarrollo Sostenible de INCAE Business School- (2019) Informe del Índice de Progreso Social de Panama con enfoque de género 2019 Dirección de Análisis Económico y Social. Ministerio de Economía y Finanzas de Panama.

Menard, S. (2008) Handbook of Longitudinal Research: Design, Measurement, and Analysis. 1st Edition. Elsevier Academic Press. Burlington, MA, USA

Michalos, A., et al. (2011). Technical report 1.0. Technical report, The Canadian Index of Wellbeing and University of Waterloo, Waterloo, ON.

MIDES, MEF & INEC (2019) Índice de Pobreza Multidimensional de Niños, Niñas y Adolescentes. Panamá 2018. Panamá, Panamá: UNICEF.

Moosa, I (2002) Foreign Direct Investment: Theory, Evidence and Practice. Palgrave. Houndmills, Basingstoke, Hampshire RG21 6XS and 175 Fifth Avenue, New York, N.Y 10010

Moral-Benito, E. (2013) Likelihood-based Estimation of Dynamic Panels with Predetermined Regressors. Journal of Business & Economic Statistics 31:451–72.

Mulgan, G. (2013) Well-being and public policy. In S. David et al. (eds), The Oxford Handbook of Happiness, Oxford: Oxford University Press.

Neter, J., Wasserman, W., Kutner M.H. (1990) Applied Linear Statistical Models: Regression, Analysis of Variance, and Experimental Designs (3rd ed.) Homewood: Irwin. 1990

Neumayer, E., & Plümper, T. (2017). Robustness Tests for Quantitative Research (Methodological Tools in the Social Sciences). Cambridge: Cambridge University Press. doi:10.1017/9781108233590

Nonneman, W.; Vanhoudt, P. (1996) A Further Augmentation of the Solow Model and the Empirics of Economic Growth for OECD Countries The Quarterly Journal of Economics, Oxford University Press, vol. 111(3), pages 943-953.

Nordhaus, W. D., and Tobin. J. (1972). "Is Growth Obsolete?" In Economic Research: and Prospect Vol 5: Economic Growth, 1-80. Cambridge, MA: National Bureau of Research, Inc.

Norlén, H., Caperna, G. (2018) The JRC Statistical Audit of the Social Progress Index (SPI). Publications Office of the European Union, Luxembourg.

OECD/DAC (1995) Development Cooperation: Efforts and Policies of the Members of the Development Assistance Committee, OECD, Paris.

OECD (2002) Foreign Direct Investment for Development. Maximizing Benefits, Minimizing Costs. OECD Publications. Paris, France.

OECD (2008) Benchmark Definition of Foreign Direct Investment 4th Edition. OECD Publications. Paris, France. ISBN 978-92-64-04573-6

OECD (2014a) Measuring International Investment by Multinational Enterprises. Implementation by the OECD's Benchmark Definition of Foreign Direct Investment, 4th edition. Retrieved from www.oecd.org/invesment/statistics.htm (Accessed on 05 January 2022)

OECD (2014b). Focus on inequality and growth—December 2014. Retrieved from http://www.oecd.org/social/inequality-and- poverty.htm (Accessed on 13 July 2021)

OECD (2020), Employment rate (indicator). doi: 10.1787/1de68a9b-en (Accessed on 21 June 2020)

OECD (2021) The Global Forum on Transparency and Exchange of Information for Tax Purposes Retrieved from www.oecd.org/publications.htm (Accessed on 04 January 2022)

Omar, D. (2020) Inter-Relationship between Economic Development and Human Development- Analytical Study of selected Arab Countries. Utopía y Praxis Latinoamericana, vol. 25, núm. Esp.1, pp. 85-95, 2020

Orbes, I.; Dang, H. M. & Eapen, A. (2019) Foreign Direct Investment and Human Development. Academy of Management Proceedings. 2019(1).

Oud, J. H. L., & Delsing, J. M. H. (2010). Continuous time modelling of panel data by means of SEM. In K. van Montfort, J. H. L. Oud, & A. Satorra (Eds.), Longitudinal research with latent variables (pp.201–244). Heidelberg: Springer.

[dataset] Panamanian National Institute from Statistics and Census -PNISCa- (2020). Non-Financial Firms Survey database from 2012 to 2017. Provided on a CD by the Panamanian National Institute from Statistics and Census on January 20th, 2020.

[dataset] Panamanian National Institute from Statistics and Census -PNISCb- (2020). General Panamanian Statistical figures publicly available database from 2010 to 2019. Retrieved from the Panamanian National Institute from Statistics and Census website on January 15th, 2020.

[dataset] Programa de las Naciones Unidas para el Desarrollo -PNUD- (2020). Human Development Index figures for Panama Province from 2010 to 2019. Shared by email by Martín Fuentes Besoain martin.fuentes@undp.org Social Research Specialist on June 17th, 2020.

Perotti, R., 1993, 'Political Equilibrium, Income Distribution, and Growth,' Review of Economic Studies, 60.

Perri, A., Peruffo, E. (2016). Knowledge spillovers from FDI: a critical review from the international business perspective. International Journal of Management Reviews, 18(1), 3- 27.

Pesaran, M.H., Shin, Y., (1998) Generalized impulse response analysis in linear multivariate models. Economics Letters 58, 17–29.

Pesaran, M.H.; Shin, Y.; Smith, R. J. (2001) Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics. John Wiley & Sons, Ltd., vol. 16(3), pages 289-326.

Pesaran, M.H. (2004) General diagnostic tests for cross-section dependence in panels, Cambridge Working Papers in Economics, 0435, University of Cambridge.

Pesaran, M.H. (2015) Testing Weak Cross-Sectional Dependence in Large Panels, Econometric Reviews, Taylor & Francis Journals, vol. 34(6-10), pages 1089-1117, December.

Porter, M. E.; Stern, S. and Green, M. (2015) Social Progress Index 2015. Washington, DC: Social Progress Imperative.

Porter, M. E.; Stern, S. and Green, M. (2017) Social Progress Index 2017. Washington, DC: Social Progress Imperative.

Porter. M, Stern Scott & Artavia R. (2013) Social Progress Index 2013. Washington, DC: Social Progress Imperative.

Plümper, T., & V. Troeger. V. (2007) Efficient estimation of time-invariant and rarely changing variables in finite sample panel analyses with unit fixed effects. Political Analysis 15:124–39.

Ramirez, A, G Ranis and F Stewart (1998): Economic Growth and Human Development, Working Paper No 18, Queen Elizabeth House, Oxford.

Ranis, G., Stewart, F., & Ramirez, A. (2000) Economic growth and human development. World Development, 28(2), 197–219.

Ranis, G., Stewart, F. (2001) Growth and Human Development: Comparative Latin American Experience, Discussion Paper No 826, Economic Growth Centre, Yale University, New Haven.

Ranis, G (2004) Human Development and Economic Growth. Working Papers 887, Economic Growth Center, Yale University.

Ranjan, V., & Agrawal, G. (2011). FDI inflow determinants in BRIC countries: A panel data analysis. International Business Research. 4(4), 255- 263.

Ravallion, M. (2012) Mashup Indices of Development. World Bank Research Observer 27(1): 1-32.

Rebelo, S. T. (1991) Long-Run Policy Analysis and Long-Run Growth. Journal of Political Economy, 99(3), 500–521.

Reimers, F. (2006) Education and Social Progress, V. Bulmer-Thomas, J. Coatsworth y R. Cortés Conde (comps.), The Cambridge Economic History of Latin America, Cambridge University Press

Reiss., P & Wolak., F. (2007) Structural Econometric Modeling: Rationale and Examples from Industrial Organization. Chapter 64. HandbookofEconometrics. Volume 6A

Reiter, S. L., & Steensma, H. K. (2010). Human development and foreign direct investment in developing countries: The influence of FDI policy and corruption. World Development,
38(12), 1678–1691.

Reyes, G.E. (2009) Teorías de desarrollo económico y social: articulación con el planteamiento de desarrollo humano. Revista de la Facultad de Ciencias Economicas y Administrativas Universidad de Nariño Volumen X No. 1 .pp 117 - 142

Roberts, M. R., & Whited, T. M. (2013). Endogeneity in empirical corporate finance. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.). Handbook of the Economics of Finance, (pp. 493-572). New York: Elsevier.

Robeyns, I. (2016) The Capability Approach in Zalta, Edward N. (ed.) The Stanford Encyclopedia of Philosophy (Winter 2016ed.), Metaphysics Research Lab, Stanford University.

Rojas, M. (2007). The complexity of well-being: A life-satisfaction conception and a domains-of-life approach. In I. Gough & A. McGregor (Eds.). Researching well-being in developing countries: From theory to research. Cambridge: Cambridge University Press. (pp. 259–280).

Rojas, M. (2011) The Measurement of Economic Performance and Social Progress Report and Quality of Life Moving Forward. Social Indicators Research. 102:169–180

Romer, P. M. (1986). Increasing returns and long-run growth. Journal of Political Economy, 94(5), 1002-1037

Romer, P. M. (1987). Growth Based on Increasing Returns Due to Specialization. The American Economic Review, 77(2), 56–62.

Romer, P. M. (1990) Endogenous technological change. Journal of Political Economy 98, S71–S102.

Romer, P. M. (1993) Idea gaps and object gaps in economic development. Journal of Monetary Economics 32, 543–573.

Romer, P. M. (1994).The Origins of Endogenous Growth The Journal of Economic Perspectives. 8(1): 3–22

Roodman, D. (2009a) How to do xtabond2. An introduction to difference and system GMM in Stata Stata Journal. 9 (1), 86–136.

Roodman, D. (2009b) Practitioner's Corner. A note on the Theme of too many Instruments. Oxford Bulletin of Economics and Statistics 71(1), 135-158.

Rugman, A., & Verbeke, A. (2001) Subsidiary specific advantages in multinational enterprises. Strategic Management Journal 22 (3), pp. 237-250.

Rugulies, R., Aust, B., Burr, H., & Bültmann, U. (2008). Job insecurity, chances on the labour market and decline in self-rated health in a representative sample of the Danish workforce. Journal of Epidemiology and Community Health, 62(3), 245–250.

Samuelson, P.A and Nordhaus, W. D. (2010) Economics. 19th Edition. McGraw-Hill/Irwin.

Santiago, R., Fuinhas, J.A., & Marques, A. (2019) Chapter 3 - Income inequality, globalization, and economic growth: a panel vector autoregressive approach for Latin American countries. The Extended Energy-Growth Nexus, Academic Press, Book Chapter. pp 57-96.

Schaffer, M. E. (2005) XTIVREG2: Stata module to perform extended IV/2SLS, GMM and AC/HAC, LIML and k-class regression for panel data models. Statistical Software Components S456501. Boston College Department of Economics

Scheve, K., & Slaughter, M. J. (2004). Economic insecurity and the globalization of production. American Journal of Political Science, 48(4), 662–674.

Selig J. P., Preacher, K. J., Little, T.D. (2012) Modeling Time-Dependent Association in Longitudinal Data: A Lag as Moderator Approach. Multivariate Behavioral Research, Taylor & Francis Group, LLC. 47, 697–716.

Sen, A.K. (1979). Utilitarianism and welfarism. The Journal of Philosophy.76(9): 463–489

Sen, A.K. (1984). Rights and capabilities. In A. Sen, Resources, values and development. Cambridge, MA: Harvard University Press.

Sen, A.K. (1985) Commodities and capabilities. Amsterdam New York New York, N.Y., U.S.A: North-Holland Sole distributors for the U.S.A. and Canada, Elsevier Science Pub. Co. ISBN 9780444877307.

Sen, A. K (1993). Capability and well-being. In M. C. Nussbaum & A. Sen (Eds.). The quality of life. Oxford: Oxford University Press, United Nations University.

Sen, S., Bhattacharya, C.B. (2001). Does doing good always lead to doing better? Consumer reactions to corporate social responsibility. Journal of Marketing Research, 38(2), 225–243.

Senacyt -Secretaria Nacional de Ciencia Tecnología e Innovación- (2019) Consultoría para el análisis de los determinantes económicos del déficit de inversión en investigación y desarrollo en Panamá. Informe Final. Consorcio Innovos Group S.A.- Bolsa de Comercio de Córdoba.

Sharma, B., & Gani, A. (2004). The effects of foreign direct investment on human development. Global Economy Journal, 4(2), 1-17.

Shrestha, M., & Bhatta, G. (2018). Selecting appropriate methodological framework for time series data analysis. *The Journal of Finance and Data Science, 4*, 71-89.

Silla, I., de Cuyper, N., Gracia, F. J., Peiró, J. M., & de Witte, H. (2009). Job insecurity and well-being: Moderation by employability. Journal of Happiness Studies, 10(6), 739–751.

Social Progress Imperative (2018) The Global Agenda Requires Rigorous Measurement: The Contribution of the Social Progress Index to the 2030 Agenda. Note retrieved January 16th, 2020 from https://www.socialprogress.org/assets/downloads/resources/2018/SDG-Methodology-note.pdf

Social Progress Imperative (2019) Calibrating the 2018 Social Progress Index to the Sustainable Development Goals Methodology Note. Retrieved January 16th, 2020 from https://www.socialprogress.org/assets/downloads/resources/2017/2017-Social-Progress-Index-Contribution-to-the-SDGs.pdf

Solow, R.M (1956) A Contribution to the Theory of Economic Growth. The Quarterly Journal of Economics, Vol. 70, No. 1 pp. 65-94

Sparks, R., Desai, N., & Thirumurthy, P. (2014) An Examination of the Country Liquidity Index to Predict A Country's Foreign Direct Investment. International Business & Economics Research Journal. 13: 359-370

Spender, D. (2013). The education papers (Vol. 1). Oxford, England: Routledge.

Srinivasan, T. N. (1994). Human Development: A New Paradigm or Reinvention of the Wheel? The American Economic Review, Vol. 84, No. 2, May 1994, 238-243

Stanton, E. (2007). The Human Development Index: A History. PERI Working Papers: 14–15.

Stern, S. and Epner, T. (2019) 2019 Social Progress Index. Methodology Summary. Washington, DC: Social Progress Imperative.

Stiglitz J.E. (2019) Selected Works of Joseph E. Stiglitz: Volume III: Rethinking Microeconomics. Oxford University Press. United Kingdom.

Stiglitz, J. E. (2006). Stability with growth: Macroeconomics, liberalization and development. Oxford, England: Oxford University Press on Demand.

Stiglitz, J.E., Amartya S., and Fitoussi, J.P. (2009) The measurement of economic performance and social progress revisited. Reflections and overview. Commission on the Measurement of Economic Performance and Social Progress, Paris

Streeten, P. (1999). Components of a future development strategy: The importance of human
development. Finance and Development, 36(4), 30–33.

Streeten, P., Burki, S.J.,ul Haq, M., Hicks, N., Stewart, F. (1981) First Things First: Meeting Basic Human Needs in the Developing Countries. New Yor: Oxford University Press

Suliman. A. H and Elian, M. I. (2014) Foreign Direct Investment, Financial Development, and Economic Growth: A Cointegration Model. The Journal of Developing Areas. 48(3), 221-243

Tocar, S. (2018) Determinants of Foreign Direct Investment: A Review. Review of Economic and Business. 11(1): 165-196

UNCTAD (2000) ASIT Advisory Studies No. 16 Tax Incentives and Foreign Direct Investment A Global Survey. United Nations, New York and Geneva.

UNCTAD (2003) The Development Dimension of FDI: Policy and Rule-Making Perspectives. Proceedings of the Expert Meeting held in Geneva from 6 to 8 November 2002. United Nations, Geneva.

UNCTAD (2010). Foreign direct investment, the transfer and diffusion of technology, and sustainable development (2010). Expert Meeting on the Contribution of Foreign Direct Investment to the Transfer and Diffusion of Technology and Know-how for Sustainable Development in Developing Countries, Especially Least Developed Countries. United Nations, Geneva.

UNCTAD (2019) World Investment Report 2019. Special Economic Zones. United Nations, New York and Geneva.

UNCTAD (2021) World Investment Report 2021. Special Economic Zones. United Nations, New York and Geneva.

UNDP - United Nations Development Programme- (1990) Human Development Report. New York: Oxford University Press.

UNDP -United Nations Development Programme- (2015). Human development report 2015.

Van de Ven, A.H. (2007) Engaged Scholarship: A Guide for Organizational and Social Research. Oxford University Press.

Vergara, C; Ellis, L (2021, August 11th). Personal interview at PROPANAMA

Vergne, J. & Durand, R. (2010). The missing link between the theory and empirics of path dependence: conceptual clarification, testability issue, and methodological implications. Journal of Management Studies 47: 736–59.

Verhulst B. (2016). In Defense of P Values. American Association of Nurse Anesthetists Journal, 84(5), 305–308

Ward, G. (2015) Is Happiness a Predictor of Election Results? CEP Discussion Paper no. 1343, Centre for Economic Performance, LSE and ESRC.

Wei, S-J. (2000) How taxing is corruption on international investors. Review of economics and statistics. 82(1), 1-11

WHR (2020) The Nordic Exceptionalism: What Explains Why the Nordic Countries Are Constantly Among the Happiest in the World. The World Happiness Report. Sustainable Development Solutions Network (Gallup World Poll) pp128-145

Wilkinson, R. G., & Pickett, K. E. (2006). Income inequality and population health: A review and explanation of the evidence. Social Science & Medicine, 62(7), 1768–1784.

Windmeijer, F (2005) A finite sample correction for the variance of linear efficient two-step GMM estimators. Journal of Econometrics 126: 25-51.

Windmeijer, F. (2018) Testing over and under-identification in linear models, with applications to dynamic panel data and asset-pricing models. Economics Discussion Paper 18/696, University of Bristol.

Wolff, H.; Chong, H. & Auffhammer, M. (2011) Classification, detection and consequences of data error: Evidence from the Human Development Index. The Economic Journal. 121(553), 843-870

Wood, A. (1994) North-South Trade, Employment and Inequality: Changing Fortunes in a Skill-Driven World,' IDS Development Studies Series, Oxford: Oxford University Press.

Wooldridge, J.M. (2002) Econometric Analysis of Cross Section and Panel Data. Cambridge, MA: MIT Press.

Wooldridge, J.M. (2018) Introductory Econometrics: A Modern Approach, 7th ed., South-Western Cengage Learning.

World Bank (2008) World Development Indicators 2008. The World Bank. Development Data Group. 1818 H Street NW, Room MC2-812, Washington D.C. 20433. USA

World Economic Forum (2013) Foreign Direct Investment as a Key Driver for Trade, Growth and Prosperity: The Case for a Multilateral Agreement on Investment. World Economic Forum. Geneva, Switzerland.

Wursten J. (2018) Testing for Serial Correlation in Fixed-effects Panel Models. The Stata Journal. 18(1):76-100.

Wursten J. (2017) xtcfd: Stata module to perform Pesaran's CD-test for cross-sectional dependence in panel context Statistical Software Components S458385, Boston College Department of Economics.

Zhang, Y., Li, H., Li, Y., & Zhou, L. A. (2010). FDI spillovers in an emerging market: The role of foreign firms' country origin diversity and domestic firms' absorptive capacity. Strategic Management Journal, 31(9), 969–989.

9 APPENDIXES

Appendix 1. Overview of the Republic of Panama

With a total population of above 4.1 million people, Panama is one of the 6 countries in the Central American region (Guatemala, El Salvador, Honduras, Nicaragua and Costa Rica are other countries) bordering both the Caribbean Sea and the North Pacific Ocean, between Colombia and Costa Rica. See Figure 1

Figure 1. Geographic location

Source: Omniatlas (2017)

Panama is presidential democracy whose dollar-based economy rests primarily on a well-developed services sector accounting for more than ¾ of its GDP. Services include operating the Panama Canal, logistics, banking, the

Colon Free Trade Zone[116], insurance, container ports, flagship registry, and tourism. More than 120 banks from diverse countries worldwide have offshore operations in Panama, comprising the Panamanian International Financial Centre. Although public debt surpassed $37 billion in 2016 because of excessive government spending and public works projects, Panama's transportation and logistics services sectors, along with infrastructure development projects, have boosted economic growth; particularly through the Panama Canal expansion project (completed in 2016 at the cost of $5.3 billion which accounted for about 10-15% of its current GDP) which more than doubled the Canal's capacity, enabling to accommodate high-capacity ships such as tankers and Neopanamax vessels that are too large to traverse the existing canal. The United States of America and China are the top users of the Canal (the United States of America and Panama Trade Promotion Agreement entered into force in 2012).

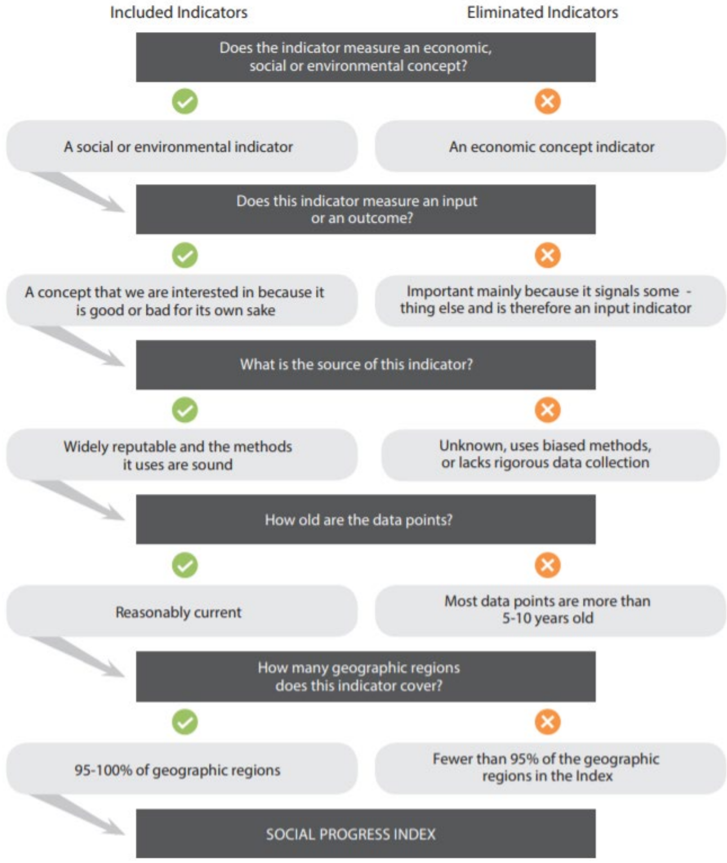
Panama is a country of demographic and economic contrasts. It is amid a demographic transition characterized by steadily declining fertility, mortality, and population growth rates, but disparities persist based on wealth, geography, and ethnicity. Panama has one of the fastest-growing economies in Latin America and dedicates substantial funding to social programs, yet poverty and inequality remain prevalent. The indigenous population (around 10% of its total population) living in 3 different reservations accounts for a growing share of Panama's poverty and extreme poverty percentage figures. In contrast, non-indigenous rural poor have been more successful at rising out of poverty via rural-to-urban labour migration. The government's large expenditures on untargeted, indirect subsidies for water, electricity, and fuel have been ineffective, but its conditional cash transfer program has shown some promise in helping to decrease extreme

[116] Commercial showcase established in 1948 to solve two basic needs at both the national and international levels: 1) Modernization of the economic service sector, 2) Streamline mechanism for regional commerce on a large scale. It has been in operation since then, becoming one of the pillars of the Panamanian economy. Imports (main ones from China, Singapore and the United States) and Exports (mainly to South America, Central America and the Caribbean) surpass annually $5 billion servicing a market of more than 525 million consumers. It captures services and centers for importation, storage, packaging and re-export of products from all parts of the world, especially electrical appliances, pharmaceutical products, liquors, among others. It contributes with almost 8 % of the GDP. Colon ZRF is first commercial free zone in the western hemisphere and the second in the world, after Hong Kong. Commercial activities are supported by transportation companies, 6 airports, 5 ocean ports equipped with up-to-date cargo handling facilities, spacious container terminals, a trans-isthmus railway and the Panama Canal annually handling 12,000 merchant vessels from 75 different countries. More than 20 banks participate have offices and branches located Colon ZFT.

poverty among the indigenous population. Panama has expanded access to education and clean water, but the availability of sanitation and, to a lesser extent, electricity remains poor. The increase in secondary schooling - led by female enrollment - is spreading to rural and indigenous areas, which would help to alleviate poverty if educational quality and the availability of skilled jobs improve. Inadequate access to sanitation contributes to a high incidence of diarrhoea in Panama's children, which is one of the leading causes of Panama's elevated chronic malnutrition rate, especially among indigenous communities.

