Cost Overruns in Transportation Infrastructure Projects: Sowing the Seeds for a Probabilistic Theory of Causation

Abstract: Understanding the cause of cost overruns in transportation infrastructure projects has been a topic that has received considerable attention from academics and the popular press. Despite studies providing the essential building blocks and frameworks for cost overrun mitigation and containment, the problem still remains a pervasive issue for Governments worldwide. The interdependency that exists between 'causes' that lead to cost overruns materializing have largely been ignored when considering the likelihood and impact of their occurrence. The vast majority of the cost overrun literature has tended to adopt a deterministic approach in examining the occurrence of the phenomenon; in this paper a shift towards the adoption of pluralistic probabilistic approach to cost overrun causation is proposed. The establishment of probabilistic theory incorporates the ability to consider the interdependencies of causes so to provide Governments with a holistic understanding of the uncertainties and risks that may derail the delivery and increase the cost of transportation infrastructure projects. This will further assist in the design of effective mitigation and containment strategies that will ensure future transportation infrastructure projects meet their expected costs as well as the need of taxpayers.

Keywords: Infrastructure, cost overrun, causal reasoning, probabilistic causation, mechanisms, dependencies

1. Introduction

Investment in transport infrastructure (e.g., roads, bridges, ports, railways) is required to meet the growing needs of an increasing population, as well as to sustain a competitive advantage in the global marketplace. For an economy to position itself to capitalize on growth and increased investment due to a burgeoning population and increasing international demand for goods and services, greater investment in transportation infrastructure is needed. In Australia, for example, it has been forecasted that over the next two decades the number of trucks on its roads will increase by 50%, rail freight by two-thirds and shipping containers through ports will double; international and domestic travel through capital city airports will double; and technology will play a significant role in meeting the needs of transport, while also improving safety (Australian Federal Government, 2014a). Yet history explicitly indicates the capital expenditure (CAPEX) of transportation infrastructure projects routinely overrun their initial cost estimates leaving asset owners, financiers, contractors and the public dissatisfied (Flyvbjerg *et al*., 2005; Flyvbjerg, 2007; Love *et al*., 2015). This is not an unusual situation for infrastructure projects, as it has been observed that on average, 48% of them fail to meet their baseline time, cost and quality objectives

(Caravel Group, 2013). Well-known Australian projects that have attracted the attention of the popular press due to cost overruns include the Melbourne's Southern Cross Railway Station, Sydney Cross City Tunnel, Brisbane's RiverCity Motorway and the M7 Clem Jones Tunnel.

If the CAPEX of a project overruns, then the scope of works in others being considered or undertaken by Government's may be reduced to accommodate the increased expenditure. Moreover, contractors could face cash flow issues, liquidity and damage to their business image while the public has to pay more when the taxpayer funds projects. This may also have a knock-on effect on the funds available for maintaining and operating the asset. For Governments, managing the cost performance of their portfolio of transportation infrastructure projects is essential for ensuring the economic competitiveness and wealth for its constituents; it is a critical metric, as it quantifies the cost efficiency of the work completed. Cost performance is generally defined as the value of the work completed compared to the actual cost or progress made on the project (Baccarini and Love, 2014). Thus, the ability to reliably estimate the final cost of construction is vital for maintaining the planning and resourcing in other projects or those in the pipeline. An issue that has been overlooked is the cost overrun that often materializes during the operation and maintenance of the asset that is constructed. Often transportation projects are delivered using Public Private Partnerships or variants thereof, though during operations and maintenance the private sector will generally be responsible managing the asset.

Put simply, a cost overrun is traditionally defined as the ratio of the actual final costs of the project to the estimate made at full funds authorization measured in escalation-adjusted terms (Merrow, 2011). In this instance, a cost overrun is treated as the margin between the authorized initial project cost and the real final costs incurred after adjusting for expenditures due to escalation terms. While not always the case, cost overruns are often accompanied by schedule overruns as well so that the Government tends to be subjected to a 'double whammy'. The Edinburgh Trams project in Scotland (discussed in more detail in Section 2.2 below) is an apt example. Cost and schedule overruns are not mutually exclusive as they have similar causes though the strategies for mitigating their consequences can be significantly different.

Despite the considerable amount of research that has been undertaken, cost overruns are a pervasive problem (e.g. Vidalis and Najafi, 2004; Cantarelli *et al*, 2012a,b,c; Odeck *et al*., 2015; Love *et al*. 2015; Verjweij *et al*., 2015). While such studies providing the essential building blocks to better understand and provide a much-needed stimulus for theory that can be used to explain cost overrun causation, they still remain a ubiquitous and on-going issue (e.g., Flyvbjerg *et al*., 2002; Bordat *et al*., 2004; Odeck, 2004; Flyvbjerg *et al*., 2005; Flyvbjerg, 2007; Cantarelli *et al*, 2012a,b,c; Love *et al*., 2015b). If cost overruns are to be mitigated, then there is a need to be able to determine whether a set of events or propositions can be validated and their causal relationships can be accepted as being true; at present, neither can be corroborated. With this in mind, this paper briefly reviews the normative literature and proposes that research should focus on developing a probabilistic theory of cost overrun causation.

2.1 Cost Overruns: Points of Conjecture

Reported cost overruns have been found to vary significantly between studies in various countries ranging, for example, from -11 to 106% (Pickrell, 1990), -59% to 183% (Odeck, 2004), and -12% and 70% (Love *et al*., 2014). A primary reason for the disparity between studies is the 'point of reference' from which the cost overrun is measured. Within the planning fraternity, cost overruns have been generally determined as the difference between initial forecast and actual construction costs (Cantarelli *et al*., 2012a). Between the initial forecast of construction costs and the commencement of construction, several estimates will be prepared and refined before being lodged for approval. Odeck (2004) has however, suggested that the reference point for determining a cost overrun should be at the detailed planning stage where design, specification and final cost are determined. The use of the aforementioned different reference points provides varying results, in the case of road projects for example, Flyvbjerg *et al*. (2002) provides a mean cost overrun of 20% whereas Odeck (2004) revealed a more modest mean cost overrun of 7.9%. Using the budget at the time of the decision to build as reference point, as advocated by Flyvbjerg *et al*. (2002), will naturally lead to an overinflated cost overrun value, as the initial budget would not include the cost the project's new characteristics and changed scope that is included when project information has become sufficiently detailed not to trigger any great variability (Allen Consulting and the University of Melbourne, 2007).

Most large publicly funded projects tend to go through a long definition period after project inception during which many changes to scope and accompanying costs occur. It would seem misleading in some cases to make direct comparisons between the initial estimate at the 'time of decision-to-build' and that at project completion, particularly if the estimate at the 'time of decision-to-build' is only based only on a conceptual design (Love *et al*., 2015b). As suggested by Ahiaga-Dagbui and Smith (2014b), a more robust explanation of a cost overrun would need to factor-in process and product, as well as changes to scope and specification. With changes in scope, the fees of consultants may increase as well. Consequently, this may lead to the pre-construction phase incurring significant *cost growth* (Ahiaga-Dagbui and Smith, 2014b). A point to also consider is that there is often a tendency for Governments to anchor themselves to the initial budget estimate and subsequently inform the public of the estimated cost of a project without providing any form of *proviso*. The time between the establishment of the initial budget and the letting of contracts for construction may be lengthy; prices of materials and labor can increase. Moreover, as more information becomes readily available during the design process scope may change, which can also lead to increases in cost.

