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Developing a new multidimensional index of bank stability and its usage in the design of optimal policy interventions

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Abstract

This study proposes an optimisation-based "benefit-of-the-doubt" (BoD) methodological framework for developing a new multidimensional index of bank stability. The proposed index has the ability to serve as a potent policy tool that overcomes the downsides of accounting- and market-based measures of bank stability. This data-driven approach generates endogenous weights for aggregating bank stability indicators and dimensions. Further, we integrate the BoD framework with a metafrontier approach, which we call a "meta-BoD framework". The final outcomes of the suggested framework go beyond a scalar measure of bank stability and provide the unique weighting matrix that offers valuable policy-relevant insights about the most precarious areas of stability that require the attention of management and regulators for both micro- and macro-level policy interventions. In addition, it draws insightful information about the instability gaps across heterogenous bank groups. The study presents an illustrative example of the proposed framework to obtain a bank stability index using the dataset of 76 Indian banks operating between 2014 and 2018. The bank stability index is made up of 14 financial ratio indicators covering five dimensions of stability: asset quality, management efficiency, capital adequacy, profitability and liquidity. The findings offer the detailed information required for comprehending the evolution of bank stability and assessing instability gaps across bank groups.

Keywords: Bank stability; Financial soundness indicators; Banking crisis; Data envelopment analysis; Benefit-of-the-doubt model; Banks; Composite index

JEL codes: G2, G21, C61

1. Introduction

In recent years, the issue of bank stability has received a great deal of serious attention from the regulators of banking systems globally. This is because any instability in the banking system can disrupt the smooth functioning of economic activities and the monetary policy transmission process (Milne and Wood, 2009). In addition, bank instability exerts a negative impact on the availability of credit and liquidity provisions in the economy (Ingves, 2011; Jokipii and Monnin, 2013). Interestingly, no standard model or analytical framework exists yet for evaluating bank stability. The majority of empirical research uses either the accounting-based Z-score or the distance-to-risk measure to figure out how stable a bank is. Notable studies that have employed the Z-score to assess bank stability include Abdelbadie and Salamaa (2019), Ahamed and Mallick (2017), Demirgüç-Kunt and Detragiache (2011), Fernández *et al.* (2016), Fiordelisi and Mare (2014), Hassan *et al.* (2019), Hafeez *et al.* (2022), Kabir and Worthington (2016), Laeven and Levine (2009), Lepetit and Strobel (2013), Schaeck and Cihák (2014), and Soedarmono *et al.* (2011), among others. In addition to the Z-score, a growing body of research suggests using market-based measures, such as early warning indicators (Kaminsky and Reinhardt, 1999), distance-to-default (Eichler and Sobański, 2016; Fiordelisi and Marqués-Ibañez, 2013; Gropp *et al.*, 2004; Milne, 2014; Nagel and Purnanandam, 2020), distance-to-capital (Chan-Lau and Sy, 2006; Daly *et al.*, 2019), and distance-to-insolvency (Daly *et al.*, 2019) as proxies to measure bank risk/distress/fragility. Recently, central banks and academic researchers have made several proactive attempts to quantify a bank stability measure using diverse sets of indicators and/or dimensions (see, for instance, Crockett, 1997; European Central Bank, 2005; Issing, 2003; Reserve Bank of India, 2010; Schinasi, 2004). This line of research entails developing an aggregate index of bank stability based on either financial soundness indicators for deposit takers compiled by the International Monetary Fund (IMF) or components of the CAMELS rating system (Čihák and Schaeck, 2010; Geršl and Heřmánek, 2007).

Soon after the global financial crisis of 2007-09, the central banks of the majority of developed and developing countries established an "independent" financial stability unit and incorporated bank stability as a fundamental policy objective[2]. The Compilation Guide on Financial Soundness Indicators by the International Monetary Fund serves as a starting point for the central banks to develop their own financial stability frameworks and bank stability indicators (IMF, 2006). The primary task of financial stability units is to track the progress of the underlined financial indicators and to advise regulators on the appropriate policy responses required to ensure bank stability. It is noteworthy here that central banks and academic experts do not agree on a unified approach to choosing the set of indicators and to quantifying a composite index of bank stability (Čihák, 2006; Geršl and Heřmánek 2007; Huljak, 2015). In their study, Gadanecz and Jayaram (2008) argued that an aggregate index is more suitable for gauging financial stability[3] than a single ratio/indicator. However, there is a lack of consensus about a holistic approach to developing a multidimensional index of bank stability. This is due to disagreements about which key indicators/ratios should be selected, how they should be weighted, and how they should be aggregated. Thus, this study contributes to the discourse on

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[2] Although numerous central banks (almost fifty) have established financial stability units and initiated publishing the financial stability reports (FSR) much earlier (see Čihák, 2006 for more details), many others considered setting up financial stability units in the aftermath of the global financial crisis of 2007-09. For example, the Reserve Bank of India (India's central bank) came up with the financial stability unit in August 2009 and published its first FSR in March 2010.

[3] Beaver (1966) concluded that "multiple ratios taken simultaneously are more effective in predicting a firm's bankruptcy than a single ratio when predicting a firm's financial condition".

how to develop an all-encompassing measure of bank stability that is more comprehensive and avoids the drawbacks of existing measures.

Notably, the most popular Z-score is an accounting-based measure that assesses bank solvency risk by contrasting risk (volatility of returns) with buffers (capitalisation and returns). Its ease of calculation distinguishes it from other measures of bank stability. It has an extremely straightforward interpretation. A higher Z-score value indicates a lower likelihood of bank insolvency or fragility (Fiordelisi and Marqués-Ibañez, 2013). The innate flaw with the Z-score is that it is primarily a backward-looking indicator, so experts or central banking authorities find it to be an inadequate measure of bank stability (Hafeez *et al.*, 2022). Although the Z-score is a potent measure of bank insolvency risk, it ignores other major risks that a bank faces, such as credit, management, and market sensitivity (Huljak, 2015; Shaddady and Moore, 2019). Distance-to-risk measures, such as distance-to-default, have also gained popularity as alternative proxies for measuring bank soundness (Daly *et al.*, 2019). A typical distance-to-risk measure is a market-based measure that calculates the probability of a firm's future insolvency based on Merton's (1974) option pricing theory. It is based on the standard assumption of lognormally distributed asset values and is calibrated using the firm's asset value and expected equity price volatility (Nagel and Purnanandam, 2020). Thus, these measures are more reliable for banks in more developed economies where equity, bonds, and derivatives are more actively traded. As emerging and developing countries do not have fully developed financial markets, and banks have a limited presence on the stock market, these market-based measures may not be appropriate measures of bank stability for these economies. Furthermore, they ignore the possibility of regulatory intervention prior to failure, such as prompt corrective action by regulators (Chan-Lau and Sy, 2006).

To date, research efforts aimed at quantifying a composite index of bank stability using the indicators and/or dimensions of the CAMELS acronym have used either the traditional linear unweighted method or principal component analysis (PCA) (see, for instance, Bitar *et al.*, 2017; Central Bank of the Republic of Turkey, 2008; Kočišová and Stavárek, 2018; Reserve Bank of India, 2010). The striking downside of the traditional linear unweighted method is that in the aggregation process, it implicitly assigns equal weights to all indicators and/or dimensions encompassing both financial strength of banks and major risks to banks, and hence overlooks policy priorities of banks to a particular indicator or set of indicators (*i.e.*, dimensions). In addition, PCA is ineffective in scenarios with a small sample size or when the indicators or dimensions have slight variations (Nardo *et al.*, 2008). Furthermore, it is always challenging to interpret PCA weights from a policy perspective and use them to draw relevant policy interventions (Paredes-Gazquez *et al.*, 2016). Overall, as stated above, there is no consensus on how to precisely quantify bank stability.

In light of this, the present study develops a framework for building a new multidimensional index of bank stability that is all-encompassing and comprehensive and incorporates major risks that a bank faces, such as credit, management, and liquidity. The proposed stability framework based on financial soundness indicators avoids the pitfalls of the Z-score and the distance-to-risk measures and can serve as a potent tool for policy analysts to quantify the level of instability and identify its sources for sample banks. An illustrative case study presents the step-by-step procedure to build a bank stability index using a dataset of 76 Indian banks, including 21 public sector banks, 19 private banks, and 36 foreign banks, operating from 2014 to 2018. In particular, we aggregate fourteen ratio indicators covering the five dimensions of bank stability: “asset quality”, “management efficiency”, “capital adequacy”, “profitability”, and “liquidity”. The outcomes of the illustrative case study provide detailed information not only to see the evolution of bank stability but also gives the in-depth diagnostic data necessary for improving the stability performance of banks across a wide spectrum of operational domains, including risk, earnings, and liquidity management.

Our work has two major novelties. First, the study is novel in that it proposes to construct a multidimensional index of bank stability using the non-parametric data envelopment analysis (DEA)-based “benefit-of-the-doubt” (hereafter, BoD) approach, which generates endogenous policy weights and helps in measuring instability gaps. Such diagnostic and policy-related information in terms of weights cannot be extracted from the alternative weighting schemes, including the popular PCA (Nardo *et al.*, 2008). The information extracted can be effectively used to formulate relevant and appropriate policy directions for the underperforming units (Nardo *et al.*, 2008). The optimal policy weights determined by the BoD for a sampled bank from our proposed framework reveal the most threatening areas of stability, necessitating immediate intervention by the bank’s management and industry regulators. In recent years, the DEA-based BoD technique has been used in a wide variety of applications in the literature[4]. The BoD approach was initially proposed by Melyn and Moesen (1991) and was

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[4] For example, Despotis (2005) and Cherchye *et al.* (2008) created variants of the Human Development Index; Zhou *et al.* (2007) created a Sustainable Energy Index; Antonio and Martin (2012) created a Child Health Index; Badasyan *et al.* (2011) worked out a Broadband Achievement Index. More recently, Giambona and Vassallo (2013) developed a Financial Development Index; Martin *et al.* (2017) constructed a Travel-tourism

further refined in-depth by Cherchye *et al.* (2004, 2007). According to the DEA literature, the BoD models are designed in a "pure output" setting with dummy input equal to one, where indicators or dimensions are aggregated to construct a composite index (so-called performance index) (Lavigne *et al.*, 2019; Mariano *et al.*, 2015; Puyenbroeck, 2018; Rogge and Puyenbroeck, 2007). One of the key advantages of the BoD modeling framework is that it works superbly well with small samples and permits a differentiated and benevolent weighting scheme that is specific to indicators and varies across sampled units (Greco *et al.*, 2019; Zhou *et al.*, 2007). By formulating such a weighting scheme, a researcher will be able to linearly aggregate multiple indicators in a meaningful and objective way. The proposed framework allows a researcher to easily rank banks according to their stability dimensions and endogenously identify a bank's policy priorities/weights on underlined dimensions of stability. Although the BoD approach has numerous benefits, working with DEA-based methods is not without risk because these methods do not account for statistical noise. Furthermore, these methods only accept positive values and do not explicitly consider exogenous factors. In addition, DEA-based models ignore some properties, particularly when ratios are used as outputs instead of absolute numbers (Emrouznejad and Amin, 2009; Hollingsworth and Smith, 2003)[5].

Second, because the banking industries in the majority of countries are structured with banks belonging to distinct ownership groups, it is pertinent to compare the stability performances of distinct bank groups over time. When using the traditional BoD model, it is almost impossible to directly capture gaps in stability and its dimensions across ownership groups that arise because of differences in technology and business model. We address this issue by integrating the metafrontier concept by O'Donnell *et al.* (2008) with that of the BoD framework. Specifically, by combining the metafrontier framework with a constrained BoD model, we compute the stability index with respect to both the industry frontier (capturing inter-group variations) and the group frontier (capturing intra-group variations) and then

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Competitiveness Index; Gulati *et al.* (2020) applied to building up the governance compliance index; among others.

[5] It is noteworthy here that Emrouznejad and Amin (2009) modified the DEA model in the presence of ratios to correct the convexity problem. However, their modified model assumes the numerator and denominator of ratio variables are known. In the case of financial firms, especially banks, the data on the numerator and denominator of a set of ratios are unknown. Banks typically report the computed values of financial ratios for benchmarking. This limitation of their model controls the ability to handle the problem using this variant. The literature suggests using BoD to aggregate the normalised form instead of the actual form of ratios. Therefore, we performed empirical normalisation of each financial indicator before aggregation. Further research can explore this concern with the possibility of variants of BoD models to deal directly with such cases.

calculate the instability gaps across bank groups, which are determined by the distance of a bank from industry and group stability frontiers. Overall, this form of analysis takes into account the inherent differences across bank groups due to differences in technology, business goals and models, factors endowment and operational environments, etc.

In the present study, we develop a two-step aggregation framework, which we call the "meta-BoD framework", to obtain the bank stability index and instability gaps (see Section 3 for more details). In particular, the industry-specific constrained BoD model yields endogenously derived weights that are unique to a bank for all indicators (at the first step of aggregation) and dimensions (at the second step of aggregation). The weights obtained from the BoD model determine the areas where sampled banks perform better or worse within the industry. Thus, we get a clear idea of a bank's positioning and preferences for each ratio indicator and dimension from the optimal weights set. This study is perhaps the first empirical endeavour to develop the meta-BoD approach to construct a non-parametric composite index of bank stability that can serve as an early warning signal of bank fragility and distress. Therefore, this work significantly contributes to existing knowledge on measuring bank stability. The calculated values of the composite index of bank stability range between 0 and 1 and indicate the relative levels of bank stability. These values can be utilised for benchmarking, classification, ranking, and optimal policy design purposes.

In a recent paper, Shaddady and Moore (2019) made an attempt to measure bank stability. However, their modelling paradigm has serious downsides. They model bank stability incorrectly using the traditional input-output framework and compute it using an "output-oriented" DEA model. Even their selection of the inputs and outputs contradicts existing literature on bank efficiency. As an example, their model does not account for undesirable outputs in bank production. In the contemporary literature on efficiency measurement, it is agreed upon that both desirable and undesirable factors should be considered concurrently to obtain robust and accurate efficiency estimates, and to make a fair assessment (see, for instance, Fujii *et al.*, 2014; Gulati, 2022; Huang and Chung, 2017; Pham and Zelenyuk, 2019; Zhu *et al.*, 2019). Also, bank equity is treated as an output, even though it is usually seen as a quasi-fixed input (see, for example, Bos *et al.*, 2009; Fare *et al.*, 2004; Maudos *et al.*, 2002; Park and Weber, 2006; Ray and Das, 2010; Simper *et al.*, 2017). Most importantly, bank stability is not viewed from a multidimensional perspective in their paper. Our work differs from that of Shaddady and Moore (2019) and others and contributes to the existing literature in the following ways. First, the proposed stability framework is more policy-oriented, as it considers a wide array of unit invariant indicators that must be regularly monitored by banks to get early warning signals. Second, the suggested stability index is multidimensional in nature and can be used as a potent tool for drawing both micro- and macro-level policy interventions to improve stability levels. Third, in contrast to the classical DEA approach, which requires inputs and outputs, the proposed meta-BoD approach is more flexible in handling multiple indicators in a “pure output” setting. Fourth, the outcomes of the proposed stability framework can be used to design more effective policy interventions for comparing the stability levels across countries and bank groups. The suggested framework can be easily tailored to fit the needs of any banking system by just changing the number of indicators, dimensions, number of banks, and ownership groups.

The remainder of the paper is organised as follows. Section 2 briefly discusses the relevant empirical literature on the measurement of bank stability. The next section elaborates on the methodological framework used in this study. The penultimate section focuses on the illustrative example and explanation of the results. The final section provides the concluding remarks of the paper.