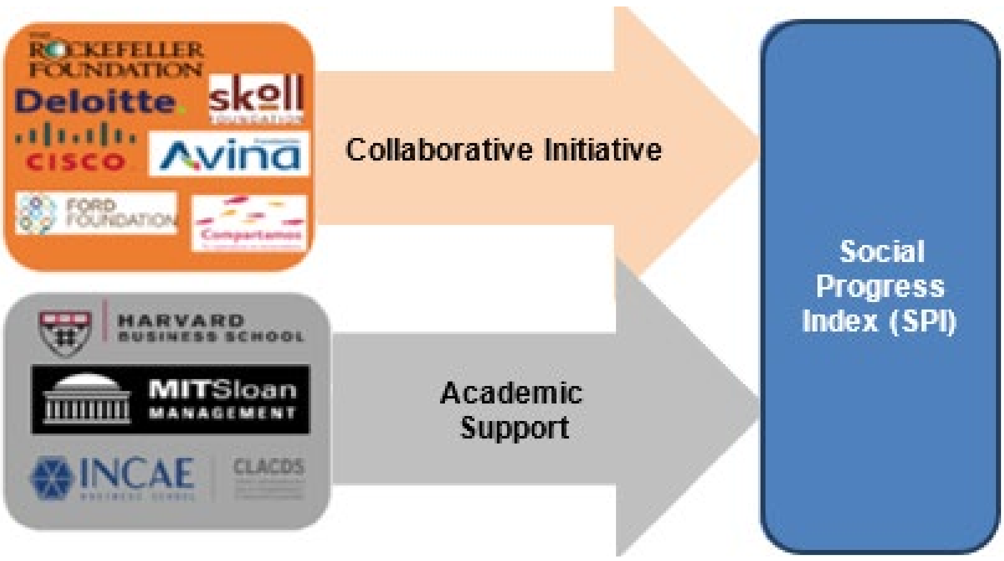
Appendix 2. Social Progress Index-related and supportive structures

Figure 1. Indicator Selection Tree



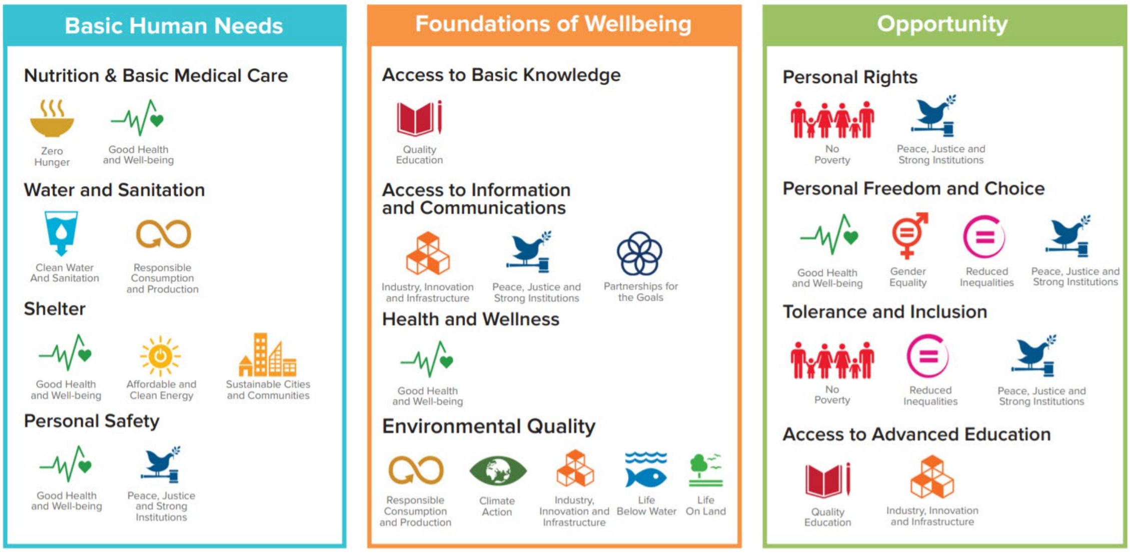
Source: Stern and Epner (2019, pp8)

Figure 2: IPS Strategic Partners.



Source: MEF and CLACDS (2019, pp15):

Figure 3. Relationship between the World Social Progress Index and the Sustainable Development Goals



Source: Social Progress Imperative (2017, pp7)

Appendix 3. Summary categories, factors, and proposed hypotheses to be researched in association with FDI.

Economic factors	1. Market size 2. Market size growth 3. Inflation 4. Trade 5. Wages 6. Income 7. Exchange rate 8. Economic Freedom 9. Economic stability 10. Liquidity 11. FDI Investment characteristics 12. Agglomeration (clustering) 13. Capital formation 14. Capital availability 15. Financial Market 16. Debt	H1: Market Size has a significant positive impact on the attraction of FDI. H2: The level of salaries correlates negatively with the volume of FDI inflows. H3: Liquidity level influences the FDI inflows positively. H4: Agglomeration has a significant positive impact on inward FDI.
Infrastructure	***17. Electric power consumption (SPI)*** ***18. Communication facilities (SPI)*** 19. ***Infrastructure (SPI)***	H5: Infrastructure facilities have a positive impact on the level of FDI inflows.
Technology	***20. Technology gap (SPI)*** 21. Technological cooperation (Proxy) ***22. Knowledge Capital (SPI)***	No hypothesis could stem from the literature review. So, this remains a factor for further studies.
Institutional Political Factors	***23. Corruption (SPI)*** 24. Privatization (Proxy) 25. Corporate Tax Rates 26. Tariffs 27. Government Intervention (Proxy) 28. Government Support (Proxy) 29. Regulatory Institutions (Proxy) ***30. Environmental Regulation Distance (SPI)*** 31. Restriction in Capital Account Transactions ***32. Property rights (SPI)*** 33. Contract enforcement (Proxy) 34. Political Constraint Index (Proxy) 35. Political Risk (Proxy) 36. Distance on political stability (Proxy) ***37. Political Democracy (SPI)*** 38. Governance Infrastructure Index (Proxy)	H6: The level of corruption has a significant negative impact on FDI inflows. H7: The level of corporate tax rates influences negatively and significantly the level of FDI. H8: Lower values of the Political risk are correlated significantly with more significant FDI inflows.
Specific Risk	39. Risk Environment (Proxy) ***40. Conflict, revolution and labour strikes (SPI)*** 41. Risk	H9: Conflicts, revolutions, and strikes negatively impact the volume of FDI in the economy. H10: Higher credit rating is positively correlated with a higher level of FDI inflows.

Human Factors	42. Population ***43. Education (SPI)*** ***44. Labor Force (SPI)*** 45. Unemployment Rate	H11: The larger population is positively and significantly correlated with FDI inflows. H12: The level of education is positively and significantly correlated with FDI inflows. H13: The higher level of unemployment has a negative impact on the volume of FDI.
Legal Integration	46. Legal Family affiliation (Proxy) 47. Bilateral Treaties 48. Supranational Integration	H14: Supranational integration and bilateral agreements have a positive and significant impact on the level of FDI inflows.
Space Factor	49. Geographic Distance 50. Distance 51. Location	H15: Greater geographical distance has a negative and significant impact on FDI flows between countries.
Entrepreneurial Matters	52. Entrepreneurial activity distance 53. Enterprise restructuring 54. Firm characteristics 55. Cost advantages 56. Economies of scales 57. Product diversification 58. Access to localized natural resources 59. Role of the oil sector	H16: Distance in entrepreneurial activity between countries is positively correlated with the FDI flow.
Cultural Factors	60. Cultural distance (Proxy) 61. Language 62. Uncertainty avoidance (Proxy) ***63. Individualism (SPI)*** ***64. Collectivism (SPI)*** 65. Power distance (Proxy) ***66. Masculinity (SPI)*** 67. Trust 68. Future orientation ***69. Egalitarianism distance (SPI)*** 70. Embeddedness/ autonomy distance (Proxy) 71. Mastery / Harmony Distance	H17: Linguistic proximity between countries has a positive and significant impact on FDI, and the linguistic distance is, respectively, associated with a low FDI flow. H18: Uncertainty avoidance is positively and significantly correlated with the FDI inflows.
Paracultural Factors	72. Psychic distance 73. Country distance 74. Socio-cultural environment 75. Colonial heritage	No hypothesis could stem from the literature review. So, this remains a factor for further studies.

Source: Tocar (2018)

Appendix 4. Overview of the philosophy of social sciences, ontology and epistemology concerning theoretical models in economics

As per the welfare economics nature of the empirical framework proposed, some ontological and epistemological notions are addressed, mainly from an economics perspective since as, quoted by Kislov et al. (2019, pp. 5): *"Diversity of philosophical and theoretical approaches, accumulated by the social sciences, genuinely reflects the complexity of the social world and the multiple ways we can make sense of it."* From a Critical Naturalism perspective (Bhaskar, 1978; Bhaskar, 1979; Bhaskar, 1998; Bhaskar & Lawson, 1998), which prioritizes/emphasizes ontology over the epistemology, in the economic systems, the object of study is the society which, in general terms is a social structure both pre-given and pre-shaped by human agents. However, those human agents are constantly shaping society, following a dynamic process of transitive knowledge flow, to which research must continuously adapt. Hence, the underlying social mechanisms associated with human agents must be profoundly and adequately researched to understand economic systems. Lawson (2006) argued that economic systems, due to their social sciences nature, are intrinsically dynamic, highly interconnected (internal social relationships), composed of open systems, structured and evolutionary. Although human and social processes may be evolutionary, they are slow, so when analyzing an economic and social phenomenon in a certain period, some elements must be considered to remain immutable.

Ontologically speaking, Coase (1992 p. 714), when referring to the growing abstraction in economic analysis, states that: "*what is studied is a system that lives in the minds of economists but not on the ground*", a phenomenon referred to as 'chalkboard economics[117]'. Additionally, Mäki (1998) contends that in economic theory, there is not only a reality associated with observable economies, but there are also 'mental economies' that do not attempt to represent or describe observable economies. Hence, establishing a single criterion according to which a theoretical economic model could be classified as irrelevant

[117] Coase (1992 p. 714) refers to a model that can be written on chalkboards using economic terms such as 'prices', 'quantities', 'factors of production', etc. , but which is clearly evident and even outrageously unrepresentative of some recognizable economic and social systems.

or unreal (due to its real or unreal characteristics or highly restrictive assumptions) becomes a cumbersome task. Consequently, the degree to which economic systems and realism are integrated depends on the notions of these two concepts (Mäki, 1998). In this sense, one can argue that there are different notions of economic reality, as it cannot be assumed that the existence of an absolute state of affairs can accurately encompass the nature of the various economic systems. This caveat may be due to how certain theorists understand the scope of the models researched. Economic models deal indirectly with reality (construed in various forms), but reality itself is not addressed due to variations in the abstraction degrees. The fact is that economic reality cannot be established as an independent object but as an interpretation based upon certain features of the analysed phenomenon and certain intellectual forms projected onto it through the models employed. In this sense, models should be considered a lens through which reality is observed so that no economic theory would escape the 'chalkboard' perspective described by Coase (1992). Thus economic reality observed from a theoretical standpoint would be a systematic interpretation of economic phenomena. Nonetheless, although there is no absolute consensus on how realism should be understood, Mäki (1998) contends that economists agree that economic realities exist, as well as economic theories capable of representing essential aspects of those realities insofar as they possess objective structures.

Economic science intends to explain observable economic phenomena directly affecting markets and population living standards, focusing on a detailed observation of facts and how theory is formulated (Lawson, 2006). Despite this, abstract economic problems continue to motivate the generation of various theories, and their promotion should not be influenced by using criteria based upon empirical verification of observable phenomena formulations. Economic theories dealing with abstract economies employ ideal notions. The underlying question on the topic is to what extent those theoretical concepts will have frequent applications. This question is answered as per Walras (1954, pp 28): *"In order to be sure to what extend academics would have the right to study sciences pursuing an end in itself, in the same way that geometers have the right [...] to study the most unique properties of the strangest figures, in the case of that they are curious [...]"*

It is worth noting that economic theory is deployed in an environment of total relativism. The defence of models of abstract economies can be mistakenly associated with arguments seeking to shield these propositions from criticisms because their nature is essentially theoretical. Instead, economic problems toward which economic analysis has been focused do not have observable referents subjected to be empirically verified. Besides, since its purpose is to determine relationships between different economic notions, this verification process should focus on corroborating the logical consistencies of these relationships. In this regard, Hausman (1989, p. 119) has highlighted that certain philosophers and theorists assert unobservable entities and properties which could be meaningful and indirectly verified, despite being impossible to verify them empirically. Hence, it is not suggested that the falsity of a claim should be ignored because such a claim could be theoretical. As per the latter, it is possible to affirm that the theoretical model is relevant since the relationships established are logically consistent. Even though the proposed theoretical model does not describe or explain observable economic events, and its structure cannot provide any economic policy recommendation, its study should not be considered irrelevant or obsolete.

Several attempts have been made to show the dangers involved in assessing all economic theories under a single criterion of confirmation or falsification, for which the only reference is the explanation of observable phenomena. Regarding the latter claim, the theoretical obsolescence of some models would result in the avoidance of studying an essential part of economic analysis that focuses on investigating empirically unobservable phenomena. For example, following this idea, many previous theoretical models would have been discarded for failing to explain relationships compared to results observed in more recent theories. This process of theory substitution, per its degree of adjustment to a relatively limited notion of reality, would show itself to be utterly deficient in contrast to a more open scientific position seeking feedback and ideas from different angles instead of imposing a preponderant vision of what a ‘good economy’ should be.

Nonetheless, as per Mäki (1998), and although not the only position, economists agree that only what possesses an empirical counterpart can be considered real. The latter means that all notions used in a theoretical model do not target to describe an empirical phenomenon that could not be regarded as real. Hence, in finding theoretical models which could potentially be empirically tested, economics research (since the early 1970s) has traditionally been carried out through econometric models (Faeth, 2009).[118] The fact is that there exist several criteria to determine the relevance of theoretical models in economics. The first criterion, proposed by Friedman (1953), establishes that a model constructed to explain a specific economic phenomenon should not be validated by the similarity of the hypotheses and the conditions of the analysed phenomenon but by its predictions about the given phenomenon. According to this criterion, the objective of a theoretical economic model is therefore not related to its explanatory power but to its predictive capacity (Hausman, 1989). The second proposed criterion states that a theoretical model should be judged by the similarity of the hypotheses formulated with empirically observable behaviour. This criterion is close to the inductive method of the economic discipline discussed by Mill (2007), which starts by formulating general premises specifying the possible causal factors of a particular observable phenomenon. A third proposed criterion revolves around assessing the relevance of a model by a) its logical consistency regardless of whether its hypotheses or predictions coincide with those of the explained phenomenon and b) its ability to solve the theoretical problem for which it was designed. Thus, depending on the position adopted, a model can be considered relevant if: 1) assumptions are adjusted to the conditions of the economic problem studied; 2) predictions are close to the phenomena sought to be explained (Friedman, 1953); and 3) comprising factors are related logically and coherently and provide answers to the questions that generated them. This third criterion highlights the logical consistency of the models, which is closely related to how economic theory is understood as a concept. The latter argument does not imply, of course, that the other criteria do not involve the logical consistency of the models as a necessary condition to consider them relevant. In passing, regarding this third criterion 3 aspects are to be highlighted:

---

[118] Until the late 1960s theorical models were majorly descriptive.

First, the criterion must be consistent with the concept of economic theory as a set of logical relationships between different well-defined factors. Thus, under this position, economic models are relevant insofar as they determine logical truths (e.g. logically consistent propositions), although they cannot directly determine 'ontological truths' about the normative or positive nature of some observable economic phenomenon. As pointed out by Rubinstein (1998, 2000, 2012), the purpose of a theoretical model is to establish logical relationships between economic notions, and the objective of a theoretical model is not exclusively to describe observable reality but try to understand the existing relationships between those notions of economic nature. In this sense, it may be possible that some typical notions of economic theory do not necessarily have an empirical reference. As argued by Lawson (2012), economics is construed upon extremely abstract formulations, which in some cases are decisively detached from a determinant empirical verification and become unsuitable platforms out of which policy recommendations could be formulated.

Second, this criterion is paramount, as some academic community members are interested in addressing theoretical problems without determining their empirical applications or economic policy implications. Hausman (1992) highlighted that some economic theory works focus on developing a 'conceptual exploration' instead of formulating theories that explain empirical phenomena. This conceptual exploration investigates the internal properties of the models without considering the relationship between the world studied by the model and observable economic events occurring (Sugden, 2000). In this way, concerns that motivate this type of research are excluded from the methodological economics visions, which focus upon empirical verification as the only criterion to assess the models' relevance.

Third, this criterion highlights the need to examine each model regarding the theoretical problems for which it was designed. While this approach seems natural, decoupling economic models from the specific issues they analysed is a common source of mistaken generalizations regarding the relevance of certain economic theory models. Hence, arguing that a particular model is obsolete implies accepting that there is only one criterion for determining the relevance of economic theories. Instead, an alternative argument is that the model is not applicable when dealing with particular economic and social problems, and its application is inappropriate for those specific situations.

In this regard, Dow (2001, p. 15) argues that classifying empirical events is only a superficial manifestation of the underlying real causal forces that cannot be directly observed. Consequently, an orthodox approach for econometric models' testing would be constrained as they only would refer to superficial characteristics[119]. Econometric models entirely rely on mathematical methods, which are basically designed to solve certain types of problems, meaning that they are incapable of solving some other paramount issues in the economics discipline, for instance, social development-related ones. However, this intellectual non-conformity in contemporary economics is not a consequence of mathematical modelling methods, mathematical-deductive reasoning, or the existence of models with highly abstract formulations. Per Lawson (2012), the true problem's origin must be sought in the model selection process, aiming to choose one that appropriately explains economic issues applied to practice. These are to be construed upon what Keynes (1938) calls "*careful observation of the operation of the system*, " which becomes crucial when linking theoretical models with practical problem-solving.

Development of theoretical models under a traditional academic knowledge approach, the traditional academic research perspective gravitates around the empirical verification of results as the preponderant position adopted. However, it is far from being the only one. Undoubtedly, it is necessary to recognize the attraction exerted by theoretical models whose results can be evidenced either through daily observation or through the design and deployment of experiments, thereby making them very popular in academic environments. An excellent example of this type is game theory, used to study problems in several knowledge fields (economics, biology, and political science, among others), and for which the results have been analyzed by experimental economics. Curiously,

[119] For instance, a critical and realistic analysis of the inflation index would seek to identify the forces that determine changes in both monetary conditions and also general price levels, rather than making specific predictions about how monetary changes would affect the general price levels.

the practical popularity of these theories does not escape from highly restrictive hypotheses and the impossibility of empirical testing, as pointed out by several criticisms. The acceptance of the models seems more closely linked with the possibility of relating their results to practical situations rather than to the presence of implausible assumptions.

If ideas about some theoretical models being obsolete or unreal are left aside, mainly leveraged on the conceptual diversity of notions of reality in social sciences, the study or research of abstract and complex theoretical models should not be constrained. On the contrary, they should be encouraged as per the following 3 arguments: 1) Commonly, theoretical models with high degrees of abstraction are regarded as the initial phase of a succession of models following a simplification pattern insofar as their levels of complexity decrease towards a close approximation of the reality of the explained phenomenon (Kanazawa, 1998, Kislov et al., 2019). Gordon (1965) implies seeing theories as accumulations of current knowledge[120], as is the trend in knowledge development in different social and natural sciences fields. In this sense, as per its close relation to Implementation research, economic models should be valued for their contributions to understanding specific issues and being exclusively recognized as the predecessors of other theories. As per Kislov et al. (2019, pp4): *"theory is a tool which should be improved with each subsequent application, rather than merely having its utility confirmed."* 2) As per Crotty (1998), as quoted in MacLean *et al.* (2002, pp192): "*any given piece of research can be described in terms of its epistemological position, the theoretical perspective taken, the methodology employed, and the specific methods chose*." So, even if the limitations of particular theoretical models are recognized, many of them are still worth being researched because they possess logical, methodological consistency and provide solutions to the questions that initially generated them, particularly if their hypotheses are subjected to empirical verification. 3) Even if a traditional theoretical model does not initially deliver practical implications, one

[120] It appears convenient to support certain theories exclusively because they served as precursors to other theories in which the potential for explaining observable phenomena turned out being higher. For instance, Koopmans (1980, p. 155) states: "*the study of the simplest models is freed from lacking realism, as they become prototypes for other more realistic but also more complicated models.*" This perspective has difficulties since it considers explaining observable economic systems' facts as the ultimate theoretical objective, and towards which economic models' construction should be directed.

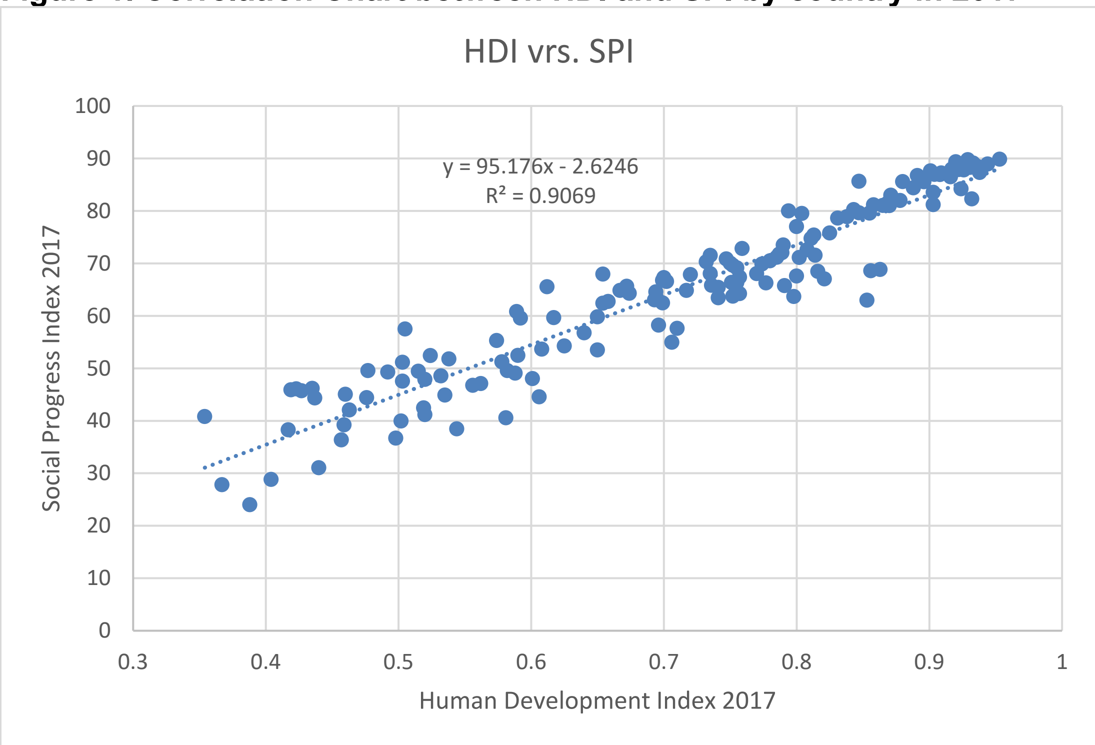
must not imply that it should be discarded because it might be capable of doing so under certain circumstances. In this regard, it has been observed since the 1970s that some models can be converted into social development models, given their implications on economic well-being (Hahn, 1970).

A myriad of arguments could potentially be used from the literature favouring the development of an academic economics discipline based on more grounded assumptions concerning the operation of economic systems, apart from being proven to be more useful in practical terms. As per Coghlan (2007, pp. 294): "*Issues of organizational concern, such as systems improvement, organizational learning, the management of change and so on are suitable subjects for action research, since (a) they are real events which must be managed in real-time, (b) they provide opportunities for both effective action and learning, and (c) they can contribute to the development of a theory of what really goes on in organizations."* Hence, from a traditional academic knowledge perspective, economics, and the theoretical models related to it, far from being in crisis, is a social science discipline going through a construction process. Migration from a traditional academic knowledge approach to an actionable-oriented knowledge production approach certainly poses challenges as it implies serious debates about knowledge and its epistemological social science research nature. The latter requires a more constructionist perspective (MacLean et al.2002, pp203) regarding the models' review process and practical applications in real social worlds. As per Coghlan (2007, pp. 295)*: "action research is not grounded in formal propositions but is a human activity which draws on different forms of knowing. In researching the actions of everyday life, the challenge is to account for the changing nature of familiar situations."* As an advantage in this transitional process, per Tanfield and Starkey (1998), as quoted in MacLean et al. (2002, pp190), social sciences research is more faithfully described by an actionable-oriented approach if compared to the traditional academic discipline-inclined approach.