2.2 Schools of Thought on Cost Overrun Causation

Two predominant schools–of-thought have emerged from the on-going discourse regarding the sources of cost overruns (Ahiaga-Dagbui and Smith, 2014). These are the 'Evolution Theorists' who suggest that overruns are the result of changes in project scope and definition between inception stage and eventual project completion (e.g., Odeyinka *et al*., 2012). Sometimes scope changes may account for up to 90% of what are traditionally called 'overruns' (Auditor General of Western Australia, 2012). The other school-of-thought, is the 'Psycho Strategists' (i.e., which is a combination of psychological contributors and business strategy) attribute overruns to deception, planning fallacy and unjustifiable optimism in the setting of initial cost targets (e.g., Flyvbjerg *et al*., 2002; Siemiatycki, 2009). Figure 1 combines these two approaches to provide an overview of cost overrun causation (Figure 1).

There has been a widespread campaign by the 'Psycho Strategists' that *optimism bias* (i.e. the underestimation of risks and overestimation of benefits) and *strategic misrepresentation* (i.e. deception) can adequately explain why transportation infrastructure projects experience cost overruns. While on face value there may be grounds for this argument, the evidence presented lacks credibility and is unscientific; no proof of any causal relationship is provided (Love *et al*., 2012; Love *et al*., 2015a). Osland and Strand (2010) have been particularly critical of the research presented in Flyvbjerg *et al*. (2002), as they conclude that they applied the logic of suspicion in their claim that inaccurate cost forecasting is a result of optimism bias and strategic misrepresentation. They specifically state, "Flyvbjerg and other proponents for the hermeneutics of suspicion, the actors actually admitting telling lies can be seen as the tip of the iceberg. However, it is also a perspective that would not be falsified if no examples of actors admitting lying were found. On the contrary, it could easily be interpreted as a verification that they were lying also for the researchers." (Osland and Strand, 2010: p.81).

Contrastingly, in support of the 'Psycho Strategists', which focuses on specific planned actions, Love *et al*. (2012) suggests that cost overruns arise as a result of a series of pathogenic influences, which lay dormant within the project system as denoted in Figure 1. However, before such influences become apparent, participants often remain unaware of the impact that particular decisions, practices and procedures can have on project performance. Pathogens can arise because of strategic decisions taken by senior management or key decision- makers. Such decisions may be mistaken in the form of optimism bias, but they also may be deliberate in the form of strategic misrepresentation or a political/economic decision; this is represented by the Psycho Strategist's 'outside' view presented in Figure 1. Latent conditions can lay dormant within a system for a considerable period of time and thus become an integral part of everyday work practices. Meanwhile once they combine with active failures, then omission errors can arise and their consequences may be result in safety incidents and/or rework, which can contribute to an increase in project costs (Figure 1).

Active failures are essentially unsafe acts (or those of an inappropriate nature) that are committed by people who are in direct contact with a system. Such acts take the form of errors, which include: slips, lapses, mistakes and procedural violations. Active failures are often difficult to foresee. As a result, simply reacting to the event that has occurred cannot eliminate them. Accordingly, this school of thought is widely supported by authors such as Odeck (2004) and Odeyinka *et al* (2012). Essentially, Love *et al*. (2012) and Ahiaga-Dagbui and Smith (2014) conclude from their research that cost overruns are not really a case of 'projects not going according to plan (budget)', but 'plans not going according to project'.

While Love *et al*. (2012) have been critical of the research promulgated by Flyvbjerg (2002), in recent works, Love *et al*. (2015a) acknowledges that political, economic, psychological and managerial factors may influence the generation of pathogenic influences (i.e. latent conditions) that may arise in projects. Subsequently, Love *et al*. (2015a) have advocated for a 'balanced approach' that focuses on how process and technological innovations can be used to improve the cost performance of infrastructure projects. Fundamentally, understanding 'why' and 'how' projects overrun, from both 'Psycho Strategist' and 'Evolution Theorists' perspectives, is pivotal to reducing their impact and occurrence; Figure 1 provides an overview of cost overrun causation (Figure 1). The absence of theory has hindered the development of a 'balanced approach', which can explain and be used to reliably predict cost overruns. Noteworthy cost overruns do not only materialize due to change orders, and rework as identified in Figure 1, but also due to safety incidents that may occur as a result of these events. For example, Love *et al*. (2015b,c) revealed that when a rework event occurred during construction, the propensity for safety incidents to materialize significantly increased, as well as project costs.

In an attempt to predict the occurrence of a cost overrun for road projects, Love *et al*. (2014) ascertained using a 'best fit' probability distribution from an empirical distribution, and revealed that a continuous *Generalised Logistic Probability Density Function* was the most appropriate to use; though, a major shortcoming of this work is that the sample size was small and limited to 50 projects. The determination of the 'best fit' probability distribution provides a reliable estimate of risk and ensures the effectiveness of the decision-making process (Love *et al*., 2014b). If an inappropriate probability distribution is selected, it will be misaligned with the nature of the data and therefore produce inappropriate results rendering any form of risk analysis undertaken to be inaccurate and unreliable. Evidence of this can be seen when a *Normal Distribution* (based upon the original works of Flyvbjerg *et al*., 2002) was assumed for predicting the cost contingency for the Edinburgh Tram System in the United Kingdom. The project was originally estimated to cost £320 million, which included a risk contingency based-estimate.