2. Measures of bank stability: A review

Since the start of the global financial crisis of 2007–09, there has been a lot more empirical research on how stable a bank is. This is a result of the increasing risks of extraneous shocks and the significant role that banks play in macroeconomic growth. The empirical research on the measurement of bank stability can be divided into three strands. The first strand of research includes the vast majority of the studies that employ the accounting-based Z-score as an indicator of bank risk/stability and explain the degree of financial fragility/distress in the banking system. The primary advantage of using the Z-score is its computational simplicity. A few prominent studies that have employed the Z-score to measure bank stability are cited in the introductory section of this paper. Lauteacru (2016) contends that the Z-score misrepresents the financial soundness of banks, particularly during times of crisis when bank returns are distorted and skewed. Hafeez *et al.* (2022) note that it is essentially a retrospective and a backward-looking measure. Huljak (2015) and Shaddady and Moore (2019) debunk the Z-score as a reliable predictor of bank stability. They assert that the Z-score is based exclusively on a bank’s profitability and capitalisation, ignoring other important indicators such as credit and liquidity risks, management efficiency, and market risk.

The second strand of research focuses on predicting bank failure/fragility using distance-to-risk measures. The distance-to-default becomes an alternative measure for predicting bank failure. It has been promoted as a substitute metric that complements traditional accounting measures and is a market-based and forward-looking indicator (see, for instance, Eichler and Sobański, 2016; Fiordelisi and Marqués-Ibañez, 2013; Gropp *et al.*, 2004; Jokipii and Monnin, 2013; Milne, 2014). Chan-Lau and Sy (2006) emphasise two downsides of the distance-to-default measure. First, it assigns higher risk scores to a bank, and second, it ignores regulatory and supervisory actions before the bank default. The authors developed the concept of distance-to-capital, which takes into account regulatory actions taken prior to default, such as prompt corrective actions. An alternative distance measure is the distance-to-insolvency measure, developed by Daly *et al.* (2019). Importantly, the distance measures supplement traditional accounting measures and calibrate the firm's market value and expected equity price volatility. However, Milne (2014) infers that a distance-to-default measure fails to perform well as a market-based predictor of bank failure during the crisis, and thus, advocates the use of risk measures in addition to regulatory measures.

The third strand of research on bank stability involves the use of mathematical and econometric models for computing a multifaceted bank stability index. Geršl and Heřmánek (2007) devised an aggregate financial stability measure for banks operating in the Czech Republic using the IMF framework. Segoviano and Goodhart (2009) developed a framework for estimating a set of bank stability indices using the multivariate density of the banking system. The probability of individual bank distress was measured considering both linear and non-linear interdependence distress structures. The Reserve Bank of India (2010) developed a five-dimensional bank stability framework and built the banking stability indicator based on the linear weighted average approach. Ghosh (2011) developed a bank fragility index using three dimensions of banking operations: stability, soundness, and profitability. A few studies used the CAMELS assessment framework for selecting indicators and/or dimensions and then employed the linear unweighted average index approach for constructing the bank stability index (see, for example, Central Bank of the Republic of Turkey, 2008; Gulati, 2022; Kočišová and Stavárek, 2018). Shaddady and Moore (2019) examined the impact of financial regulation and supervision on the DEA-based bank stability index using data from 47 European nations. This strand of research is associated with two significant concerns. First, there is the issue of selecting potential indicators and dimensions to evaluate the stability of banks. Second, the methodological framework for aggregating the underlined indicators and dimensions to compute a composite index of bank stability is questionable. Prior literature has generally relied on three methods: the traditional linear unweighted average approach, the Principal Component Analysis (PCA), and the DEA approach using the CAMELS ratios as inputs and outputs. Some of the major flaws of these methods are already highlighted in the introductory section. Table 1 reports notable empirical works that attempted to build a bank stability index using methodological frameworks other than the Z-score.

The following points are based on a careful review of the existing research and are highly relevant. First, traditional measures, such as the accounting-based Z-score and the market-based distance-to-default, are the most widely used methods for measuring bank failure, despite their inherent flaws. Second, there is no uniformly agreed-upon method for building the composite index of bank stability. Third, the majority of empirical studies on bank stability used a limited set of indicators. Fourth, most investigations have constructed the bank stability index using the traditional unweighted method, which does not address the issue of indicators being unable to compensate or substitute for one another. In addition, the PCA approach is not recommended when the sample size is small, and the variations in the underlined indicators and dimensions are not large. Fifth, the heterogeneity in technology and business models is not taken into account, and instability gaps are not measured across ownership groups. The present study rationally addresses all of the above issues.

Table 1: Studies on the bank stability index other than the Z-score

Author (Year)	**Country(ies)**	**Indicators/dimensions**	**Measure/Index methodology**
Geršl and Heřmánek (2007)	Czech Republic	Capital adequacy, Asset quality, Profitability, Liquidity, Interest rate risk, Foreign exchange risk	Weights by expert judgment
Central Bank of the Republic of Turkey (2008)	Turkey	Capital adequacy, Asset quality, Profitability, Liquidity, Interest rate risk, Exchange rate risk	Linear unweighted average index
Segoviano and Goodhart (2009)	US and Europe	Quantification of linear and non-linear (a) “common” distress of the banks in a banking system, (b) distress between specific banks, and (c) distress in the banking system associated with a specific bank	Consistent Information Multivariate Density Optimising method
Čihák and Schaeck (2010)	100 economies	Prudential ratios based on IMF Compilation Guide on Financial Soundness indicators	Logit model for predicting banking crisis
Reserve Bank of India (2010)	India	Soundness, Asset quality, Profitability, Liquidity, Efficiency	Linear unweighted average index
Ghosh (2011)	India	Loan loss provisions, Capital to risk-weighted assets, Return-on-assets	Inverse Euclidean distance
Jokipii and Monnin (2013)	18 OECD countries	Probability of default using asset market value, volatility rate and debt	Distance-to-Default measure
Kočišová and Stavárek (2018)	10 European countries	Capital adequacy, Asset quality, Earning & Profitability, Liquidity, Exposure to foreign exchange risk	Linear unweighted average index

Daly *et al.* (2019)	91 banks from 20 countries (including G8 and BRICS)	Distance to risk measures	Distance-to-default, distance-to-capital and distance-to-insolvency & Multinomial logistic model for prediction
Shaddady and Moore (2019)	47 European countries	Inputs: Loan loss provisions, Total expenses Outputs: Total equity, Total net income, Liquid assets, Total assets	CAMELS-DEA using output-oriented DEA approach

Source: Authors' elaboration

3. Methodological framework

This section presents the proposed meta-BoD framework for constructing BSI. The meta-BoD approach combines the meta-frontier analysis developed by O'Donnell *et al.* (2008) with a BoD model to account for group heterogeneity and identify instability gaps. In this paper, we employ a BoD model known as the constrained BoD model. A two-step aggregation process is suggested for computing bank-specific BSI values. In the first step, a set of dimension-specific indicators are used to generate dimensional indices for underlined stability dimensions. This step generates data-driven, endogenously determined optimal policy weights for stability indicators that are distinct for each bank. In the second step, the constrained BoD model is reapplied to aggregate the dimensional indices for computing the values of BSI for each bank and generating policy weights for the underlined dimensions. It is worth noting that the proposed two-step aggregation process using a constrained BoD model generates two optimal policy weight matrices that can be used for micro- and macro-level planning. In particular, the first step of the aggregation provides a weight matrix for stability indicators, which can be used by bank managers to identify financial ratios that undermine stability performance and help them to take effective micro-level policy interventions. The second step of the aggregation generates a weight matrix for the underlined dimensions. Regulators and policymakers can use these dimensional weights to implement effective macroeconomic policy interventions that have far-reaching effects on the growth and stability of the banking system. The details of the meta-BoD approach are outlined below.

3.1 Constrained 'Benefit-of-the-Doubt' (BoD) model

The constrained BoD model employed here belongs to a family of BoD models that are similar to DEA models. These models are formulated in a "pure output" setting that does not have any input(s) requirements (Cherchye *et al.*, 2004, 2007). A particular model is fundamentally inspired to be solved in the "multiplier" form of the CCR model developed by Charnes, Cooper, and Rhodes (1978). Contrary to the classic BoD model, we propose to use the constrained BoD model as the purpose is to show how a bank can set its priorities on a set of indicators and dimensions. A typical BoD model aggregates indicators using weights derived from the actual data, hence eliminating subjectivity in selecting these weights (Zhou *et al.*, 2007). In addition, we are not constrained to combine the underlined indicators and dimensions based on any a priori statistical assumptions. The subsequent advantage is that a BoD model is based on positive and optimistic perspectives and generates the most favourable weighting scheme (Charles and Díaz, 2017). Additionally, binding weighting constraints, as we have done, can be incorporated into a BoD framework to ensure that no indicator or dimension is overemphasised or overlooked (Zanella *et al.*, 2015). Lastly, the BoD framework performs well with a small sample.

3.1.1. Bank stability index with respect to group frontier using the constrained BoD model

The essential premise of the proposed meta-BoD approach is to compute the BSI indices relative to group and meta frontiers and then compare these indices to calculate the stability gaps between ownership groups. To compute the BSI with respect to a particular group frontier, we use the data points for that frontier and employ the two-step aggregation process described above. In the first step of the aggregation, we compute distinct dimensional indices of bank stability. Assume that there are *N* banks and that these banks are classified into *K* ownership groups. N_k represents the number of banks in the *k*th group such that $\sum_{k=1}^{K} N_k = N$. Let us further assume that we have a set of '*s*' stability indicators (*r*=1,…,*s*) with normalised values $I_1,...,I_s$ that correspond to the *i*th stability dimension (*i*=1,…,*m*). The policy weights for each indicator of the *i*th dimension for the *o*th bank in the *k*th group are defined as $v_{1,o}, v_{2,o},...,v_{s,o}$. The aggregation of '*s*' stability indicators generates the *i*th stability dimension ($D_{i,o}^{k}$) for the *o*th bank that belongs to the *k*th group. The linear programming problem (LPP) employed for constructing the *ith* dimensional index ($D_{i,o}^{k*}$) for banks belonging to the *k*th group is represented by Model (A). The optimal solution to Model (A) yields the non-negative values of the policy weights $v_{r,o}^{k*}$ used to construct the *i*th dimensional index ($D_{i,o}^{k*}$).

Step 1: Dimensional Index ($D_{i,o}^{k*}$) with respect to the k^{th} group frontier	**Step 2: Bank Stability Index (BSI_{o}^{k*}) with respect to the k^{th} group frontier**
$D_{i,o}^{k*} = \max_{v_{r,o}} \sum_{r=1}^{s} v_{r,o}^{k} I_{r,o}^{k}$ subject to $\sum_{r=1}^{s} v_{r,o}^{k} I_{r,j}^{k} \le 1 \qquad j = 1,\ldots,N_k \qquad \text{(i)}$ $v_{r,o}^{k} \ge 0 \qquad r = 1,\ldots,s \qquad \text{(ii)} \quad \text{(A)}$ $\alpha \le \frac{v_{r,j}^{k} I_{r,j}^{k}}{\sum_{r=1}^{s} v_{r,j}^{k} I_{r,j}^{k}} \le \beta \qquad \text{(iii)}$	$BSI_{o}^{k*} = \max_{w_{i,o}} \sum_{i=1}^{m} w_{i,o}^{k} D_{i,o}^{k}$ subject to $\sum_{i=1}^{m} w_{i,o}^{k} D_{i,j}^{k} \le 1 \qquad j = 1,\ldots,N_k \qquad \text{(i)}$ $w_{i,o}^{k} \ge 0 \qquad i = 1,\ldots,m \qquad \text{(ii)} \quad \text{(B)}$ $\alpha^{'} \le \frac{w_{i,j}^{k} D_{i,j}^{k}}{\sum_{i=1}^{m} w_{i,j}^{k} D_{i,j}^{k}} \le \beta^{'} \qquad \text{(iii)}$

The second step of aggregation entails aggregating the *m* dimensional indices that are generated in the first step using Model (A) in order to obtain the BSI_{o}^{k*} for the o^{th} bank in the k^{th} group using Model (B). Note that because the BoD model is sensitive to the dimensional scores of 0 and 1, before combining, each dimensional index is normalised (at mean 100 and standard deviation 10) to account for zero and one values of dimension (Vidoli and Fusco, 2018). The optimal solution to Model (B) provides the optimal non-negative values of the policy weights to the i^{th} dimensions (i.e., $w_{i,o}^{k*}$) and the composite bank stability index (BSI_{o}^{k*}) for the o^{th} bank that belongs to the k^{th} bank group. The major drawback of the basic BoD model is that it can provide zero weights for one or more fundamental indicators or dimensions. We overcome this limitation by introducing the assurance region type I weight constraint (iii) in Models (A) and (B), which establishes the lower and upper limits on the proportional share of the *s* indicators and *m* dimensions, respectively. For example, when computing the values of the dimensional indices, if we set the lower limit for the ratio indicator as α percent in Model (A), the upper bound will be at $100-[(s-1)\times\alpha]$ percent. Similarly, if the lower bound for a dimension while computing BSI is fixed as α' percent in Model (B), the upper bound will be at $100-[(m-1)\times\alpha^{'}]$ percent. This adjustment addresses the major flaw of completely disregarding the worst-performing ratio indicator or dimension or overfocusing on the best-performing ratio indicator or dimension (see Allen *et al.*, 1997; Athanassoglou, 2016; Cherchye *et al.*, 2007; Wong and Beasley, 1990; Zanella *et al.*, 2015; for more details).

3.1.2 Bank stability index with respect to metafrontier using the constrained BoD model

To account for group heterogeneity, the bank stability index for an individual bank in the sample has been computed with respect to a meta frontier. The metafrontier envelops all group frontiers and is an ideal benchmark for assessing stability levels. The mathematical formulation of constrained BoD models for estimating the dimensional indices and the composite bank stability index for the *o*th bank with respect to the metafrontier are represented in Models (C) and (D), respectively. The optimal solutions to Models (C) and (D) provide the non-negative values of the policy weights assigned by a bank to the *r*th stability indicator and *m*th dimension, *i.e.*, $v_{r,o}^{\text{meta}*}$ and $w_{i,o}^{\text{meta}*}$, for the *o*th bank with respect to the industry frontier, respectively.

Step 1: Dimensional Index ($D_{i,o}^{\text{meta}*}$) with respect to meta frontier	**Step 2: Bank Stability Index ($BSI_o^{\text{meta}*}$) with respect to meta frontier**
$D_o^{\text{meta}*} = \max_{v_{r,o}} \sum_{r=1}^{s} v_{r,o}^{\text{meta}} I_{r,o}^{\text{meta}}$ subject to $\sum_{r=1}^{s} v_{r,o}^{\text{meta}} I_{r,j}^{\text{meta}} \leq 1 \qquad j = 1,...,N \quad \text{(i)}$ $v_{r,o}^{\text{meta}} \geq 0 \qquad r = 1,...,s \quad \text{(ii)} \quad \text{(C)}$ $\alpha \leq \frac{v_{r,j}^{\text{meta}} I_{r,j}^{\text{meta}}}{\sum_{r=1}^{s} v_{r,j}^{\text{meta}} I_{r,j}^{\text{meta}}} \leq \beta \; j = 1,...,N \quad \text{(iii)}$	$BSI_o^{\text{meta}*} = \max_{w_{i,o}} \sum_{i=1}^{m} w_{i,o}^{\text{meta}} D_{i,o}^{\text{meta}}$ subject to $\sum_{i=1}^{m} w_{i,o}^{\text{meta}} D_{i,j}^{\text{meta}} \leq 1 \qquad j = 1,...,N \quad \text{(i)}$ $w_{i,o}^{\text{meta}} \geq 0 \qquad i = 1,...,m \quad \text{(ii)} \quad \text{(D)}$ $\alpha' \leq \frac{w_{i,j}^{\text{meta}} D_{i,j}^{\text{meta}}}{\sum_{i=1}^{m} w_{i,j}^{\text{meta}} D_{i,j}^{\text{meta}}} \leq \beta' \qquad \text{(iii)}$

The stability gap ratio (*SGR*) for the *o*th bank is then defined as the ratio of the BSI score obtained using Model (D) to the optimal BSI score derived from Model (B), *i.e.*, $SGR_o^k = BSI_o^{\text{meta}*} / BSI_o^{k*}$. Note that *SGR* lies between (0,1] and is measured as the ratio of the closeness of a particular bank on the meta frontier to the group frontier. The stability gap is thus computed as $1 - SGR_o^k$. The similar procedure is implemented to obtain the gap ratios corresponding to the underlined dimensions.