Appendix 5. Employed methodology for SPI components estimation

A significant statistical correlation between the United Nations Human Developing Index (HDI) and the Social Progress Index (SPI) could be empirically demonstrated. Porter et al. (2013) reported this statistically strong association when beta-launching the SPI, as the index directly challenged HDI as the most spread-out and commonly used social development indicator in academia and the practitioner dimension. The R2 value for the 50 countries included in the beta test for SPI vs HDI in 2013 was, in passing, 0.86. This high R2 correlation value may suggest that HDI values may become suitable predictors of SPI figures. The equation in Figure 1 shows the R2 value for SPI and the HDI figures for 2017, illustratively the year chosen, for being the last year employed for the panel data set (a similar statistical pattern would emerge for the other years in the panel data). The R2 value calculated for both variables via a simple multi-variable regression is nearly 0.91. The latter corroborates the strong statistical correlation between the variables, including a higher sample of 150 countries.

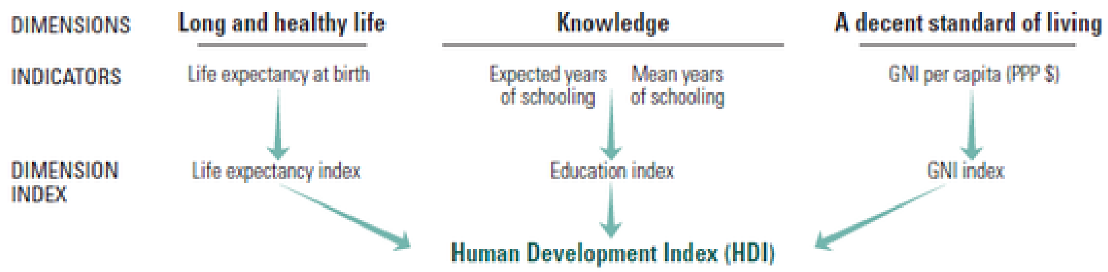
Figure 1. Correlation Chart between HDI and SPI by country in 2017



Source: Author's estimates employing Microsoft Excel®

As per the latter existing empirical relationship, in the absence of SPI panel data figures for Panama's provinces for 2012, 2013, 2014, 2015, 2016 and 2017, one may use HDI comprising indicators (shown in Figure 2) per province as regressors to predict them.

Figure 2. Human Developing Index comprising indicators



Source: PNUD (2020)

Therefore, a set of equations for projecting SPI and its comprising dimensions and indicators could be obtained via backwards-step multivariable regressions employing derived/transformed HDI indicators as predictors. A summary of the relevant statistical quality indicators for the calculated equations is depicted in Table 33.

Table 33. Statistical quality indicators summary for SPI forecasting equations.

	Multiple R	R-square	Adjusted R-square	Estimation error	F	p value (F test)
Social Progress Index	0.99	0.98	0.96	2.12	60.89	< 0.0001
Basic Human Needs	1.00	0.99	0.97	1.76	48.20	0.0044
Foundations of Wellbeing	0.99	0.97	0.95	2.73	49.13	< 0.0001
Oportunities	0.98	0.96	0.93	2.81	31.11	0.0001
Nutrition and Basic Medical Care	0.97	0.95	0.91	0.02	24.89	0.0003
Water and Sanitation	1.00	1.00	0.98	2.26	72.17	0.0024
Shelter	1.00	1.00	1.00	0.42	4495.33	< 0.0001
Personal Safety	1.00	1.00	0.99	1.60	105.36	0.0094
Access to Basic Knowlegde	0.97	0.94	***0.86***	3.52	11.12	0.0087
Access to Information and Communication	1.00	1.00	0.99	1.70	346.65	< 0.0001
Health and Wellness	1.00	1.00	0.96	1.85	25.28	***0.1540***
Environmental Quality	1.00	1.00	1.00	0.35	2486.09	0.0004
Personal Rights	0.98	0.97	0.92	0.03	20.32	0.0022
Personal Freedom and Choice	0.99	0.99	0.95	0.02	26.43	0.0105
Inclusiveness	1.00	0.99	0.99	0.87	138.56	< 0.0001
Access to Advance Education	1.00	1.00	1.00	0.27	3096.01	0.0140

Source: Author’s estimates employing Stat Tools 7.6 ® from Palisade

Out of the equations obtained, only one depicts an Adjusted R-Square figure of 0.86, as the rest ranges between 0.92 and 1.00, evidencing an extremely favourable statistical goodness of fit (GOF). Moreover, except for the Health and Wellness equation F-test p-value being 0.15, the remaining F-test p-values are below the 0.05 threshold value, indicating that the equations are all statistically suitable for forecasting purposes. Hence, indicators, dimensions and aggregated SPI figures were calculated per each Panamanian province using HDI individual comprising indicators per province (ranging from 2012-2017) as predictors. Furthermore, all the latter figures obtained were corroborated via Palisade's Neural Networks ®, where values ranged between -5% and 4% from the values calculated by multivariate regressions.

It is worth noting that provinces' specific values in a particular year were validated and adjusted -in some cases- using the pondering ratios calculations obtained from Panama's 2019 SPI report dataset (MEF & CLACDS, 2019), which as per the methodology guidelines reported in Stern & Epner (2019) allowed using a geometric average instead of an arithmetic average.

Appendix 6. Summary of Variables Descriptive Statistics and 'Non-Financial Firms Survey' database breakdown of comprising fields used for the Independent, Dependent and Moderating Variables.

A. Variables Descriptive Statistics.

Variable	Mean	Std. dev.	Min	Max	Observations
Social Progress Index	77.43	3.03	62.10	80.29	N = 860 n = 168 bar = 5.11905
FDI (Main Income Sources)	95.37	17.36	0.00	100.00	N = 860 n = 168 bar = 5.11905
Total Compensation (Household Income)	20.59	17.35	10.11	30.33	N = 852 n = 166 bar = 5.13253
Third Parties Expenditure (Productive Linkages)	17.35	17.77	0.00	92.10	N = 852 n = 166 bar = 5.13253
Masculinity Ratio	99.74	1.72	98.80	120.11	N = 860 n = 168 bar = 5.11905
Population covered by SS	81.69	13.16	70.45	89.94	N = 860 n = 168 bar = 5.11905
Average School Years	11.53	0.46	8.15	11.93	N = 860 n = 168 bar = 5.11905
Informality rate	45.55	3.31	40.15	55.03	N = 860 n = 168 bar = 5.11905
Employment rate	94.81	1.74	89.60	98.53	N = 860 n = 168 bar = 5.11905

B. Industry Percentage Composition of the sample

	Industry	Total amount ($ Millions)	Percentage
1	Wholesale and retail trade, repair of motor vehicule and motorcycles	$ 36,621.44	28.79%
2	Manufacturing	$ 21,359.54	16.79%
3	Transportation and storage	$ 15,900.26	12.50%
4	Information and communication	$ 14,019.46	11.02%
5	Administrative and support service activities	$ 13,855.04	10.89%
6	Other services activities	$ 6,471.47	5.09%
7	Education	$ 5,120.86	4.03%
8	Accommodation and food services activities	$ 4,842.22	3.81%
9	Professional, scientific and technical activities	$ 4,476.88	3.52%
10	Human health and social work activities	$ 1,865.05	1.47%
11	Arts, entertainment and recreation	$ 1,087.80	0.86%
12	Water supply, sewage, waste management and remediation activities	$ 829.05	0.65%
13	Real estate activities	$ 323.15	0.25%
14	Agriculture, forestry and fishing	$ 301.92	0.24%
15	Electricity, gas, steam and air conditioning supply	$ 117.07	0.09%
16	Mining and quarrying	$ 17.45	0.01%
	Total general	**$ 127,208.67**	**100.00%**

C. ‘Non-Financial Firms Survey’ database breakdown by variable.

Income sources break down for the Independent Variables

Classification	Description	Survey Code
Main Income sources	Income generated through products sold by the firm (Only for manufacturing industries)	CELD_1001
	Income generated through repair and maintainance of machinery and equipment	CELD_1002
	Sales of Merchandise bought for resaling (Only for Whole Sale Industries)	CELD_1003
	Sales of Merchandise bought for resaling (Only for Retail Industries)	CELD_1004
	Sales of Merchandise bought for resaling (Only for Repair and Mantainance of Vehicles Industries)	CELD_1005
	Commissions paid for merchandise sales	CELD_1006
	Electric power sales	CELD_1007
	Restaurants and affine.	CELD_1008
	Hotels and lodging in general	CELD_1009
	Storage / Warehousing	CELD_1010
	Transportation	CELD_1011
	Income generated by renting facilities (expect land)	CELD_1012
	Income generated by renting machinery and equipment (without the operator)	CELD_1013
	Income generated by renting transport means (without the driver)	CELD_1014
	Income generated by renting land	CELD_1015
	Income generated by renting royalties (patents, author's rights, brand rights, etc)	CELD_1016
	Income generated by other types of rents	CELD_1017
	Description of other types of rents	CELD_1017_DESCRIP
	Other activities 1 (specify)	CELD_1018
	Other activities 1 (specify). International Industry Code	CELD_1018_CIIU
	Other activities 1 Description (specify)	CELD_1018_DESCRIP
	Other activities 2 (specify)	CELD_1019
	Other activities 2 (specify). International Industry Code	CELD_1019_CIIU
	Other activities 2 Description (specify)	CELD_1019_DESCRIP
Financial Income	Income for received interests	CELD_1020
	Income for received dividends	CELD_1021
	Income for monetary fluctuation gains	CELD_1022
	Profit generated by sales of non financial assests	CELD_1023
	Profit generated by sales of financial assests (stock)	CELD_1024
	Profit generated by sales of financial assests (different from stock)	CELD_1025
	Financial leasing	CELD_1026
	Other financial profits	CELD_1027
	Description de other financial profits	CELD_1027_DESCRIP
Other Income	Other income. Sales of raw materials and supplies.	CELD_1028
	Other income. Other commissions for provision of services.	CELD_1029
	Despripcion of other income. Other commissions for provision of services.	CELD_1029_DESCRIP
	Other income for subsidies and incentives.	CELD_1030
	Wire money transfers and donations received (Local and abroad).	CELD_1031 + CELD_1032
	Other income generated by sales of waste, except the one resulting from industrial processes.	CELD_1033
	Other income generated by insurance claims	CELD_1034
	Other income generated through bad debt recovery.	CELD_1035
	Other income generated by cash flow surplus.	CELD_1036
	Other income sources	CELD_1037
Total Income		CELD_1000

Source: Translated by the author as extracted from the ‘Non-Financial Firms Survey’ deployed by the Panamanian National Institute from Statistics and Census.

Services Provided by Third parties comprising factors break down

Classification	Description	Sub-description	Code
Services provided by third parties	Industrial works perfomed by third parties (include home workers)		CELD_2071
	Freight and transportation expenses	Over expenses	CELD_2072
		Over income	CELD_2073
		Parking and tolls fees	CELD_2074
		Other freights	CELD_2075
	Airfares		CELD_2076
	Customs and marine agencies' expenses		CELD_2077
	Storage		CELD_2078
	Patents, trade marks, copyrights, authorrights, exploitation permits,		CELD_2079
	Telematics and informatics (except computers' rents)		CELD_2080
	Professional fees and technical assistance	Legal	CELD_2081
		Audit and accounting	CELD_2082
		Technical assitance and surveying	CELD_2083
		Engeneering and architectural services	CELD_2084
	Personnel recruitment services		CELD_2085
	Cleaning and maintenance services (except for supplies)		CELD_2086
	Reserch and development		CELD_2087
	Training		CELD_2088
	Security		CELD_2089
	Exploration and prospectation (Research and drilling)		CELD_2090
	Commision paid to third parties		CELD_2091
	Factoring Expenses		CELD_2092
	Administrative Services		CELD_2093
	Other services provided by third parties		CELD_2094

Source: Translated by the author as extracted from the 'Non-Financial Firms Survey' deployed by the Panamanian National Institute from Statistics and Census.

Total compensation comprising factors break down

Classification	Description	Sub-description	Code
Compensation	Wages and salaries	Cash	CELD_2031
		In kind	CELD_2032
	Bonuses and XIII month compensation bonus		CELD_2033+CELD_2034
	Employer's contributions (Official and private)	Employer's social security contribution	CELD_2035
		Employer's social security contribution (XIII month	CELD_2036
		Employer's education security	CELD_2037
		Proffesional risk	CELD_2038
		Health insurance	CELD_2039
		Life insurance	CELD_2040
	Other employer's expenses	Insurance claims and indemnizations	CELD_2041
		Senority	CELD_2042
		Severance paid accruel	CELD_2043
		Paid leaves for maternity, sickness or accidents	CELD_2044
		Advance notice payment	CELD_2045
		Familiar bonuses, scholarships, pluses	CELD_2046
		Employer's contribution to worker's union	CELD_2047
		Pension funds and retirement plans' contributions	CELD_2048
		Other allowances and bonuses	CELD_2049
	Business Expenses		CELD_2050

Source: Translated by the author as extracted from the 'Non-Financial Firms Survey' deployed by the Panamanian National Institute from Statistics and Census.

Appendix 7. Tests' Summary for Identifying and Circumventing Missspecifications

A. Tests for identification of endogeneity misspecifications

A.1. Omitted Variables

The 5 chosen control variables target maintaining -as much as possible- a 'ceteris paribus' assumption concerning observed heterogeneity (Barros *et al.*, 2020). Nevertheless, searching for causal associations between FDI and social development becomes a complex social science phenomenon that does not escape from the issues associated with unobserved heterogeneity (omitted variables). One may generally express in an equation the panel data that pertains to this research as $SPI_{it} = \alpha + \beta{*}MIS_{it} + \delta{*}\omega_i + \varepsilon_{it}$., in which *i* corresponds to the *i-th* panel data group (industry type) and *t* to the *t-th* year, and in which correlation between ε and the independent variable MIS (Main Income Sources as a proxy for FDI) is assumed, directly introducing endogeneity and biasing the β coefficient estimates. In turn, ω is presented in the expression as an additional variable to represent the omitted variables. In this sense, by simultaneously influencing the dependent variable SPI (as a proxy for Social Development) and independent variable (MIS), ω is hypothetically assumed to function as a control variable pursuing the 'ceteris paribus' conditions above mentioned (Barros *et al.*, 2020). In effect, as per Barros *et al.* (2020) also, this practice is considered the most common and practical solution to engage endogeneity introduced by unobserved heterogeneity, which is, in turn, identified as the most common and probably the most evident source of endogeneity (another statistically acceptable practice would include transforming MIS into other variables such as MIS^2 or MIS^3 to test some non-linear effects on SPI).

Given the latter, the arising problem now is to hypothesise which other potential omitted variables ω are explanatory of the associations between SPI and MIS, becoming, in passing, a theoretical exercise more rash than challenging. For instance, omitted variables in this research could be represented by institutional development in Panama, governmental support to MNEs, organizational culture characteristics within MNEs or competitive advantages of MNEs possibly correlated with SPI and MIS. Moreover, MNE's investing power and corporate governance practices simultaneously impacting their growth opportunities, market penetration, market value, and cost structure may also be sources of unobserved heterogeneity. The common practice in a large proportion of empirical economics research (if not all) is indeed not to search and identify the omitted variables as they are intrinsically unmeasurable or their measurement is unreliable (Barros *et al.*, 2020). Hence, omitted variables are ignored in this study due to identification restrictions, data availability constraints, and/or difficulties in computing proxy variables that effectively capture the phenomenon.

Unfortunately, excluding omitted variables identification does not imply that the endogeneity issues caused by them will not be present in the research performed, for which panel data-based approaches[121] have been contented to be useful in circumventing them. Depending on the coefficients estimator used, panel data-based approaches may effectively mitigate or eliminate the omitted variables issues, implying that they have been identified.

The chi-square hypothesis Hausman Specification Test (Hausman,1978; Hausman & McFadden, 1984) confirms the omitted variables' existence as a source of endogeneity. As per Greene (2020), the Hausman Test focuses on determining systematic and significant differences in a) estimators' consistency and b) variables' relevance (or not). Hausman Specification Test evaluates the consistency of an estimator compared to an alternative, less efficient, but known consistent estimator. From a methodological perspective, which is often the general case of econometric studies (Greene, 2020), the OLS-RE and OLS-FE[122]

[121] Panel data-based models are generally grouped into Pooled Ordinary Least Squares (Pooled OLS), Least Squares Dummy Variables Estimator (LSDV) which is closely related to Ordinary Least Squares Fixed Effects (OLS-FE) and Ordinary Least Squares Random Effects (OLS-RE).

[122] As per the Within Transformation performed, OLS-FE models are argued (Baltagi *et al.*, 2003) to be well suited to control the omitted variable bias. The only requirement for the 'unobserved heterogeneity' is to vary between panel data groups (industry type), assuming it is constant over time (or time-invariant). This implication is that every panel group (industry type) related to 'unobserved heterogeneity' is time invariantly captured over the sampling period (Fixed Effects -FE-). OLS-FE model assumes longitudinal observations exist for the same subject, so subject-specific means are estimated (Greene, 2012). The Within Transformation then eliminates FE from the data by demeaning the variables via subtraction of the group-level average overtime or taking the first difference, seeking to remove any time-invariant components in the model. Contrarily, OLS-RE and mixed models consider some or all model parameters to be random

coefficient estimators (β) are employed for this statistically sound comparison. Both methods differ because OLS-RE assumes non-correlation between regressors and unobserved heterogeneity while OLS-FE assumes its existence. Hence, the consistent estimation of their coefficients (β) fundamentally depends on assuming strict exogeneity: non-correlation between FDI and the idiosyncratic error (ε) term observed at any point in time. Given the latter, the Generalized Least Squares (GLS) estimator used to calculate the OLS-RE coefficients may be biased (Plümper & Troeger, 2007; Baltagi *et al.*, 2003), hence requiring to verify that the set of regressors is both the same for OLS-RE and OLS-FE. Encountering differences between the models (assumption of non-correlation between the regressors and the 'unobserved heterogeneity' is proven unrealistic) thereby suggests that at least one of the variables is linked to endogeneity, pointing at OLS-FE, in principle, as the most suitable model (Kohler & Kreuter, 2009). The OLS-FE, OLS-RE and the Hausman Specification Test are respectively shown in Table 34, Table 35 and Table 36.

variables, where group means are a random sample taken from the population. In this sense, time-invariant variables play an explanatory role in OLS-RE; meanwhile, in OLS-FE, they are absorbed by the intercept. This latter difference between OLS-FE and OLS-RE is advantageous provided that the individual characteristics that may or may not influence the regressors could be specified; else, it may lead to omitted variable bias in the model.

Table 34. OLS-FE Results

OLS-Fixed-Effects (Within) Regression			Number of obs	=	852	
Group variable: Industry/Sector			Number of groups	=	166	
R-squared:			Obs per group:			
Within	=	0.6506	min	=	1	
Between	=	0.7747	avg	=	5.1	
Overall	=	0.8244	max	=	6	
			F(8,678)	=	157.82	
corr(u_i, Xb) = 0.2097			Prob > F	=	0	

Social Progress Index	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
Main Variables						
FDI (Main Income Sources)	-0.0017	0.0036	-0.4800	0.6290	-0.0087	0.0053
Total Compensation (Moderating)	-0.0052	0.0044	-1.1800	0.2360	-0.0139	0.0034
Third parties expenditure (Moderating)	0.0034	0.0031	1.0800	0.2800	-0.0027	0.0094
Control Variables						
Masculinity Ratio	-1.3989	0.0678	-20.6200	0.0000	-1.5321	-1.2657
Population covered by SS	-0.0280	0.0033	-8.5800	0.0000	-0.0345	-0.0216
Average School Years	-0.7288	0.1293	-5.6400	0.0000	-0.9826	-0.4750
Employment rate	-0.2235	0.0232	-9.6300	0.0000	-0.2691	-0.1779
Informality rate	-0.2958	0.0214	-13.8000	0.0000	-0.3379	-0.2537
Constant	259.0956	6.9231	37.4200	0.0000	245.5022	272.6889

sigma_u	1.6693	
sigma_e	0.7359	
rho	0.8373	(fraction of variance due to u_i)
F test that all u_i = 0 : F(165, 678) = 8.20		Prob > F = 0.0000

Source: Author's estimates based on Stata17®

As expected from an OLS-FE model, as per Table 34, corr(u_i, Xb) is greater than 0. This figure of 0.2097 suggests a low correlation between FE (time-invariant effects or observed heterogeneity) and the explanatory variables. Nonetheless, although this correlation magnitude may appear negligible, it preliminarily indicates the existence of omitted variables potentially impacting the model. A sigma_u (standard deviation of residual within groups -industry types-) figure of 1.66 (σu) and a sigma_e (standard deviation of residuals -overall error term-) figure of 0.73 (σe) allows calculating a 'rho' estimate (intraclass correlation) of 0.83. This value indicates that up to 83% of the model's error variance may be attributed to unobserved heterogeneity (ui) stemming from the differences across industry types.

Table 35. OLS-RE Results

OLS-Random-Effects GLS Regression			Number of obs		=	852
Group variable: Industry/Sector			Number of groups		=	166
R-squared:			Obs per group:			
Within	=	0.6186	min		=	1
Between	=	0.8219	avg		=	5.1
Overall	=	0.8525	max		=	6
			Wald chi2(8)		=	2773.15
corr(u_i, Xb) = 0 (assumed)			Prob > chi2		=	0

			Theta		
	Min	**0.05**	**Median**	**0.95**	**Max**
	0.1961	0.309	0.5168	0.5168	0.5168

Social Progress Index	**Coefficient**	**Std. err.**	**t**	**P>|t|**	**[95% conf. interval]**	
Main Variables						
FDI (Main Income Sources)	-0.0098	0.0029	-3.3700	0.0010	-0.0156	-0.0041
Total Compensation (Moderating)	0.0062	0.0031	1.9900	0.0460	0.0001	0.0123
Third parties expenditure (Moderating)	0.0093	0.0027	3.4600	0.0010	0.0040	0.0145
Control Variables						
Masculinity Ratio	-1.3013	0.0440	-29.5700	0.0000	-1.3875	-1.2150
Population covered by SS	-0.0255	0.0032	-7.9200	0.0000	-0.0319	-0.0192
Average School Years	-0.1787	0.1474	-1.2100	0.2250	-0.4676	0.1101
Employment rate	-0.1188	0.0230	-5.1700	0.0000	-0.1638	-0.0738
Informality rate	-0.2366	0.0181	-13.0500	0.0000	-0.2722	-0.2011
Constant	231.3548	5.8493	39.5500	0.0000	219.8904	242.8193

sigma_u	0.54436795	
sigma_e	0.73587477	
rho	0.35368756	(fraction of variance due to u_i)

Source: Author's estimates based on Stata17®

Table 35 assumes corr(u_i, Xb) to be equal to 0, an expected figure for an OLS-RE model, as variation across industries (unobserved heterogeneity / omitted variables) is assumed to be random and uncorrelated with the regressors. A sigma_u (standard deviation of residuals within groups -industry types-) figure of 0.54 (σu) and a sigma_e (standard deviation of residuals -overall error term-) figure of 0.73 (σe) allows computing a 'rho' estimate of 0.35. As per this latter figure, one may argue that 35% of the model's error variance may be attributed to the unobserved heterogeneity (ui) stemming from the differences across industry types.

Table 36. Hausman Test Results

	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b - V_B))
	Fixed	**Random**	**Difference**	**Std. Err.**
FDI (Main Income Sources)	-0.002	-0.010	0.008	0.003
Total Compensation (Moderating)	-0.005	0.006	-0.011	0.005
Third parties expenditure (Moderating)	0.003	0.009	-0.006	0.003
Masculinity Ratio	-1.399	-1.301	-0.098	0.072
Population covered by SS	-0.028	-0.026	-0.002	0.002
Average School Years	-0.729	-0.179	-0.550	0.063
Employment rate	-0.224	-0.119	-0.105	0.017
Informality rate	-0.296	-0.237	-0.059	0.019

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha; efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(8)	=	(b-B) ' [(V_b-V_B) ^ (-1)] (b-B)
	=	315.07
Prob > chi2	**=**	**0**

Source: Author's estimates based on Stata17®

Via the Stata17® 'Hausman' command, the Hausman Specification Test was implemented. As mentioned above, the core assumption concerning OLS-RE is omitted variables being uncorrelated with regressors, contrarily to OLS-FE, which assumes they are correlated. Under this perspective, and for the Hausman Specification Test purposes, if this OLS-RE model assumption holds, its estimator becomes more efficient than the OLS-FE estimator. Nonetheless, if this assumption does not hold, the OLS-RE estimator becomes inconsistent, pointing at the OLS-FE as better a suited consistent estimator. As stemming from Table 36, results lead to the strong rejection of the null hypothesis that OLS-RE provides consistent estimates, confirming OLS-FE to arrive at better statistical performance over OLS-RE regarding coefficients' calculations. *Choosing the OLS-FE over the OLS-RE corroborates the requirement of controlling for unobserved heterogeneity. Thereby, the high suspected existence of the omitted variables is confirmed as a source of endogeneity issues.*

The results above were obtained using the 'sigmamore' subcommand on the 'Hausman' command in Stata 17®, targeting to force the contrast test to use the σ^2 estimator based on the OLS-RE estimates (8 degrees of freedom). It is worth noting that the 'sigmaless' option was also employed, complementary forcing the contrast test to employ the σ^2estimator based on the OLS-FE estimates, also resulting in the null hypothesis being rejected in favour of OLS-FE (8 degrees of freedom). Moreover, the same rejection results (with the same 8 degrees of freedom) were obtained when running both the ‘sigmamore’ and ‘sigmaless’ subcommand with the ‘constant’ option, also aiming to include the OLS-RE and the OLS-FE intercepts in the Hausman Test computation.