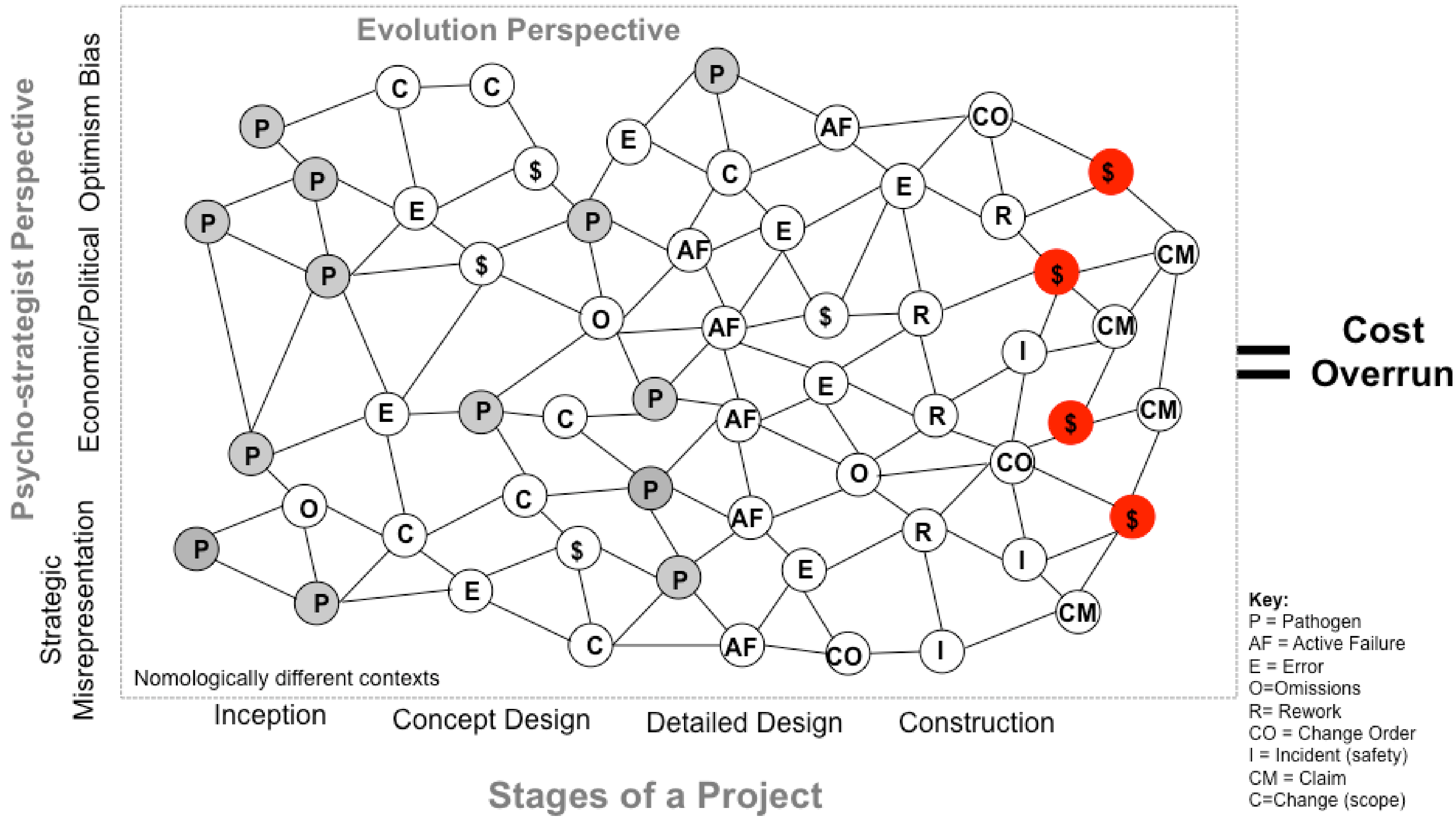


Figure 1. Current view(s) of cost overruns in transportation infrastructure projects

Taking all the available distributional information into account, by considering a reference class of comparable rail projects (e.g. London Docklands Light Rail); the reference class estimated an 80th percentile value of £400 million (Auditor General for Scotland and Accounts Commission, 2011). The project was completed three years late in the summer of 2014 at a reported construction cost of £776 million (City of Edinburgh Council, 2014). Considering claims and contractual disputes, which partly occurred due to errors and omissions in contract documentation, a revised estimated final cost of over £1 billion has been forecasted, including £228 million interest payments on a 30-year loan to cover the funding shortfall.

Despite the use of an inappropriate probability distribution, Reference Class Forecasting (RCF), propagated by Flyvbjerg and Cowi (2004), has a number of other limitations such lack of large heterogeneous samples, scarcity of project types, and an over reliance on the dependence of singular causal factors to derive the estimated uplift (Liu and Napier, 2009; Liu *et al*., 2010; Love *et al*. 2015d). The interdependency that prevails between causal variables and subsequent coupling of risks that materialise are negated under this approach. Thus, the accuracy and reliability of RCF to be able to assess a risk of a cost overrun (using a percentage up-lift), which is added to estimate as a risk contingency is questionable, especially considering the example of the Edinburgh Tram System project. Surprisingly, this limitation has not been identified in the extant literature, yet RCF is being used and advocated by several governments throughout Europe. It is suggested that if RCF is solely relied upon to determine the issues over and above the estimated 'contingency for transportation projects, then Government's will continue to inaccurately forecast construction costs.

2.3 Moving from Independent to Interdependent Causes

There has been a proclivity for studies to explain the cause of cost overruns as 'independent' rather 'interdependent' causal influences within the transportation literature (e.g., Cantarelli, 2010; Verjweij *et al*., 2015). While such studies have attempted to provide a context to explain 'why' and 'how' cost overruns arose, the views of those participants involved in the chain of events that lead to their occurrence are generally limited to specific points in time. Thus, the determination of causation is narrowly and superficially defined, which potentially leads to an innate *bias* being reported (Ahiaga-Dagbui *et al*, 2015). Furthermore, researchers have sought to pinpoint a single 'root cause' for a cost overrun and then suggest that an intervention to change and/or prevents its occurrence (e.g. Rosenfeld, 2014). However, 'the root cause' often represents the place in a point of time where a researcher decided to complete their investigation (Dekker, 2006). The use of the singular, independent-cause identification approaches have led to inappropriate risk assessments for cost overrun to be developed; the interdependency between causal variables has not been effectively considered and accommodated. Cost overruns seldom occur as a result of a stand-alone cause. Even though they may superficially appear to be different, the causes of poor performance in infrastructure projects are interwoven and form a complex network. The is therefore a need to move beyond simply developing lists or ranks of independent factors to understanding dynamic connections between various causal factors and how they materialise during the course of a project (Ahiaga-Dagbui, *et al.,* 2015; Love *et al*., 2016). Failure to adequately understand and accommodate this inherent interdependency can led to the development of sub-optimal solutions for mitigating cost overruns; for example RCF does not accommodate the coupling of risks that can contribute to increasing a project's cost.

Techniques such as System Dynamics (SD) have been used extensively to model the interdependencies between causal variables of cost overruns (e.g., Reichelt and Lynies, 1999; Eden *et al*. 2005; Parvan *et al*., 2015). The causal loop diagrams that emerge are invariably derived from interview data whereby memory and judgment are relied upon to give an account of what transpired. Thus, conditional statements are used to create an association or determine an influence and while plausible, the issue of causation remains an unaddressed issue (Love *et al*., 2016). Moreover, a lack of real-life industry data to create and simulate the dynamic nature of cost overruns using stock-flows also diminishes the accuracy, validity and reliability of SD models (Tombesi, 2000). Considering that cost overruns have become an innate feature of transportation infrastructure projects, it is now time to remedy this issue and develop a cost overrun theory of causation that recognizes the interdependency that prevails within causal claims.

3. Toward a Probabilistic Theory of Causation

The development of such a theory should be able to explain and predict the occurrence of cost overruns thus accommodate risk and uncertainty that can emerge in projects. However, in the case of potential 'unknown, unknown' causes (also referred to as Black Swans) cannot be predicted using Bayesian decision theory (Feduzi and Runde, 2014). According to Feduzi and Runde (2014) the problem of uncovering 'unknown unknowns is connected with the practicalities of 'state space construction'; that is, "the activities of generating, evaluating and a then accepting or rejecting candidate hypotheses about how the world might turn out" (p.281). Prior to the introduction a way forward in the development of a theory for cost overrun causation, it should be acknowledged that there are many competing theories of causation in the philosophical and wider literature, but in this paper probabilistic causation is the focus as it can characterize the relationship between cause (C) and effect (E) using the tools of probability theory; causes change the probabilities of their effects. Under the auspices of a probabilistic theory decision-makers could be confronted with alternatives involving risk and may invariably need to rely on the use of probabilities rather than heuristics when making a prediction of a cost overrun. This is supported by Kahneman and Tversky (1982) who have distinguished between two modes of judgement during decision-making under uncertainty: (1) a singular mode that generates an "inside view", which is subjective in nature and based on heuristics and biases; (2) a distributional mode that generates an "outside view" based on aleatory sides of probability (p.518).