It is important to note that the above optimisation models (A)-(D) used in this paper are just for illustrative purposes so that novice readers can better grasp the proposed methodological framework and its capabilities in measuring bank stability. Although the constrained BoD model has many advantages, it does not account for statistical noise, confines itself only to positive values, and does not explicitly consider the impact of exogenous factors on the underlined dimension. Researchers can overcome these drawbacks by replacing the constrained BoD model with other robust variants like robust BoD, slack-based measure BoD, range-adjusted measure BoD, etc., for constructing the composite index of bank stability (refer to Mariano *et al*., 2021 for more details on other variants). Even if the robust BoD model accounts for statistical noise, the advantage of calculating the policy weight matrix needed for micro- and macro-level planning is not empirically viable because it is based on the bootstrap method, and there is no routine available for obtaining the weights. Therefore, we demonstrate a two-step stability framework using the constrained BoD model. As a robustness test, we compare the ranking of banks obtained using the constrained BoD with the aggregate stability score computed using the alternative BoD models and other competitive methods for obtaining BSI scores (for some extensions to the BoD model, see Aparicio and Kapelko, 2019; Puyenbroeck *et al*., 2021; Vidoli *et al*., 2015).

In particular, we compare the ranking of banks obtained from a two-step constrained BoD at 10 percent weight restriction ($BSI_{\text{BoD0.10\_TwoStep}}$) with alternative BSI indices that are obtained using the one-step constrained BoD ($BSI_{\text{BoD0.10\_OneStep}}$) obtained by aggregating all the ratio indicators at 10 percent weight restriction[6], unrestricted BoD (BSI_{UBoD}) with no weight restriction, robust BoD (BSI_{RBoD}) based on re-sampling procedure, and the linear unweighted index framework (BSI_{L}). In constructing the BSI_{UBoD} index, we avoid imposing weight restrictions (minimum importance) on stability dimensions. The *BSIL* score corresponds to a linear unweighted average of all stability dimensions. It is important to note that the estimated *BSI* scores derived from the above approaches/variants are deterministic and do not account for potential noise or statistical errors. We addressed the issue of potential noise or statistical errors in the indicators and dimensions by employing a robust version of the BoD model[7]. Here,

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[6] It is worthy to note that although the BSI can be constructed by simply aggregating the selected financial indicators, this one-step aggregation procedure does not provide the most needed dimensional indices that are of immense use from the perspective of the macro policy design by the regulators. The bankers and policy formulators are generally more interested in the broad dimensions of bank underperformance than simply relying on the individual financial ratios because they can easily comprehend the grey areas for stability performance using the underlined dimensions. With this in mind, we propose a two-step aggregation procedure instead of a one-step aggregation method to construct a bank stability index for sampled banks.

[7] Depending upon requirement, interested researchers can compute the overall score or dimensional scores by employing distinct variants of the BoD model. In the present study, we employ a constrained BoD model and present a two-step aggregation process as a practical guide to policymakers for the computation of the weight matrix for macro- and micro-planning, which is practically difficult using the order-*m* robust or bootstrap version of the BoD model since no such programme routine is available. Nevertheless, we validated the ranking of banks on constrained BoD-built BSI score with the BSI derived using robust BoD or other related variants.

robust BSI is computed by employing the robust BoD model at m=5 (BSI_{RBoD5}) and m=10 (BSI_{RBoD10}) with 1000 simulations. These variants are based on the order-m approach developed by Daraio and Simar (2005) and involve the relative comparison of the bank's composite stability index with a subsample of m banks randomly selected with equal or better performance on m dimensions. This variant was earlier applied by Vidoli and Mazziotta (2013) in index construction.

4. Illustrated Application

This section illustrates how we can implement the proposed meta-BoD framework to assess the stability performance of 76 Indian banks over the period 2014/15 - 2017/18. The sample includes 21 public sector banks (PSBs), 19 private banks (PBs), and 36 foreign banks (FBs) that were operating in the Indian banking industry. Sub-section 4.1 describes the indicators, dimensions, and procedures for aggregating indicators and dimensions for estimating the BSI scores for individual banks. According to the ownership type of each bank, we construct both meta (BSI_o^{meta}) and group (BSI_o^k) composite indices for the bank o under evaluation using a two-step constrained meta-BoD aggregation procedure, as elaborated in the preceding section. The empirical results are presented in sub-section 4.2.

4.1 Indicators, dimensions, and the Bank Stability Index

To begin with, we construct five distinct dimensional indices using 14 financial ratio indicators. The underlined dimensions embrace five key aspects of bank stability, namely, "asset quality", "management efficiency", "capital adequacy", "profitability", and "liquidity"[8]. The data on all the financial ratio indicators at the bank level are extracted from the "Statistical Table Relating to Banks in India", a yearly publication provided by the Reserve Bank of India (India's Central Bank). Our choice of indicators and dimensions is based on the IMF's financial soundness indicators for deposit-taking institutions (IMF, 2006) and the work of the Reserve Bank of India (2010). These dimensions clearly reflect the ability of banks to assess their financial strength and the major risks (credit, equity, and liquidity risks) they face. Credit risk is assessed in the first dimension. Asset quality index (D_{A}) is computed as a proxy to credit risk and is based on the aggregation of net NPLs to total advances (y_{A1}) and gross NPLs to total advances

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[8] We did not include the sensitivity to market risk as an aspect of bank stability for two reasons. First, many central bank authorities in developing countries have not viewed this as a crucial aspect of their bank stability framework. Second, the data on market-risk indicators are not easily accessible for commercial banks in developing nations. Given the availability of data and the banks' listing status, the present framework can be extended to include the additional dimension of market risk.

(y_{A2})[9]. The second dimension is to highlight the management's efforts towards rationalising personnel expenses and operational costs associated with banking operations and monitoring of loans. An index of management efficiency (D_M) is obtained using intermediation cost to total assets (y_{M1}) and the wage bill to total expense (y_{M2}) ratios. A bank's capital strength and buffer against potential risks are indicated by the dimensional index of capital adequacy (D_C). Three indicators, namely, capital to risky assets ratio (y_{S1}), tier 1 capital to tier 2 capital (y_{S2}), and leverage ratio (y_{S3}), are used to compute this dimensional index. The profitability index (D_P) reflects how a bank generates income from interest and non-interest sources, as well as from investments. This dimension is defined on four indicators, namely, non-interest income to total assets (y_{P1}), return-on-assets (y_{P2}), return-on-equity (y_{P3}), and net interest margin (y_{P4}). Finally, the banks are exposed to liquidity risk, so the fifth dimensional index is considered as liquidity (D_L). It is computed by aggregating three indicators, namely, total demand deposits to total assets (y_{L1}), liquid assets to total assets (y_{L2}), and demand and saving bank deposits to total assets (y_{L3}). The descriptive statistics of the stability indicators, along with their polarity with the bank stability index, are provided in Table 2. From the table, we note that, on an average, public and private banks performed relatively better in terms of management efficiency. It is reflected in the lower values of intermediation costs to total assets and wage bill to total expense ratios for PSBs and PBs when compared to FBs during the sample period. However, when it comes to profitability ratios, it appears that FBs perform fairly well on an average. In the last column of the table, we find that the underlined indicators vary significantly across ownership groups.

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[9] There are a few other indicators that can capture the asset quality, including loan loss provisions to total assets, sub-standard advances to gross NPLs, and restructured standard advances to standard advances. However, due to the non-availability of bank-level data on these indicators, the present study is limited to gross NPLs to total advances and net NPLs to total advances ratios.

Table 2: Summary statistics of the ratio indicators of bank stability

Dimension (D)	**Ratio indicators (y)**	**Polarity with bank stability index**	**All banks**	**PSBs**	**PBs**	**FBs**	**Kruskal-Wallis H-statistics**
Asset quality (D_A)	Net NPLs to total advances	Negative#	3.071 (6.287)	6.071 (3.578)	1.689 (1.468)	2.051 (8.233)	168.45***
	Gross NPLs to total advances	Negative#	6.298 (10.711)	10.650 (6.786)	3.34 (2.62)	5.321 (13.995)	112.45***
Management Efficiency (D_M)	Intermediation cost to total assets	Negative#	2.468 (2.481)	1.557 (0.266)	2.252 (0.423)	3.113 (3.459)	73.16***
	Ratio of wage bill to total expense	Negative#	16.906 (9.187)	12.914 (2.991)	13.480 (3.091)	21.042 (11.649)	59.67***
Capital adequacy (D_C)	Capital to risky asset ratio	Positive	26.148 (36.712)	11.329 (1.057)	13.994 (2.356)	41.206 (49.141)	258.30***
	Tier I capital to Tier II capital	Positive	131.18 (1702.15)	3.52 (1.34)	13.57 (11.06)	267.72 (2469.59)	191.63***
	Leverage ratio	Negative#	0.171 (0.158)	0.056 (0.008)	0.086 (0.224)	0.283 (0.170)	304.32***
Profitability (D_P)	Non-interest income to total assets	Positive	1.807 (2.774)	0.925 (0.270)	1.350 (2.564)	2.564 (3.866)	36.36***
	Return on Assets	Positive	0.684 (1.577)	-0.184 (0.790)	0.934 (0.894)	1.060 (1.967)	109.08***
	Return on Equity	Positive	3.409 (11.769)	-3.567 (14.299)	9.200 (11.521)	4.423 (7.575)	83.12***
	Net Interest Margin	Positive	2.861 (1.157)	2.065 (0.333)	2.869 (0.535)	3.321 (1.427)	114.02***
Liquidity (D_L)	Total demand deposits to total assets	Positive	30.131 (20.044)	31.623 (7.265)	30.782 (10.536)	28.917 (27.545)	21.07***
	Liquid assets to total assets	Positive	10.153 (11.193)	6.447 (2.649)	7.304 (5.933)	13.819 (14.726)	23.66***
	Demand and saving bank deposits to total deposits	Positive	8.919 (10.012)	5.574 (1.553)	7.460 (3.035)	11.641 (13.816)	10.60***

Notes: This table lists the indicators and dimensions used in constructing the bank stability index. '#' indicates that max-min normalisation criteria are adopted for indicators that are perceived to have a negative polarity with stability. Figures in parentheses are standard deviations. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.
Source: Authors' elaboration.

Before aggregating the ratio indicators to obtain the dimensional indices, we make some data adjustments, including orthogonalisation, winsorisation, and normalisation.

Orthogonalisation: Because the various aspects and characteristics of banking stability are interrelated and influence each other, the ratio indicators may not be completely independent. As a result, we orthogonalise ratio indicators with respect to each other using the modified Gram-Schmidt orthogonalisation approach. Our purpose is to avoid the interdependence of a particular ratio with others used in the analysis.

Winsorisation: We winsorise all 14 financial ratios at 99 percent to minimise the influence of outliers in our dataset. This step of data adjustment is in line with other studies on the financial and ratio datasets in the banking literature (Beck *et al.*, 2013; Cerutti *et al.*, 2017; Davis *et al.*, 2020).

Normalisation: We normalise all financial ratio indicators based on their polarity (correlation) with bank stability (see Table 2 for the polarity of each ratio indicator with BSI). For all such indicators that are perceived to positively correlate with bank stability, we adopt the min-max normalisation method as $I_{r,j} = \left(y_{r,j} - \min_j(y_r)\right) / \left(\max_j(y_r) - \min_j(y_r)\right)$, whereas negatively correlated ratios are normalised using the max-min formula as $I_{r,j} = \left(\max_j(y_r) - y_{r,j}\right) / \left(\max_j(y_r) - \min_j(y_r)\right)$. Here $I_{r,j}$ is the normalised value of the r^{th} ratio indicator for the j^{th} bank, $y_{r,j}$ is the actual value of the r^{th} ratio indicator for the j^{th} bank, $\min_j(y_r)$ is the minimum observed value of the r^{th} ratio indicator across all banks, and $\max_j(y_r)$ is the maximum observed value of the r^{th} ratio indicator across all banks. The above normalisation adjustments also convert the data set of indicators on a uniform scale of 0 to 1 (Cherchye *et al.*, 2011)[10].

After making the required data adjustments, we adopt a two-step aggregation procedure. In the first step, a set of normalised ratio indicators that are specific to a particular stability dimension are aggregated using the constrained BoD approach to build five dimensional index. For instance, the dimensional index of asset quality (DI_{A}) is estimated by aggregating the normalised values of net NPLs to total advances ($I_{\mathrm{A}1}$) and gross NPLs to total advances ($I_{\mathrm{A}2}$) by means of endogenously determined optimal weights obtained from the constrained BoD models (A) and (C) corresponding to group and meta frontiers, respectively. A similar approach is used to obtain the remaining dimensional indices. Before moving to the second step, we first apply a normalisation procedure suggested by Vidoli and Fusco (2018). This normalisation requires adjusting all BoD-based dimensional indices obtained in the first step at mean 100 and standard deviation 10. This normalisation allows accounting for zero and one (extreme) values of dimensional indices. Finally, five normalised dimensional indices are then aggregated in the second step by applying the constrained BoD models (B) and (D) (as

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[10] By definition, the BoD model and its variants only examine positive values of indicators/dimensions in the aggregation process (Vidoli and Fusco, 2018). Because data on financial ratios for the sampled banks can have a range of values (positive, negative, or zero), normalising indicators on a standard scale before aggregation makes sense. Furthermore, all ratios are adjusted based on their polarity with the composite index. Therefore, the aggregation process is unaffected.

explained in the previous section) to get bank-wise values of *BSI* with respect to group and meta frontiers.

4.2 Results, interpretation, and robustness

4.2.1 The bank stability index and its dimensions

We begin our discussion by explaining evolutionary trends in the levels of bank stability and its distinct dimensional indices. To determine how far a specific bank is from the industry stability frontier, we utilise the value of the stability index for the o^{th} bank corresponding to the meta frontier (BSI^{meta}) that is obtained using model (D) of our proposed methodological framework. It is important to note that the *BSI* for a bank ranges between a minimum of 0 (the least stable) and a maximum of 1 (the most stable). The BSI^{meta} score for a sampled bank, as well as the corresponding rank in each year of the sample period, are reported in Table A1 of Appendix A. In this section, we focus our discussion around mean estimates of the stability index. Table 3 reports the mean estimates of the dimensional indices and *BSI*.

From Table 3, we observe that the estimated mean *BSI* value across banks and years for the entire banking industry is 0.9435. Thus, it is evident that an average bank in India operates below the stability frontier and can achieve the status of a "fully stable bank" by raising its stability level by only 5.65 percent across all dimensions. However, a careful interpretation of the results obtained is required. In particular, we need to keep in mind that the BSI is sample-specific and a relative index, reflecting how well the bank performs relative to other banks in its industry. If we use the proposed framework to simulate stability for a different sample size or another variant of the BoD model, the *BSI* values will undoubtedly alter.