A.2. Measurement errors

Measurements errors are a common constraint generally found in economics research since the assumption of all variables employed in a study being measured with high precision is a premise likely to be proven wrong. In this sense, failing to appropriately measure relevant explanatory variables causes fractions of the variables’ effect to be embodied into the error term, inducing endogeneity issues (Roberts & Whited, 2013). See Appendix 7 Mathematical explanation of endogeneity sources derived from measurement errors.

Imprecision in the variable measurements for this dissertation may stem from 1) recoding errors (typos or rounding factors), which is the most evident source, 2) using proxies that diverge from the ‘real’ construct targeted to be observed, creating, in turn, underestimation effects as other explanatory variables/factors are left aside, and 3) employing averages, ratios, indexes or percentages, among others as measures for the proxy variables. Their impact on the resulting estimations depends on the assumptions made about the measurement errors’ behaviour. Table 37 summarises this research’s variables characteristics identified as measurement error sources potentially inducing endogeneity.

Table 37. Explanatory summary of variables’ measurement errors identified

Type of variable	Estimation description	Sensibility to recording errors	Proxy	Transformation required based on other figures
Dependent: Social development	Matching SPI figures per industry type was estimated as the average number of MNEs comprising a given industry in a specific province and one specific year. SPI is calculated as the geometric average of 3 dimensions of the SPI.	Low	Yes	Yes

	In turn, each dimension was calculated through the geometric average by also employing its 4 related components. As per Appendix 5, the 12 components for each year (2012 to 2017) were projected through 1) Backward-step multivariable regressions with derived/transformed independent variables (HDI comprising variables per province as predictors; 2) Neural networks 3) Pondering ratios obtained from Panama's 2019 SPI report.			
Independent : Foreign Direct Investment	Aggregated average Main Income Sources figures as a percentage of Total Income per industry type	Low	Yes	Yes
Moderating 1: Productive Linkages	Aggregated average figure per industry type (percentage of total Costs and Expenses) of 'Services provided by Third-parties'.	Low	Yes	Yes
Moderating 2: Household income	Aggregated average per industry type of amounts spent in 'compensation packages (percentage of total Costs and Expenses)	Low	Yes	Yes
Control 1	Masculinity Ratio figures were obtained by dividing the total population of males per province by the total female population per province between 2012 and 2017. Data was obtained from official publicly available Panamanian National Institute of Statistics and Census databases.	Low	No	Yes
Control 2	The total population covered by social security services figures per province ranging from 2012 to 2019 was obtained from the Panamanian National Institute of Statistics and Census. Calculations were made as a percentage of the total population registered under the Panamanian national social security system divided by the total population in the country.	Low	No	Yes
Control 3	Employment rate figures were obtained from publicly available sources at the Panamanian National Institute from Statistics and Census per province from 2012 to 2019.	Low	No	Yes
Control 4	Informal work rate figures were obtained per province from publicly available data sources from the Panamanian National Institute of Statistics and Census ranging from 2012 to 2019.	Low	No	Yes
Control 5	Figures of the average school years of the employed workforce were obtained per province from	Low	No	Yes

	the publicly available data sources from the Panamanian National Institute of Statistics and Census from 2012 to 2019.			

Source: Author

A.3. Simultaneity (Reverse Causality)

First, it is worth noting that although ‘simultaneity’ is a term associated with bidirectionally, it is nonetheless commonly referred to as ‘reciprocal causality’ or ‘reverse causality (following Leszczensky & Wolbring (2019); some authors define ‘reverse causality’ as only the unidirectional impact of the dependent variable on the regressors). For the purposes of this dissertation, the terms ‘simultaneity’, ‘reverse causality’ or ‘reciprocal causality’ will be used interchangeably.

Simultaneity between the SPI and the FDI would imply that both variables could be considered independent or dependent in relation to each other. Hence, a correlation magnitude between the regressors (either SPI or FDI, depending on their role as the dependent or independent variable) and the model’s error would be induced, making the coefficient estimators (β) biased and inconsistent (Barros *et al.*, 2020). If, for instance, SPI -as a dependent variable- directly affects the FDI, one cannot correctly identify the causal effect of FDI on the SPI. Under this perspective, statistically speaking, part of the correlation between FDI and SPI would not be driven by a causal effect of the former over the latter, or else, due to the latter affecting the former. In the presence of this positive mutual effect, simultaneity generally leads to an overestimation of the ‘true’ impact.

Furthermore, as per Li *et al.* (2021), a particular case of simultaneity -referred to as *dynamic endogeneity*- surfaces when contemporary values of independent variables are impacted by past values of the dependent variables, leading to biased estimates. As per its research design, this study, in effect, pursues testing the existence of simultaneity since a ‘vicious’ or ‘virtuous circles’ between FDI and SPI and vice versa is sought. As earlier exposed, the primary theoretical grounded causal direction points to FDI inducing economic improvement, consequently leading to social development creation. The other causal direction, meaning social development impacting FDI, is additionally targeted to be proven existent. Those potential bidirectional associations between the two variables would certainly induce endogeneity, which must be tackled.

As quoted from Gujarati & Porter (2009, pp703), *"a test of simultaneity is essentially a test of whether (an endogenous) regressor is correlated with the error term",* and so, a more focused version of the exogeneity test above presented when confirming the overall existence of endogeneity could also be employed to test the presence of simultaneity (only run considering endogenous the effects of SPI over FDI and vice versa). Table 38 exhibits the OLS regression as per Gujarati & Porter (2009, pp705) methodology, employing SPI as a dependent variable and using Main Income Sources (FDI) and its projected value (Main Income Sources Forecast) as an endogenous variable, treating the rest of the regressors as exogenous. The F-test renders the rejection of the null hypothesis, suggesting Main Income Sources (FDI) to be an endogenous variable.

Table 38. Simultaneity test as per Gujarati & Porter (2009): FDI (Main Income Sources)

Source	SS	df	MS			
				Number of obs	=	852
				F(9, 842)	>	99999
Model	7846.75	9.00	871.86	Prob > F	=	0.00
Residual	1.7E-09	842.00	2.0E-12	R-squared	=	1.00
				Adj R-squared	=	1.00
Total	7846.75	851.00	9.22	Root MSE	=	1.4E-06

Social Progress Index	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
Main Variables						
FDI (Main Income Sources)	0.0000	3.0E-09	-2.6E+00	0.010	0.0000	0.0000
Total Compensation (Moderating)	-0.0785	4.7E-09	-1.7E+07	0.000	-0.0785	-0.0785
Third parties expenditure (Moderating)	0.0303	2.9E-09	1.0E+07	0.000	0.0303	0.0303
Main Variables (Forecasted)						
Main Income Sources (Forescast)	-0.6512	2.8E-08	-2.3E+07	0.000	-0.6512	-0.6512
Control Variables						
Masculinity Ratio	-2.7875	7.9E-08	-3.5E+07	0.000	-2.7875	-2.7875
Population covered by SS	-0.0537	4.3E-09	-1.2E+07	0.000	-0.0537	-0.0537
Average School Years	-3.8121	2.8E-07	-1.4E+07	0.000	-3.8121	-3.8121
Employment rate	-0.3493	3.4E-08	-1.0E+07	0.000	-0.3493	-0.3493
Informality rate	-0.3174	2.1E-08	-1.5E+07	0.000	-0.3174	-0.3174
Constant	511.0726	1.5E-05	3.5E+07	0.000	511.0726	511.0726

(1)	Main Income Sources Forecast = 0	F(1, 842) = 5.5e+14
		Prob > F = 0.0000

Source: Author’s estimates based on Stata17®

As per the same token, Table 39 exhibits OLS regression findings when employing Main Income Sources (FDI) as a dependent variable and Social Progress Index and its projected value (Social Progress Index Forecast) as endogenous variables leaving the rest of the regressors as exogenous. In the same way, rejection of the null hypothesis as per the F-test value confirms Social Progress Index to be an endogenous variable.

Table 39. Simultaneity test as per Gujarati & Porter (2009): SPI

Source	SS	df	MS			
				Number of obs	=	852
				F(9, 842)	>	99999
Model	231547.54	9	25727.5	Prob > F	=	0.00
Residual	0.0001	842	8.1E-08	R-squared	=	1.00
				Adj R-squared	=	1.00
Total	231547.54	851	272.1	Root MSE	=	0.00028

FDI (Main Income Sources)	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
Main Variables						
Social Progress Index	0.0000	8.6E-06	9.2E-01	0.3560	0.0000	0.0000
Total Compensation (Moderating)	0.9109	8.5E-07	1.1E+06	0.0000	0.9109	0.9109
Third parties expenditure (Moderating)	0.7789	7.1E-07	1.1E+06	0.0000	0.7789	0.7789
Main Variables (Forecasted)						
Social Progress Index (Forescast)	-130.5383	7.9E-05	-1.7E+06	0.0000	-130.538	-130.538
Control Variables						
Masculinity Ratio	-183.0	1.1E-04	-1.7E+06	0.0000	-182.955	-182.954
Population covered by SS	-4.4	2.8E-06	-1.6E+06	0.0000	-4.367	-4.367
Average School Years	48.0	5.4E-05	8.9E+05	0.0000	48.042	48.043
Employment rate	-1.5	6.2E-06	-2.4E+05	0.0000	-1.488	-1.487
Informality rate	-25.5	1.6E-05	-1.6E+06	0.0000	-25.544	-25.544
Constant	29230.6	1.7E-02	1.7E+06	0.0000	29230.5	29230.6

(1)	Social Progress Index Forecast = 0	F(1, 842) = 2.7e+12
		Prob > F = 0.0000

Source: Author's estimates based on Stata17®

As previously hypothesised, the latter two F-tests confirm simultaneity as a source of endogeneity in this research, preliminarily pointing to the requirement of a Dynamic Panel Data (DPD) Model approach.

A.4. Non-random selection (selection bias)

When no clear rules are established on random sampling regarding obtaining the samples from the underlying population, selection bias is induced in panel data (Wooldridge, 2002). This absence of a random sampling process distorts the 'true population' representation, consequently distorting the potential inferences made based on the observed data. Self-selection and/or non-response decisions of respondents, in addition to the sample survey decisions made by researchers, may generally be derived from unbalanced panel data (missing observations), hence, becoming sources of endogeneity (Wooldridge, 2002).

Concerning the latter arguments, missing values in this dissertation's unbalanced panel data may stem from 1) non-responses of the MNEs personnel who filled out the surveys and 2) survey records for all MNEs in some cases do not account for all 6 years. Besides, bias selection may also be induced by the individual decisions of the officers at the Panamanian National Institute of Statistics and Census in charge of designing the 'Non-Financial Firms Survey' (e.g. using particular fields and wording for the questions and as regards the entire survey's structure). Additionally, the personnel in the field collecting the data year by year may also become a source of selection bias (e.g. they may have chosen to leave out one particular MNE in one specific year for some unknown reason). In any case, endogeneity stemming from the non-random selection is strongly suggested to be present in this study.

B. Test for identification of Heteroskedasticity and autocorrelation consistency (HAC), Cross-Sectional correlation and Autoregression

B.1. Heteroskedasticity

Heteroskedasticity [123] is of major concern in regression and variance analysis, as it invalidates statistical significance tests by assuming that models' errors have the same variance (Greene, 2000; Gujarati & Porter, 2009; Woolridge, 2018). Assumptions that variables are homoskedastic cause unbiased but inefficient coefficient estimators besides biased standard errors (SE)[124], resulting in an overestimation of the GOF (Goodness of Fit), calculated via Pearson coefficient.

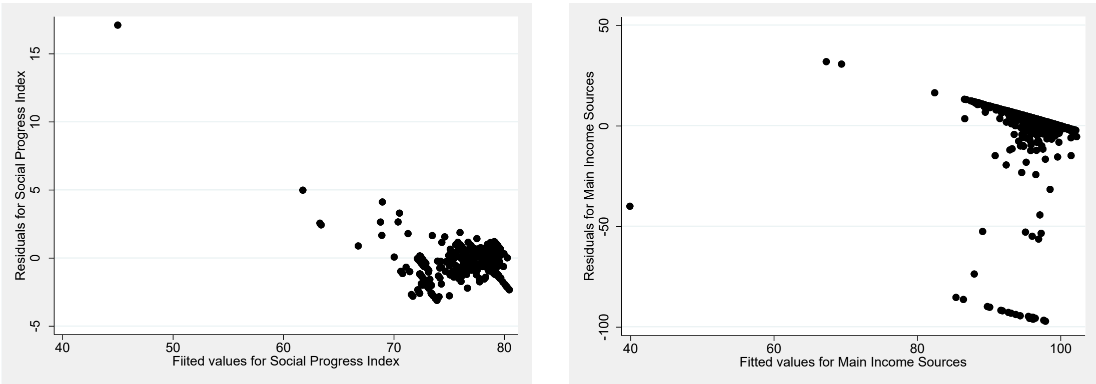
Models' error variance for this research is suggested to be random rather than constant, exhibiting a heteroskedastic pattern (implying errors' variances are not the same from observation to observation). This assumption stems from two

[123] As per Greene (2000), Gujarati & Porter (2009), and Woolridge (2018), homoscedasticity occurs when all variables in a sequence of random variables have the same finite variance. (known as homogeneity of variance). Complementary heteroskedasticity occurs when the variability of the random disturbance is different across elements.

[124] For instance, in the case of OLS, although a coefficient estimator remains unbiased in the presence of heteroskedasticity, it becomes inefficient (related to its errors variances), and so the GLS (generalized least squares) approach becomes a better suited estimator.

facts: 1) endogeneity induced by measurement errors (independent, moderating or control variables are obtained by some sort of transformation of individual figures from different sources, and 2) industry-type figures not exhibiting homogeneous behaviours (as per their different operational, technological, and cost-structural natures, as also argued when discussing time-invariant effects -FE-). As shown in Chart 10, when Forecasted Values (Fitted Values) are graphed in a scatter plot vs their residuals for both the SPI and Main Income Sources as dependent and independent variables, 3 clear facts strongly suggest the presence of heteroskedasticity: 1) residuals are not randomly distributed around the 0 line, thereby depicting a no linear relationship, 2) residuals do not form a 'horizontal band' around the 0 line, confirming that no error terms variances are not equal, and 3) several residuals are outliers as they 'stand out' within the clustered patterns.

Chart 11. Heteroskedasticity patterns for Social Progress Index and Main Income Sources



Source: Author's estimates based on Stata17®

Following Greene (2000, p. 598), a modified Wald hypothesis test specifically intended for the FE model's residuals (Stata17® community-contributed *xttest3* command) is employed to confirm or discard groupwise heteroskedasticity. The hypothesis tested is that $sigma^2$ *(i)* = $sigma^2$ for all *I,* where *N_g* is the number of cross-sectional units (industry types), with a test statistic outcome of a distributed chi-squared (*N_g*) under a null hypothesis of homoskedasticity. As per Table 40 results, the null hypothesis of homoskedasticity is rejected, thus confirming the presence of heteroskedasticity in the model's SE variance.

Table 40. Modified Wald Test for Heteroskedasticity

Modified Wald Test for groupwise heteroskedasticity in Fixed Effect Regression Model	
H0: sigma (i) ^ 2 = sigma ^ 2 for all i	
Chi2 (166)	8.60E+27
Prob > chi2	0.00000

Source: Author's estimates based on Stata17®

Although heteroskedasticity does not directly bias coefficient estimates, it does bias coefficient variance and hence their SE, likely above or below the true variance of the population. Therefore, controlling for heteroskedasticity-robust standard errors (referred to as 'Huber/White Sandwich Estimator', Eicker–Huber–White SE or simply as White standard errors) via the *'robust'* option from Stata17®. Such Huber/White Sandwich Estimators are calculated by employing the maximum likelihood estimation (MLE[125]) variance, pursuing the correction of the model's second-order misspecification (heteroskedasticity concerns expectations of the second moment of the errors) caused by classical SE (King & Roberts, 2015; Freedman, 2006). Hence, as SE stemmed from the data rather than the model, they are considered robust to many of the model's assumptions.

B.2. Serial Correlation (Autocorrelation)

Serial correlation[126] (also called autocorrelation or lagged correlation) occurs when error terms in a cross-sectional time series (panel data) are transferred from one period to another (Greene, 2000; Gujarati & Porter, 2009; Woolridge, 2018). In this sense, the error for one period *t* is correlated with the error of a subsequent *t + 1* period, so they cannot be considered statistically

[125] MLE maximises the parameters' estimation by means of a probability distribution under which the observed data is most probable for the assumed statistical model (point estimates in the parameter space that maximizes the likelihood function are known as MLE). MLE has become a dominant means of statistical inference for both being intuitive and flexible.
[126] Serial correlation frequently occurs when data is sampled at a much higher frequency than the changes occurring in the underlying phenomena. Serial correlation may be the result of several issues: 1) Inefficient estimates and forecasted figures stemmed from those estimates (Inefficient estimators perform well in the presence of larger sample sizes, in comparison to efficient estimators which provide the most information about a sample); 2) Exaggerated GOF and tendency of SE to be small (for positive serial correlations in cross-sectional time series and an independent variable with growing trends as time advances); 3) T-statistics and R-square values tend to be large; and 4) False positives for significant coefficients, meaning that regression coefficients wrongly appear to be statistically significant.

independent samples. This ‘error rollover effect’ in the residuals often results in the model´s misspecification, generally perceived as noise rather than information (Wursten, 2018; Baum & Schaffer, 2013). Compared to heteroskedasticity, serial correlation induces dynamic misspecifications by wrongly assuming ‘true models’ as static. The most common form is first-order serial correlation [127] which can either be positive when the error in period *t* is carried over into a positive error in period *t+1*; or negative by following the same rationale. Second-order serial correlation implies that errors in period *t* also impact period *t+2* (usually in data exhibiting seasonality). Rarely orders above the second order occur. Serial correlation does not affect data directly, and although the estimated coefficients remain unbiased, SEs related to those coefficients are highly impacted. By artificially inflating SE's statistical power, independent tests are assumed to show more statistical power than in reality, leading to wrong/unreliable results (e.g. t-statistic, confidence intervals).

As per Baum & Schaffer (2013), micro panels (few periods) do not often exhibit serial correlation effects in comparison to macro panels (long time series over 20-30 years), where tests usually focus on revealing their existence. Nonetheless, when more data points are available in macro panels’ samples, estimators’ efficiency gains are favoured, so serial correlation effects are ignored, especially in the eyes of practitioners. Hence, although applying statistical significance tests would reveal a static model that should be replaced by a more suitable Dynamic Panel Data Model, testing for serial correlation is frequently avoided in research.

Even when several hypothesis tests specifically address serial correlation detection, not all are appropriate for fitting FE regressions (Wursten, 2018). For instance, the *abar* test proposed by Arellano & Bond (1991) and implemented by Roodman (2009) as a command in Stata17® is a spread-out test for serial correlation in Dynamic Panel Data (DPD) models (Wursten, 2018), which

[127] Serial correlation can stem from various sources: 1) Incomplete/incorrectly modelled persistency in the dependent variable, 2) Time-varying omitted variables; 3) Changes in time-invariant variables’ effect strengths; 4) Regressors misspecified lagged effects; 5) Treatment effects conditionality on unobserved time-varying variables; and 6) Spatial dependence.

unfortunately can not be directly applied after the *xtreg* command[128]. Wursten (2018) reports 5 tests -contemporarily cited in the literature- applicable to FE: 1) a generalization for FE of the Durbin-Watson test (based on the work of Bhargava *et al.*, 1982), which is unsuitable for unbalanced panel data. Additionally, it relies on critical values reference tables depending on two parameters (cross-sections (N) and periods (T)) which may not be available when either N or T o both are large; 2) the Breusch-Godfrey LM (Lagrange Multiplier) statistics, which is unsuitable for first-order serial correlation testing. Besides, although the version based on the work of Baltagi & Wu (1999) is suitable for unbalanced panel data, the one based on the developments of Baltagi & Li (1991, 1995) is not; and 3) Wooldridge–Drukker (WD) test (articulated as the *xtserial* command in Stata17®), performs a Wald test based on OLS residuals of the first-differenced model (Stemming from the development of Drukker (2003) based upon the original idea of Wooldridge (2002)). Unfortunately, it is limited to first-order serial correlation under the assumption of constant variance over time. Furthermore, it is cumbersome when applied to many or large models; 4) Two residual-based tests developed upon the work of Born & Breitung (2016) and implemented as the *xthrtest* and *xtqptest* commands in Stata17®. Although it relaxes the constant variance assumption, the former is unfortunately only suited for first-order serial correlation, contrarily to the latter, which tests serial correlation of any order. Nonetheless, neither of those two latter tests is appropriate for unbalanced panel data; and 5) A LM portmanteau test statistic proposed by Inoue & Solon (2006) and implemented by Wursten (2018) in Stata17® via the *xtistest* command. This residual-based test is suitable for unbalanced panels with small T and could test serial correlation up to any order, thereby becoming the best available option to determine serial correlation. Table 41 shows Inoue & Solon's (2006) test results for up to 6 order serial correlation (the 6 years that pertain to this research), where all p-values are found below the 0.05 threshold. If the null hypothesis is accepted, serial correlation is nonexistent; as in this case, rejection confirms the existence of serial correlation in all 6 time periods (2012 – 2017).

---

[128] The rationale is that the *abar* test assumes right-hand-side variables not being post-determined, meaning uncorrelated with future errors. Future values of regressors for dynamic settings can be dependable on future errors. Future values of original regressors impact contemporary values of the mean-deviations transformed versions (Roodman, 2009).

Table 41. Inoue-Solon test of serial correlation

Inoue and Solon (2006) LM-test as post-estimation
Panelvar: Industry/Sector
Timevar: Year
p (lags): 6

Up to order	IS-stat	p-value
1	17.58	0.0040
2	23.28	0.0060
3	26.3	0.0100
4	26.57	0.0220
5	26.57	0.0320
6	24.41	0.0070

Notes: Under N0, LM ~ chi2((T-1)(T-2)/2)
H0: No auto-correlation of any order
Ha: Auto-correlation up to order 6

Source: Author's estimates based on Stata17®

Results of Table 41 could be further corroborated or discarded via the Cumby-Huizinga (C-H) general test for autocorrelation, which applies to cross-sectional times series with fixed-T and large-N, as is the case of this research panel data. In the C-H test (based on the work of Cumby & Huizinga (1990, 1992) and implemented in Stata17® by Baum & Schaffer (2013) via the *actest* post-estimation command), the null hypothesis assumes that time-series are moving average (MA) of known order q (either zero or a positive value). MA models do not rely on past values to predict future figures; instead, they employ errors from previous forecasts (In other words, it depends on residuals of past values to make predictions). The generic alternative is that time series autocorrelations are nonzero at lags greater than q. The C-H test is general enough for testing the hypothesis that the cross-sectional time series does not show serial correlation (q=0) or the null hypothesis of its existence vanishing in time at a known finite lag (q>0). The C-H test is advantageous in a sense; it tests autocorrelation at lag orders (q+1)...(q+s) under the null hypothesis that the series being tested is MA(q).[129]

[129] Generally, a C-H test, when applied to lag order m, implies the null hypothesis that the time series is MA(q) where $q = m – 1$, so that suitable for testing overlapping data, which usually becomes an issue as observation interval is shorter than the holding period.

As a post-estimation command, *actest* operates on its residuals after several regression types (Stata17® regress, *newey, ivreg, ivregress, ivreg2* and *newey2* commands) which unfortunately do not include Stata17®'s *xtreg, fe* command. Hence, it is worth noting that an equivalent *non-dynamic* pooled OLS panel data model using the Stata17® *regress* command with dummy variables for the panels (industry types) and Time Effects could be employed to obtain an equivalent model as if the Stata17® *xtreg, fe* command were being used (Roodman (2009) and Baum & Schaffer (2013)). This equivalent model is required to be *non-dynamic* as the C-H test aims to corroborate the existence of serial correlation. Contrarily, having employed a *dynamic model* would have directly sought autoregression, meaning that the dependent variable lagged values would also become regressors, a distinctive characteristic of any Dynamic Panel Data (DPD) model. Results up to the 6-order are shown in Table 42. A q=0 option, specifying no serial correlation, is assumed under the null hypothesis for individual lag-order tests.