In contrast to popular belief within the transportation infrastructure literature, it should be acknowledged that probability theory might not be sufficient in this case to assist with predicting cost overruns. According to Gigerenzer and Hoffrage (1995) and Gigerenzer and Todd (1999) people can use smart heuristics, that is, rules of thumb to make decisions when minimal information is provided to them. Gigerenzer and Hoffrage (1995) have proffered that heuristics should not lead decision-makers to conceive of human thinking as riddled with irrational cognitive biases, but rather to consider rationality as an adaptive tool that is not identical to the rules of formal logic or probability calculus. Yet, the use of probability calculus has become a norm when conducting risk analysis for infrastructure projects (e.g., Flyvbjerg and Cowi, 2004; Signor *et al*., 2015); an alternative is to use frequency formats that they are expressed as Bayesian algorithms, which have been identified as being computationally simpler to calculate (Gigerenzer and Hoffrage, 1995). A thorough discussion of decision making under uncertainty using the laws of probabilities (e.g., Kahneman and Tversky, 1979;1982) or bounded rationality by employing heuristics (e.g., Gigerenzer and Murray, 1987; Kruger *et al*., 1987; Gigerenzer and Reinhard, 2002) is outside the scope of this paper. However, probability and heuristics *via* the use of frequencies can be incorporated within a theory of probabilistic causation and used to predict a cost overrun.

3.1 Simpson's Paradox: From Statistical to Causal Reasoning

A caveat, however, is that if frequency data is used, then possible emergence of *Simpson's Paradox* needs to borne in mind (Simpson, 1951; Pearl, 2009). It refers to a phenomenon whereby the association between a pair of variables (X,Y) reverses sign upon conditioning of a third variable (Z), regardless of the value Z takes when data is divided into subpopulations, each representing a specific value of the third variable (Z) (Pearl, 2014:p.8). The phenomenon appears as sign reversal between the associations measured in the disaggregated subpopulations relative to the aggregated data, which describes the population as whole.

Path analysis and structural equation methods have been used extensively for analyzing causal systems that have direct and indirect effects on other variables, but are also prone to experiencing Simpson's Paradox (Kock, 2015). A simple example, derived from Kock (2015), is used to demonstrate this phenomenon for public sector clients and the like within the context of variables that have been found to contribute to cost overruns in the transportation projects. It is assumed that data from 500 road projects is collected for two variables: 'degree of quality assurance of the cost estimate' provided by an external consultant to government (X) (Odeck *et al*., 2015) and the extent of a cost overrun (Z). In Figure 2a a two variable path model representing this relationship is presented. As this path model contains only two variables, then $p_{zx} = r_{zx} = 0.5$; where p_{zx} and r_{zx} denote the path coefficient and the correlation between the two variables. In Figure 2b an additional variable is introduced which is directed at Z: the degree of errors contained in the Bill of Quantities (BoQ) (Y). The BoQ can be used to ensure the accuracy of the cost estimate prior to the commencement of construction; hence the link $X \rightarrow Y$. The addition of the new variable led to the path coefficient p_{zx} for the link between variables 'degree of quality assurance of the cost estimate' (X) and 'cost overrun' (Z) to assume a negative value (-0.2), in contrast with the positive correlation r_{zx} (0.5). This sign reversal characterizes Simpson's Paradox in a path model (Kock, 2015).

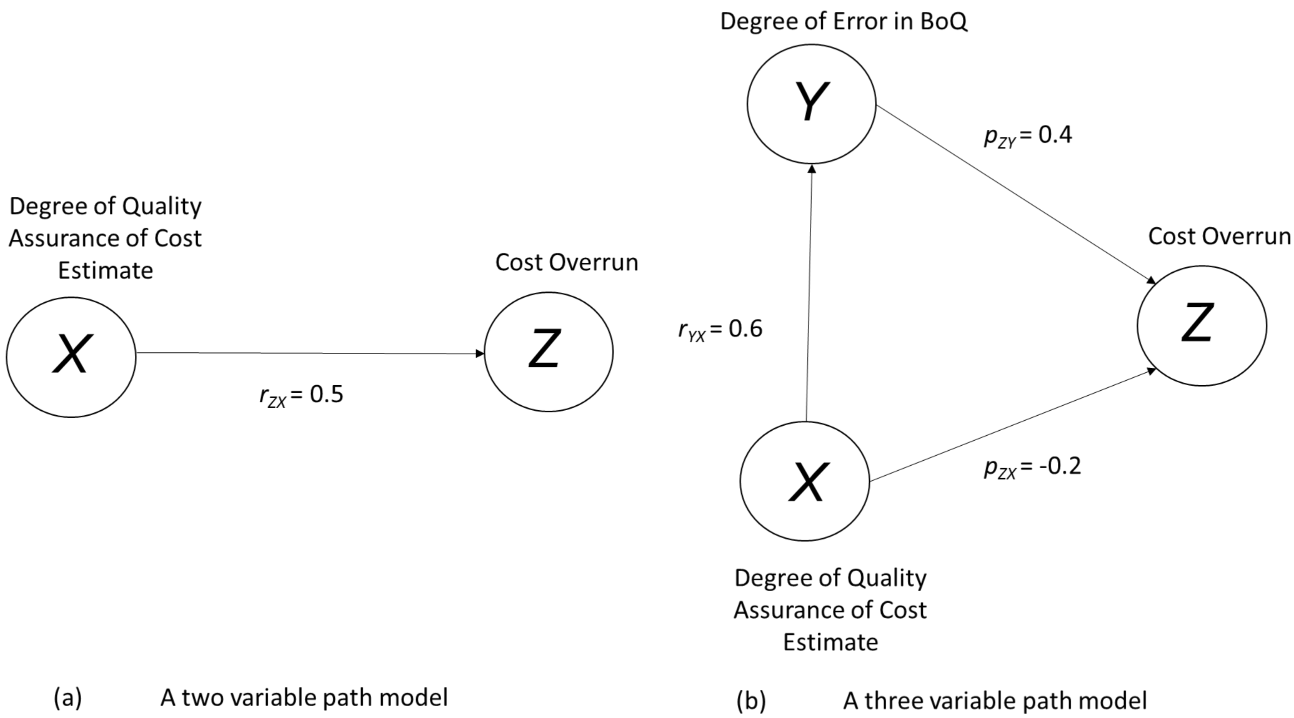


Figure 2. Path model demonstrating Simpson's Paradox

Attempts to address Simpson's Paradox had been widespread, which led Lindley and Novick (1981) to conclude that there was no statistical criterion that could be used to forewarn someone from drawing the wrong conclusions or indicating which data represented the correct answer. Acknowledging the need to combat this problem, Pearl (1993) has shown that this statistical irregularity has causal roots and that the determination of the correct answer is insensitive to temporal information. Thus, Pearl (2009; 2014) used *causal reasoning* (i.e., ability to identify causality: the relationship between a cause and its effect, $C \rightarrow E$) to legitimize the cause-effect relationship through the use of graphical condition referred to as 'back door' (i.e., non-causal path between two variables). Pearl (2009; 2014) trace causal paths using a Directed Acyclic Graph (DAG), which is used to assure that spurious paths are intercepted by the third variable; in doing so, Pearl (2014) has announced that Simpson's Paradox is now resolved using causal reasoning. Pearl (2014) points out that Simpson's Paradox "is a reminder of how easy it is to fall into a web of paradoxical conclusions when relying solely on intuition, unaided by rigorous statistical methods (p.8)

3.2 Probabilistic Causation

Causality (also referred to as causation) governs the relationship between events and as such has been at the heart of philosophy since Aristotle. A plethora of theories of causality have evolved (e.g., Hume, 1896; Russell, 1913; Gasking, 1955; Lewis, 1973; McDermott, 1995; Ramachandran, 1997; Nordoff, 1999). According to Williamson (2009) philosophical theories of causation can be categorized according to the way they answer a range of questions such as: (a) Are causal relata single-case or generic? (b) Is there a physical connection between the cause and effect or is it a feature of an individual’s epistemic state? And (c) Does the theory in question attempt to understand actual or potential causality?