The empirical estimates of the bank stability index in Table 3 show that the Indian banking sector was almost stable during the sample period. This observed stability performance of the banking sector over the sample period can be attributed largely to countercyclical measures that were taken by the RBI in response to the 2007-09 Global Financial Crisis. The prominent measures in this direction were the deployment of a prudent monetary policy to ensure effective monetary transmission and the implementation of a set of policy actions to maintain enough liquidity in the economy. These measures kept the banks safe from the ill effects of the GFC and helped them to achieve higher levels of soundness. Interestingly, during the early years of the sample period, the Indian banking sector also experienced a local NPLs crisis, which resulted in a decline in profitability levels of commercial banks (especially of public sector banks), increased liquidity stress, low-interest margins, restricted exposure to offbalance-sheet activities, a drop in income from non-traditional sources, and increased loan loss provisioning (Gulati, 2022; Reserve Bank of India, 2017). This NPLs crisis placed a significant financial strain on the Indian banking system, jeopardising its overall stability. Despite the disruption caused by the NPLs crisis, the Indian banking sector has consistently outperformed in terms of stability, with no discernible and marked difference in yearly stability levels.

Table 3: Bank stability and its dimensions with respect to the meta frontier

Year→	**Bank groups↓**	**2013/14**	**2014/15**	**2015/16**	**2016/17**	**2017/18**	**2013/14-2017/18**
Dimensional indices (D^{meta})							
Asset quality	PSBs	0.9163	0.9159	0.9182	0.9105	0.9073	0.9136
	PBs	0.9166	0.9158	0.9164	0.9090	0.9053	0.9126
	FBs	0.9003	0.9009	0.8799	0.8765	0.8914	0.8898
	All banks	0.9160	0.9158	0.9163	0.9100	0.9084	***0.9133***
Management efficiency	PSBs	0.9084	0.9087	0.8872	0.8803	0.8972	0.8964
	PBs	0.9135	0.9126	0.8891	0.8806	0.9029	0.8997
	FBs	0.9003	0.9009	0.8799	0.8765	0.8914	0.8898
	All banks	0.9058	0.9060	0.8842	0.8786	0.8959	***0.8941***
Capital adequacy	PSBs	0.8728	0.8765	0.8739	0.8767	0.8728	0.8746
	PBs	0.8742	0.8775	0.8746	0.8768	0.8714	0.8749
	FBs	0.8678	0.8697	0.8703	0.8760	0.8692	0.8706
	All banks	0.8708	0.8735	0.8724	0.8764	0.8708	***0.8728***
Profitability	PSBs	0.9266	0.9227	0.9190	0.9100	0.9231	0.9203
	PBs	0.9280	0.9277	0.9188	0.9191	0.9233	0.9234
	FBs	0.9257	0.9259	0.9174	0.9137	0.9163	0.9198
	All banks	0.9265	0.9255	0.9182	0.9140	0.9199	***0.9208***
Liquidity	PSBs	0.9027	0.9107	0.8860	0.8999	0.8680	0.8935
	PBs	0.9035	0.9090	0.8846	0.8952	0.8669	0.8918
	FBs	0.9018	0.9094	0.8839	0.8962	0.8664	0.8915
	All banks	0.9025	0.9097	0.8847	0.8969	0.8670	***0.8921***
Bank stability index (BSI^{meta})							
BSI	PSBs	0.9566	0.9530	0.9372	0.9505	0.9429	0.9481
	PBs	0.9574	0.9545	0.9361	0.9485	0.9391	0.9471
	FBs	0.9489	0.9446	0.9303	0.9388	0.9322	0.9390
	All banks	0.9532	0.9494	0.9337	0.9445	0.9369	***0.9435***

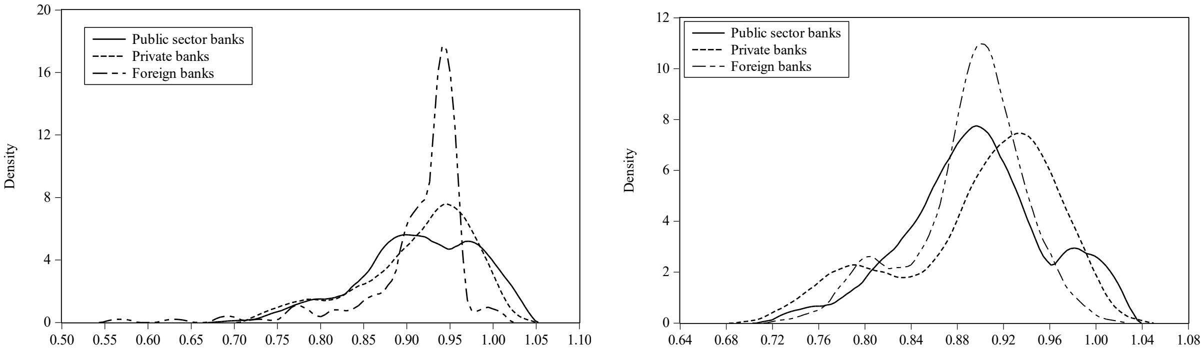
Source: Authors' calculations.

To ascertain whether banks with distinct ownership types maintained a similar level of stability, we compare the BSI^{meta} across bank groups. Table 3 also presents the relevant estimates of dimensional indices and BSI for public, private, and foreign bank groups. We find that domestic banks did relatively better than their foreign counterparts. In terms of average stability performance, public and private bank groups performed similarly. The overall stability performance of the bank groups indicates that PSBs=PBs>FBs. Additionally, all bank groups maintained higher stability levels in the first two years of the study period; however, this tendency changed after the local NPLs crisis and an economic downturn jolted the industry, which reversed the trend in stability levels. Notably, the stability performance of all groups recovered in the later years of the sample period. These findings also get strong statistical support from the results of the Simar-Zelenyuk-adapted-Li (*SZL*) test. The test results support the null hypothesis of the equality of distribution in stability levels between public and private banks. On the meta frontier, however, there are statistically significant variations in bank stability levels between public and foreign banks and private and foreign banks (see Table 4). The examination of the kernel density distributions of BSI for bank groups, as visualised in Figure 1, reflects that the density curve for the PSBs group is somewhat bimodal and flatter. The density curve of the FBs group, on the other hand, has a slightly higher mode and is to the left of the density curve for the PSBs and PBs groups. The comparison of the shapes of kernel densities corroborates the earlier observation that the PSB and PB groups behaved similarly and outperformed FBs in terms of bank stability during the sample period. It is possible that the superior stability performance of domestic banks is due to the implicit guarantee and favourable local conditions that they enjoy over foreign banks. Overall, the empirical findings indicate that all banks, regardless of ownership type, can improve their stability performance and operate on the "meta" stability frontier.

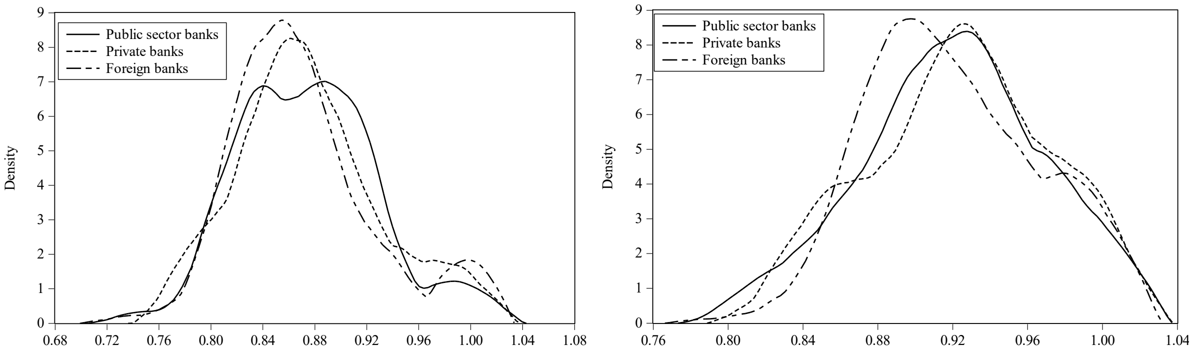
Table 4: *SZL* test statistics for equality of distribution in stability levels across the ownership groups

Null hypothesis (*Ho*)	**Test statistics** (*p*-value)
H0: $pdf(BSI^{\text{meta}}_{\text{Private}}) = pdf(BSI^{\text{meta}}_{\text{Public}})$	4.040 (0.458)
H0: $pdf(BSI^{\text{meta}}_{\text{Private}}) = pdf(BSI^{\text{meta}}_{\text{Foreign}})$	5.083*** (0.002)
H0: $pdf(BSI^{\text{meta}}_{\text{Public}}) = pdf(BSI^{\text{meta}}_{\text{Foreign}})$	1.345*** (0.005)

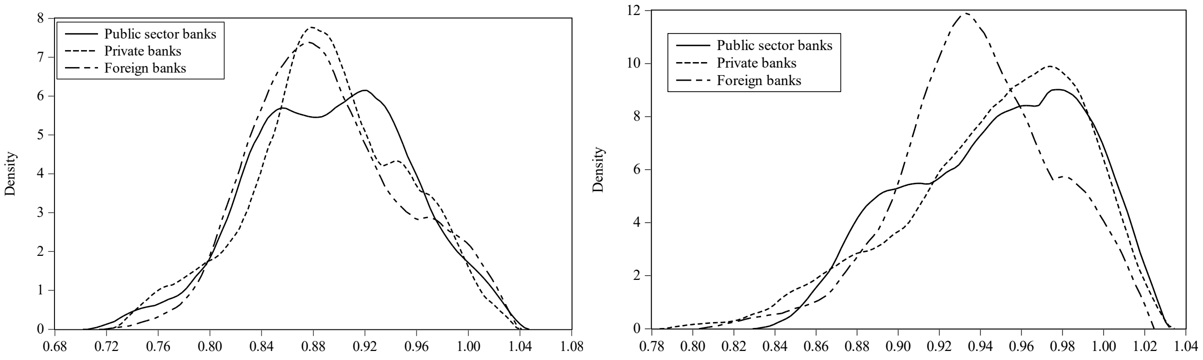
Notes: This table provides the test results for Simar-Zelenyuk adapted-Li (SZL) test. *BSI*= Bank stability index; *pdf* stands for probability density function. Figures in parentheses are respective *p*-values. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.
Source: Authors' calculations.



Asset quality **Management efficiency**



Capital adequacy **Profitability**



Liquidity **Bank stability index**

Figure 1: Kernel distribution of bank stability and its dimensions across bank groups.

4.2.2 Optimal policy weights on dimensions of bank stability

In the BoD modelling framework, information regarding the weighting scheme ($w_{i,o}^{\text{meta*}}$) is intuitive and imperative as it gives a clear understanding of the most precarious aspects of stability that require immediate attention from regulators and bank management in order to achieve desired macro-level policy interventions. It is important to note that higher values of weights provide sufficient information on bank stability dimensions that were accorded higher priority, and vice-versa. The mean weighting structure, as reported in Table 5, demonstrates the differences in policy priorities placed by bank groups[11]. We observe that an average bank gives higher priority to asset quality and profitability dimensions followed by management efficiency. Banks paid more or less the same importance to liquidity and capital adequacy dimensions. Among bank groups, an average private bank placed around 19 percent of its emphasis on profitability and management efficiency, and about 29 percent on asset quality. Capital adequacy and liquidity were relatively less prioritised dimensions by PBs. In contrast, FBs prioritised asset quality more during the study period. With the changing market dynamics, the policy priorities of PSBs, PBs, and FBs on distinct dimensions have changed over the years. In light of the NPLs crisis, PBs turned their priority to asset quality in 2015/16. However, in 2016/17, banks paid greater attention to profitability and management efficiency, as well as asset quality.

Table 5: Policy priorities assigned to dimensions of bank stability across ownership groups

Year→ Dimensions↓	**Bank groups↓**	**2013/14**	**2014/15**	**2015/16**	**2016/17**	**2017/18**	**2013/14-2017/18**
Asset quality ($w_{\text{A}}^{\text{meta*}}$)	PSBs	28.3	27.2	33.2	27.9	31.9	***29.7***
	PBs	25.6	28.7	31.7	27.9	31.1	***29.0***
	FBs	30.8	34.6	36.3	30.6	33.2	***33.1***
	All banks	28.8	31.1	34.3	29.2	32.3	***31.1***
Management efficiency ($w_{\text{M}}^{\text{meta*}}$)	PSBs	18.5	15.9	13.2	22.2	18.6	***17.7***
	PBs	19.6	18.1	16.5	25.1	19.1	***19.7***
	FBs	15.6	14.0	15.4	22.9	15.9	***16.7***
	All banks	17.4	15.5	15.0	23.3	17.4	***17.7***
Capital adequacy ($w_{\text{C}}^{\text{meta*}}$)	PSBs	16.5	13.8	18.4	15.7	17.0	***16.3***
	PBs	16.3	13.8	16.3	12.8	16.9	***15.2***
	FBs	16.5	13.2	12.8	15.2	21.2	***15.8***
	All banks	16.4	13.5	15.2	14.7	19.0	***15.8***
Profitability ($w_{\text{P}}^{\text{meta*}}$)	PSBs	21.4	22.0	15.2	19.5	18.7	***19.4***
	PBs	22.8	20.5	14.7	20.4	19.4	***19.6***
	FBs	22.9	20.6	14.6	17.2	15.4	***18.1***
	All banks	22.5	20.9	14.8	18.7	17.3	***18.8***
Liquidity ($w_{\text{L}}^{\text{meta*}}$)	PSBs	15.3	21.2	20.0	14.6	13.8	***17.0***
	PBs	15.7	18.9	20.8	13.8	13.5	***16.5***
	FBs	14.2	17.6	20.9	14.1	14.3	***16.2***
	All banks	14.9	18.9	20.6	14.2	14.0	***16.5***

Note: This table presents the policy priorities placed by banks on underlined dimensions. $w_{\text{A}}^{\text{meta*}}$, $w_{\text{M}}^{\text{meta*}}$, $w_{\text{C}}^{\text{meta*}}$, $w_{\text{P}}^{\text{meta*}}$, and $w_{\text{L}}^{\text{meta*}}$ are weights pertaining to the five dimensions of bank stability. Figures in **bold** and ***italic*** are the averages for the analysed period.
Source: Authors' calculations.

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[11] For the sake of brevity, we present and discuss yearly mean weights/priorities corresponding to stability dimensions here. However, bank-wise policy weights can be available upon request from the authors.

4.2.3 Weight analysis for domestic systemically important banks (D-SIBs)

Through the application of the meta-BoD models (C) and (D), we are able to generate 76 unique weighting schemes for our sample banks. The differences in how indicators and dimensions are weighted reveal asymmetries in the policy priorities of banks. To keep things brief and succinct, we will just look at indicator ($\upsilon_{r,o}^{\text{meta}*}$) and dimension ($w_{i,o}^{\text{meta}*}$) weights for three domestic systemically important banks (D-SIBs) identified by the RBI. These banks are the State Bank of India, the ICICI Bank, and the HDFC Bank. It is worth noting that this kind of analysis can be replicated for other sampled banks. Tables 6 and 7 provide bank-wise mean optimal weights for D-SIBs. Note that a higher weight indicates a higher priority accorded by a bank to a particular indicator/dimension, while the lower weights give enough information about an indicator/dimension that is under-emphasised. Such a weighting scheme allows for the design of the re-adjustments required for an unstable bank. From Table 6, we note that the State Bank of India and HDFC Bank place a higher priority on asset quality and liquidity dimensions than on other dimensions. In the case of ICICI Bank, capital adequacy, followed by management efficiency, captures 70% of the attention. This bank gives almost equal importance to the remaining stability dimensions. Also, we note that the distribution of weights by D-SIBs to distinct dimensions of bank stability is not static.

