

The impact of overconfidence bias on firm performance:

An empirical analysis of S&P 1500 firms

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Declaration

I, Wayne Grant Borchardt, hereby declare that the work on which this dissertation is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other university. I have not allowed and will not allow anyone to copy any part of this thesis with the intention of passing it off as his or her own work.

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Abstract

In the context of public firms competing for profitable growth, there is abundant evidence that a high proportion of strategic decisions are value destructive. When managers make strategic decisions to position their firms for competitive advantage, they do so in a context of uncertainty and, in so doing, they apply heuristics or intuition, which makes them vulnerable to cognitive biases.

We focused on overconfidence bias and its impact on firm performance. Overconfidence is considered to manifest in three distinct forms, namely overestimation, overprecision, and overplacement. While there are numerous gaps and conflicts in the literature, the most notable issues are conflicting results on the overall impact of overestimation, a paucity of studies on the impact of overprecision, and a focus on the overconfidence of the CEO, rather than on the management team making the strategic decisions.

Our review of theory and empirical studies led us to hypothesise a negative relationship between firm performance and overestimation, and a positive relationship with overprecision.

We examined the impact of overestimation and overprecision by analysing the performance of the largest public firms, excluding financial services, in the United States over the period 2009 to 2019.

We measured firm performance using industry-adjusted return on assets. We derived proxies for overestimation and overprecision from management earnings guidance. Since strategic decisions play out over various time horizons, we considered one to five-year lags between our treatment and dependent variables. We estimated our panel data using a year and firm fixed-effects model.

We found support for our hypotheses with a sizeable effect size and statistical significance. We also considered the combined impact of overestimation and overprecision and found that the “specific pessimist” management teams, those that express the greatest underestimation (negative overestimation) and the greatest overprecision, deliver the best firm performance. In contrast, the “vague optimist” management teams deliver the worst firm performance.

Our theoretical contribution enriches the debate on the overall impact of group-level overestimation and overprecision on firm performance. Our findings also have practical implications in corporate governance, investment strategies, and the recruitment and promotion of senior executives.

Acknowledgments

Although I had wanted to do a PhD for many decades, when I eventually began my PhD journey it was with trepidation. Would I have what it takes to get through what I expected to be an arduous process? Well, now as I bring the process to closure, it has certainly been challenging, but it's been fun too. And, like most great efforts, it has not been the work of a single person, but rather the collective work of the scholarly giants whose shoulders I have stood on and the community of friends and colleagues that I have engaged with. As is typical, there are many people to name, but I call out below those that have made the greatest impact.

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This PhD process needed to start somewhere and if I try to locate the event that triggered it for real, it was probably one of the forum meetings hosted by Grant Sieff. A little chat with Bev Shrand after that meeting was probably the tipping point and I thank Bev for that. I also thank Bev for introducing me to Mikael – the best supervisor I could have hoped for. A thank you too to Grant Sieff and Reza Daniels for their endorsement of my PhD application.

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1 Introduction

*“To know that we know what we know,
and to know that we do not know what we do not know,
that is true knowledge”*

Copernicus

In April 2014 Woolworths Holdings¹ (WHL) bought David Jones² (DJs) for R21.4bn³. The strategic rationale for the purchase was communicated to the market (Woolworths Holdings Limited, 2014) with language that included these phrases: “strong platform for continued expansion”, “strengthening our talent pool”, “growth of WHL brands”, “strong earnings growth”. This acquisition was made with a 25% premium and was seen by analysts as expensive, as evidenced by the 7.5% drop in share price when the deal was announced.

Four years later, in July 2018, WHL wrote off R6.9 billion of DJs. Then, in August 2019, WHL wrote off a further R4.3bn, collectively amounting to more than half of the deal value. With these impairments the strategic rationale was in tatters. While there had been some revenue growth in the first financial year after the acquisition, revenue was then flat for the next three years. Since the acquisition, WHL lost three DJs CEOs, some of them leaving with immediate effect. DJs brands, which were introduced to the Woolworths stores, have since been extracted. And, the forecasted earnings (EBIT) margin has been consistently under-delivered. The financial year 2018 earnings margin expectation of 10% or more became 4% in actuals. The FY19 expectation was also 10%, yet the actuals were a mere 2%. WHL revised down their guidance for FY20 to 7-9%, but still only delivered a 2% result. WHL revised down their guidance for FY21 to 6-8%, but still only delivered a 2% result. This progression of guidance and the actuals that consistently fell below is illustrated in Figure 1.