The philosophy of causation, however, has been typically dominated by advocates of a causal mechanical view (e.g., Salmon, 1984, Salmon, 2000), those that take a counterfactual stand, which have been based primarily upon the work of Lewis (1973), and dualists, who seek to combine both the aforementioned perspectives (e.g., Hall, 2004). These theoretical viewpoints have tended to conceptually analyse casual claims in an everyday language and the metaphysical issues of causation (Weber, 2009). Yet, to analyse how causation functions in science requires the use of a probabilistic approach (Weber, 2009).

Fundamentally, probabilistic theories of causality aim to characterise or analyse causality in terms of probabilistic dependencies. Such theories try to provide probabilistic criteria for determining whether *A* causes *B* maintaining that causality just is the corresponding pattern of probabilistic relationship (Williamson, 2009). A wealth of probabilistic theories have been proposed over the last century, with the most notable philosophers laying its foundations being Reichenbach (1923), Good (1959), Suppres (1970), Humphreys (1989) and Eells (1991). According to Williamson (2009) probabilistic theories that have been developed focus on the following key elements: “(a) changing a cause makes a difference to its effects, and (b) this difference –making shows up in probabilistic dependencies” (p.187). In addition, proponents of probabilistic theories have also maintained that probabilistic dependencies characterise the causal relation; that is, “provide the necessary and sufficient condition for causal connection of the form: *C* causes *E* if and only if appropriate probabilistic dependencies obtain” (Williamson, 2009:p.187).

A detailed critique of the probabilistic theories of causation can be found in Williamson (2009), Weber (2009) and with additional limitations regarding counterfactuals and pre-emption being addressed in Noordorf (1999). However, the specific limitations are briefly presented and brought to the fore, which include the discounting of mechanistic evidence and context unanimity. For example, Suppres (1970) assumed genuine probabilistic causes are prima facie (i.e., a first appearance) and not spurious. A prima facie cause is defined when (Suppres, 1970; p.12):

The event B_t is a prima facia cause of event A_t, if and only if:

$t' < t$

$P(B_{t'}) > 0$

$P(A_t | B_{t'}) > P(A_t)$

Furthermore, spurious causes are defined as:

An event $B_{t'}$ is a spurious cause in the sense of A_t, if and only if, B_t is a prima facie cause of A_t and there is a $t'' < t'$ and an event $C_{t''}$ such that:

$P(B_{t'} C_{t''}) > 0,$

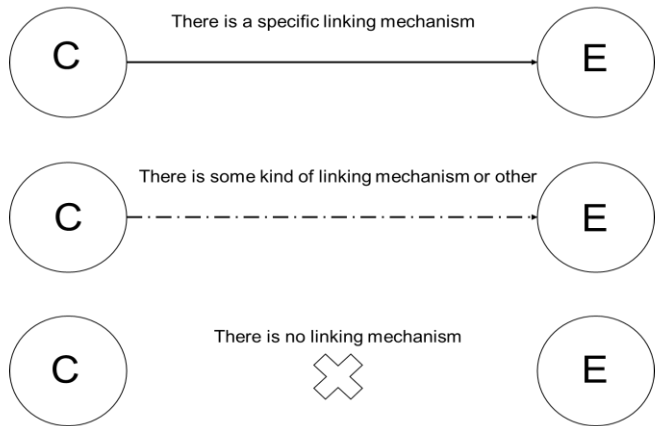
$P(At | B_{t'} C_{t''}) > P(At | C_{t''}),$

$P(At | B_{t'} C_{t''}) \geq (At | B_{t'})$

Suppres (1971) answers the question "What do probabilistic chains mean?" and reveals that presence and absence of statistical relevance relations in the real world. For policy makers, such as Government, they would be supplied with causal knowledge and with no explicit link between causation and policy, as it refers to the real world and not the hypothetical that they like to create. In addition, mechanistic evidence is discounted when probabilistic evidence is introduced. Here specific information (probabilistic dependencies) is used to define the meaning of causation (Weber, 2009).

Eells (1991) also defines causation in terms of positive statistical relevance, and thus faced a similar problem to Suppres (1971). However, Eells (1991) introduced the concept of *context unanimity* whereby a cause must raise the probability of its effect in *every* background context. Thus Eells (1991) states: "X is a *positive causal factor* for Y if and only if, for each i, $Pr(Y|K_i\&X) > Pr(Y|K_i\& \sim X)$. Negative causal factorhood and neutrality are defined by changing the "always rises" (>) idea t0 "always lowers" (<) and "always leaves unchanged" (=), respectively. The idea that the inequality or equality must hold for each of the background contexts $K_{i.}$ (p.86). The characteristic property of causes here is unable to be reversed (from positive to negative) or overpowered (from positive or negative to casually neutral) in a subpopulation. Bearing this this in mind Governments (who are policy-makers), for example, are only concerned with average effects of cost overruns on their projects, not the causes in the sense of context unanimity. In summary, governments would be interested in likelihood of a project experiencing a cost overrun and not necessarily the specific causes that would potentially arise.

To establish a causal claim, there is a need for mutual support of both mechanisms and dependencies (Russo and Williamson, 2007); this view is referred to by Weber (2009) as *evidential pluralism*. It has been proposed by Russo and Williamson (2007) that to establish a causal claim two things are required: (1) a cause makes a difference to the effect, and (2) that there is a mechanism from cause to effect. In the case of being able to establish a causal claim for cost overruns, the evidence-based medicine can be drawn upon, whereby both mechanistic (bottom-up evidence) and probabilistic evidence is required to substantiate a causal claim. Glennan (1996) states a mechanism underlying behaviour is a complex system, which produces that behaviour by the interaction of a number of parts to direct causal laws (p.52). The inclusion of such a mechanism in a theory of probabilistic causation for cost overruns is deemed to be necessary as it can accommodate the social system and subsequent interactions that invariably prevail within project environments used to deliver transportation infrastructure. Sources of evidence of mechanisms may include direct observation, experiments, statistical analysis, documentary sources, simulation, and experience (Clarke *et al*., 2014). Figure 3 categorizes of evidence of mechanisms linking an assumed cause (C) with effect (E) are presented (Clarke *et al*., 2014).