Table 6: Policy priorities assigned on distinct dimensions of BSI by D-SIBs

Year→ D-SIBs↓	**Dimensional weights ↓**	**2013/14**	**2014/15**	**2015/16**	**2016/17**	**2017/18**	**2013/14-2017/18**
State Bank of India	$w_{\mathrm{A}}^{\text{meta}*}$	49.7	43.3	60.0	60.0	43.2	***51.2***
	$w_{\mathrm{M}}^{\text{meta}*}$	10.0	10.0	10.0	10.0	14.7	***10.9***
	$w_{\mathrm{C}}^{\text{meta}*}$	10.0	10.0	10.0	10.0	22.0	***12.4***
	$w_{\mathrm{P}}^{\text{meta}*}$	11.8	12.1	10.0	10.0	10.0	***10.8***
	$w_{\mathrm{L}}^{\text{meta}*}$	18.5	24.6	10.0	10.0	10.0	***14.6***
ICICI Bank	$w_{\mathrm{A}}^{\text{meta}*}$	10.0	10.0	10.0	10.0	10.0	***10.0***
	$w_{\mathrm{M}}^{\text{meta}*}$	34.2	27.1	10.0	51.2	19.8	***28.5***
	$w_{\mathrm{C}}^{\text{meta}*}$	20.2	42.9	57.8	18.8	50.2	***38.0***
	$w_{\mathrm{P}}^{\text{meta}*}$	25.5	10.0	12.2	10.0	10.0	***13.5***
	$w_{\mathrm{L}}^{\text{meta}*}$	10.0	10.0	10.0	10.0	10.0	***10.0***
HDFC Bank	$w_{\mathrm{A}}^{\text{meta}*}$	50.6	46.1	40.6	41.4	30.6	***41.9***
	$w_{\mathrm{M}}^{\text{meta}*}$	10.0	10.0	10.0	18.3	10.0	***11.7***
	$w_{\mathrm{C}}^{\text{meta}*}$	10.0	10.0	10.0	10.0	10.0	***10.0***
	$w_{\mathrm{P}}^{\text{meta}*}$	11.3	12.4	10.0	14.6	39.4	***17.5***
	$w_{\mathrm{L}}^{\text{meta}*}$	18.1	21.6	29.4	15.6	10.0	***18.9***

Note: This table presents the policy priorities placed on underlined dimensions by D-SIBs. $w_{\mathrm{A}}^{\mathrm{meta}*}$, $w_{\mathrm{M}}^{\mathrm{meta}*}$, $w_{\mathrm{C}}^{\mathrm{meta}*}$, $w_{\mathrm{P}}^{\mathrm{meta}*}$, and $w_{\mathrm{L}}^{\mathrm{meta}*}$ are weights pertaining to the five dimensions of bank stability**.** Figures in **bold** and ***italic*** are the averages for the analysed period.
Source: Authors' calculations.

Some valuable insights are also drawn from policy weights on stability indicators ($\upsilon_{r,o}^{\mathrm{meta}*}$). Table 7 provides the policy weights for the set of underlined indicators for D-SIBs. All three D-SIBs, on an average, prioritise reducing the net NPLs to total advances ratio (adjusted for loss provisions) in order to lower overall default risk. When contemplating ways to enhance management efficiency, these banks accord higher priority to the wage bill to total expense indicator. In their pursuit to achieve higher profitability, the State Bank of India and ICICI Bank prioritise the ratio of non-interest revenue to total assets. At the same time, HDFC Bank makes every effort to improve ROA. The micro-level policy weight analysis shown in Table 7 suggests that less stable banks can rejig their primacies on benchmark ratios to move on distinct dimensional frontiers. From the perspective of overall bank stability, we observe diverse preferences among banks for various dimensions and indicators. Overall, our analysis provides a wealth of information about the optimal weight structure for more stable banks. Less stable banks can use this information to change the order of their priorities on stability indicators and dimensions, allowing them to move up the stability ladder.

Table 7: Policy priorities on stability indicators of BSI by D-SIBs

Dimensions→		**Asset Quality (A)**		**Management Efficiency (M)**		**Soundness (S)**			**Profitability (P)**				**Liquidity (L)**		
D-SIBs↓	**Indicator weights→ Year↓**	$\upsilon^{\text{meta*}}_{\text{A1}}$	$\upsilon^{\text{meta*}}_{\text{A2}}$	$\upsilon^{\text{meta*}}_{\text{M1}}$	$\upsilon^{\text{meta*}}_{\text{M2}}$	$\upsilon^{\text{meta*}}_{\text{C1}}$	$\upsilon^{\text{meta*}}_{\text{C2}}$	$\upsilon^{\text{meta*}}_{\text{C3}}$	$\upsilon^{\text{meta*}}_{\text{P1}}$	$\upsilon^{\text{meta*}}_{\text{P2}}$	$\upsilon^{\text{meta*}}_{\text{P3}}$	$\upsilon^{\text{meta*}}_{\text{P4}}$	$\upsilon^{\text{meta*}}_{\text{L1}}$	$\upsilon^{\text{meta*}}_{\text{L2}}$	$\upsilon^{\text{meta*}}_{\text{L3}}$
State Bank of India	2013/14	0.555	0.445	0.100	0.900	0.600	0.270	0.129	0.616	0.100	0.100	0.184	0.553	0.204	0.244
	2014/15	0.561	0.439	0.100	0.900	0.473	0.128	0.399	0.488	0.272	0.100	0.140	0.338	0.163	0.499
	2015/16	0.900	0.100	0.900	0.100	0.370	0.100	0.530	0.431	0.177	0.161	0.231	0.377	0.165	0.458
	2016/17	0.626	0.374	0.100	0.900	0.333	0.100	0.567	0.534	0.100	0.100	0.266	0.249	0.159	0.592
	2017/18	0.629	0.371	0.124	0.876	0.376	0.100	0.524	0.452	0.329	0.118	0.100	0.518	0.100	0.382
	2013/14-2017/18	***0.654***	***0.346***	***0.265***	***0.735***	***0.430***	***0.140***	***0.430***	***0.504***	***0.196***	***0.116***	***0.184***	***0.407***	***0.158***	***0.435***
ICICI Bank	2013/14	0.518	0.482	0.137	0.863	0.479	0.100	0.421	0.416	0.100	0.384	0.100	0.555	0.198	0.247
	2014/15	0.543	0.457	0.190	0.810	0.364	0.100	0.536	0.528	0.100	0.272	0.100	0.748	0.135	0.117
	2015/16	0.547	0.453	0.100	0.900	0.395	0.100	0.505	0.484	0.100	0.316	0.100	0.100	0.347	0.553
	2016/17	0.597	0.403	0.581	0.419	0.376	0.100	0.524	0.205	0.482	0.213	0.100	0.262	0.188	0.551
	2017/18	0.578	0.422	0.257	0.743	0.607	0.111	0.282	0.444	0.335	0.121	0.100	0.365	0.284	0.351
	2013/14-2017/18	***0.557***	***0.443***	***0.253***	***0.747***	***0.444***	***0.102***	***0.454***	***0.415***	***0.223***	***0.261***	***0.100***	***0.406***	***0.230***	***0.364***
HDFC Bank	2013/14	0.763	0.237	0.100	0.900	0.633	0.242	0.125	0.100	0.595	0.115	0.191	0.607	0.178	0.215
	2014/15	0.758	0.242	0.174	0.826	0.514	0.100	0.386	0.100	0.698	0.100	0.102	0.341	0.100	0.559
	2015/16	0.900	0.100	0.100	0.900	0.406	0.100	0.494	0.100	0.651	0.100	0.149	0.389	0.190	0.421
	2016/17	0.623	0.377	0.100	0.900	0.296	0.210	0.494	0.108	0.540	0.100	0.251	0.265	0.174	0.561
	2017/18	0.628	0.372	0.245	0.755	0.293	0.146	0.561	0.100	0.700	0.100	0.100	0.622	0.278	0.100
	2013/14-2017/18	***0.734***	***0.266***	***0.144***	***0.856***	***0.428***	***0.160***	***0.412***	***0.102***	***0.637***	***0.103***	***0.159***	***0.444***	***0.184***	***0.371***

Notes: This table presents the bank-wise optimal policy weights on the underlined set of ratio indicators by D-SIBs. $\upsilon^{\text{meta*}}_{\text{A1}}$ and $\upsilon^{\text{meta*}}_{\text{A2}}$ are weights that correspond to the dimension of asset quality; $\upsilon^{\text{meta*}}_{\text{M1}}$ and $\upsilon^{\text{meta*}}_{\text{M2}}$ relate to the dimension of management efficiency; $\upsilon^{\text{meta*}}_{\text{C1}}, \upsilon^{\text{meta*}}_{\text{C2}}$ and $\upsilon^{\text{meta*}}_{\text{C3}}$ belong to the dimension of soundness; $\upsilon^{\text{meta*}}_{\text{P1}}, \upsilon^{\text{meta*}}_{\text{P2}}, \upsilon^{\text{meta*}}_{\text{P3}}$ and $\upsilon^{\text{meta*}}_{\text{P4}}$ pertain to the dimension of profitability; and $\upsilon^{\text{meta*}}_{\text{L1}}, \upsilon^{\text{meta*}}_{\text{L2}}$ and $\upsilon^{\text{meta*}}_{\text{L3}}$ associate with the liquidity dimension. Figures in **bold** and ***italic*** are the averages for the analysed period.

Source: Author's calculations.

4.2.4 Group heterogeneity and gaps across dimensions and composite index

As noted in sub-section 3.2, technology heterogeneity and differences in business and legal environments across bank groups lead to differences in production technologies. Therefore, a meta frontier analysis must be adopted to capture the instability gaps across bank groups. Table 8 presents the estimated mean stability gaps across bank groups based on the meta-BoD technique. The higher (lower) the value of SGIE (in percent), the farther (closer) the bank is to the respective dimensional or overall stability frontier. Based on the estimates, we draw the following key inferences. First, banks are progressing faster on profitability and liquidity fronts. Although banks emphasised a higher priority on asset quality, larger instability gaps are observed for asset quality, followed by management efficiency and capital adequacy. Second, across bank groups, the observed instability gaps on distinct aspects (except for liquidity) have narrowed for PSBs and enlarged for PBs and FBs in the later years of the study. The finding further suggests that PSBs have moved relatively closer to the asset quality and management efficiency frontiers. The enhanced stability performance of PSBs on the asset quality aspect could be attributed to the sound resolution strategies taken by regulators and policymakers to dispel the fog of the NPLs crisis in the form of restructuring, recapitalisation, and enlisting many PSBs under the prompt corrective action framework, particularly after 2015/16. Third, foreign banks performed well in terms of capital adequacy and operated closer to the meta frontier in this regard. Overall, irrespective of bank group, on an average, SGIEs are greater than zero (*i.e.*, SGRs less than one) across periods and bank groups, implying that banks have room to improve their stability levels in specific aspects.

Table 8: Group heterogeneity and gaps across dimensions and composite index (in percent)

Dimensions↓	Bank groups↓	2013/14	2014/15	2015/16	2016/17	2017/18	2013/14-2017/18
Asset quality	PSBs	3.43	3.45	0.31	0.43	2.65	***2.05***
	PBs	1.88	2.77	2.53	3.23	2.07	***2.49***
	FBs	5.17	5.41	5.53	7.20	6.84	***6.03***
	All banks	3.87	4.21	3.34	4.34	4.49	***4.05***
Management efficiency	PSBs	0.38	0.16	0.20	0.21	0.77	***0.35***
	PBs	1.95	2.98	5.28	4.61	3.52	***3.67***
	FBs	4.63	2.98	6.74	7.06	6.10	***5.50***
	All banks	2.78	2.20	4.57	4.56	3.98	***3.62***
Capital adequacy	PSBs	3.57	2.58	4.32	2.81	6.89	***4.03***
	PBs	5.93	5.41	7.09	6.31	5.68	***6.08***
	FBs	3.87	1.36	0.10	3.71	0.74	***1.95***
	All banks	4.30	2.71	3.01	4.11	3.67	***3.56***
Profitability	PSBs	2.94	2.13	2.62	1.85	2.00	***2.31***
	PBs	2.09	2.90	2.95	3.11	2.92	***2.79***
	FBs	0.90	0.69	1.31	1.66	0.82	***1.08***
	All banks	1.76	1.64	2.08	2.08	1.67	***1.85***
Liquidity	PSBs	5.26	1.88	5.77	3.42	5.16	***4.30***
	PBs	2.68	3.84	5.70	5.30	7.40	***4.98***
	FBs	0.31	0.62	1.29	0.12	2.17	***0.90***
	All banks	2.27	1.77	3.63	2.33	4.30	***2.86***
Bank stability index							
BSI	PSBs	1.34	1.44	3.44	1.80	2.63	***2.13***
	PBs	0.56	1.86	2.84	1.85	3.03	***2.03***
	FBs	1.05	0.74	2.79	1.96	1.13	***1.53***
	All banks	1.01	1.21	2.98	1.89	2.02	***1.82***

Notes: This table presents the stability gaps (in percent) across bank groups. Figures in **bold** and ***italic*** are the averages for the analysed period.
Source: Author's calculations.

4.3 Robustness checks

4.3.1 Rank consistency of a bank on BSI over the sample years

As a first robustness check, we examine the rank consistency of banks on *BSI* based on the two-step constrained BoD model ($BSI_{\mathrm{BoD0.10\_TwoStep}}$). Interested readers can refer to Table A1 of Appendix A for the index score and corresponding rank of a bank on *BSI* in a particular year[12]. Additionally, we can see how a bank's rank changed between the first year (2013/14) and last year (2017/18) of the examined period. In this regard, we note changes in the stability position of sample banks, with some banks demonstrating rank improvement (positive change in rank) and others demonstrating a fall in the rank on *BSI* (negative change in rank) in 2017/18 compared to the rank observed in 2013/14. To ascertain the statistical significance of the

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[12] The authors would like to sincerely thank the anonymous reviewer for this suggestion.

differences in the ranking of banks on *BSI* across sample years, we apply the non-parametric Kendall tau's rank correlation test. For this, we compute the rank correlation coefficients of a bank on *BSI* score in year *t* with the year *t*+1, *t*+2,…,*T*, respectively. These rank correlation coefficients are shown in Table 9. In general, we note that, while the rank concordance of banks on the stability index has weakened over the years, the correlation coefficients remain statistically significant. This suggests that the ranking of banks on the stability position has not changed much over the study period.

Table 9: Rank consistency test across sampled years

Year	2013/14	2014/15	2015/16	2016/17	2017/18
2013/14	1.000				
2014/15	0.601***	1.000			
2015/16	0.446***	0.531***	1.000		
2016/17	0.295***	0.375***	0.413***	1.000	
2017/18	0.2643**	0.308**	0.414***	0.311**	1.000

Note: *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.
Source: Authors' calculations.

4.3.2 Rank sensitivity to alternative methodologies

As mentioned in the methodology section, we also see the differences in the ranking of banks across alternative variants of BoD. To do this, we compare the ranking of banks based on $BSI_{\text{BoD0.10\_TwoStep}}$ with alternative *BSI* indices that are obtained using the one-step constrained BoD ($BSI_{\text{BoD0.10\_OneStep}}$), unrestricted BoD ($BSI_{\text{UBoD}}$), robust BoD ($BSI_{\text{RBoD}}$), and the linear unweighted average index (BSI_{L}). Table A2 of Appendix A reports the bank-wise average *BSI* indices and ranking of the sampled banks corresponding to alternative variants of BoD during the study period. In addition, Figure 2 displays the kernel density distribution of $BSI_{\text{BoD0.10\_TwoStep}}$ and other BSI indices derived from BoD variants. Overall, findings reveal that the ranking of the sampled banks based on stability scores computed using different variants is highly consistent. In our illustrative example, the Bank of Baroda appears to be a top performer on the BSI score in each scenario. To establish the statistical significance of the differences in the ranking across alternative variants, we again apply Kendall tau's rank correlation test. Table 10 reports these rank correlation coefficients. We find that the rank correlation coefficients for alternative approaches are found to be statistically significant. In particular, the correlation coefficients between $BSI_{\text{BoD0.10\_TwoStep}}$ and BSI_{RBoD} variants are moderately high, indicating that both variants provide a significantly high concordance in the ranking of banks. This result allows us to safely infer that the constrained BoD model can produce an adequate measure of bank stability and can be used as a tool for designing optimal policy interventions at both the micro and macro levels. But, the constrained BoD model can be easily replaced with a robust BoD variant for estimating *BSI*.