Table 42. Cumby-Huizinga (C-H) test of autocorrelation (serial correlation)

Cumby-Huizinga test for autocorrelation
H0: variable is MA process up to order q
HA: serial correlation present at specified lags > q

H0: q=0 (serially uncorrelated) HA: s.c. present at range specified				H0: q=0 (serially uncorrelated) HA: s.c. present at lag specified			
lags	**chi2**	**df**	**p-val**	**lag**	**chi2**	**df**	**p-val**
1 - 1	13.443	1	0.0002	1	13.443	1	0.0002
1 - 2	61.319	2	0.0000	2	44.29	1	0.0000
1 - 3	220.206	3	0.0000	3	172.26	1	0.0000
1 - 4	322.743	4	0.0000	4	35.122	1	0.0000
1 - 5	674.004	5	0.0000	5	10.439	1	0.0012
1 - 6	674.004	6	0.0000	6	0	1	1.0000

Test allows predetermined regresors / instruments
Test requires conditional homoskedasticity

Source: Author's estimates based on Stata17®

As per the latter table's results, the null hypothesis is rejected as per the left block values, confirming serial correlation existence in every possible time range (t-1 or t-6). Furthermore, rejection of the null hypothesis on the right block is additionally confirmed, providing evidence of serial correlation at every individual lag up to q=6. In summary, both test block sides corroborate the existence of serial correlation for the model, characterised as a moving average function up to the order of 6: MA(6). Furthermore, the presence of serial correlation up to t-6 also suggests that the independent variable exerts some lagged effect on the dependent variable over the entire time range (Selig *et al.*, 2012).

It is worth mentioning that the C-H test is, in essence, a Stata17® *abar* post-estimation test (Baum & Schaffer, 2013), which, as aforementioned, cannot, unfortunately, be directly executed after the *xtreg, fe* command. However, as in the case of the C-H test, an equivalent *non-dynamic* pooled OLS FE panel data model is employed using Stata17®'s *regress* command to develop an equivalent model upon which the *abar* post-estimation test could be run seeking to buttress the presence of serial correlation further. Findings are exhibited in Table 43.

Table 43. Arellano-Bond test of autocorrelation (serial correlation)

Arellano Bond Autocorrelation Test (abar), lags (5)							
Arellano-Bond test for	AR(1): z	=	3.25	Pr	>	z =	0.001
Arellano-Bond test for	AR(2): z	=	-5.91	Pr	>	z =	0.000
Arellano-Bond test for	AR(3): z	=	-11.65	Pr	>	z =	0.000
Arellano-Bond test for	AR(4): z	=	-5.26	Pr	>	z =	0.000
Arellano-Bond test for	AR(5): z	=	-2.87	Pr	>	z =	0.004

Source: Author's estimates based on Stata17®

The *abar* test assumes no autocorrelation under the null (q = 0) for a particular lag. As per the z-values for every single lag (based on the Chi-Square hypothesis test), the null hypothesis is rejected to corroborate the existence of a serial correlation up the 5 lagged order.

B.3. Cross-sectional Correlation

Cross-sectional dependence (also referred to as spatial correlation) occurs when within the same cross-section, all units are correlated. Cross-sectional dependence is often attributed to unobserved factors (including the nature of cross-sectional correlation itself and the correlations' magnitude across cross-sections) that are common to all units and impact each of them, although likely in different ways[130]. Cross-sectional correlation impacts coefficients' estimation by making them inconsistent and inefficient. [131] Moreover, as per De Hoyos & Sarafidis (2006), cross-sectional is usually present in unbalanced data panels with many cross-sectional units and few time series, which is the case of this research. Moreover, having confirmed the existence of omitted variables, cross-sectional correlation is suggested to present in the model, a premise that must be formally tested.

Wursten (2017) reports several tests implemented in Stata17® for testing cross-sectional dependence, some commands specifically implemented for FE (*xtreg, fe* regressions): 1) *xtcsd*, only employed as a post-estimation command; 2) *xtcd,* which allows testing any variable in the regression to be analysed; 3) *xtcd2*, based on *xtcd* plus additional features (correlations' histograms and more post-estimation possibilities), and 4) *xtcdf* as per the development of Wursten (2017) based upon the work of Pesaran (2004, 2015) which is the test herein chosen as it is appropriate for both balanced and unbalanced panels. This test is reported to perform similarly to the abovementioned tests but runs significantly faster. It explores the mean correlation between panel units, assuming that the transformation of the sum of pairwise correlations between panel units follows the standard normal distribution (Pesaran, 2004). The null hypothesis is either strict cross-sectional independence (Pesaran, 2004) or weak cross-sectional dependence (Pesaran, 2015). The findings are shown in Table 44.

[130] De Hoyos & Sarafidis (2006) argue that the emergence of cross-sectional correlation in data appears to exhibit a growing trend in the specialized literature. The justifying rationale seems to lay on the fact that during previous decades globalization has created a phenomenon of ever-increasing integration of systems (countries, organizations, industries, among others), which implies strong interdependencies between cross-sectional units in the data employed in research.
[131] When common factors (omitted variables or unobserved heterogeneity manifested through the disturbance term) are uncorrelated with regressors (which is unusual), the standard homogeneous estimators for panel data (FE, RE, or FD) become inefficient but consistent, in turn causing SE to be biased (also called contemporaneous correlation).

Table 44. Cross-sectional correlation test based on Pesaran (2004, 2015)

xtcd test on variables Social Progress Index errors
Panelvar: Industry/Sector
Timevar: Year

Variable	CD-test	p-value	Average joint T	mean p	mean abs(p)
Social Progress Index	176.834	0.000	5.12	0.59	0.67
Residuals	39.685	0.000	5.17	0.13	0.5

Notes: Under the null hypothesis of cross-section independence, CD ~ N(0,1)
P-values close to zero indicate data are correlated across panel groups.

Source: Author's estimates based on Stata17®

As per the p-value figure, the null hypothesis of cross-sectional independence / weak cross-sectional dependence (CD-statistic is distributed ~ N (0,1)) is rejected, indicating the strong correlation between panel units. It is worth noting that when dealing with unbalanced panel data, the test ignores combinations of panel units with fewer than 3 joint observations, as those correlations are considered unmeaningful.

B.4. Autoregression

Under Baltagi (2011), autoregression occurs when one regressor predicts its future behaviour based on past behaviour. In Dynamic Panel Data (DPD) models, the dependent variable is lagged to become a regressor (an additional independent variable), pursuing testing the extent to which past values are explanatory of its contemporary or future values. The Stata17® *abar* test command has been previously suggested to perform better on dynamic models, making it more suitable for Autoregression testing. Thus, based upon the same transformation rationale previously applied to obtain *non-dynamic* pooled OLS FE, a DPD Model could also be estimated by lagging the dependent variable (SPI) either 1 or 2 orders (years) in a Pooled OLS-FE regression with Time Effects. SPI then becomes an additional regressor(s), explanatory of its future values: (L(0/1).SocialProgressIndex or L(0/2).SocialProgressIndex in Stata17® notation. Results of the *abar* test are shown as follows as per Table 45.

Table 45. Arellano-Bond test of Autoregression

xtcd test on variables Social Progress Index errors										
Panelvar: Industry/Sector										
Timevar: Year										
1-year lag of dependent variable	Arellano-AR(1):	z	=	1.18	Pr	>	z	=	0.23680
	Arellano-AR(2):	z	=	-3.97	Pr	>	z	=	0.00010
	Arellano-AR(3):	z	=	-3.88	Pr	>	z	=	0.00010
	Arellano-AR(4):	z	=	-2.04	Pr	>	z	=	0.04120
2-year lag of dependent variable	Arellano-AR(1):	z	=	-2.92	Pr	>	z	=	0.0035
	Arellano-AR(2):	z	=	-2.51	Pr	>	z	=	0.0121
	Arellano-AR(3):	z	=	-2.26	Pr	>	z	=	0.0241

Source: Author's estimates based on Stata17®

Although when employing the dependent variable's 1-year lag, the null hypothesis of no Autoregression is accepted for AR(1) so that confirming no autoregression, findings AR(2), AR(3) and AR(4) confirm otherwise. When employing a 2-year lag of dependent variable, all 3 figures, AR(1), AR(2) and AR(3), confirm the existence of autoregression when treating the model as a dynamic pooled OLS FE model. This significant incidence of autocorrelation (all but one AR() value) is, in effect, an expectable finding in this research, where endogeneity by simultaneity was confirmed.

Appendix 8. List of Instrumental Variables (IVs) employed in the DPD Models using two steps GMM-System iterative estimator

Total Compensation as a moderating variable

```
Instruments corresponding to the linear moment conditions:
 1, model(fodev):
   L1.SocialProgressIndex L2.SocialProgressIndex
 3, model(fodev):
   L1.TotalCompensation
 4, model(fodev):
   L3.MainIncomeSources L2.TotalCompensation L3.TotalCompensation
   L2.(c.MainIncomeSources#c.TotalCompensation)
   L3.(c.MainIncomeSources#c.TotalCompensation)
   L4.(c.MainIncomeSources#c.TotalCompensation)
 5, model(fodev):
   MainIncomeSources L2.MainIncomeSources L4.MainIncomeSources
   L.MainIncomeSources c.MainIncomeSources#c.MainIncomeSources
   L1.(c.MainIncomeSources#c.MainIncomeSources)
   L2.(c.MainIncomeSources#c.MainIncomeSources)
   L3.(c.MainIncomeSources#c.MainIncomeSources)
   L4.(c.MainIncomeSources#c.MainIncomeSources)
   c.MainIncomeSources#cL.MainIncomeSources
   L1.(c.MainIncomeSources#cL.MainIncomeSources)
   L2.(c.MainIncomeSources#cL.MainIncomeSources)
   L3.(c.MainIncomeSources#cL.MainIncomeSources)
   c.MainIncomeSources#cL2.MainIncomeSources
   L1.(c.MainIncomeSources#cL2.MainIncomeSources)
   L2.(c.MainIncomeSources#cL2.MainIncomeSources)
   L3.(cL.MainIncomeSources#cL.MainIncomeSources) L4.TotalCompensation
   c.TotalCompensation#c.TotalCompensation
   L1.(c.TotalCompensation#c.TotalCompensation)
   L2.(c.TotalCompensation#c.TotalCompensation)
   L3.(c.TotalCompensation#c.TotalCompensation)
   L4.(c.TotalCompensation#c.TotalCompensation) L3.L.MainIncomeSources
   TotalCompensation c.MainIncomeSources#c.TotalCompensation
   L1.(c.MainIncomeSources#c.TotalCompensation)
   cL.MainIncomeSources#c.TotalCompensation
   L1.(cL.MainIncomeSources#c.TotalCompensation)
   L2.(cL.MainIncomeSources#c.TotalCompensation)
   L3.(cL.MainIncomeSources#c.TotalCompensation)
   cL2.MainIncomeSources#c.TotalCompensation
   L1.(cL2.MainIncomeSources#c.TotalCompensation)
   L2.(cL2.MainIncomeSources#c.TotalCompensation)
 6, model(mdev):
   MasculinityRatio PopcoveredbySS Averageschoolyearsofemployed Employmentrate
   Informalworkrate
 7, model(level):
   D.L2.MainIncomeSources D.(c.MainIncomeSources#c.Thirdpartiesexpend)
   D.(cL.MainIncomeSources#c.Thirdpartiesexpend)
   D.(cL2.MainIncomeSources#c.Thirdpartiesexpend) D.MainIncomeSources
   D.L.MainIncomeSources D.TotalCompensation
   D.(c.MainIncomeSources#c.TotalCompensation)
   D.(cL.MainIncomeSources#c.TotalCompensation)
   D.(cL2.MainIncomeSources#c.TotalCompensation) D.Thirdpartiesexpend
   D.(c.TotalCompensation#c.Thirdpartiesexpend)
   D.(c.MainIncomeSources#c.TotalCompensation#c.Thirdpartiesexpend)
   D.(cL.MainIncomeSources#c.TotalCompensation#c.Thirdpartiesexpend)
   D.(cL2.MainIncomeSources#c.TotalCompensation#c.Thirdpartiesexpend)
 8, model(level):
   2015bn.Year 2016.Year 2017.Year
 9, model(level):
   _cons
```

Source: Author's estimates based on Stata17®

Third Parties Expenditure as a moderating variable

```
Instruments corresponding to the linear moment conditions:
 1, model(fodev):
   L1.SocialProgressIndex L2.SocialProgressIndex
 2, model(fodev):
   L2.MainIncomeSources
 4, model(fodev):
   L3.MainIncomeSources L4.MainIncomeSources L1.Thirdpartiesexpend
   L1.(c.MainIncomeSources#c.Thirdpartiesexpend)
   L2.(c.MainIncomeSources#c.Thirdpartiesexpend)
   L3.(c.MainIncomeSources#c.Thirdpartiesexpend)
   L4.(c.MainIncomeSources#c.Thirdpartiesexpend)
 5, model(fodev):
   MainIncomeSources L.MainIncomeSources
   c.MainIncomeSources#c.MainIncomeSources
   c.MainIncomeSources#cL.MainIncomeSources
   c.MainIncomeSources#cL2.MainIncomeSources
   cL.MainIncomeSources#cL.MainIncomeSources
   cL.MainIncomeSources#cL2.MainIncomeSources
   cL2.MainIncomeSources#cL2.MainIncomeSources
 6, model(fodev):
   L2.Thirdpartiesexpend L3.Thirdpartiesexpend L4.Thirdpartiesexpend
   c.Thirdpartiesexpend#c.Thirdpartiesexpend
   L1.(c.Thirdpartiesexpend#c.Thirdpartiesexpend)
   L2.(c.Thirdpartiesexpend#c.Thirdpartiesexpend)
   L3.(c.Thirdpartiesexpend#c.Thirdpartiesexpend)
   L4.(c.Thirdpartiesexpend#c.Thirdpartiesexpend)
 7, model(fodev):
   Thirdpartiesexpend c.MainIncomeSources#c.Thirdpartiesexpend
   cL.MainIncomeSources#c.Thirdpartiesexpend
   cL2.MainIncomeSources#c.Thirdpartiesexpend
 8, model(mdev):
   MasculinityRatio PopcoveredbySS Averageschoolyearsofemployed Employmentrate
   Informalworkrate
 9, model(level):
   D.TotalCompensation D.MainIncomeSources D.L.MainIncomeSources
   D.L2.MainIncomeSources D.(c.MainIncomeSources#c.TotalCompensation)
   D.(cL.MainIncomeSources#c.TotalCompensation)
   D.(cL2.MainIncomeSources#c.TotalCompensation) D.Thirdpartiesexpend
   D.(c.MainIncomeSources#c.Thirdpartiesexpend)
   D.(cL.MainIncomeSources#c.Thirdpartiesexpend)
   D.(cL2.MainIncomeSources#c.Thirdpartiesexpend)
   D.(c.Thirdpartiesexpend#c.TotalCompensation)
   D.(c.MainIncomeSources#c.Thirdpartiesexpend#c.TotalCompensation)
   D.(cL.MainIncomeSources#c.Thirdpartiesexpend#c.TotalCompensation)
   D.(cL2.MainIncomeSources#c.Thirdpartiesexpend#c.TotalCompensation)
 10, model(level):
   2015bn.Year 2016.Year 2017.Year
 11, model(level):
   _cons
```

Source: Author’s estimates based on Stata17®

Appendix 9. GMM-System estimations with dummy variables for major industrial sectors

Total Compensation as a moderating variable

```
Group variable: COD_CIIU                  Number of obs        =       518
Time variable: Year                       Number of groups     =       149

Moment conditions:     linear =      67     Obs per group:    min =         1
                    nonlinear =       0                       avg =   3.47651
                        total =      67                       max =         4

                                 (Std. err. adjusted for 149 clusters in COD_CIIU)
```

SocialProgressIndex		Coefficient	WC-Robust std. err.	t	P>|t|	[95% conf.	interval]
SocialProgressIndex							
L1.		-0.0109712	0.0473506	-0.23	0.817	-0.1045418	0.0825993
L2.		-0.0129145	0.0333498	-0.39	0.699	-0.0788178	0.0529889
MainIncomeSources							
-.		-0.0195513	0.014799	-1.32	0.188	-0.048796	0.0096933
L1.		0.0021696	0.0085785	0.25	0.801	-0.0147826	0.0191219
L2.		0.002419	0.007954	0.3	0.761	-0.0132991	0.0181371
TotalCompensation		-0.0585542	0.0534324	-1.1	0.275	-0.1641432	0.0470349
c.MainIncomeSources#c.TotalCompensation		0.0004874	0.0004816	1.01	0.313	-0.0004643	0.0014391
cL.MainIncomeSources#c.TotalCompensation		0.0001204	0.0004705	0.26	0.798	-0.0008094	0.0010502
cL2.MainIncomeSources#c.TotalCompensation		9.81E-06	0.0003702	0.03	0.979	-0.0007218	0.0007414
StructureDummy							
	2	0	(empty)				
	3	-184.8097	211.8743	-0.87	0.384	-603.4992	233.8798
	4	-171.9637	208.2618	-0.83	0.41	-583.5145	239.587
	5	-189.0085	211.6697	-0.89	0.373	-607.2939	229.2768
	6	-193.0753	219.1551	-0.88	0.38	-626.1526	240.002
	7	-191.1219	218.6277	-0.87	0.383	-623.157	240.9133
	8	-229.8929	321.0371	-0.72	0.475	-864.3015	404.5158
	9	-188.3373	215.4612	-0.87	0.383	-614.115	237.4405
	10	-407.0886	490.5998	-0.83	0.408	-1376.574	562.3967
	11	-185.0681	220.8223	-0.84	0.403	-621.4401	251.3038
	12	-197.5731	221.6862	-0.89	0.374	-635.6523	240.5061
	13	-99.30399	199.6766	-0.5	0.62	-493.8894	295.2814
	14	-343.4001	374.8861	-0.92	0.361	-1084.221	397.4207
	15	-221.9614	247.0307	-0.9	0.37	-710.1243	266.2014
	16	-198.5387	226.1064	-0.88	0.381	-645.3527	248.2752
MasculinityRatio		-1.109308	0.3780423	-2.93	0.004	-1.856366	-0.3622505
PopcoveredbySS		-0.0264193	0.011523	-2.29	0.023	-0.0491902	-0.0036484
Averageschoolyearsofemployed		0.1130392	0.5990465	0.19	0.851	-1.07075	1.296828
Employmentrate		-0.1029183	0.1069593	-0.96	0.338	-0.314283	0.1084464
Informalworkrate		-0.287006	0.0362772	-7.91	0	-0.3586943	-0.2153178
Year							
	2015	-0.5185186	0.2859638	-1.81	0.072	-1.083618	0.0465808
	2016	0.0088292	0.2529268	0.03	0.972	-0.4909852	0.5086436
	2017	-0.0546263	0.2930022	-0.19	0.852	-0.6336345	0.5243818
_cons		405.527	245.6471	1.65	0.101	-79.90169	890.9557

Note 1: Industry Dummy 1 is omitted to avoid the Dummy Trap
Note 2: Industry Dummy 2 is dropped as there is only 1 observation on the sample

```
Instruments corresponding to the linear moment conditions:
 1, model(fodev):
   L1.SocialProgressIndex L2.SocialProgressIndex
 4, model(fodev):
   L4.MainIncomeSources L3.TotalCompensation L4.TotalCompensation
   L1.(c.MainIncomeSources#c.TotalCompensation)
   L3.(c.MainIncomeSour ces#c.TotalCompensation)
 5, model(fodev):
   L1.MainIncomeSources c.MainIncomeSources#c.MainIncomeSources
   L1.(c.MainIncomeSources#c.MainIncomeSources)
   L3.(c.MainIncomeSources#c.MainIncomeSources)
   L4.(c.MainIncomeSources#c.MainIncomeSources)
   c.MainIncomeSources#cL.MainIncomeSources
   L3.(c.MainIncomeSources#cL.MainIncomeSources)
   c.MainIncomeSources#cL2.MainIncomeSources
   L1.(c.MainIncomeSources#c L2.MainIncomeSources)
   L2.(c.MainIncomeSources#cL2.MainIncomeSources)
   L1.(cL.MainIncomeSources#cL.MainIncomeSources)
   L3.(cL.MainIncomeSources#cL.MainIncomeSources)
   cL.MainIncomeSources#cL2.MainIncomeSources
   L1.(cL.MainIncomeSources#cL2.MainIncomeSources)
 6, model(fodev):
   L1.TotalCompensation L2.TotalCompensation
   c.TotalCompensation#c.TotalCompensation
   L1.(c.TotalCompen sation#c.TotalCompensation)
   L2.(c.TotalCompensation#c.TotalCompensation)
   L3.(c.TotalCompensation#c.TotalCompensation)
   L4.(c.TotalCompensation#c.TotalCompensation)
 7, model(fodev):
   MainIncomeSources L2.MainIncomeSources L3.MainIncomeSources
   L3.L.MainIncomeSources TotalCompensation
   c.MainIncomeSources#c.TotalCompensation
   L2.(c.MainIncomeSources#c.TotalCompensation)
   L4.(c.MainIncome Sources#c.TotalCompensation)
   cL.MainIncomeSources#c.TotalCompensation
   L1.(cL.MainIncomeSources#c.TotalCompensation)
   L2.(cL.MainIncomeSources#c.TotalCompensation)
   L3.(cL.MainIncomeSources#c.TotalCompensation)
   cL2.MainIncomeSources#c.TotalCompensation
   L1.(cL2.MainIncomeSources#c.TotalCompensation)
   L2.(cL2.MainIncomeSources#c.TotalCompensation)
 8, model(mdev):
   MasculinityRatio PopcoveredbySS Average schoolyearsofemployed Employmentrate
   Informalworkrate
 9, model(level):
   D.MainIncomeSources D.(c.MainIncomeSources#c.Thirdpartiesexpend)
   D.(cL.MainIncomeSources#c.Thirdpartiesexpend)
   D.(cL2.MainIncomeSources#c.Thirdpartiesexpend) D.L.MainIncomeSources
   D.L2.MainIncomeSources D.TotalCompensation
   D.(c.MainIncomeSources#c.TotalCompensation)
   D.(cL.MainIncomeSources#c.TotalCompensation)
   D.(cL2.MainIncomeSources#c.TotalCompensation) D.Thirdpartiesexpend
   D.(c.TotalCompensation#c.Thirdpartiesexpend)
   D.(c.MainIncomeSources#c.TotalCompensation#c.Thirdpartiesexpend)
   D.(cL.MainIncomeSources#c.TotalCompensation#c.Thirdpartiesexpend)
   D.(cL2.MainIncomeSources#c.TotalCompensation#c.Thirdpartiesexpend)
 10, model(level):
   2015bn.Year 2016.Year 2017.Year
 11, model(level):
   _cons
```

Sargan-Hansen test of the overidentifying restrictions	0.01189023
H0: overidentifying restrictions are valid	29.6405779

2-step moment function chi2(23)	=	29.64
Prob > chi2	=	0.8409

Sargan-Hansen (difference) test of the overidentifying restrictions
H0: (additional) overidentifying restrictions are valid

2-step weighting matrix from full model

Moment conditions	Excluding chi2	df	p	Difference chi2	df	p
1, model(fodev)	23.0647	22	0.3981	12.9722	1	0.2334
2, model(fodev)	33.9459	23	0.1659	2.0909	0	.
4, model(fodev)	28.1554	16	0.1303	7.8814	7	0.3432
5, model(fodev)	23.4829	17	0.1342	12.554	6	0.2507
6, model(fodev)	28.4456	17	0.44	7.5912	6	0.2696
7, model(fodev)	19.6085	18	0.3553	16.4284	5	0.1573
8, model(mdev)	24.9131	18	0.1273	11.1237	5	0.149
9, model(level)	27.6523	18	0.2675	8.3846	5	0.1363
10, model(level)	32.3429	22	0.3717	3.6939	1	0.03546
model(fodev)	.	-7	.	.	.	.
model(level)	27.6523	5	0	8.3846	18	0.9723

```
Arellano-Bond test for autocorrelation of the first-differenced residuals
H0: no autocorrelation of order 1      z =   -3.7949   Prob > |z|   =    0.0001
H0: no autocorrelation of order 2      z =    0.0561   Prob > |z|   =    0.9553
```

Third Parties Expenditure as a moderating variable

```
Group variable: COD_CIIU                    Number of obs        =       518
Time variable: Year                         Number of groups     =       149

Moment conditions:     linear =      54     Obs per group:    min =         1
                    nonlinear =       0                       avg =   3.47651
                        total =      54                       max =         4

                                           (Std. err. adjusted for 149 clusters in COD_CIIU)
```