(Adapted from Russo, 2014)

Figure 3. Categories of evidence of mechanism

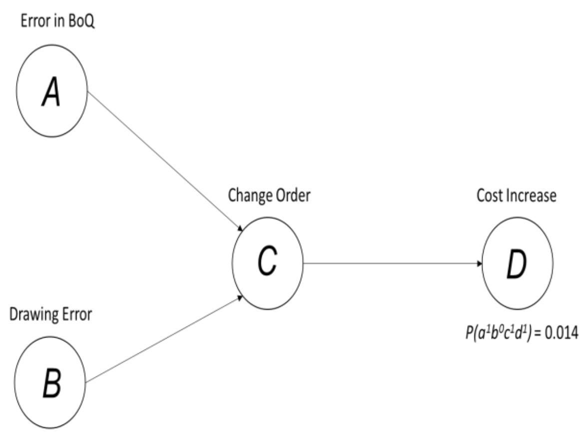
In the first instance, the evidence of mechanism explicitly indicates that provided is relevant. For example, it has been widely demonstrated that there is a correlation between change orders and cost increases in projects (e.g., Bordat *et al*., 2004); this is not to say that such statistical analysis should be solely replied upon, but it can provide a high degree of confidence that $C \rightarrow E$. In the second instance, presented in Figure 2, there is an initial reason to believe that $C \rightarrow E$, for example a drawing error contributes to a change order but whether error was created by an architect or structural engineer is difficult to determine as it could appear on both sets of drawings that were created. Interrogation of correspondence and documentation would reveal why and how the cause originated. Such a process, however, should not be about apportioning blame but understanding why it occurred and assessing the likelihood it would occur again, even if an intervention strategy were introduced. In the final example evidence of mechanism is self-explanatory, there is no mechanism, but it is important to acknowledge as it can be used to define the space of possible mechanisms of action and the likely causal relations between C and E.

Ultimately, whether a causal claim is accepted or not is dependent on the quality of evidence that can be accumulated and underlying reasoning between causal connections. Commencing the evidence gathering process from a tactical level (i.e., bottom-up) can provide assumptions and insights about the rational/or non-ration decision-making that determine the behaviour of people that lead to events where a cost increase was incurred. The established assumptions can be used to infer causal relations on the higher level (i.e. operational).

4. Future Research

Probabilistic causal inferences about cost overruns can be acquired from a combination of assumptions, experiments and data. But, the challenge for researchers addressing this pervasive and complex problem has been the lack of a formal language that can be used to explicate, determine, and predict their occurrence. Causal graphical models have been advocated as a formalism for learning and reasoning about causal relationships (e.g. Pearl, 2009). Such models are often referred to as Bayesian Networks (BN) and provide a means of specifying the causal relationships that hold among a set of variables. A central feature of BN is the DAG that provides an intuitive representation for the causal structure relating to a set of variables. An example of DAG and a simple example of how a cost increase arises due to result of errors in BoQ and drawings, which lead to a change order is presented in Figure 4. In this instance both mechanisms and dependencies could be used to construct a DAG, but the nature of relationships is not defined; they can be deterministic or probabilistic. Moreover, multiple causes of an effect can act independently or strongly interact.

Determining the nature relationship between variables to establish a causal claim is an issue that needs to be considered when developing a theory for cost overrun causation; essentially this is an epistemological issue, which can be addressed through evidence of mechanisms (Clarke *et al*., 2014). Another consideration to be borne in mind when establishing a causal claim is methodological; that is, the evidence-gathering methods to be used. Consideration of the type of information and how it is collected needs to be made with specific emphasis being placed on establishing causal claims within a project. A major limitation of previous cost overrun research that has examined causation in transportation infrastructure projects has been its emphasis on the creation of causal claims from heterogeneous samples.



Here there are four two-valued variables, *A*, *B*, *C*, *D*. A BN can be formed by taking the DAG of and specifying the probability distribution of each variable conditional on its parents:

$$P(a^1) = 0.2\,,\ P(a^0) = 0.8$$
$$P(b^1) = 0.7\,,\ P(b^0) = 0.3$$
$$P(c^1|a^1b^1) = 0.4\,,\ P(c^0|a^1b^1) = 0.6$$
$$P(c^1|a^0b^1) = 0.5\,,\ P(c^0|a^0b^1) = 0.5$$
$$P(c^1|a^1b^0) = 0.2\,,\ P(c^0|a^1b^0) = 0.8$$
$$P(c^1|a^0b^0) = 0.3\,,\ P(c^0|a^0b^0) = 0.7$$
$$P(d^1|c^1) = 0.8\,,\ P(d^0|c^1) = 0.2$$
$$P(d^1|c^0) = 0.6\,,\ P(d^0|c^0) = 0.4$$

In this instance,

$$P(a^1b^0c^1d^1) = P(a^1)P(b^0)P(c^1|a^1b^0)P(d^1|c^1) = 0.0144$$

Figure 4. Hypothetical example of a DAG for a cost increase

This aggregation of data has resulted in a high degree of causal ambiguity and limited understanding about causal inferences of cost overruns within the extant transportation literature. Future research therefore should place emphasis on deconstructing what is already known about the causal nature of cost overruns to arrive at point where the ‘noise’ within the data is reduced and causal reasoning can be applied. From a practical perspective, this poses a major challenge, as more often than not access is restricted to organizations and participants within a project due to commercially sensitive reasons. The challenge here is for researchers to actively engage with government and organizations to ensure that they are able to capture the ‘practice’ that contributes to cost overruns. To understand the nomological context of cost overruns that may prevail, it is suggested that ‘sensemaking’ (e.g., Wieck *et al*, 1988, 1993; 1995; Goh *et al*., 2012) form the epistemological underpinning used to derive causal inferences. Here ‘sensemaking’ can be used as process to ensure evidence of mechanism, as people can provide meaning to experience through the ‘practice’ used to deliver projects. Notwithstanding, there are several broad philosophical questions that need to be explored about their causal reasoning of cost overruns.

Drawing on the work of Claveau (2013:p.122) the following questions are proposed: (1) What are the meaning of causal chains? Here the inferential relationships between events are determined. (2) How can causal chains be supported by evidence? This is necessary considering the multiple parties involved in a project and the complexity of relationships that exist. (3) How are causal beliefs affected by new information (e.g., with the advent of BIM, how will beliefs be influenced)? Once a causal chain is established and new information is made available, will the underlying dynamics of it change? Addressing such questions will provide the seeding for the development of a theory for cost overrun causation.

5. Conclusion

Transportation infrastructure is pivotal to improving an economy's productivity and society's over all well-being. Thus, when cost overruns are experienced this has a direct negative impact on the economy, and the taxpayer. Unfortunately cost overruns are a norm rather than an exception; despite the accumulated knowledge that has sought to explain and predict their occurrence, there remains limited understanding about their causal nature. To make decisions and implement risk mitigation strategies to contain and reduce the likelihood of a cost overrun being experienced, requires diagnosis – to determine its probable causes. Research undertaken to date has not been able to effectively undertake this task regardless of the well-intentioned studies that have been conducted.