Table 10: Rank consistency test across alternative methodologies

Method	$BSI_{\text{BoD0.10Two-Step}}$	BSI_{UBoD}	$BSI_{\text{BoD0.10OneStep}}$	BSI_{RBoD5}	BSI_{RBoD10}	BSI_{L}
$BSI_{\text{BoD0.10TwoStep}}$	1.000					
BSI_{UBoD}	0.640***	1.000				
$BSI_{\text{BoD0.10OneStep}}$	0.517***	0.553***	1.000			
BSI_{RBoD5}	0.615***	0.655	0.728	1.000		
BSI_{RBoD10}	0.661***	0.675***	0.698***	0.863***	1.000	
BSI_{L}	0.552***	0.350**	0.384**	0.443**	0.459**	1.000

Note: This table reports the rank correlation coefficients for sampled banks on BSI corresponding to alternative variations of BoD and linear weighted average methods. $BSI_{\text{BoD0.10TwoStep}}$= BSI obtained using constrained BoD with 10 percent weight restriction using a two-step aggregation procedure, $BSI_{\text{BoD0.10OneStep}}$= BSI obtained using constrained BoD with 10 percent weight restriction using a one-step procedure, BSI_{UBoD}= BSI scores based on unrestricted BoD/classic BoD with no weight restriction, BSI_{RBoD5} = Order-*m* BSI at M=5 & B=1000, BSI_{RBoD10}= Order-*m* BSI at M=10 & B=1000. Here, M= subset of observations randomly drawn to compare the stability score and B=Bootstrap replications. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Source: Authors' calculations.

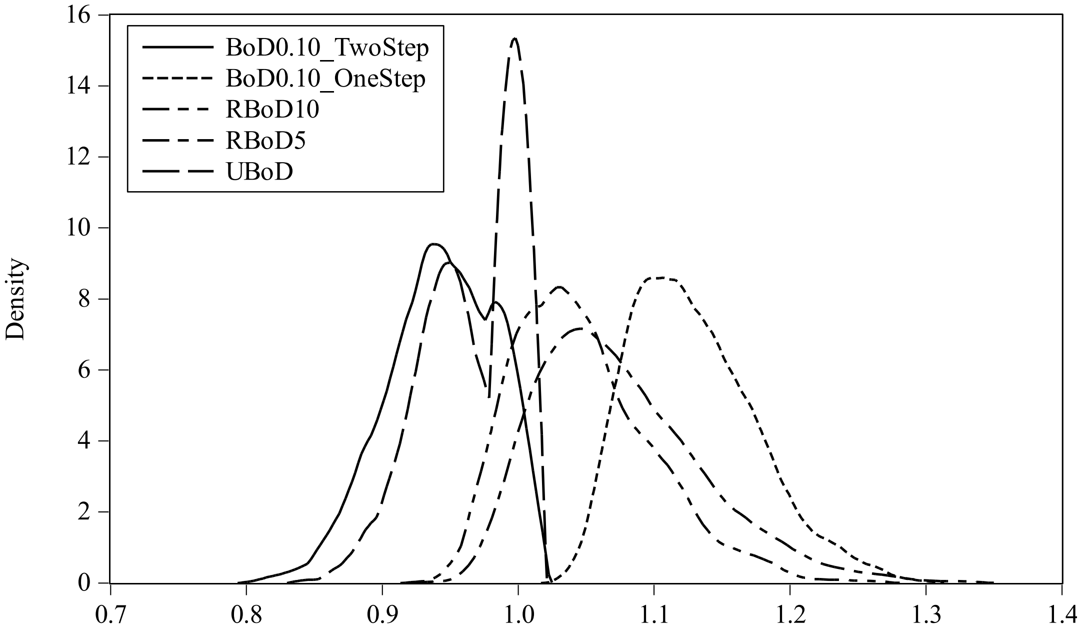

Figure 2: Kernel distribution of bank stability index obtained from BoD-based alternatives.

Overall, the proposed meta-BoD framework is a robust methodological framework that aggregates stability indicators and dimensions in a way that is holistic, avoids any subjective judgement in choosing weights, prudently assigning endogenous data-driven policy weights, and accounts for group heterogeneity. Furthermore, it is quite adaptable, simple to use, and unquestionably adaptive to the variety of indicators, dimensions, levels of aggregation, and variants of BoD. Additionally, the proposed framework makes it possible to carefully evaluate a bank's priorities in relation to different indicators and dimensions of stability.

5. Conclusions

Over the past two decades, there have been several attempts to quantify a measure of bank stability. However, there is no consensus on an adequate and all-encompassing approach to measuring bank stability. This study develops a framework for building a new multidimensional composite index of bank stability based on the non-parametric DEA-based BoD approach. This framework generates endogenous policy weights and helps in measuring stability gaps between banks with different types of ownership. We call this framework as the "meta-BoD" approach because it accounts for differences in technological, operational, and regulatory environments embedded across bank groups. The proposed approach yields a composite index that may be utilised by policy analysts and regulators as an effective tool to benchmark stability levels and for designing optimal policy interventions at both the micro and macro levels. We illustrate the proposed meta-BoD approach for computing the composite index of bank stability for a sample of 76 Indian banks operating between 2013/14 and 2017/18. The composite index is derived from financial soundness indicators and overcomes the drawbacks of both accounting-based Z-score and market-based distance-to-default measures. The proposed meta-BoD framework is conceptually based on a two-step step aggregation procedure that, in the first step, calculates five distinct dimensional indices using a set of stability indicators that capture various dimensions of bank stability. The second step combines the dimensional indices obtained in the first step to generate the composite index of bank stability. The stability gaps between bank groups can be easily worked out by computing the bank stability indices with respect to a meta frontier (capturing inter-group variations) and group frontiers (capturing intra-group variations). The ranking of banks on the stability front computed using the meta-BoD approach is validated using alternative variants of the BoD method. The empirical findings shed light on a unique weighting matrix that reveals a bank's preference for underlined indicators and dimensions, as well as those areas of bank stability that need quick policy interventions.

Based on the empirical illustration, the following conclusions can be drawn. First, on an average, Indian banks typically operate below the stability frontier and have room to improve their stability performance. Second, domestic banks outperformed their foreign counterparts in terms of maintaining their stability levels during the study period. Third, Indian banks prioritised the asset quality and profitability dimensions, followed by management efficiency, during the sample period. The banks gave almost equal weight to both liquidity and capital adequacy dimensions. This result suggests that banks should pay more attention to raising capital adequacy and liquidity. Fourth, there are clear asymmetries in the weighting structure and relative priorities for different indicators and dimensions across bank groups and time periods. As a result, the study recommends that less stable banks might benchmark against the cohort of more stable banks and re-shuffle their priorities on stability indicators and dimensions to climb the stability ladder. Finally, public sector banks have seen their stability gaps narrow across all dimensions except the liquidity dimension. Foreign banks performed well in terms of capital adequacy and operated closer to the industry frontier. The robustness checks reveal that the stability estimates have a high rank concordance across BoD variants and sample years.

Overall, we are confident that the outcomes of the proposed meta-BoD framework will assist managers and bank boards better align their policy focus at the bank level, as well as provide regulators and policymakers with the instrument they need to make effective policy interventions to improve bank stability. This framework can be easily customised and adapted to any banking system. Researchers can use this framework to benchmark bank stability within a country (as we did) or to compare bank stability across countries using a cross-country sample of bank-year data. Furthermore, variants of the BoD model can be developed to deal directly with situations in which ratios rather than absolute numbers are used as outputs. Because banks usually report the financial ratios, we are limited in what we can learn from them. Future research could address this issue.

Statements and Declaration

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

All authors contributed to the study's conception and design. Material preparation, data collection and analysis were performed by Rachita Gulati, M. Kabir Hassan, and Vincent Charles. The first draft of the manuscript was written by Rachita Gulati and all authors commented on the previous versions of the manuscript. All authors read and approved the final manuscript.

References

Abdelbadie, R.A. & Salamaa, A. (2019). Corporate governance and financial stability in US banks: Do indirect interlocks matter? *Journal of Business Research, 104*(C), 85-105.

Ahamed, M.M. & Mallick, S. (2017). Does regulatory forbearance matter for bank stability? Evidence from creditors' perspective. *Journal of Financial Stability, 28*(C), 163-180.

Allen, R., Athanassopoulos, A.D., Dyson, R.G. & Thanassoulis, E. (1997). Weight restrictions and value judgements in DEA: Evolution, development and future directions. *Annals of Operations Research, 73*(0), 13-34.

Antonio, J. & Martin, R. (2012). An index of child health in the least developed countries (LDCs) of Africa. *Social Indicators Research, 105*(3), 309-322.

Aparicio, J. & Kapelko, M. (2019). Enhancing the measurement of composite indicators of corporate social performance. *Social Indicators Research*, *144*(2), 807–826.

Athanassoglou, S. (2016). Revisiting worst-case DEA for composite indicators. *Social Indicators Research, 128*(3), 1259-1272.

Badasyan, N., Shideler, D. & Silva, S. (2011). *Broadband achievement index: Moving beyond availability. Telecommunications Policy, 35*(11), 933-950.

Beaver, W. (1966). Financial ratios as predictors of failure, *Journal of Accounting Research*, 4, Issue: Empirical Research in Accounting: Selected Studies, 71-111.

Beck, T., De Jonghe, O. & Schepens, G. 2013. Bank competition and stability: Cross-country heterogeneity. *Journal of Financial Intermediation, 22*(2), 218–244.

Bitar, M., Hassan, M. K., & Walker, T. (2017). Political systems and the financial soundness of Islamic banks. *Journal of Financial Stability*, *31*(C), 18-44.

Bos, J. W. B., Koetter, M., Kolari, J. W. & Kool, C. J. M. (2009). Effects of heterogeneity on bank efficiency scores. *European Journal of Operational Research*, *195*(1), 251–261.

Central Bank of the Republic of Turkey. (2008). *Financial Stability Report*. Central Bank of the Republic of Turkey, Ankara.

Cerutti, E., Claessens, S., Laeven, L. (2017). The use and effectiveness of macroprudential policies: New evidence. *Journal of Financial Stability 28*(C), 203–224.

Chan-Lau, J.A & Sy, A.N. (2006). Distance-to-default in banking: A bridge too far? IMF Working Paper 2006/215, International Monetary Fund.

Charles, V. & Díaz, G. (2017). A non-radial DEA index for Peruvian regional competitiveness. *Social Indicators Research, 134*(2): 747-770.

Charnes, A., Cooper, W.W. & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429-444.

Cherchye, L., Moesen, W. & Puyenbroeck, V.T. (2004). Legitimately diverse, yet comparable: On synthesising social inclusion performance in the EU. *Journal of Common Market Studies, 42*(5), 919-955.

Cherchye, L., Moesen, W., Rogge, N. & Puyenbroeck, V.T. (2007). An introduction to 'benefit of the doubt' composite indicators. *Social Indicators Research, 82*(1), 111-145.

Cherchye, L., Moesen, W., Rogge, N. & Puyenbroeck, V.T. (2011). Constructing composite indicators with imprecise data: A proposal. *Expert Systems with Applications, 38*(9), 10940-10949.

Cherchye, L., Ooghe, E. & Puyenbroeck, V.T. (2008). Robust human development rankings. *Journal of Economic Inequality, 6*(4), 287-321.

Čihák, M. & Schaeck, K. (2010). How well do aggregate prudential ratios identify banking system problems? *Journal of Financial Stability*, *6*(C), 130-144.

Čihák, M. (2006). How do central banks write on financial stability? IMF Working Paper Monetary, WP/06/13, International Monetary Fund.

Crockett, A. (1997). Why is financial stability a goal of public policy? *Economic Review, 82* (Q IV), 5-22.

Daly, K., Batten, J.A. & Mishra, A.V. and Choudhury, T. (2019). Contagion risk in global banking sector. *Journal of International Financial Markets, Institutions and Money*, 63(C), DOI: https://doi.org/10.1016/j.intfin.2019.101136.

Daraio, C. & Simar, L. (2005). Introducing environmental variables in non-parametric frontier models: a probabilistic approach. *Journal of Productivity Analysis*, *24*(1), 93–121.

Davis, E.P. Karim, D. & Noel, D. (2020). The bank capital-competition-risk nexus – A global perspective. *Journal of International Financial Markets, Institutions and Money, 65*, DOI: https://doi.org/10.1016/j.intfin.2019.101169

Demirgüç-Kunt, A. & Detragiache, E. (2011). Basel core principles and bank soundness: Does compliance matter? *Journal of Financial Stability, 7*(4), 179-190.

Despotis, D.K. (2005). A reassessment of the Human Development Index via data envelopment analysis. *The Journal of the Operational Research Society, 56*(8), 969-980.

Eichler, S. & Sobański, K. (2016). National politics and bank default risk in the eurozone. *Journal of Financial Stability, 26*(C), 247-256.

Emrouznejad, A., & Amin, G. (2009). DEA models for ratio data: Convexity consideration. *Applied Mathematics Modelling, 33*(1):486-498.

European Central Bank (2005), *Financial Stability Review*. June 2005. Germany, Europe. Available at: https://www.ecb.europa.eu/pub/pdf/fsr/financialstabilityreview200506en.pdf?0b80e9a06597ab3dd84ab4f5a6780d45

Färe, R., Grosskopf, S. & Weber, W. L. (2004). The effect of risk-based capital requirements on profit efficiency in banking. *Applied Economics*, *36*(15), 1731-1743.

Fernández. A. I., González, F. & Suárez, N. (2016). Banking stability, competition, and economic volatility. *Journal of Financial Stability, 22*(C), 101-120.

Fiordelisi, F. & Mare, D.S. (2014). Competition and financial stability in European cooperative banks. *Journal of International Money and Finance, 45*(C), 1-16.

Fiordelisi, F. & Marqués-Ibañez, D. (2013). Is bank default risk systematic? *Journal of Banking & Finance, 37*(6), 2000-2010.

Fujii, H., Managi, S. & Matousek, R. (2014). Indian bank efficiency and productivity changes with undesirable output: A disaggregate approach. Journal of Banking and Finance, *38*(C), 41-50.

Gadanecz, B. & Jayaram, K. (2008). Measures of financial stability – a review. IFC Bulletin No. 31, Bank for International Settlements. https://www.bis.org/ifc/publ/ifcb31ab.pdf

Geršl, A. & Heřmánek, J. (2007). Financial stability indicators: Advantages and disadvantages of their use in the assessment of financial system stability. CNB Financial Stability Report 2006, Czech National Bank, Research Department, pp. 69-79. Available at: http://www.cnb.cz/en/financial_stability/fs_reports/fsr_2006/FSR_2006_article_2.pdf

Ghosh, S. (2011). A simple index of banking fragility: Application to Indian data. *The Journal of Risk Finance, 12*(2), 112-120.

Giambona, F. & Vassallo, E. (2013). Composite indicator of financial development in a benefit-of-doubt approach. *Economic Notes, 42*(2), 171-202.