			WC-Robust				
SocialProgressIndex		**Coefficient**	**std. err.**	**t**	**P>|t|**	**[95% conf.**	**interval]**
SocialProgressIndex							
L1.		-0.0290104	0.0374436	-0.77	0.44	-0.1030036	0.0449828
L2.		-0.039201	0.0264944	-1.48	0.141	-0.0915573	0.0131552
MainIncomeSources							
-.		0.0336503	0.0322782	1.04	0.299	-0.0301354	0.0974359
L1.		-0.0093252	0.0067792	-1.38	0.171	-0.0227218	0.0040713
L2.		0.0094799	0.0069411	1.37	0.174	-0.0042366	0.0231965
Thirdpartiesexpend		0.2152792	0.2144342	1	0.317	-0.208469	0.6390274
c.MainIncomeSources#c.Thirdpartiesexpend		-0.0022932	0.0017234	-1.33	0.185	-0.005699	0.0011125
cL.MainIncomeSources#c.Thirdpartiesexpend		0.0003108	0.0004164	0.75	0.457	-0.000512	0.0011336
cL2.MainIncomeSources#c.Thirdpartiesexpend		-2.86E-04	0.0003119	-0.92	0.361	-0.0009019	0.0003308
StructureDummy							
	2	0	(empty)				
	3	-14.8465	143.8162	-0.1	0.718	-299.045	269.352
	4	-8.075224	133.1249	-0.06	0.652	-271.1463	254.9959
	5	-8.614795	142.169	-0.06	0.552	-289.5581	272.3285
	6	-16.52246	151.5004	-0.11	0.713	-315.9058	282.8609
	7	-17.50465	150.4661	-0.12	0.708	-314.8441	279.8348
	8	-36.77154	217.1993	-0.17	0.866	-465.9839	392.4409
	9	-17.79469	146.3573	-0.12	0.703	-307.0147	271.4253
	10	-50.497	323.1718	-0.16	0.876	-689.124	588.13
	11	-13.39101	150.2805	-0.09	0.962	-310.3636	283.5816
	12	-14.32628	157.0645	-0.09	0.627	-324.7049	296.0523
	13	-11.23365	77.48835	-0.14	0.685	-164.3601	141.8928
	14	-34.02122	259.0007	-0.13	0.696	-545.8383	477.7959
	15	-23.99511	163.6991	-0.15	0.684	-347.4846	299.4944
	16	-19.91568	160.9809	-0.12	0.702	-338.0337	298.2023
MasculinityRatio		-1.484094	0.5418044	-2.74	0.007	-2.554766	-0.4134219
PopcoveredbySS		-0.0390036	0.0134827	-2.89	0.004	-0.065647	-0.0123603
Averageschoolyearsofemployed		-0.814985	1.031734	-0.79	0.431	-2.853817	1.223847
Employmentrate		-0.2013926	0.0898151	-2.24	0.026	-0.3788782	-0.0239069
Informalworkrate		-0.3259218	0.0417734	-7.8	0	-0.4084712	-0.2433724
Year							
	2015	-0.2648481	0.2813838	-0.94	0.348	-0.8208971	0.2912008
	2016	0.1424756	0.1953523	0.73	0.467	-0.2435645	0.5285157
	2017	0.2430149	0.3070478	0.79	0.43	-0.3637491	0.8497789
_cons		287.4484	161.6162	1.78	0.077	-31.92508	606.8218

Note 1: Industry Dummy 1 is omitted to avoid the Dummy Trap
Note 2: Industry Dummy 2 is dropped as there is only 1 observation on the sample

```
Instruments corresponding to the linear moment conditions:
 1, model(fodev):
   L1.SocialProgressIndex L2.SocialProgressIndex
 2, model(fodev):
   L1.MainIncomeSources
 4, model(fodev):
   L3.MainIncomeSources L4.MainIncomeSources L2.Thirdpartiesexpend
   L3.Thirdpartiesexpend L1.(c.MainIncomeSources#c.Thirdpartiesexpend)
   L2.(c.MainIncomeSources#c.Thirdpartiesexpend)
   L3.(c.MainIncomeSources#c.Thirdpartiesexpend)
   L4.(c.MainIncomeSources#c.Thirdpartiesexpend)
 5, model(fodev):
   L2.MainIncomeSources c.MainIncomeSources#c.MainIncomeSources
   c.MainIncomeSources#cL.MainIncomeSources
   c.MainIncomeSources#cL2.MainIncomeSources
   cL.MainIncomeSources#cL.MainIncomeSources
   cL.MainIncomeSources#cL2.MainIncomeSources
   cL2.MainIncomeSources#cL2.MainIncomeSources
 6, model(fodev):
   L1.Thirdpartiesexpend L4.Thirdpartiesexpend
   c.Thirdpartiesexpend#c.Thirdpartiesexpend
   L1.(c.Thirdpartiesexpend#c.Thirdpartiesexpend)
   L2.(c.Thirdpartiesexpend#c.Thirdpartiesexpend)
   L3.(c.Thirdpartiesexpend#c.Thirdpartiesexpend)
   L4.(c.Thirdpartiesexpend#c.Thirdpartiesexpend)
 7, model(fodev):
   MainIncomeSources Thirdpartiesexpend
   c.MainIncomeSources#c.Thirdpartiesexpend
   cL.MainIncomeSources#c.Thirdpartiesexpend
   cL2.MainIncomeSources#c.Thirdpartiesexpend
 8, model(mdev):
   MasculinityRatio PopcoveredbySS Averageschoolyearsofemployed Employmentrate
   Informalworkrate
 9, model(level):
   D.MainIncomeSources D.L.MainIncomeSources
   D.(c.MainIncomeSources#c.TotalCompensation)
   D.(cL.MainIncomeSources#c.TotalCompensation)
   D.(cL2.MainIncomeSources#c.TotalCompensation) D.L2.MainIncomeSources
   D.Thirdpartiesexpend D.(c.MainIncomeSources#c.Thirdpartiesexpend)
   D.(cL.MainIncomeSources#c.Thirdpartiesexpend)
   D.(cL2.MainIncomeSources#c.Thirdpartiesexpend) D.TotalCompensation
   D.(c.Thirdpartiesexpend#c.TotalCompensation)
   D.(c.MainIncomeSources#c.Thirdpartiesexpend#c.TotalCompensation)
   D.(cL.MainIncomeSources#c.Thirdpartiesexpend#c.TotalCompensation)
   D.(cL2.MainIncomeSources#c.Thirdpartiesexpend#c.TotalCompensation)
 10, model(level):
   2015bn.Year 2016.Year 2017.Year
 11, model(level):
   _cons
```

Sargan-Hansen test of the overidentifying restrictions
H0: overidentifying restrictions are valid

2-step moment functions, 2-step weighting matrix	chi2(37)	=	36.2563
	Prob > chi2	=	0.5037

```
Sargan-Hansen (difference) test of the overidentifying restrictions
H0: (additional) overidentifying restrictions are valid

2-step weighting matrix from full model
```

Moment conditions	Excluding chi2	df	p	Difference chi2	df	p
1, model(fodev)	33.3197	36	0.5967	2.9366	1	0.2866
4, model(fodev)	33.5299	33	0.4416	2.7264	4	0.6046
5, model(fodev)	24.8778	23	0.3566	11.3785	14	0.6561
6, model(fodev)	33.7843	31	0.3344	2.472	6	0.8716
7, model(fodev)	21.919	22	0.4647	14.3373	15	0.5001
8, model(mdev)	29.9928	33	0.6176	6.2636	4	0.1803
9, model(level)	23.648	31	0.8246	12.6083	6	0.1497
10, model(level)	24.3737	35	0.9108	11.8826	2	0.2226
model(fodev)	.	-6	.	.	.	.
model(level)	23.648	19	0.21	12.6083	18	0.8143

```
Arellano-Bond test for autocorrelation of the first-differenced residuals
H0: no autocorrelation of order 1      z =    -3.4453    Prob > |z|   =     0.0006
H0: no autocorrelation of order 2      z =     0.9356    Prob > |z|   =     0.3495
```

Appendix 10. Panel Vector Autoregression Reduced-Form Model and IRFs per Moderating Variable.

After testing the non-existence Unit-Root effects (hence exhibiting stationarity) on the 4 core variables and finding that a first-order model is the most suitable choice per the latter 2 subsections' results, PVAR reduced forms are constructed employing the *gmm estimator*. The PVAR approach, stemming from the work of Holtz-Eakin *et al.* (1988) and implemented in Stata17® by Abrigo & Love (2016) through the *pvar* community-contributed command, controls for autocorrelations and time trends, additionally allows handling unobserved heterogeneity (from a cross-sectional perspective) over the basis of a *gmm estimator* and GMM-System calculations. It fits multivariate panel regression of each dependent variable on lags of itself, lags of all other dependent variables and exogenous variables. Besides SPI and Main Income Sources, the moderating variables and interaction effects were included in the PVAR Reduced-Form models to explore their interactions. As per the model selection subsection 6.2.2, only 1-order lags were used (*lags(1)*) for the following models shown in Table 46 and Table 47.

Table 46. PVAR Reduced-Form model employing Total Compensation as a moderating variable.

Panel Vector Autoregression
GMM Estimation

Number of obs	=	236
Number of panels	=	128
Ave. no. of T	=	1.844

Final GMM Criterion Q(b) = 0.127
Initial weight matrix: Indentity
GMM weight matrix: Robust

		Coefficient	**Std. err.**	**z**	**P>|z|**	**[95% conf. interval]**	
Social Progress Index							
Social Progress Index	L1.	-0.1090	0.0363	-3.0100	0.0030	-0.1801	-0.0379
Main Income Sources	L1.	0.0280	0.0076	3.6900	0.0000	0.0131	0.0430
Total Compensation	L1.	0.0810	0.0181	4.4800	0.0000	0.0455	0.1165
Main Income Sources x Total Compensation	L1.	-0.0009	0.0002	-4.5400	0.0000	-0.0012	-0.0005
Masculinity Ratio		-3.3638	0.2420	-13.9000	0.0000	-3.8381	-2.8896
Population covered by SS		-0.0740	0.0076	-9.7800	0.0000	-0.0888	-0.0591
Average School Years		-3.8867	0.7745	-5.0200	0.0000	-5.4046	-2.3688
Employment rate		0.1742	0.0377	4.6200	0.0000	0.1003	0.2481
Informality rate		0.1463	0.0448	3.2700	0.0010	0.0585	0.2341
Main Income Sources							
Social Progress Index	L1.	1.2173	0.4683	2.6000	0.0090	0.2995	2.1352
Main Income Sources	L1.	-0.5279	0.1493	-3.5400	0.0000	-0.8205	-0.2353
Total Compensation	L1.	-2.0541	0.3895	-5.2700	0.0000	-2.8176	-1.2907
Main Income Sources x Total Compensation	L1.	0.0220	0.0041	5.3800	0.0000	0.0140	0.0301
Masculinity Ratio		11.0036	4.4394	2.4800	0.0130	2.3025	19.7048
Population covered by SS		0.0835	0.1454	0.5700	0.5660	-0.2014	0.3684
Average School Years		45.5936	12.3473	3.6900	0.0000	21.3934	69.7938
Employment rate		-2.1225	0.5398	-3.9300	0.0000	-3.1804	-1.0645
Informality rate		-2.4938	0.5871	-4.2500	0.0000	-3.6444	-1.3431
Total Compensation							
Social Progress Index	L1.	4.4390	1.5829	2.8000	0.0050	1.3367	7.5414
Main Income Sources	L1.	-0.5554	0.5528	-1.0000	0.0454	-1.6388	0.5280
Total Compensation	L1.	-0.4601	1.3480	-0.3400	0.7330	-3.1022	2.1820
Main Income Sources x Total Compensation	L1.	0.0087	0.0141	0.6200	0.5380	-0.0190	0.0363
Masculinity Ratio		6.3640	14.5172	0.4400	0.6610	-22.0892	34.8171
Population covered by SS		0.1042	0.5322	0.2000	0.8450	-0.9390	1.1473
Average School Years		52.5220	33.0476	1.5900	0.1120	-12.2501	117.2942
Employment rate		-4.5958	1.6157	-2.8400	0.0040	-7.7626	-1.4290
Informality rate		-4.4940	1.6887	-2.6600	0.0080	-7.8037	-1.1843
Main Incomes Sources x Total Compensation							
Social Progress Index	L1.	462.1515	155.1887	2.9800	0.0030	157.9872	766.3158
Main Income Sources	L1.	-65.2339	54.7068	-1.1900	0.2330	-172.4573	41.9895
Total Compensation	L1.	-129.3077	134.1767	-0.9600	0.3350	-392.2892	133.6737
Main Income Sources x Total Compensation	L1.	1.7001	1.4047	1.2100	0.2260	-1.0531	4.4533
Masculinity Ratio		1030.4260	1375.4820	0.7500	0.4540	-1665.4680	3726.3210
Population covered by SS		28.2849	51.7129	0.5500	0.5840	-73.0706	129.6403
Average School Years		5327.0330	3170.3300	1.6800	0.0930	-886.6997	11540.7700
Employment rate		-456.2492	157.3560	-2.9000	0.0040	-764.6612	-147.8372
Informality rate		-429.3235	163.2774	-2.6300	0.0090	-749.3414	-109.3056

Instruments: l(1/3).(SPI MIS TC MISxTC) MasculinityRatio PopcoveredbySS Averageschoolyearsofemployed Employmentrate Informalworkrate

Test of overidentifying restriction:
Hansen's J chi2(32) = 29.98(p = 0.569)

Source: Author's estimates based on Stata17®

In Table 46, contemporary values and lags 1-3 for SPI, Main Income Sources, Total Compensation and the interaction of Total Compensation and Main Income Sources employed as endogenous variables were additionally employed as IVs via the *instlags(0/3)* sub-option. The forward orthogonal deviation option was employed to remove the Fixed Effects (fod) in light of unbalanced panel data[132]. Additionally, the *td* option, subtracting its cross-sectional mean before estimating each variable, was employed to remove time-fixed effects from all the variables before any other transformation. Control variables were treated as exogenous and employed as IVs. The *overid* option was also used to calculate the Hansen J estimator to test IVs' validity. Although one deal with unbalanced panel data, the *gmmstyle*[133] option was not required to arrive at valid and reliable IVs.

The Hansen's J Test exhibits a p-value = 0.569, confirming that the IVs used in the PVAR model are relevant and valid. Since one is not dealing with the GMM-Sys regression model but a PVAR model that employs the *gmm estimator*, the p-values threshold specification for the variables' coefficients proposed by Kiviet (2019, pp19) no longer are applicable. Instead, a threshold p-value of 0.10, as proposed in the work of Abrigo & Love (2016), is employed. For the specifications that pertain Social Progress Index and Main Income Sources, none of the endogenous variables lay above the 0.10 p-value suggested threshold. Moreover, as regards the control variables, only Population covered by SS (p-value=0.566) in the regression where Main Income Sources is the dependent variable lay above the 0.10 threshold p-value. In light of this p-value being associated with control variables (1 out 5 per each PVAR regression) but above all, given the Hansen's J Test corroborating that IVs for the PVAR regression are reliable and valid, their statistical significance compliance is to be considered

[132] Under Abrigo & Love (2016), theoretically speaking, employing FOD or FD should not make a diffentrece when dealing with balance panel data and a large number of cross-sectional panels. Nonetheless, unbalance panel data magnifies the problem when using FD, which generally speaking requires a longer time dimension than FOD, which may become a problem for short panels PVAR models.

[133] As per Holtz-Eakin *et al.* (1988), missing observations are replaced with zeroes to create IVs from observed realizations (upon the standard assumption that IVs are uncorrelated with the errors) to produce more efficient estimates (Observations with no valid IVs are excluded). Efficiency is improved by including a longer set of lags as IVs, which unfortunetally is unattractive as it reduces observations especially with unbalanced panels or with missing observations.

negligible. Findings from the PVAR shown in Table 46 could be written in two mathematical expressions representing a set of bidirectional equations for the association between Main Income Sources as a proxy for FDI and the Social Progress Index as a proxy for social development when using Total Compensation as a moderating variable. See Equation 8 and Equation 9.

Equation 8

$$\boldsymbol{SPI_{it-1}} = -(0.10 * SPI_{it-1}) + (0.028 * MIS_{it-1}) + (0.081 * TC_{it-1}) - (0.0009 * (MIS * TC)_{it-1}) -(3.36 * MR) - (0.074 * PCSS) - (3.88 * \mathrm{ASY}) + (0.17 * ER) + (0.14 * IR) + \varepsilon_{it\mathrm{j}}$$

Equation 9

$$\boldsymbol{MIS_{it-1}} = +(1.21 * SPI_{it-1}) - (0.527 * MIS_{it-1}) - (2.05 * TC_{it-1}) + (0.022 * (MIS * TC)_{it-1}) +(11.00 * MR) + (0.083 * PCSS) + (45.59 * \mathrm{ASY}) - (2.12 * ER) - (2.49 * IR) + \varepsilon_{it\mathrm{j}}$$

where,

Endogenous variables	Exogenous (Control Variables)	Error term
SPI= Social Progress Index MIS= Main Income Sources TC=Total Compensation TC * MIS = Total Compensation	MR= Masculinity Rate PCSS = Population Covered by Social Services AV = Average School Years ER = Employment Rate IR = Informality Rate	$\varepsilon_{it\mathrm{j}}$

In broader economic terms, by adding the constant coefficients to both Equation 8 and Equation 9 and by extending both expressions to comprise a higher number of lags, the following set of *bidirectional structural equations,* as proposed *in* Equation 10 and Equation 11

Equation 10

$$\boldsymbol{SD_{it}} = \alpha_0 + \sum_{j=1}^{n}(\beta_j * SD_{it-j}) + \sum_{j=0}^{n}(\gamma_j * FDI_{it-j}) + + \sum_{j=0}^{n}(\delta_j * HI_{it-j}) + \sum_{j=0}^{n}\lambda_j * (HI * FDI)_{it-j} + A + \varepsilon_{it\mathrm{j}}$$

Equation 11

$$\boldsymbol{FDI_{it}} = \alpha'_0 + \sum_{j=1}^{n}(\beta'_j * SD_{it-j}) + \sum_{j=0}^{n}(\gamma'_j * FDI_{it-j}) + \sum_{j=0}^{n}(\delta'_j * HI_{it-j}) + \sum_{j=0}^{n}\lambda'_j * (HI * FDI)_{it-j} + A + \varepsilon'_{it\mathrm{j}}$$

Where SD_{it} and FDI_{it} represent the contemporary values for Social Development (SD) and Foreign Direct Investment (FDI) as the dependent variables in either equation. The coefficients α_o and α'_o are the constants for the two entire regressions and the β_j, γ_j, δ_0, λ'_j β'_j, γ'_j, δ'_0 and λ_j values are the coefficients for the remaining independent and interaction variables for both equations. The terms SD_{it-j} , FDI_{it-j} , HI_{it-j} and $(HI * FDI)_{it-j}$ comprise up to *n* lagged values of Social Development (SD), Foreign Direct Investment (*FDI*), Household Income (*HI)* and the interaction moderating effect of Household Income and Foreign Direct Investment *HI * FDI* as endogenous variables. A represents a set of control and policy variables treated as exogenous, which may be frequently included in empirical research as determinants of Social Development (SD) and Foreign Direct Investment (FDI). $\varepsilon_{it\mathrm{j}}$ and $\varepsilon'_{it\mathrm{j}}$ are the error terms to encompass all the other variables that have not been accounted for and are likely to impact Social Development (SD) and Foreign Direct Investment (FDI).

Table 47. PVAR Reduced-Form model employing Third Parties Expenditure as a moderating variable.

Panel Vector Autoregression		Number of obs	=	523			
GMM Estimation		Number of panels	=	149			
		Ave. no. of T	=	3.51			
Final GMM Criterion Q(b) = 0.147							
Initial weight matrix: Indentity							
GMM weight matrix: Robust							

		Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Social Progress Index							
Social Progress Index	L1.	-0.0342	0.0185	-1.8500	0.0650	-0.0705	0.0021
Main Income Sources	L1.	-0.0093	0.0022	-4.3100	0.0000	-0.0136	-0.0051
Third Parties Expenditure	L1.	-0.0464	0.0132	-3.5100	0.0000	-0.0723	-0.0205
Main Income Sources x Third Parties Expenditure	L1.	0.0005	0.0001	3.3000	0.0010	0.0002	0.0007
Masculinity Ratio		-1.5164	0.2662	-5.7000	0.0000	-2.0382	-0.9946
Population covered by SS		-0.0216	0.0070	-3.1100	0.0020	-0.0352	-0.0080
Average School Years		-0.8364	0.5510	-1.5200	0.1290	-1.9163	0.2435
Employment rate		-0.0626	0.0154	-4.0700	0.0000	-0.0927	-0.0325
Informality rate		-0.1805	0.0250	-7.2100	0.0000	-0.2295	-0.1314
Main Income Sources							
Social Progress Index	L1.	-3.0508	0.6694	-4.5600	0.0000	-4.3629	-1.7388
Main Income Sources	L1.	0.2909	0.0672	4.3300	0.0000	0.1591	0.4226
Third Parties Expenditure	L1.	2.4464	0.4792	5.1100	0.0000	1.5072	3.3855
Main Income Sources x Third Parties Expenditure	L1.	-0.0238	0.0049	-4.8900	0.0000	-0.0334	-0.0143
Masculinity Ratio		-12.9389	6.9951	-1.8500	0.0640	-26.6491	0.7713
Population covered by SS		-0.0155	0.1697	-0.0900	0.9270	-0.3481	0.3172
Average School Years		-21.3926	12.3671	-1.7300	0.0840	-45.6316	2.8464
Employment rate		0.9673	0.3601	2.6900	0.0070	0.2615	1.6731
Informality rate		0.8327	0.4417	1.8900	0.0590	-0.0330	1.6985
Third Parties Expenditure							
Social Progress Index	L1.	0.5970	1.6152	0.3700	0.7120	-2.5687	3.7627
Main Income Sources	L1.	-0.2806	0.1496	-1.8800	0.0480	-0.5737	0.0126
Third Parties Expenditure	L1.	-1.3120	0.7045	-1.8600	0.0630	-2.6928	0.0688
Main Income Sources x Third Parties Expenditure	L1.	0.0130	0.0076	1.7000	0.0900	-0.0020	0.0279
Masculinity Ratio		20.2498	21.3858	0.9500	0.3440	-21.6656	62.1652
Population covered by SS		2.9717	0.7505	3.9600	0.0000	1.5008	4.4426
Average School Years		12.3648	47.3147	0.2600	0.7940	-80.3703	105.1000
Employment rate		-4.1605	1.3360	-3.1100	0.0020	-6.7790	-1.5419
Informality rate		-3.7350	1.7465	-2.1400	0.0320	-7.1581	-0.3119
Main Incomes Sources x Third Parties Expenditure							
Social Progress Index	L1.	79.1605	172.7126	0.4600	0.6470	-259.3500	417.6709
Main Income Sources	L1.	-28.5120	14.9045	-1.9100	0.0560	-57.7243	0.7002
Third Parties Expenditure	L1.	-97.1749	70.3641	-1.3800	0.1670	-235.0860	40.7363
Main Income Sources x Third Parties Expenditure	L1.	0.9441	0.7613	1.2400	0.2150	-0.5481	2.4363
Masculinity Ratio		2534.4010	2239.9030	1.1300	0.2580	-1855.7270	6924.5300
Population covered by SS		315.2933	77.5354	4.0700	0.0000	163.3267	467.2598
Average School Years		2136.2830	4914.3350	0.4300	0.6640	-7495.6370	11768.2000
Employment rate		-434.9719	137.3514	-3.1700	0.0020	-704.1756	-165.7682
Informality rate		-378.0712	179.1204	-2.1100	0.0350	-729.1408	-27.0017

Instruments: l(1/4).(SPI MIS TPE MISxTPE) MasculinityRatio PopcoveredbySS Averageschoolyearsofemployed Employmentrate Informalworkrate

Test of overidentifying restriction:
Hansen's J chi2(64) = 76.84(p = 0.130)

Source: Author's estimates based on Stata17®

In Table 47, similarly to Table 46, contemporary values and lags 1-4 for SPI, Main Income Sources, Third-Parties Expenditure and the interaction of Third-Parties Expenditure and Main Income Sources are employed as endogenous variables were additionally employed as IVs via the *instlags(0/4)* sub-option. The forward orthogonal deviation option removes the Fixed Effects (fod) in light of unbalanced panel data[134]. The *td* option is also used to subtract its cross-sectional mean before estimating each variable, thereby removing time-fixed effects from all the variables before any other transformation. Control variables are treated as exogenous and also employed as IVs. The *overid* option was also used to calculate the Hansen J estimator to test IVs' validity. Contrarily to the model shown in Table 46, the *gmmstyle*[135] was employed to arrive at valid and reliable IVs, particularly because one is dealing with unbalanced panel data.