Hindering this process of knowledge creation has been the absence of 'theory' and an epistemological lens that can enable 'practice' to be captured, dissected and put together to develop causal claims. In addressing this issue, this paper has suggested that there is a need re-examine cost overrun from the perspective of pluralistic probabilistic causation so that it can be explained, predicted and managed. In particular, it has been promulgated that the use of pluralistic approach that considers mutual support of both mechanisms and dependencies is required so that 'practice' that arises during the delivery of transportation infrastructure projects can be realized and used to construct causal graphical models. Such models provide a formalism for learning and reasoning about causal relationships that contribute to cost overruns. It is recognized that the establishment of such causal relationships will be an arduous process considering the multitude of organizations involved in delivering transportation infrastructure projects. If, however, headway is to be made in tackling the cost overrun phenomena, then there is a need to acknowledge, understand, and become immersed in practice rather than cherry picking from it using epistemological and methodological approaches that are unable to accommodate for the creation of the situational awareness required to develop the basis for causal claims.

This paper has not sought to provide a solution but instead sow the seeds for the development of a theory of probabilistic causation for cost overruns in transportation infrastructure. A wealth of research will be required to develop such a theory, but the authors hope that this paper provides a way forward in this fertile area for Governments to consider in the future policy-making.

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References

Ahiaga-Dagbui, D. D., and Smith, S.D. (2014a). Rethinking construction cost overruns: Cognition, learning and estimation. *Journal of Financial Management of Property and Construction* **19**(1), pp.38 - 54.

Ahiaga-Dagbui, D.D and Smith, S. D. (2014b). Dealing with construction cost overruns using data mining. *Construction Management and Economics*, **32** (7-8), pp.628-694

Ahiaga-Dagbui DD, Smith SD, Love PED, Ackermann F (2015) Spotlight on construction cost overrun research: superficial, replicative and Stagnated, In: Procs 31st Annual ARCOM Conference, Raiden A and Aboagye-Nimo E (Eds), Association of Researchers in Construction Management 7-9th Sept, 2015 Lincoln, UK, pg. 863-872.

Allen Consulting and the University of Melbourne (2007) Performance of PPPs and Traditional Procurement in Australia, Final Report for Infrastructure Partnerships Australia, November.

Auditor General for Scotland and the Accounts Commission. (2011). Edinburgh Trams: Interim Report. (Accessed 29th April 2013 from www.audit-Scotland.gov.uk)

Auditor General of Western Australia (2012) *Managing Capital Projects*, Perth, Australia: Office of the Auditor General of Western Australia, http://tinyurl.com/l9ymlqu (Accessed in 18th November 2015).

Australian Government (2014a). *Budget 2014/2015, Building Australia's Infrastructure*. May, (Accessed 22nd July, 2015, http://www.budget.gov.au/2014-15/content/glossy/infrastructure/download/Infrastructure.pdf)

Australian Government (2014b). *Trends: Infrastructure and Transport to 2030*. Department of Infrastructure and Regional Development, Australian Government (Accessed 22nd January, 2015, http://www.infrastructure.gov.au/infrastructure/publications/files/Trends_Infrastructure_and_Transport_to_2030.pdf)

Baccarini, D., and Love, P.E.D. (2014). Statistical characteristics of contingency in water infrastructure projects. *ASCE Journal of Construction Engineering and Management*, **140**(3), 04013063.

Bordat, C.B., McCulloch, K.C., Sinha, K.C., and Labi, S. (2004) *An Analysis of Cost Overruns and Time Delays of INDOT Projects*. Publication FHWA/IN/TRP-2007.04. Joint Transportation Research Program, Indiana Department of Transportation and Purdue University, West Lafayette, Indiana, 2004. doi 10.573/1288284313134.

Cantarelli, C.C. van Wee, B., Molin, E.J.E., and Flyvbjerg, B. (2012a) Characteristics of cost overruns for Dutch transport infrastructure projects and the importance of the decision to build and project phases. *Transport Policy*, **22**, pp.49-56.

Cantarelli, C.C. van Wee, B., Molin, E.J.E., and Flyvbjerg, B. (2012b) Different cost performance: different determinants? The case of cost overruns in Dutch transport projects. *Transport Policy*, **22**, pp.88-95.

Cantarelli, C.C., Flyvbjerg, B. and Buhl, S.L. (2012c) Geographical variation in project cost performance: the Netherlands versus worldwide. *Journal of Transport Geography*, **24**, pp.324-331.

Caraval Group (2013). *A Review of Project Governance Effectiveness in Australia*. A Report to Australian Government, Infrastructure Australia, March 2013 Available at http://www.infrastructureaustralia.gov.au, Accessed 28th December 2014)

City of Edinburgh Council (2014). *The Tram Project*. [http://www.edinburgh.gov.uk/trams.] Accessed 28th May 2015.

Claveau, F. (2013). Causal reasoning in economics: a selective exploration of semantic, epistemic and dynamical aspects. *Erasmus Journal for Philosophy and Economics*, **6**(2), p.122-124

Clarke, B., Gillies, Illari, P., Russo, F., and Williamson, J. (2014). Mechanisms and the evidence of hierarchy. *Topoi: The International Review of Philosophy*: **33**(2), pp 339-360

Eden, C., Williams, T., and Ackermann, F. (2005). Analysing project cost overruns: Comparing the 'measured mile' analsyis and systems dynamics modelling, *International Journal of Project Management*, **23**(2), pp.135-139

Eells, E. (1991). *Probabilistic Causality*. Cambridge University Press, Cambridge.

Feduzi, A., and Runde, J. (2014). Uncovering unknown unknowns: Towards a Baconian approach to decision-making. *Organizational Behaviour and Human Decision Processes*, **124**, pp.268-283.

Flyvbjerg, B., Holm, M.K.S. and Buhl, S.L. (2002) Understanding costs in public works projects: Error or lie? *Journal of the American Planning Association*, **68**, pp.279-295.

Flyvbjerg, B., and Cowi (2004). *Procedures for Dealing with Optimism Bias in Transport Planning: Guidance Document*. UK Department of Transport, London, UK.

Flyvbjerg, B, Mette K. Skamris Holm, and Søren L. Buhl, (2005). How (In)accurate are demand forecasts in public works projects? The case of transportation. *Journal of the American Planning Association*, **71**(2), pp 131-146.

Flyvbjerg, B. (2007). Cost overruns and demand shortfalls in urban rail and other infrastructure. *Transportation Planning and Technology*, **30**(1), pp.9-30.

Gasking, D. (1955). Causation and recipes. *Mind* (64), pp. 479-487.

Gigerenzer, G., and Murray, D. J. (1987). *Cognition as Intuitive Statistics*. Hillsdale, NJ: Erlbaum.

Gigerenzer, G., and Reinhard, S. (2002). *Bounded Rationality: The Adaptive Toolbox*. MIT Press.

Goh, Y., Love, P.E.D. Spickett, J., and Brown, H. (2012). Organisational accidents: A systemic model of production versus protection. *Journal of Management Studies*, **49**(1), pp. 52-76.