Greco, S., Ishizaka, A., Tasiou, M. & Torrisi, G. (2019). On the methodological framework of composite indices: A review of the issues of weighting, aggregation, and robustness. *Social Indicators Research. 141*(C), 61-94.

Gropp, R., Vesala, J., Vulpes, G. (2004). Market indicators, bank fragility, and indirect market discipline. *Economic Policy Review*, *10*(2),53-62.

Gulati, R. (2022). Global and local banking crises and risk-adjusted efficiency of Indian banks: Are the impacts really perspective-dependent? *The Quarterly Review of Economics and Finance*, DoI: https://doi.org/10.1016/j.qref.2022.01.004

Gulati, R., Kattumuri, R. & Kumar, S. (2020). A non-parametric index of corporate governance for banking firms: An application to India data. Socio-Economic Planning and Sciences, 70, Available at: doi: https://doi.org/10.1016/j.seps.2019.03.008

Hafeez, B., Xiping, L., Humayun, K. &Tripe, D. (2022). Measuring bank risk: Forward-looking z-score. *International Review of Financial Analysis*, 80, Available at: doi: https://doi.org/10.1016/j.irfa.2022.102039

Hassan, M. K., Khan, A. & Paltrinieri, A. (2019). Liquidity risk, credit risk and stability in Islamic and conventional banks. *Research in International Business and Finance*, *48*, 17–31.

Hollingsworth, B. & Smith, P. (2003). Use of ratios in data envelopment analysis, *Applied Economics Letters, 10*(11), 733-735

Huang, T-H. & Chung, M-T. (2017). Do undesirables matter on the examination of banking efficiency using stochastic directional distance functions. *The Quarterly Review of Economics and Finance*, *65*(C), 194-211.

Huljak, I. (2015). Market power and stability of CEE banks. *Business Systems Research, 6*(2), 74-90.

Ingves, S. (2011). Central bank governance and financial stability. Bank of International Settlements, A Report by a Study Group, May 2011, Available at: https://www.bis.org/publ/othp14.pdf

International Monetary Fund (IMF). (2006). *Financial Soundness Indicators-Compilation Guide*. IMF, Washington, D.C.

Issing, O. (2003). Monetary stability, financial stability and the business cycle: Five views. Bank for International Settlements (BIS) Working Paper No. 18, 16-23. Available at: https://www.bis.org/publ/bppdf/bispap18.pdf

Jokipii, T. & Monnin, P. (2013). The impact of banking sector stability on the real economy. *Journal of International Money and Finance, 32*(C), 1-16.

Kabir, M.N. & Worthington, A.C. (2017). The 'competition–stability/fragility' nexus: A comparative analysis of Islamic and conventional banks. *International Review of Financial Analysis*, *50*(C), 111–128.

Kaminsky, G.L. & Reinhart, C.M. (1999). The twin crises: The causes of banking and balance-of-payments problems. *American Economic Review, 89*(3), 473-500.

Kočišová, K. & Stavárek, D. (2018). The evaluation of banking stability in the European Union countries. *International Journal of Monetary Economics and Finance, 11*(2), 36-55.

Laeven, L. & Levine, R. (2009). Bank governance, regulation, and risk taking. *Journal of Financial Economics, 93*(2), 259-275.

Lapteacru, I. (2016). On the consistency of the Z-score to measure the bank risk. LAREFI Working Paper No. 2016-05.

Lavigne, C., Jaeger, S.D. & Rogge, N. (2019). Identifying the most relevant peers for benchmarking waste management performance: A conditional directional distance Benefit-of-the-Doubt approach. *Waste Management, 89*(C), 418-429.

Lepetit, L. & Strobel, F. (2013). Bank insolvency risk and time-varying Z-score measures. *Journal of International Financial Markets, Institutions & Money, 25*(C), 73-87.

Mariano, E.B., Sobreiro, V.A. & Rebelatto, D.A.N. (2015). Human development and data envelopment analysis: A structured literature review. *Omega, 54*(C), 33-49.

Martin, J. C., Mendoza, C. & Roman, C. (2017). A DEA travel–tourism competitiveness index. *Social Indicators Research, 130*(3), 937-957.

Maudos, J., Pastor, J. M., Perez, F. & Quesada, J. (2002). Cost and profit efficiency in European banks. *Journal of International Financial Markets, Institutions and Money, 12*(1), 33–58.

Melyn, W. & Moesen, W. (1991). Towards a synthetic indicator of macroeconomic performance: unequal weighting when limited information is available. Public Economics Research Paper- Leuven, ZDB-ID 26175691, No. 17, CES, KU Leuven.

Merton, R.C. (1974). On the pricing of corporate debt: the risk structure of interest rates. *Journal of Finance, 29*(2), 449-470.

Milne, A. & Wood, G. (2009). Shattered on the rock? British financial stability from 1866 to 2007, *Journal of Banking Regulation*, 10(2), 89-127.

Milne, A. (2014), Distance to default and the financial crisis, *Journal of Financial Stability*, 12(C), 26-36.

Nagel, S. & Purnanandam, A. (2020). Banks' risk dynamics and distance to default. *The Review of Financial Studies*, 33(6), 2421-2467.

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffmann, A. & Giovannini, E. (2008). Handbook on constructing composite indicators: Methodology and users guide. Organisation for Economic Co-operation and Development. Available at: http://www.oecd.org/sdd/42495745.pdf

O'Donnell, C. J., Rao, D. S. P. & Battese, G.E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics, 34*(2), 231–255.

Paredes-Gazqueza, J.D., Rodriguez-Fernandezb, J. M. & Cuesta-Gonzalez, M. (2016). Measuring corporate social responsibility using composite indices: Mission impossible? The case of the electricity utility industry. *Revista de Contabilidad – Spanish Accounting Review, 19*(1), 142–153.

Park, K. & Weber, W. (2006). A note on efficiency and productivity growth in the Korean banking industry 1992–2002. *Journal of Banking and Finance*, *30*(8), 2371–2386.

Pham, M.D. & Zelenyuk, V. (2019). Weak disposability in nonparametric production analysis: A new taxonomy of reference technology sets. *European Journal of Operational Research*, *274*(1), 186-198.

Puyenbroeck, T. (2018). On the output orientation of the benefit-of-the-doubt-model. *Social Indicators Research, 139*(2): 415-431.

Puyenbroeck, T.V. & Rogge, N. (2020). Comparing regional human development using global frontier difference indices, *Socio-Economic Planning Sciences*, 70, 100663. DOI: https://doi.org/10.1016/j.seps.2018.10.014

Ray, S. & Das, A. (2010). Distribution of cost and profit efficiency: Evidence from Indian banking. *European Journal of Operational Research, 201*(1), 297–307.

Reserve Bank of India. (2010). *Financial Stability Report*. March 2010. Mumbai, India.

Reserve Bank of India. (2017). Report on Trend and Progress of Banking in India 2016-17. Mumbai, India

Rogge, N. & Puyenbroeck, T.V. (2007). An introduction to 'benefit-of-the-doubt' composite indicators. *Social Indicators Research, 82*(1), 111-145.

Schaeck, K. & Cihák, M. (2014). Competition, efficiency, and stability in banking. *Financial Management, 43*(1), 215-241.

Schinasi G.J. (2004). Defining financial stability. IMF Working Paper No. WP/04/187. Available at: https://www.imf.org/external/pubs/ft/wp/2004/wp04187.pdf

Segoviano, M.A. & Goodhart, C. (2009). Banking Stability Measures. IMF Working Paper No. WP/09/4. Available at: https://www.imf.org/external/pubs/ft/wp/2009/wp0904.pdf

Shaddady, A. & Moore, T. (2019). Investigation of the effects of financial regulation and supervision on bank stability: The application of CAMELS-DEA to quantile regressions. *Journal of International Financial Markets, Institutions & Money, 58*(C), 96-116.

Simar, L. & Zelenyuk, V. (2006). On testing equality of distributions of technical efficiency scores. *Econometric Reviews, 25* (4), 497-522.

Simper, R., Hall, M.J.B., Liu, W., Zelenyuk, V. & Zhou, Z. (2017). How relevant is the choice of risk management control variable to non-parametric bank profit efficiency analysis? The case of South Korean banks. *Annals of Operations Research*, *250*(1), 105-127.

Soedarmono, W., Machrouh, F. & Tarazi, A. (2011). Bank market power, economic growth and financial stability: Evidence from Asian banks. *Journal of Asian Economics, 22*(6), 460-470.

Vidoli F. & Mazziotta C. (2013). Robust weighted composite indicators by means of frontier methods with an application to European infrastructure endowment. *Statistica Applicata, Italian Journal of Applied Statistics*.

Vidoli, F. & Fusco, E. (2018). Compind: Composite indicators functions based on frontiers in R (Compind package version 2.0). Available at: https://cran.r-project.org/web/packages/Compind/vignettes/Compind_vignette.pdf

Vidoli, F., Fusco, E. & Mazziotta, C. (2015). Non-compensability in composite indicators: A robust directional frontier method. *Social Indicators Research, 122,* 635–652.

Wong, Y.H.B. & Beasley, J.E. (1990). Restricting weight flexibility in data envelopment analysis. *Journal of Operational Research Society, 41*(9), 829-835.

Zanella, A., Camanho A.S. & Dias T.G. (2015). Undesirable outputs and weighting schemes in composite indicators based on data envelopment analysis. *European Journal of Operational Research*, *245*(2), 517-530.

Zhou, P., Ang, B.W. & Poh, K.L. (2007). A mathematical programming approach to constructing composite indicators. *Ecological Economics, 62*(2), 291-297.

Zhu, N., Wu, Y., Wang, B. & Yu, Z. (2019). Risk preference and efficiency in Chinese banking. *China Economic Review*, *53*(C), 324-341.

Appendix A

Table A1: Ranking of banks on the meta-BoD-based stability index

Bank code↓	**Year→** **Bank name↓**	**2013/14**	**Rank**	**2014/15**	**Rank**	**2015/16**	**Rank**	**2016/17**	**Rank**	**2017/18**	**Rank**	**Δ^{Rank}=** Rank2013/14-Rank2018	**2013/14-2017/18**	**Overall rank**
Public sector banks														
B1	Allahabad Bank	0.9861	18	0.9844	17	0.9389	35	0.9184	58	0.9288	46	-28	0.9513	33
B2	Andhra Bank	0.9608	36	0.9608	34	0.9718	17	0.9718	23	0.9630	21	+15	0.9656	16
B3	Bank of Baroda	1.0000	1	1.0000	1	0.9723	15	1.0000	1	1.0000	1	0	0.9945	3
B4	Bank of India	0.8877	72	0.8769	76	0.8693	71	0.9457	39	0.9517	27	+45	0.9063	67
B5	Bank of Maharashtra	0.9201	60	0.9097	65	0.9767	10	0.8970	66	0.9862	10	+50	0.9380	45
B6	Canara Bank	0.9738	26	0.9842	18	0.9004	61	0.9342	48	0.9502	28	-2	0.9486	34
B7	Central Bank Of India	0.8964	71	0.8957	69	0.8789	68	0.9008	64	0.9126	57	+14	0.8969	71
B8	Corporation Bank	0.9574	40	0.9454	45	0.9477	26	1.0000	1	0.9353	40	0	0.9572	25
B9	Dena Bank	0.9696	29	0.9664	24	0.9028	60	0.8687	74	0.9583	23	+6	0.9331	53
B10	IDBI Ltd.	1.0000	1	1.0000	1	1.0000	1	1.0000	1	0.9583	22	-21	0.9917	6
B11	Indian Bank	0.9941	14	0.9765	21	0.9880	9	0.9974	10	0.9938	7	+7	0.9899	7
B12	Indian Overseas Bank	0.8986	70	0.8994	67	0.8619	74	0.8868	71	0.8776	71	-1	0.8849	72
B13	Oriental Bank Of Commerce	0.9952	13	0.9873	13	0.9466	29	0.9445	41	0.9210	51	-38	0.9589	22
B14	Punjab & Sind Bank	0.9316	55	0.9319	52	0.9757	12	0.9575	31	0.9281	47	+8	0.9450	37
B15	Punjab National Bank	0.8812	73	0.8830	75	0.8920	65	1.0000	1	0.9069	60	+13	0.9126	65
B16	State Bank Of India	0.9871	17	0.9892	12	0.9521	21	1.0000	1	0.9813	14	+3	0.9819	10
B17	Syndicate Bank	1.0000	1	0.9862	14	0.9454	31	0.9001	65	0.9356	38	-37	0.9535	31
B18	UCO Bank	1.0000	1	1.0000	1	0.9379	36	0.9635	28	0.8990	66	-65	0.9601	21
B19	Union Bank Of India	0.9770	25	0.9600	35	0.9665	18	0.9465	38	0.9289	45	-20	0.9558	28
B20	United Bank Of India	0.9187	61	0.9278	53	0.9064	58	0.9525	32	0.8848	69	-8	0.9180	64
B21	Vijaya Bank	0.9538	44	0.9483	41	0.9507	23	0.9745	20	1.0000	1	+43	0.9655	17
Private banks														
B22	Axis Bank	0.9722	27	0.9969	8	0.9989	6	0.9982	9	0.9822	11	+16	0.9897	8
B23	Catholic Syrian Bank	0.9184	63	0.8909	71	0.8541	75	0.8494	75	0.8192	76	-13	0.8664	76
B24	City Union Bank	0.9613	34	0.9974	7	0.9479	25	0.9404	44	0.9466	31	+3	0.9587	23
B25	Development Credit Bank	0.9029	69	0.8981	68	0.8725	69	0.9075	62	0.9196	53	+16	0.9001	70
B26	Dhana Lakshmi Bank	0.8680	74	0.8884	73	0.8721	70	0.8710	73	0.8687	73	+1	0.8736	74
B27	Federal Bank	1.0000	1	0.9439	46	0.9110	56	0.9506	34	0.9266	48	-47	0.9464	35
B28	HDFC Bank	0.9369	52	0.9657	25	0.9619	19	0.9767	18	1.0000	1	+51	0.9683	15
B29	ICICI Bank	0.9934	15	0.9854	16	0.9343	38	0.9443	42	0.9582	24	-9	0.9631	19
B30	IndusInd Bank	0.9980	12	0.9916	9	1.0000	1	0.9882	12	0.9884	9	+3	0.9932	5
B31	Jammu & Kashmir Bank	1.0000	1	0.9828	20	0.9507	24	0.8937	68	0.9424	34	-33	0.9539	30
B32	Karnataka Bank	0.9477	45	0.9643	30	0.9205	54	0.9262	54	0.9018	63	-18	0.9321	54
B33	Karur Vysya Bank	0.9811	21	0.9643	29	0.9934	7	0.9828	15	0.9047	61	-40	0.9653	18
B34	Kotak Mahindra Bank	0.9688	30	0.9383	47	0.9268	45	0.9734	22	0.9736	17	+13	0.9562	27
B35	Lakshmi Vilas Bank	0.9596	38	0.9500	39	0.9395	34	0.9844	14	0.8573	74	-36	0.9382	43
B36	Nainital Bank	0.9779	24	0.9839	19	0.9722	16	1.0000	1	0.9933	8	+16	0.9855	9
B37	Ratnakar Bank	0.9838	20	0.9737	23	0.9755	13	0.9745	19	0.9656	20	0	0.9746	12
B38	South Indian Bank	0.9185	62	0.9481	42	0.8923	64	0.9635	27	0.9298	44	+18	0.9304	56
B39	Tamilnad Mercantile Bank	0.9351	53	0.9257	55	0.9257	48	0.9584	30	0.9820	13	+40	0.9454	36
B40	Yes Bank	0.9669	31	0.9461	44	0.9363	37	0.9392	45	0.9821	12	+19	0.9541	29