The Hansen's J Test exhibits a p-value = 0.13, confirming that the IVs used in the PVAR model are relevant and valid. The same 0.1 p-value threshold used in the model shown in Table 46 is employed (Abrigo & Love, 2016). Hence, for the specifications pertaining Social Progress Index and Main Income Sources, none of the endogenous variables lay above the 0.10 p-value and therefore confirmed as statistically significant. Moreover, as regards the control variables, only Average School Years (p-value = 0.129) for the regression where Social Progress Index is employed as a dependent variable and Population covered by SS (p-value=0.927) for the regression where Main Income Sources is the dependent variable lay above the 0.10 p-value threshold. As in the case of the PVAR model stemming from Table 46, p-values being associated with controlling variables (1 out 5 per each PVAR regression) and Hansen's J Test corroborating IVs being reliable and valid, their statistical significance not complying with a 0.10 below p-value are to be considered negligible. In a similar war to results from

[134] Under Abrigo & Love (2016), theoretically speaking, employing FOD or FD should not make a diffentrece when dealing with balance panel data and a large number of cross-sectional panels. Nonetheless, unbalance panel data magnifies the problem when using FD, which generally speaking requires a longer time dimension than FOD, which may become a problem for short panels PVAR models.

[135] As per Holtz-Eakin *et al.* (1988), missing observations are replaced with zeroes to create IVs from observed realizations (upon the standard assumption that IVs are uncorrelated with the errors) to produce more efficient estimates (Observations with no valid IVs are excluded). Efficiency is improved by including a longer set of lags as IVs, which unfortunetally is unattractive as it reduces observations especially with unbalanced panels or with missing observations.

Table 46, PVAR model findings from Table 47 could also be expressed in a set of bidirectional mathematical equations for the association between Main Income Sources as a proxy for FDI and the Social Progress Index as a proxy for social development when employing Third Parties Expenditure as a moderating variable. See Equation 12 and Equation 13.

Equation 12

$$\boldsymbol{SPI_{it-1}} = -(0.034 * SPI_{it-1}) - (0.0093 * MIS_{it-1}) - (0.046 * TPE_{it-1}) + (0.0005 * (MIS * TPE)_{it-1}) - (1.51 * MR) - (0.02 * PCSS) - (0.83 * \mathrm{ASY}) - (0.06 * ER) - (0.18 * IR) + \varepsilon_{it\mathrm{j}}$$

Equation 13

$$\boldsymbol{MIS_{it-1}} = -(3.05 * SPI_{it-1}) + (0.29 * MIS_{it-1}) + (2.44 * TPE_{it-1}) - (0.023 * (MIS * TPE)_{it-1}) - (12.93 * MR) - (0.015 * PCSS) - (21.39 * \mathrm{ASY}) + (0.96 * ER) + (0.83 * IR) + \varepsilon_{it\mathrm{j}}$$

where,

Endogenous variables	Exogenous (Control Variables)	Error term
SPI= Social Progress Index MIS= Main Income Sources TC=Total Compensation TC * MIS = Total Compensation	MR= Masculinity Rate PCSS = Population Covered by Social Services AV = Average School Years ER = Employment Rate IR = Informality Rate	$\varepsilon_{it\mathrm{j}}$

Adding constant coefficients to Equations 12 and 13 and extending their potential lag range, the following *two bidirectional structural equations* could be expressed to encompass more ample economic terms. See Equation 14 and Equation 15.

Equation 14

$$\boldsymbol{SD_{it}} = \alpha_0 + \sum_{j=1}^{n}(\beta_j * SD_{it-j}) + \sum_{j=0}^{n}(\gamma_j * FDI_{it-j}) + + \sum_{j=0}^{n}(\delta_j * PL_{it-j}) + \sum_{j=0}^{n}\lambda_j * (PL * FDI)_{it-j} + A + \varepsilon_{it\mathrm{j}}$$

Equation 15

$$\boldsymbol{FDI_{it}} = \alpha'_0 + \sum_{j=1}^{n}(\beta'_j * SD_{it-j}) + \sum_{j=0}^{n}(\gamma'_j * FDI_{it-j}) + \sum_{j=0}^{n}(\delta'_j * PL_{it-j}) + \sum_{j=0}^{n}\lambda'_j * (PL * FDI)_{it-j} + A + \varepsilon'_{it\mathrm{j}}$$

Similar to the previous set of proposed equations, SD_{it} and FDI_{it} represent the contemporary values for Social Development (SD) and Foreign Direct Investment (FDI) as the dependent variables in both equations. The coefficients

α_o and α'_o are the regressions' constants for both equations and the β_j, γ_j, δ_0, λ'_j β'_j, γ'_j, δ'_0 and λ_j values are the coefficients for the remaining independent and interaction variables. The terms $SD_{it\text{-}j}$, $FDI_{it\text{-}j}$, PL_{it-j} and $(PL * FDI)_{it-j}$ respectively comprise up to *n* lagged values of Social Development (SD), Foreign Direct Investment (*FDI*), Productive Linkages (*PL)* and the interaction moderating effect of Productive Linkages and Foreign Direct Investment *PL * FDI* as endogenous variables. A represents the control and policy variables treated as exogenous, which may be frequently employed in empirical research as determinants of Social Development (SD) and Foreign Direct Investment (FDI). $\varepsilon_{it\text{j}}$ and $\varepsilon'_{it\text{j}}$ are the error terms which account for all the other omitted variables but which are likely to impact Social Development (SD) and Foreign Direct Investment (FDI).

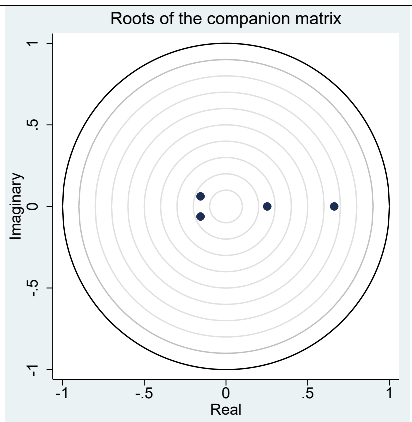
Reduced-form PVAR's coefficients cannot be interpreted as causal influences without priorly imposing identifying parameters' restrictions. Hence, the two latter-fitted PVAR Reduce models must be tested for stability, reformulating it as an infinite-order Vector Moving Average Model (VMAM) by imposing assumptions about the error covariance matrix (Abrigo & Love, 2016). Table 48 shows the results of both stability tests.

Table 48. Eigenvalue stability condition for PVAR models

a. PVAR Reduced-Form model employing Third Parties Expenditure as a moderating variable

Eigenvalue stability condition		
Real	**Imaginary**	**Modulus**
0.6623	0.0000	0.6623
0.2524	0.0000	0.2524
-0.1558	-0.0618	0.1676
-0.1558	0.0618	0.1676

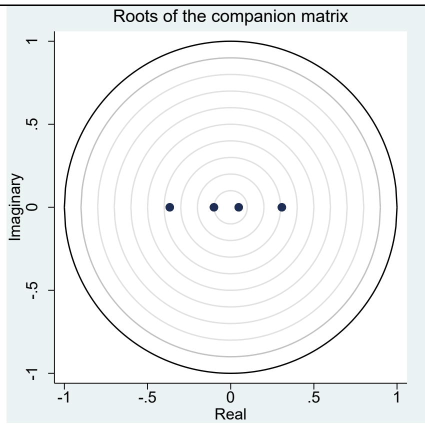
All the eigenvaues lie inside the unit circle
PVAR satisfies stability condition



b. PVAR Reduced-Form model employing Third Parties Expenditure as a moderating variable

Eigenvalue stability condition		
Real	**Imaginary**	**Modulus**
-0.3663	0.0000	0.3663
0.3076	0.0000	0.3076
-0.1008	0.0000	0.1008
0.0482	0.0000	0.0482

All the eigenvaues lie inside the unit circle
PVAR satisfies stability condition



Source: Author’s estimates based on Stata17®

As per the results, PVAR model stability is corroborated since all moduli of the companion matrix figures -based on the estimated parameters- lay below 1. Besides, as all eigenvalues lie inside the unit circle, PVAR's stability condition is satisfied, indicating that the variables employed are stationary (Santiago et al., 2019), aligning with the findings from subsection 6.2.1. The existence of *bidirectional causality* for the models derived from the reported regressions in Table 46 and Table 47 is sought via the Granger causality test and Impulse-Response Function (IRF) approaches.

As quoted from Bayraktar-Sağlam & Sayek (2017, pp5): “*over the past decade, the notion of Granger causality tests are well accepted and widely used in the panel econometrics’,* as predictive causality and feedback is an essential aspect of longitudinal analysis. From a broad perspective concerning causality testing, Shrestha & Batta (2018) state that if two variables, Y (dependent variable) and X (independent variable), are cointegrated, then there may exist any of the 3 relationships: a) X affects Y, b) Y affects X and c) X and Y affect each other. The first two show a unidirectional relationship, while the third depicts a bidirectional relationship. If two variables are not cointegrated, one is independent and does not affect the other. The causality test method developed by Granger (1969) determines the underlying pattern for such a relationship. See Appendix 10 for The Granger Causality Test Mathematical Rationale.

The initial choice to perform the Granger Causality Test was via the implemented community-written *xtgcause* command (developed by Lopez & Weber (2017) upon the proposed work of Dumitrescu & Hurlin (2012)). Nonetheless, the procedure was found unsuitable for unbalanced panel data with gaps. Alternatively, the Granger Causality Test was developed for PVAR and implemented as a separate Wald test (Stata17® pvargranger command). Its null hypothesis assumes that coefficients on all the lags of an endogenous variable are jointly equal to zero; thus, coefficients may be excluded in an equation of the PVAR model. Causal links among all the variables comprising the PVAR Reduced-Form model employing Total Compensation as a moderating variable (Table 46) after performing the Granger Causality Test are shown in Table 49.

Table 49. Granger Causality Test for Regression employing Total Compensation as a moderating variable.

Panel VAR-Granger causality Wald test Ho: Excluded variable does not Granger-cause Equation variable Ha: Excluded variable Granger-causes Equation variable			
Equation / Excluded	**chi2**	**df**	**Prob > chi2**
Social Progress Index			
Main Income Sources	13.6010	1.0000	0.0000
Total Compensation	20.0300	1.0000	0.0000
Main Income Sources x Total Compensation	20.6280	1.0000	0.0000
ALL	24.5130	3.0000	0.0000
Main Income Sources			
Social Progress Index	6.7570	1.0000	0.0090
Total Compensation	27.8120	1.0000	0.0000
Main Income Sources x Total Compensation	28.9580	1.0000	0.0000
ALL	29.8040	3.0000	0.0000
Total Compensation			
Social Progress Index	7.8650	1.0000	0.0050
Main Income Sources	1.0100	1.0000	0.0454
Main Income Sources x Total Compensation	0.3790	1.0000	0.5380
ALL	10.7400	3.0000	0.0130
Main Income Sources x Total Compensation			
Social Progress Index	8.8680	1.0000	0.0030
Main Income Sources	1.4220	1.0000	0.2330
Total Compensation	0.9290	1.0000	0.3350
ALL	12.3720	3.0000	0.0060

Source: Author's estimates based on Stata17®

Stemming from Table 49, one may notice that the 4 secondary tests labelled ALL, which refer to the coefficients of all the endogenous variables' lags in the PVAR model (other than those of the dependent variable) being jointly zero, report a p-value below 0.05 corroborating that all comprising variables in the each of the 4 blocks are endogenous. The main interactions concerning hypotheses posed in the Research Design are highlighted in grey, where it is to be noticed that p-values are reported below the 0.05 threshold, thereby statistically corroborating the existence of causality links to each of those interactions. One may notice from block 1 that Main Income Sources (proxy for FDI) 'grainger causes' SPI (a proxy for social development) or $(MIS \rightarrow SPI)$ as per Granger Causality Testing Notation (p-value = 0.000). Conversely, as per block 2, SPI 'grainger causes' Main Income Sources or $(SPI \rightarrow MIS)$ as per Granger Causality Testing Notation (p-value = 0.000). In this sense, Equation 8 and Equation 9 not only suggest that the bidirectional structural link between FDI and social performance (and vice versa) is a statistically valid association but also a causal relationship, thereby corroborating H1.

As suggested in the literature review and hypothesised in the research design, FDI may induce ‘economic spillovers’, such as increasing Household Income (HI). This causal link is corroborated in block 3 by Main Income Sources (a proxy for FDI) ‘grainger causing’ Total Compensation (a proxy for Household Income) per the p-value of 0.0454 reported. Once Household Income is induced, it becomes a moderating variable, as posed in H2. One then may observe that the interaction variable Main Income Sources x Total Compensation (a proxy for FDI x HI) ‘grainger causes’ SPI or in Granger Causality Testing Notation $(MIS\ x\ TC \rightarrow SPI)$ as per p-value = 0.000 in block 1. Conversely, as per block 2 findings, Main Income Sources x Total Compensation as interaction variable ‘grainger causes’ MIS or in Granger Causality Testing Notation $(MIS\ x\ TC \rightarrow FDI)$ as per p-value = 0.000. The *causal impact* of this interaction variable on both SPI (the proxy for social development) and MIS (the proxy for FDI) corroborates H2.

Nonetheless, as earlier discussed, it is paramount to note that the latter corroborations, particularly the one pertaining to H1, could only be established as *potentially possible*, as the limited longitudinal panel data coverage of only 6 years, unfortunately, restricts a statistically rigourous categorical affirmation.

Table 50. Granger Causality Test for Regression employing Third Parties Expenditure as a moderating variable.

Panel VAR-Granger causality Wald test Ho: Excluded variable does not Granger-cause Equation variable Ha: Excluded variable Granger-causes Equation variable			
Equation / Excluded	**chi2**	**df**	**Prob > chi2**
Social Progress Index			
Main Income Sources	18.6140	1.0000	0.0000
Third Parties Expenditure	12.3280	1.0000	0.0000
Main Income Sources x Third Parties Expenditure	10.8800	1.0000	0.0010
ALL	30.9710	3.0000	0.0000
Main Income Sources			
Social Progress Index	20.7700	1.0000	0.0000
Total Compensation	26.0660	1.0000	0.0000
Main Income Sources x Third Parties Expenditure	23.8890	1.0000	0.0000
ALL	54.4810	3.0000	0.0000
Third Parties Expenditure			
Social Progress Index	0.1370	1.0000	0.7120
Main Income Sources	3.5190	1.0000	0.0480
Main Income Sources x Third Parties Expenditure	2.8820	1.0000	0.0900
ALL	3.9710	3.0000	0.2650
Main Income Sources x Third Parties Expenditure			
Social Progress Index	0.2100	1.0000	0.6470
Main Income Sources	3.6600	1.0000	0.0560
Third Parties Expenditure	1.9070	1.0000	0.1670
ALL	3.9640	3.0000	0.2650

Source: Author's estimates based on Stata17®

Similarly to Table 49, one may notice from Table 50 that only block 1 and block 2, out of the 4 secondary tests labelled ALL, report p-values below 0.05. In that sense, variables in block 3 and block 4 (p-value = 0.265 in both cases) could not be considered statistically endogenous in their entire interaction in their respective blocks. In any case, the latter does not become an issue as this requirement for statistical causal validity is only necessary for blocks 1 and 2, and the only causal link of importance runs from Main Income Sources to Third Parties Expenditure (p-value: 0.048). Similarly to Table 49, the main interactions concerning hypotheses are highlighted in grey, with all p-values below the 0.05 threshold. In block 1, Main Income Sources 'grainger causes' SPI ($MIS \rightarrow SPI$) as per p-value = 0.000. Conversely, as per block 2, SPI 'grainger causes' Main Income Sources or ($SPI \rightarrow MIS$) as per p-value = 0.000. Equations 13 and 14 suggest a bidirectional structural association between FDI and social performance (and vice versa), further corroborating H1.

As also suggested in the literature review and research design sections, Productive Linkages (PL) are another 'economic spillover' that FDI may induce.

As mentioned in the previous paragraph, this causal link is corroborated in block 3 by Main Income Sources (a proxy for FDI) ‘grainger causing’ Third Parties Expenditure (a proxy for Productive Linkages) per the p-value of 0.048 reported. Once Productive Linkages have been induced, it also becomes a moderating variable, as posed in H3. One then may observe that the interaction variable Main Income Sources x Third Parties Expenditure (proxy for FDI x PL) ‘grainger causes’ SPI ($MIS\ x\ TPE \rightarrow SPI$) as per p-value = 0.001 in block 1. Conversely, as per block 2, Main Income Sources x Third Parties Expenditure ‘grainger causes’ MIS ($MIS\ x\ TPE \rightarrow MIS$) as per p-value = 0.000. The *causal impact* of this interaction variable on both SPI (the proxy for social development) and MIS (the proxy for FDI) corroborates H3.

One may imply that the same restrictions regarding making a statistically rigourous categorical affirmation and instead establishing a *potential possibility* must be made in the light of this research being based upon limited longitudinal panel data (6 years only)

Causal association and causal directions from Table 50 and Table 51 only provide a notion of the *causal mechanisms*. Nonetheless, if the aim is to understand the underlying *causal mechanisms* in the long run, the Grainger Causality Test fails to achieve this goal. Hence, the Impulse Response Functions (IRFs) must additionally be computed since, as per Abrigo & Love (2016), they are suggested to have a known interpretation in the light of complying with the eigenvalue stability condition (explained in subsection 6.2.4), implying that the PVAR model is invertible and has an infinite-order vector moving-average representation.

By confirming the existence of a reserve causality association between FDI and social development, H1 has been fully confirmed, which implies that RQ2 is partially answered as this reverse causality association has still to be corroborated/rejected to comply with a long-run pattern. Hence, targeting to fully provide an answer to RQ2, IRFs (Impulse – Response Functions) are employed. As per the same token, although RQ3 was answered since subsection 5.1.4 (re-engaged in subsection 6.1), a long-run pattern for path dependencies will also be fully explored in the following subsection via IRFs.

Impulse Response Functions (IRFs) combine the effect of multiple parameters into one summary (per period). IRFs summarise a given variable's temporal response pattern (behaviour) when it faces shocks or innovations in another variable. Additionally, IRFs reveal the time required by a variable to return to equilibrium after the shock or innovation occurs. IRFs are computed from the 'exact' posterior distribution of IRFs; hence relying on the asymptotic normality assumption is not required. An entire Markov Chain Monte Carlo (MCMC) sample of IRFs simulated from this posterior distribution is summarised into a single statistic: posterior mean IRF or posterior median IRF. In addition, IRFs provide more stable estimates for small datasets due to the prior incorporation of model parameters. It is essential to mention that the IRF plots' analysis, in general terms, aims to understand the nature of relationships between variables, where figures are set as mean coefficient factors or dynamic multipliers. Thereby, IRF plots are usually interpreted in terms of standard deviation (StDev) measures instead of coefficient estimates per se.

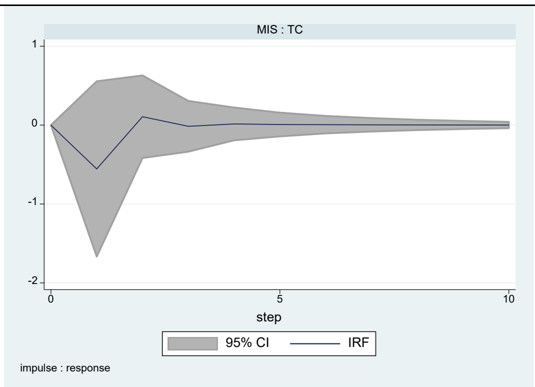
Having previously corroborated the stability of the PVAR model, one may calculate IRFs to assess the *long-run behaviours* of the 4 core endogenous variables in conjunction with their 2 moderating effects. In this analysis, the association between FDI and Social Development becomes central, for which assessing the change (shock or innovation) in Social Progress (response) induced by MIS (impulse) and vice versa is required to corroborate H1 and provide an answer to RQ1. Table 51 and Table 52 show the results from the Stata17®'s *pvarirf* post-estimation command to calculate and plot IRFs at a 10 periods horizon with a Gaussian approximation based on 1000 Monte Carlo simulations (*mc(1000)*) for SE and confidence intervals purposes. It is crucial to notice that although the order of the variables does not affect PVAR estimates, it does affect IRFs calculations. So, the Stata17® *porder()* subcommand[136] is

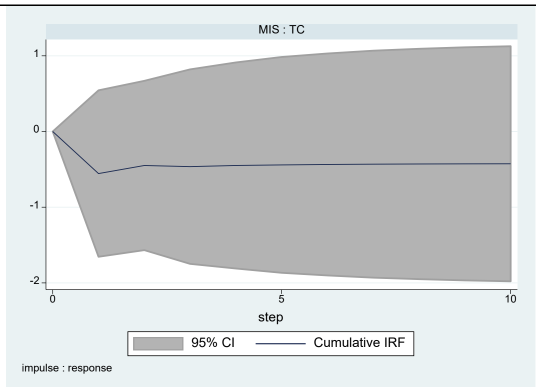
[136] It is paramount mentioning that IRFs may change depending on how the endogenous variables are ordered in the Cholesky decomposition. As Abrigo & Love (2016) state, variables order constrains responses' timing: shocks/innovations on variables that come earlier in the order subsequently impact variables contemporaneously. Besides, shocks/innovations on variables that come later in the order only impact the previous variables with 1-period lag. In this sense, since variable order is likely to affect IRFs and their interpretation, variable order should be based

employed based on the predetermined causal order hypothesised in the Research Design and corroborated as per the findings in subsection 6.2.5, FDI triggers economic spillovers, household income and productive linkages in this case. Subsequently, Household Income (HI) and Productive Linkages (PL) directly affect social development and interact by moderating the association between FDI and social development.

Table 51. Impulse Response Functions (Total Compensation as a Moderating Variable)

A. Impulse: Main Incomes Sources / Response: Total Compensation

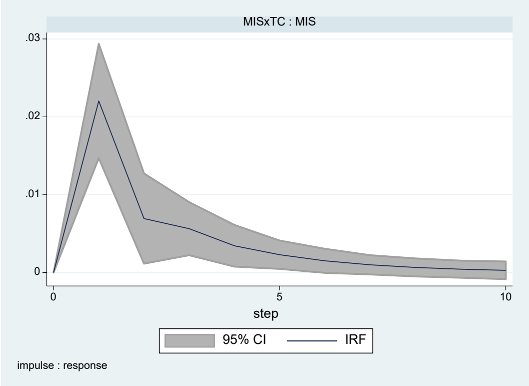


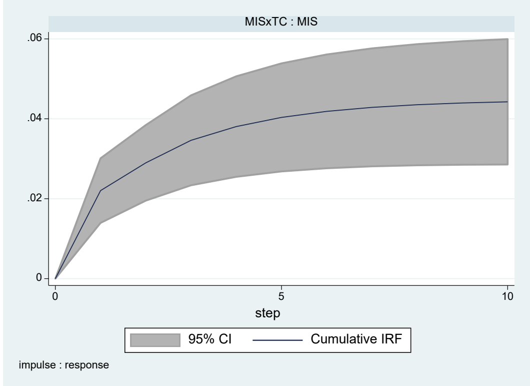


Response variable and Forecast Horizon	Impulse variable Main Income Sources (Individual Effect)	Impulse variable Main Income Sources (Cumulative Effect)
Total Compensation		
0	0.0000	0.00000
1	-0.5554	-0.55541
2	0.1066	-0.44877
3	-0.0151	-0.46387
4	0.0151	-0.44874
5	0.0076	-0.44118
6	0.0058	-0.43536
7	0.0039	-0.43150
8	0.0026	-0.42893
9	0.0017	-0.42721
10	0.0011	-0.42608

B. Impulse: Main Incomes Sources x Total Compensation / Response: Main Incomes Sources

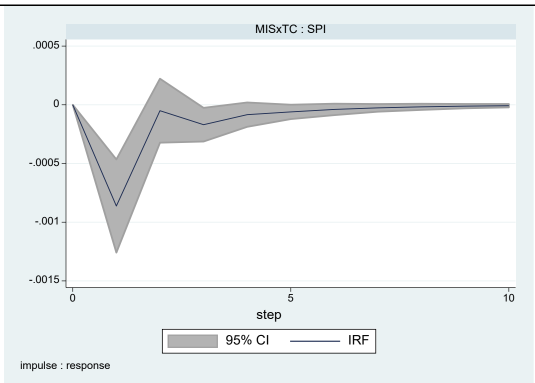
upon a robust theoretical background since there is no empirical test for those purposes (unfortunately, not the case of this study). Nevertheless, the Granger Causality Test results can be employed to allocate weight to a theoretically chosen order (Abrigo & Love, 2016). When estimating IRFs, the variables' order is defined in the PVAR. However, this order could be changed via the *porder()* option, which implements the Cholesky-order approach, preventing the need to recalculate the PVAR model with a different order of endogenous variables.