Hall, N. (2004). *Two Concepts of Causation. In Causation and Counterfactuals*, In Hall, N. Collions, J. and Paul, L.A. (Eds.). MIT Press, Cambridge

Hume, D. (1896) [1739], Selby-Bigge, Ed., *A Treatise of Human Nature*, Clarendon Press

Kahneman, D., and Tversky, A. (1979). Prospect Theory: An analysis of decision under risk. *Econometrica*, **47**(2), pp. 263-291

Kahneman, D., and Tversky, A. (1982). Variants of uncertainty. In Judgments und Uncertainty

Kock, N. (2015). How likely is Simpson's Paradox in path models. *International Journal of e-Collaboration*, **11**(1), pp.1-7

Krüger, L., Gigerenzer, G., and Morgan, M. (Eds.). (1987). *The Probabilistic Revolution*. Vol. II: Ideas in the Sciences. Cambridge, MA: MIT Press

Lewis, D. (1973), Causation. *Journal of Philosophy*, **60**, pp.17-25.

Lindley, D. and Novick, M. (1981). The role of exchangeability in inference. *The Annals of Statistics*, **9**, pp.45-58.

Liu, L. and Napier, Z. (2009). The accuracy of risk-based estimation for water infrastructure projects. *Construction Management and Economics*, **28**(1), pp.89-100

Liu, L., Wehbe, G., and Sisovic, J. (2010). The accuracy of hybrid estimating approaches. A case study of an Aust`ralian State road and traffic authority. *The Engineering Economist*, **55**, pp.225-245.

Love, P.E.D, Edwards, D.J., and Irani, Z. (2012). Moving beyond optimism bias and strategic misrepresentation: An explanation for social infrastructure project cost overruns. *IEEE Transactions on Engineering Management* **59**(4), pp. 560 – 571.

Love, P.E.D., Sing, C-P., Wang, X, and Tiong, R. (2013). Determining the probability of cost overruns in Australian construction and engineering projects. *ASCE Journal of Construction Engineering and Management*, **139**(3), pp. 321–330.

Love, P.E.D. Wang, X., Sing, C-P. Irani, Z., and Thwala, D. (2014). Overruns in transportation infrastructure projects. *Structure and Infrastructure Engineering*, **10**(2), pp.141-159

Love, P.E.D., Smith, J., Simpson, I., Regan, M., and Olatunji, O. (2015a). Understanding the landscape of overruns in transportation infrastructure projects. *Environment and Planning B: Planning and Design*, **42**(3), pp. 490–509.

Love, P.E.D., Sing, C-P., Carey, B. and Kim, J-T. (2015b). Estimating construction contingency: Accommodating the potential for cost overruns in road construction projects *ASCE Journal of Infrastructure Systems*, **21**(2) 04014035.

Love, P.E.D., Teo, P., Carey, B., Ackerman, F., and Sing, C-P. (2015c). The symbiotic nature of safety and quality: Incidents and rework non-conformances. *Safety Science*, **79**, pp. 55–62.

Love, P.E.D., Edwards, D.J., and Smith, J. (2016). Rework causation: Emergent insights and implications for research. *ASCE Journal of Construction Engineering and Management* 10.1061/(ASCE)CO.1943-7862.0001114

McDermot, M. (1995). Redundant causation. *The British Journal for the Philosophy of Science*, **46**, pp.323-344.

Merrow, E. (2011) *Industrial Mega-projects: Concepts, Strategies and Practices for Success*. Wiley, Hoboken, NJ, USA.

Noordhof, P. (1999). Probabilistic causation, preemption and counterfactuals. *Mind*, 108, pp.95–125

Odeck, J. (2004) Cost overruns in road construction – what are their sizes and determinants. *Transport Policy*, **24**, pp.43-53.

Odeck, J., Welde, M., and Volden, G.H. (2015). The impact of external quality assurance of costs estimates on cost overruns: Empirical evidence from the Norwegian road sector. *European Journal of Transport Infrastructure Research*, **15**(3), pp.286-303.

Odeyinka, H., Larkin, K., Weatherup, R., Cunningham, G., McKane, M. and Bogle, G. (2012) *Modelling risk impacts on the variability between contract sum and final account* (A research report submitted to Royal Institution of Chartered Surveyors. London, UK

Osland O, Strand A, (2010). The politics and institutions of project approval: critical-constructive comment on the theory of strategic misrepresentation. *European Journal of Transport and Infrastructure Research* **10** pp.77–88

Parvan, K., Rahmandad, H., and Haghani, A. (2015). Inter-phase feedbacks in construction projects. *Journal of Operations Management*, 39-40, pp.48-62.

Pearl, J. (1993). Comment: Graphical models, causality and intervention. *Statistical Science*, **8**, pp.266-269.

Pearl, J. (2009). Causality: Models, Reasoning and Inference. 2nd Edition, Cambridge University Press.

Pear, J. (2014). *Comment: Understanding Simpson's Paradox*. The American Statistician, **68**(1), pp.8-13.

Pickrell, D.H. (1990) *Urban Rail Projects: Forecast versus Actual Ridership Cost*. Publication DOT-T91-04, October, US Department of Transportation, Washington DC.

Ramachandran, M. (1997). A counterfactual analysis of causation. *Mind*, **106**, pp. 855-875

Recihelt, K., and Lyneis, J. (1999). The dynamics of project performance: benchmarking the drivers of cost and schedule overrun. *European Journal of Management*, **17**(2), pp.135-150

Russo, F. (2014). Mechanisms and the Evidence Hierarchy. Dipartimento di Studi Umanistici, Universitá di Ferrara. (Accessed 25th November 2015, Available at: http://www.slideshare.net/titalla/mechanisms-and-the-evidence-hierarchy)

Russo, F., and Williams, J. (2007). Interpreting causality in the health science. *International Studies in the Philosophy of Science*, **21**(2), pp.157-170.

Russell, B. (1913). *On the notion of cause*. Proceedings of the Aristotelian Society, **13**, pp.1-26.

Salmon, W. (1984), *Scientific Explanation and the Causal Structure of the World*. Princeton University Press, Princeton, New Jersey

Salmon, W. (2000). Causality and explanation. *Journal of Philosophy* **97**(9), pp.523-527

Siemiatycki, M. (2009). Comparing perspectives on transportation project cost overruns. *Journal of Planning Education and Research*, **29**(2) pp.142-156.

Tombesi, P. (2000). Modelling the dynamics of design error induced rework in construction: comment. *Construction Management and Economics*, **18**(7), pp. 727-732.

Weber. E. (2009). How probabilistic causation can account for the use of mechanistic evidence *International Studies in the Philosophy of Science* 23(3), pp.277-295

Weick, K. (1988). Enacted sensemaking in crisis situations. *Journal of Management Studies*, **25**, pp.305–317

Weick, K. (1993). The collapse of sensemaking in organizations: The Mann Gulch disaster. *Administrative Science Quarterly*, **38**, pp. 628–652

Weick, K. (1995). *Sensemaking in Organisations*. Sage, London

Williamson, J. (2009). *Probabilistic Theories of Causality*. In Beebee, H. Hitchcock,C., and Peter Menzies, P. (Ed), Handbook of Causation. Oxford Handbooks on Philosphy, Oxford University Press pp. 185-212

Verweji, S., Van Meerkerk, I.F., and Korthagen, I.A. (2015). Reasons for contract changes in implementing Dutch transportation infrastructure projects: An empirical exploration. *Transport Policy*, **37**(1), pp.195-202

Vidalis, S.M and Najafi, F.T. (2004) *Cost and time overruns in highway construction.* Proceedings of 4th Transportation Specialty Conference of Canadian Society of Civil Engineering, Canadian Society of Civil Engineering, Montreal, QC, Canada.