Contd…

Bank code	Bank name	2013/14	Rank	2014/15	Rank	2015/16	Rank	2016/17	Rank	2017/18	Rank	Δ^{Rank}= Rank2014-Rank2018	2013/14-2017/18	Overall rank
Foreign Banks														
B41	Ab Bank	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1	0	1.0000	1
B42	Abu Dhabi Commercial Bank	0.9474	47	0.9255	56	0.9315	42	0.9156	60	0.9254	49	-2	0.9291	57
B43	American Express Bank	0.9167	65	0.9238	58	0.8933	63	0.8917	69	0.8909	68	-3	0.9033	69
B44	Australia and New Zealand Bank	0.9203	59	0.9151	63	0.9060	59	0.8880	70	0.9155	54	+5	0.9090	66
B45	Bank of America	0.9448	48	0.9540	37	0.9291	44	0.9252	56	0.9355	39	+9	0.9377	46
B46	Bank of Bahrain & Kuwait	0.9607	37	0.8916	70	0.9234	49	0.9503	35	0.9333	41	-4	0.9319	55
B47	Bank of Ceylon	1.0000	1	1.0000	1	0.9914	8	1.0000	1	1.0000	1	0	0.9983	2
B48	Bank of Nova Scotia	0.9570	41	0.9617	33	0.9107	57	0.9438	43	0.9207	52	-11	0.9388	42
B49	Bank of Tokyo-Mitsubishi UFJ	0.9587	39	0.9553	36	0.9217	51	0.9347	47	0.9151	55	-16	0.9371	47
B50	Barclays Bank	0.9031	68	0.9152	62	0.9213	52	0.9174	59	0.9461	32	+36	0.9206	60
B51	BNP Paribas	0.9427	49	0.9367	49	0.9308	43	0.9258	55	0.9448	33	+16	0.9362	50
B52	Citibank	0.9779	23	0.9905	10	0.9470	28	0.9744	21	0.8996	65	-42	0.9579	24
B53	Credit Agricole	0.9297	56	0.9258	54	0.8909	66	0.9025	63	0.8794	70	-14	0.9057	68
B54	Credit Suisse	0.9292	57	0.9638	31	0.9324	39	0.9491	36	0.9393	36	+21	0.9428	40
B55	CTBC Bank	0.9609	35	0.9527	38	0.8682	73	0.9809	16	0.9482	29	+6	0.9422	41
B56	DBS Bank	0.8579	76	0.9050	66	0.8808	67	0.8962	67	0.8718	72	+4	0.8823	73
B57	Deutsche Bank	0.9634	33	0.9746	22	0.9998	5	0.9392	46	0.9306	43	-10	0.9615	20
B58	First Rand Bank	0.9848	19	0.8842	74	0.8684	72	0.9446	40	0.9134	56	-37	0.9191	63
B59	Hong Kong and Shanghai Bank	0.9474	46	0.9254	57	0.9267	46	0.9293	51	0.9374	37	+9	0.9332	52
B60	Industrial and Commercial Bank of China	0.9913	16	0.9205	61	0.8960	62	0.9187	57	0.9092	58	-42	0.9271	58
B61	JP Morgan Chase Bank	0.9543	43	0.9647	28	0.9470	27	0.9689	25	0.9476	30	+13	0.9565	26
B62	Krung Thai Bank	1.0000	1	1.0000	1	1.0000	1	0.9693	24	1.0000	1	0	0.9939	4
B63	Mashreq Bank	1.0000	1	0.9861	15	0.9735	14	0.9619	29	0.9314	42	-41	0.9706	13
B64	Mizuho Bank	0.9336	54	0.9137	64	0.9508	22	0.9335	49	0.9531	26	+28	0.9369	48
B65	National Australia Bank	1.0000	1	0.9618	32	0.9586	20	0.9521	33	0.9798	15	-14	0.9705	14
B66	Rabo Bank International	0.9129	66	0.9359	50	0.9211	53	0.9868	13	0.8461	75	-9	0.9206	61
B67	Royal Bank Of Scotland	0.9780	22	0.9346	51	0.9318	40	0.8850	72	0.8918	67	-45	0.9242	59
B68	SBER Bank	0.8646	75	0.8900	72	0.8365	76	0.8276	76	0.9420	35	+40	0.8722	75
B69	Shinhan Bank	0.9713	28	0.9647	27	0.9428	32	0.9268	53	0.9085	59	-31	0.9428	39
B70	Societe Generale	0.9423	51	0.9224	59	0.9225	50	0.9128	61	0.8996	64	-13	0.9199	62
B71	Sonali Bank	0.9425	50	0.9486	40	0.9266	47	0.9686	26	0.9036	62	-12	0.9380	44
B72	Standard Chartered Bank	0.9635	32	0.9901	11	0.9761	11	0.9907	11	0.9564	25	+7	0.9754	11
B73	State Bank of Mauritius	0.9038	67	0.9464	43	0.9315	41	0.9781	17	0.9239	50	+17	0.9367	49
B74	Sumitomo Mitsui Bank	0.9545	42	0.9657	26	0.9424	33	0.9269	52	0.9730	19	+23	0.9525	32
B75	United Overseas Bank	0.9168	64	0.9381	48	0.9154	55	0.9334	50	0.9739	16	+48	0.9355	51
B76	Westpac Banking Corporation	0.9289	58	0.9209	60	0.9457	30	0.9478	37	0.9731	18	+40	0.9433	38

Notes: This table reports the meta-BoD-based BSI score and corresponding rank of a bank on BSI in a particular year. Δ^{Rank} is the change in rank of a bank in the first year (2013/14) and the last year (2017/18) of the examined period. The positive sign (+) indicates the rank improvement and the negative sign (-) reflects the deterioration in the rank on the stability position of a sampled bank.

Source: Authors' calculations.

Table A2: Robustness check across alternative variants of the BoD

Bank code	BSI$_{BOD\_0.10}$	Rank	BSI$_{UBoD}$	Rank	BSI$_{BoD\_O}$	Rank	BSI$_{RBoD5}$	Rank	BSI$_{RBoD10}$	Rank	BSI$_{L}$	Rank
B1	0.9513	32	1.1610	12	0.9741	32	1.0920	21	1.0576	23	0.5242	36
B2	0.9656	16	1.1524	17	0.9714	35	1.1054	18	1.0716	17	0.5487	18
B3	0.9945	3	1.1375	28	1.0000	1	1.1259	10	1.0908	11	0.5705	7
B4	0.9063	67	1.0962	63	0.9174	74	1.0387	58	1.0101	64	0.4791	63
B5	0.9380	46	1.1395	27	0.9666	42	1.0827	28	1.0501	30	0.5183	43
B6	0.9486	35	1.1219	40	0.9723	33	1.0584	48	1.0398	44	0.5149	48
B7	0.8969	71	1.1046	58	0.9256	68	1.0397	57	1.0092	65	0.4774	65
B8	0.9572	25	1.1144	46	0.9927	17	1.0856	25	1.0607	21	0.5353	26
B9	0.9331	53	1.1512	19	0.9751	31	1.0827	29	1.0493	33	0.5127	50
B10	0.9917	6	1.1793	7	1.0000	1	1.1558	7	1.1219	7	0.6122	2
B11	0.9899	7	1.2003	5	1.0000	1	1.1660	5	1.1225	6	0.5819	6
B12	0.8849	72	1.1085	52	0.9221	71	1.0384	59	1.0195	58	0.4594	69
B13	0.9589	23	1.1298	34	0.9715	34	1.0789	32	1.0531	27	0.5507	16
B14	0.9450	38	1.1211	41	0.9869	20	1.0670	38	1.0418	41	0.5011	56
B15	0.9126	65	1.1254	37	0.9403	62	1.0401	56	1.0178	59	0.4567	72
B16	0.9819	10	1.1522	18	0.9985	12	1.1073	17	1.0821	14	0.5587	11
B17	0.9535	31	1.1078	54	0.9838	23	1.0633	42	1.0442	38	0.5024	55
B18	0.9601	22	1.1275	35	0.9908	19	1.1025	19	1.0697	18	0.5068	54
B19	0.9558	28	1.1131	49	0.9705	37	1.0597	46	1.0438	39	0.5364	25
B20	0.9180	63	1.1446	23	0.9635	44	1.0562	49	1.0279	50	0.4678	67
B21	0.9655	17	1.1071	55	0.9998	11	1.0677	37	1.0407	42	0.5107	52
B22	0.9897	8	1.1435	25	0.9975	13	1.1201	12	1.0835	12	0.5949	4
B23	0.8664	75	1.0974	61	0.9197	73	1.0100	72	0.9830	75	0.4160	75
B24	0.9587	24	1.1525	16	0.9672	41	1.1007	20	1.0577	22	0.5504	17
B25	0.9001	70	1.0883	68	0.9382	65	1.0147	69	0.9948	69	0.4589	70
B26	0.8736	74	1.0838	69	0.9109	75	1.0185	68	0.9940	70	0.4347	74
B27	0.9464	36	1.1268	36	0.9704	38	1.0741	34	1.0498	32	0.5165	45
B28	0.9683	14	1.1190	43	0.9780	27	1.0669	39	1.0459	36	0.5450	20
B29	0.9631	20	1.1437	24	0.9941	16	1.1149	13	1.0803	15	0.5446	21
B30	0.9932	5	1.1613	11	1.0000	10	1.1258	11	1.0911	10	0.5671	8
B31	0.9539	30	1.1500	21	0.9854	21	1.0843	27	1.0529	28	0.5207	39
B32	0.9321	54	1.1105	50	0.9528	53	1.0481	53	1.0272	51	0.5206	40
B33	0.9653	18	1.1598	13	0.9763	29	1.1093	16	1.0691	19	0.5597	10
B34	0.9562	27	1.1580	14	0.9816	25	1.0892	22	1.0632	20	0.5337	27
B35	0.9382	45	1.1200	42	0.9492	55	1.0663	40	1.0406	43	0.5165	46
B36	0.9855	9	1.1825	6	0.9962	15	1.1617	6	1.1229	5	0.5535	13
B37	0.9746	11	1.1417	26	0.9972	14	1.0851	26	1.0566	24	0.5316	30
B38	0.9304	57	1.1055	57	0.9675	40	1.0630	43	1.0357	47	0.4862	60
B39	0.9454	37	1.1133	48	0.9593	47	1.0650	41	1.0489	35	0.5215	37
B40	0.9541	29	1.1189	44	0.9825	24	1.0695	36	1.0443	37	0.5134	49
B41	1.0000	1	1.2095	3	1.0000	1	1.1768	3	1.1329	4	0.5932	5
B42	0.9291	59	1.0752	72	0.9364	66	1.0315	64	1.0113	62	0.5312	31
B43	0.9033	69	1.0965	62	0.9778	28	1.0611	45	1.0306	48	0.4566	73
B44	0.9090	66	1.0617	76	0.9215	72	0.9955	75	0.9877	73	0.4789	64
B45	0.9377	47	1.0924	67	0.9383	64	1.0193	67	1.0070	67	0.5198	41
B46	0.9319	55	1.1222	39	0.9410	59	1.0791	31	1.0501	31	0.5210	38
B47	0.9983	2	1.2093	4	1.0000	1	1.1742	4	1.1347	3	0.6000	3
B48	0.9388	44	1.1020	59	0.9542	51	1.0436	54	1.0259	52	0.5326	29
B49	0.9389	43	1.1061	56	0.9425	58	1.0384	60	1.0217	54	0.5476	19
B50	0.9144	64	1.0726	74	0.9229	69	1.0106	71	0.9925	71	0.4939	58
B51	0.9364	50	1.0757	71	0.9457	56	1.0241	66	1.0082	66	0.5332	28
B52	0.9669	15	1.1505	20	1.0000	1	1.1096	15	1.0737	16	0.5556	12
B53	0.9057	68	1.0742	73	0.9222	70	1.0064	73	0.9902	72	0.4794	62
B54	0.9428	40	1.0996	60	0.9546	49	1.0363	62	1.0169	60	0.5304	32
B55	0.9422	41	1.1556	15	0.9853	22	1.0887	23	1.0564	25	0.5267	35
B56	0.8823	73	1.0690	75	0.9060	76	1.0032	74	0.9840	74	0.4572	71
B57	0.9615	21	1.1335	31	0.9758	30	1.0750	33	1.0426	40	0.5671	9
B58	0.9191	62	1.1224	38	0.9632	45	1.0592	47	1.0300	49	0.4662	68
B59	0.9332	52	1.0945	65	0.9391	63	1.0331	63	1.0102	63	0.5387	24
B60	0.9271	60	1.1155	45	0.9426	57	1.0503	52	1.0247	53	0.4849	61
B61	0.9565	26	1.1354	30	0.9593	46	1.0624	44	1.0392	45	0.5534	14
B62	0.9939	4	1.2456	1	1.0000	1	1.2544	1	1.1979	1	0.6391	1
B63	0.9706	12	1.1701	10	0.9914	18	1.1129	14	1.0834	13	0.5170	44
B64	0.9369	49	1.1086	51	0.9408	60	1.0289	65	1.0156	61	0.5278	34
B65	0.9705	13	1.2434	2	1.0000	1	1.2207	2	1.1639	2	0.5297	33
B66	0.9313	56	1.1143	47	0.9537	52	1.0505	51	1.0197	56	0.5115	51
B67	0.9405	42	1.1361	29	0.9714	36	1.0875	24	1.0558	26	0.4974	57
B68	0.8530	76	1.0939	66	0.9259	67	0.9923	76	0.9729	76	0.3958	76

B69	0.9495	33	1.0949	64	0.9517	54	1.0412	55	1.0197	57	0.5522	15
B70	0.9217	61	1.0823	70	0.9403	61	1.0146	70	0.9995	68	0.5087	53
B71	0.9372	48	1.1755	9	1.0000	1	1.1469	9	1.0987	8	0.4707	66
B72	0.9648	19	1.1777	8	0.9791	26	1.1527	8	1.0944	9	0.5431	22
B73	0.9303	58	1.1326	32	0.9664	43	1.0720	35	1.0493	34	0.5160	47
B74	0.9492	34	1.1308	33	0.9678	39	1.0555	50	1.0361	46	0.5411	23
B75	0.9355	51	1.1477	22	0.9546	50	1.0812	30	1.0503	29	0.4937	59
B76	0.9433	39	1.1082	53	0.9589	48	1.0373	61	1.0209	55	0.5187	42

Notes: This table reports the BSI score and rank of sampled banks corresponding to alternative methodologies. $\text{BSI}_{\text{BoD0.10TwoStep}}$= BSI obtained using constrained BoD with 10 percent weight restriction using two-step aggregation procedure, $\text{BSI}_{\text{BoD0.10OneStep}}$= BSI estimated using constrained BoD with 10 percent weight restriction using one-step procedure, BSI_{UBoD}= BSI score based on unrestricted BoD/classic BoD with no weight restriction, $\text{BSI}_{\text{RBoD5}}$ = Order-*m* BSI at M=5 & B=1000, $\text{BSI}_{\text{RBoD10}}$= Order-*m* BSI at M=10 & B=1000. Here, M= subset of observations randomly drawn to compare the stability score and B=Bootstrap replications. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Source: Authors' calculations.

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Dear Dr. Hassan,

We are pleased to inform you that your manuscript, "Developing a new multidimensional index of bank stability and its usage in the design of optimal policy interventions", has been accepted for publication in Computational Economics.

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Computational Economics

COMMENTS TO THE AUTHOR:

Reviewer #2: The authors have incorporated all my previous comments into the revised version of the manuscript. From my point of view, the current version of the manuscript is publishable. The only (rather technical) comment I would have is about large tables such as Table 7 - whether it would not be better to have such large tables in an appendix in the final version of the publication. However, the authors will probably address this directly with the Layout Editor/Technical Editor.

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