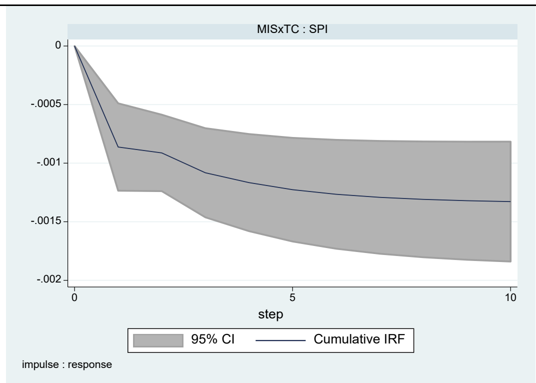




Response variable and Forecast Horizon	Impulse variable Main Income Sources and Total Compensation (Individual Effect)	Impulse variable Main Income Sources and Total Compensation (Cumulative Effect)
Main Income Sources		
0	0.00000	0.00000
1	0.02204	0.02204
2	0.00694	0.02898
3	0.00564	0.03462
4	0.00344	0.03806
5	0.00229	0.04035
6	0.00151	0.04186
7	0.00100	0.04286
8	0.00066	0.04352
9	0.00044	0.04396
10	0.00029	0.04425

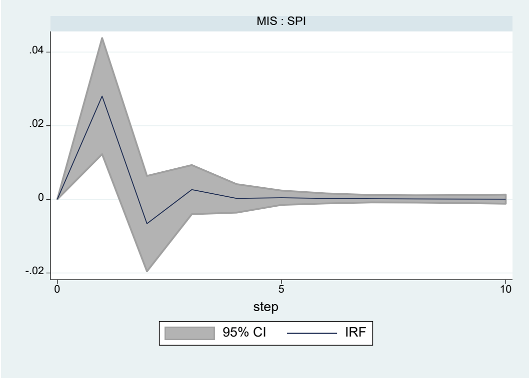
C. Impulse: Main Incomes Sources x Total Compensation / Response: SPI

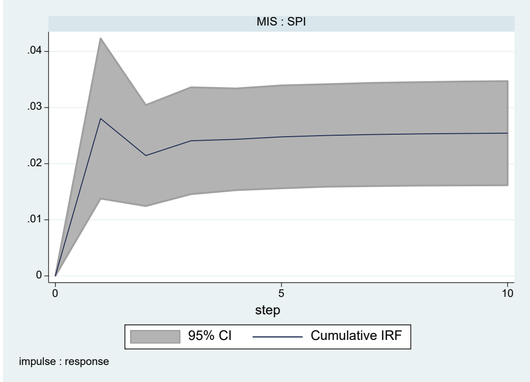




Response variable and Forecast Horizon	Impulse variable Main Income Sources and Total Compensation (Individual Effect)	Impulse variable Main Income Sources and Total Compensation (Cumulative Effect)
Social Progress Index		
0	0.00000	0.00000
1	-0.00086	-0.00086
2	-0.00005	-0.00091
3	-0.00017	-0.00108
4	-0.00008	-0.00117
5	-0.00006	-0.00123
6	-0.00004	-0.00127
7	-0.00003	-0.00129
8	-0.00002	-0.00131
9	-0.00001	-0.00132
10	-0.00001	-0.00133

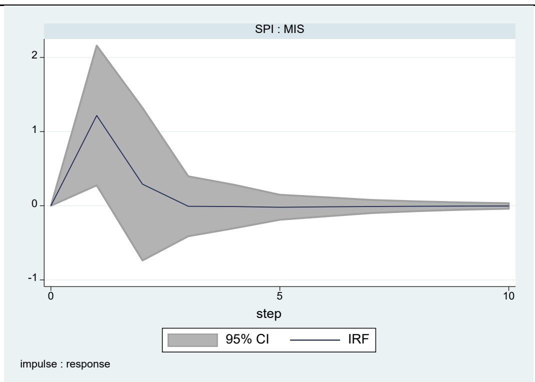
D. Impulse: Main Incomes Sources / Response: SPI

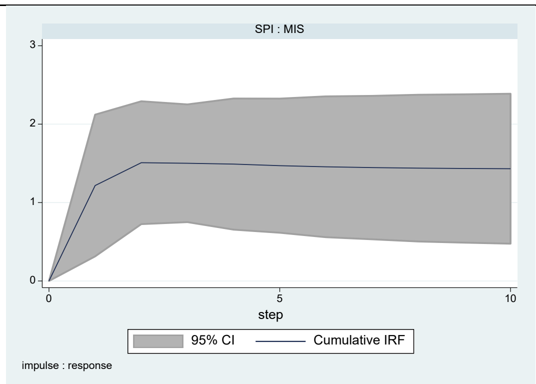




Response variable and Forecast Horizon	Impulse variable Main Income Sources (Individual Effect)	Impulse variable Main Income Sources (Cumulative Effect)
Social Progress Index		
0	0.000000	0.0000
1	0.028046	0.0280
2	-0.006601	0.0214
3	0.002640	0.0241
4	0.000259	0.0243
5	0.000436	0.0248
6	0.000247	0.0250
7	0.000169	0.0252
8	0.000111	0.0253
9	0.000074	0.0254
10	0.000049	0.0254

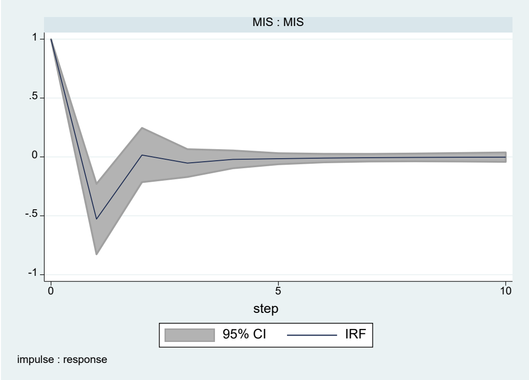
E. Impulse: SPI / Response: Main Incomes Sources

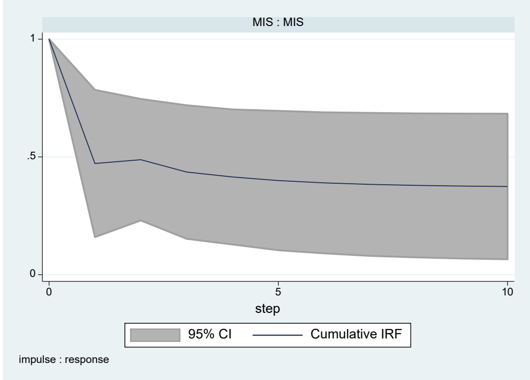




Response variable and Forecast Horizon	Impulse variable Social Progress Index (Individual Effect)	Impulse variable Social Progress Index (Cumulative Effect)
Main Income Sources		
0	0.0000	0.0000
1	1.2173	1.2173
2	0.2911	1.5084
3	-0.0072	1.5012
4	-0.0104	1.4908
5	-0.0203	1.4705
6	-0.0143	1.4562
7	-0.0102	1.4460
8	-0.0068	1.4392
9	-0.0046	1.4346
10	-0.0030	1.4316

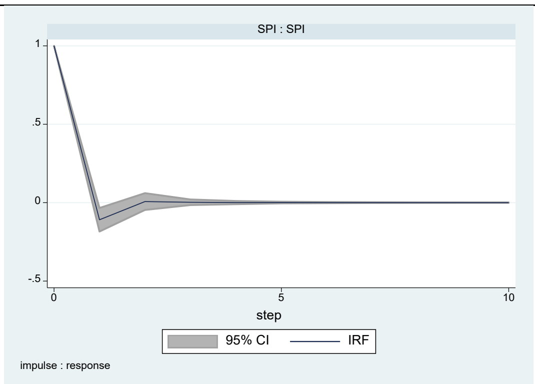
F. Impulse: Main Incomes Sources / Response: Main Incomes Sources

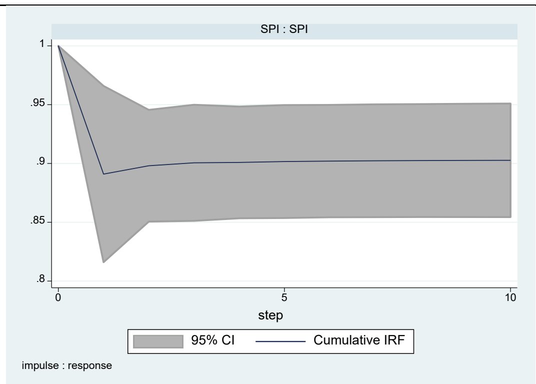




Response variable and Forecast Horizon	Impulse variable Main Income Sources (Individual Effect)	Impulse variable Main Income Sources (Cumulative Effect)
Main Income Sources		
0	1.0000	1.0000
1	-0.5279	0.4721
2	0.0161	0.4882
3	-0.0524	0.4358
4	-0.0209	0.4149
5	-0.0153	0.3997
6	-0.0098	0.3899
7	-0.0065	0.3834
8	-0.0043	0.3792
9	-0.0028	0.3763
10	-0.0019	0.3745

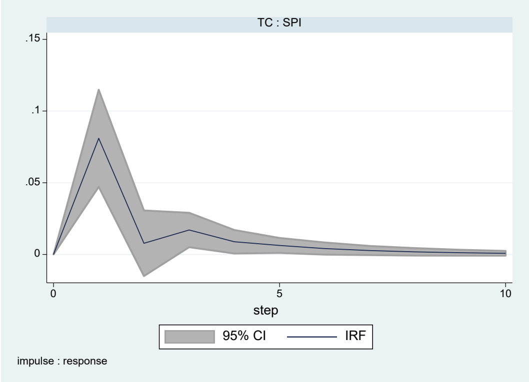
G. Impulse: SPI / Response: SPI

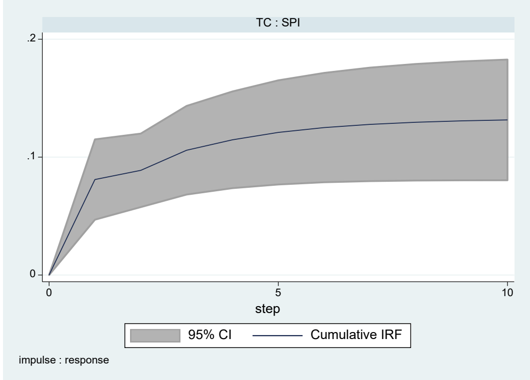




Response variable and Forecast Horizon	Impulse variable Social Progress Index (Individual Effect)	Impulse variable Social Progress Index (Cumulative Effect)
Social Progress Index		
0	1.0000	1.0000
1	-0.1090	0.8910
2	0.0071	0.8980
3	0.0025	0.9006
4	0.0003	0.9009
5	0.0007	0.9016
6	0.0004	0.9020
7	0.0003	0.9023
8	0.0002	0.9025
9	0.0001	0.9026
10	0.0001	0.9027

H. Impulse: TC / Response: SPI



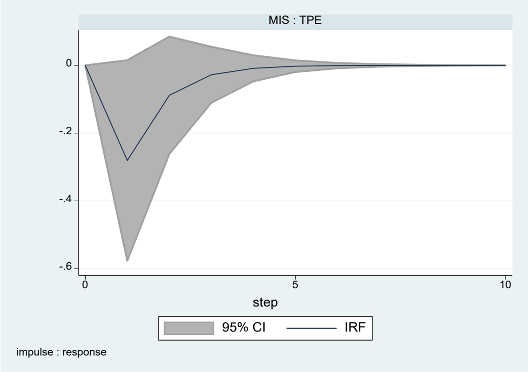


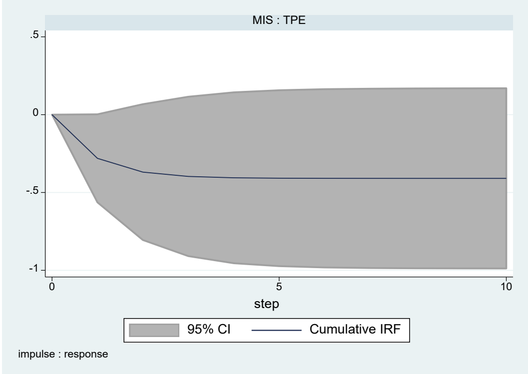
Response variable and Forecast Horizon	Impulse variable Total Compensation (Individual Effect)	Impulse variable Total Compensation (Cumulative Effect)
Social Progress Index		
0	0.0000	0.0000
1	0.0810	0.0810
2	0.0078	0.0888
3	0.0171	0.1058
4	0.0088	0.1147
5	0.0063	0.1210
6	0.0041	0.1250
7	0.0027	0.1278
8	0.0018	0.1296
9	0.0012	0.1308
10	0.0008	0.1316

Source: Author’s estimates based on Stata17®

Table 52. Impulse Response Functions (Third Parties Expenditure as a Moderating Variable)

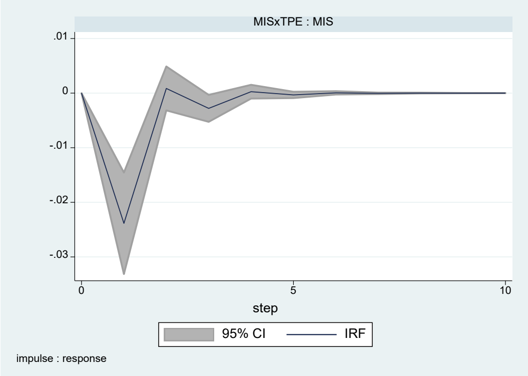
A. Impulse: Main Incomes Sources / Response: Third Parties Expenditure

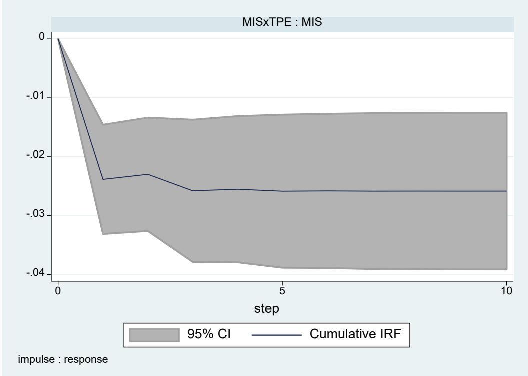




Response variable and Forecast Horizon	Impulse variable Main Income Sources (Individual Effect)	Impulse variable Main Income Sources (Cumulative Effect)
Third Parties Expenditure		
0	0.00000	0.00000
1	-0.28056	-0.28056
2	-0.08845	-0.36901
3	-0.02779	-0.39679
4	-0.00877	-0.40557
5	-0.00260	-0.40817
6	-0.00084	-0.40900
7	-0.00024	-0.40925
8	-0.00008	-0.40933
9	-0.00002	-0.40935
10	-0.00001	-0.40936

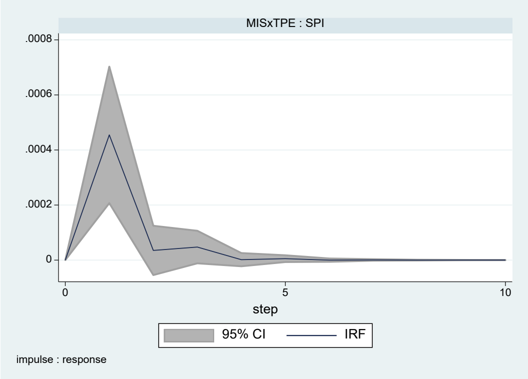
B. Impulse: Main Incomes Sources x Third Parties Expenditure / Response: Main Incomes Sources

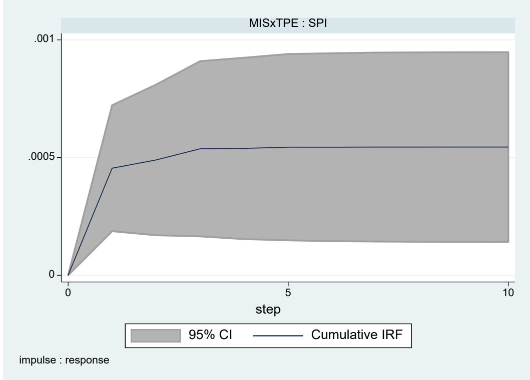




Response variable and Forecast Horizon	Impulse variable Main Income Sources and Third Parties Expenditure (Individual Effect)	Impulse variable Main Income Sources and Third Parties Expenditure (Cumulative Effect)
Main Income Sources		
0	0.00000	0.00000
1	-0.02385	-0.02385
2	0.00086	-0.02299
3	-0.00279	-0.02578
4	0.00026	-0.02552
5	-0.00033	-0.02585
6	0.00005	-0.02580
7	-0.00004	-0.02584
8	0.00001	-0.02584
9	0.00000	-0.02584
10	0.00000	-0.02584

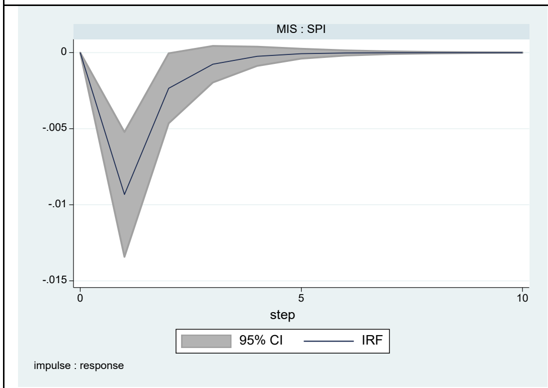
C. Impulse: Main Incomes Sources x Third Parties Expenditure / Response: SPI

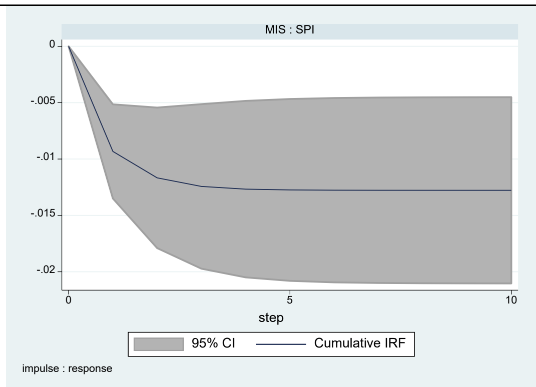




Response variable and Forecast Horizon	Impulse variable Main Income Sources and Third Parties Expenditure (Individual Effect)	Impulse variable Main Income Sources and Third Parties Expenditure (Cumulative Effect)
Social Progress Index		
0	0.000000	0.00000
1	0.000455	0.00045
2	0.000035	0.00049
3	0.000047	0.00054
4	0.000002	0.00054
5	0.000005	0.00054
6	0.000000	0.00054
7	0.000001	0.00054
8	0.000000	0.00054
9	0.000000	0.00054
10	0.000000	0.00054

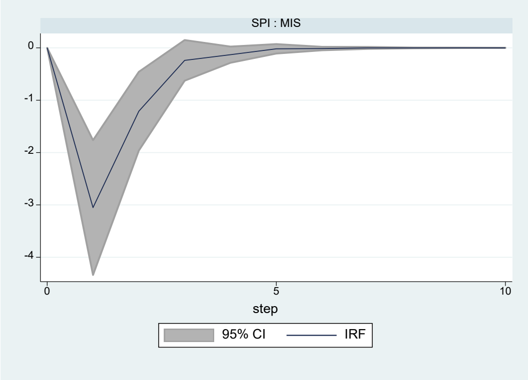
D. Impulse: Main Incomes Sources / Response: SPI

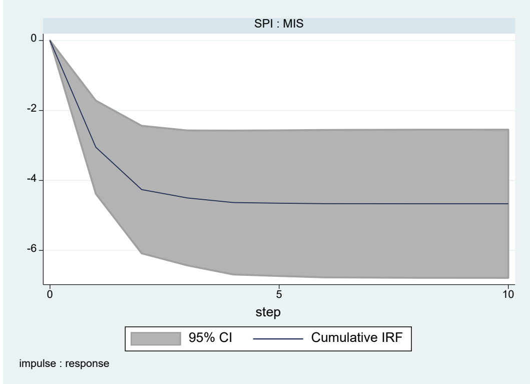




Response variable and Forecast Horizon	Impulse variable Main Income Sources (Individual Effect)	Impulse variable Main Income Sources (Cumulative Effect)
Social Progress Index		
0	0.00000	0.0000
1	-0.00932	-0.0093
2	-0.00235	-0.0117
3	-0.00076	-0.0124
4	-0.00024	-0.0127
5	-0.00007	-0.0127
6	-0.00002	-0.0128
7	-0.00001	-0.0128
8	0.00000	-0.0128
9	0.00000	-0.0128
10	0.00000	-0.0128

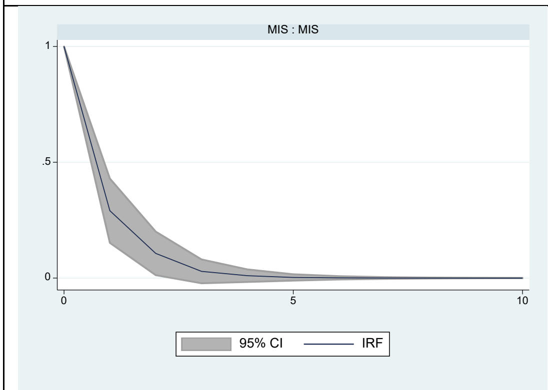
E. Impulse: SPI / Response: Main Incomes Sources

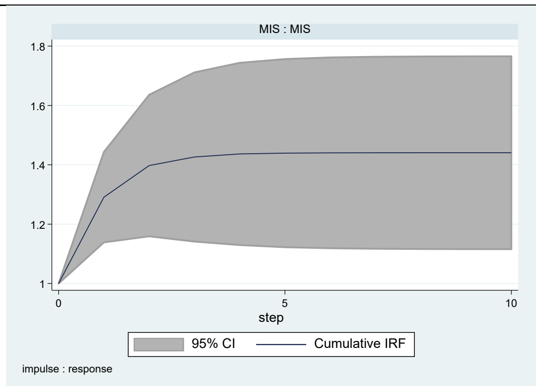




Response variable and Forecast Horizon	Impulse variable Social Progress Index (Individual Effect)	Impulse variable Social Progress Index (Cumulative Effect)
Main Income Sources		
0	0.0000	0.0000
1	-3.0508	-3.0508
2	-1.2101	-4.2609
3	-0.2395	-4.5004
4	-0.1308	-4.6312
5	-0.0187	-4.6499
6	-0.0137	-4.6636
7	-0.0013	-4.6649
8	-0.0015	-4.6664
9	-0.0001	-4.6664
10	-0.0002	-4.6666

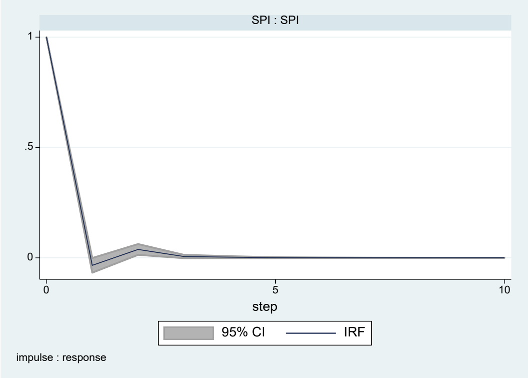
F. Impulse: Main Incomes Sources / Response: Main Incomes Sources

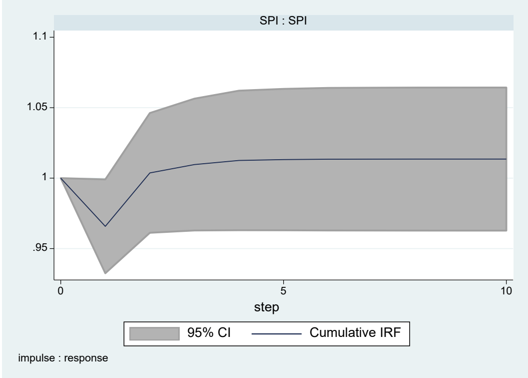




Response variable and Forecast Horizon	Impulse variable Main Income Sources (Individual Effect)	Impulse variable Main Income Sources (Cumulative Effect)
Main Income Sources		
0	1.00000	1.0000
1	0.29087	1.2909
2	0.10659	1.3975
3	0.02890	1.4264
4	0.01024	1.4366
5	0.00267	1.4393
6	0.00100	1.4403
7	0.00024	1.4405
8	0.00010	1.4406
9	0.00002	1.4406
10	0.00001	1.4406

G. Impulse: SPI / Response: SPI





Response variable and Forecast Horizon	Impulse variable Social Progress Index (Individual Effect)	Impulse variable Social Progress Index (Cumulative Effect)
Social Progress Index		
0	1.00000	1.0000
1	-0.03421	0.9658
2	0.03792	1.0037
3	0.00592	1.0096
4	0.00292	1.0126
5	0.00061	1.0132
6	0.00028	1.0134
7	0.00005	1.0135
8	0.00003	1.0135
9	0.00000	1.0135
10	0.00000	1.0135

Source: Author’s estimates based on Stata17®