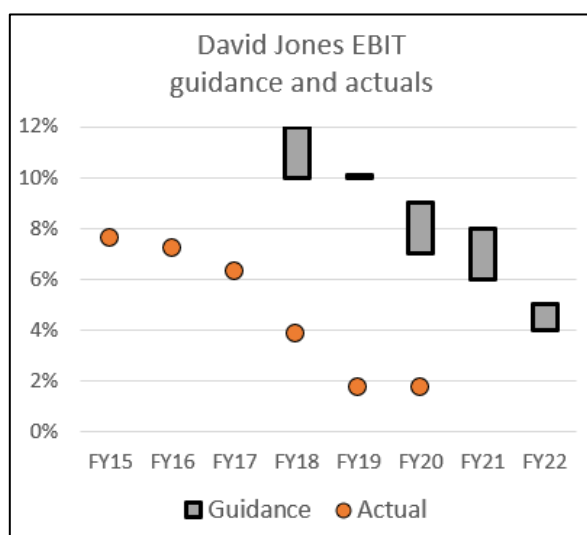


Figure 1: WHL guidance and actuals on David Jones EBIT.

1. Woolworths Holdings is a retail company domiciled in South African and listed on the Johannesburg Stock Exchange.
 2. David Jones is a retail company based in Australia.
 3. R is the currency symbol for the South African Rand (ZAR). At the time of the transaction, the exchange rate to Australian dollar (AUD) was almost exactly 10:1, that is 10 ZAR bought 1 AUD.

At the time of announcing the DJs acquisition, WHL's share price was R69. More than five years later, at the time of the second impairment (August 1st, 2019), the shares had fallen to R55. This drop of 20% relative to the pre-acquisition price occurred at a time when the median performance of WHL's peer set was +40%. In other words, in those 5 years WHL has underperformed its peers in share price growth by 60%! A further indication that WHL's collapse in value was not due to broader market issues is that in January 2015 WHL comprised 0.8% of the JSE Top-40⁴ and by January 2020 they comprised 0.4%.

While senior executives of WHL will have no shortage of explanations for these dire outcomes, it should not come as a surprise. Large acquisitions, like WHL's acquisition of DJs, have only a 44% chance of delivering returns above the industry average (Rehm, Uhlaner, & West, 2012) and show a negative median excess TRS⁵. Other authors find even more concerning results regarding M&A⁶ in general: *"M&A is a mug's game, in which typically 70%–90% of acquisitions are abysmal failures"* (Martin, 2016).

It is not just M&A. Internal moves like corporate reorganisations result in fewer than one-third producing any meaningful improvement in performance, with the other two-thirds not improving performance or destroying value (Blenko, Mankins, & Rogers, 2010). Furthermore, generalising beyond M&A and corporate reorganisations, Paul Nutt, a leader in strategic decision making research, has studied over 400 strategic decisions and has published extensively in the field, finds that *"Half of the decisions studied failed⁷; generalizing this finding suggests that failed decisions are a commonplace event in organizations, producing both wasted resources and forgone benefits."* (Nutt, 2010b). A meta-analysis finds the estimates of the failure rate⁸ of strategic decisions is above 40% (Cândido & Santos, 2015).

Of the firms that comprised the S&P 500⁹ in the year 2010 less than two thirds (64%) were still members of that index at the beginning of 2019. In other words, more than one third of the S&P 500 turned over in the last decade during the longest running bull market in history (J. Chen, 2019). An analysis of deletions from the S&P 500 (Chan, Kot, & Tang, 2013) finds that about two thirds are due to having been acquired¹⁰, about one quarter due to no longer being a leading company in a leading industry and/or a decrease in market capitalisation, and the balance for a variety of reasons that includes spin-offs, divestiture, bankruptcy, and delisting. Some of those firms might have voluntarily left the S&P 500, but three quarters of the time firms leave involuntarily (Platikanova, 2016). In a dynamic competitive market, these involuntary departures might not be due to "failed" strategic decisions, using the definitions of Nutt (2010b) or Cândido and Santos (2015), instead the departures might be due to being outcompeted by peers.

4. The JSE Top-40 are the public companies with the largest market caps on the Johannesburg Stock Exchange.

5. Excess TRS refers to outperformance in total returns to shareholders against the global industry index.

6. M&A refers to mergers and acquisitions.

7. Nutt's primary indicator of success was whether the decision was put to use. If not, it is deemed a failure.

8. Cândido and Santos define failure as "either a new strategy that was formulated but not implemented, or it was implemented but with poor results". But they also acknowledge that their meta-analysis is challenged by significant inconsistency in the definition of failure across the studies that they reviewed.

9. The S&P U.S. Indices are a family of equity indices designed to measure the market performance of U.S. stocks trading on U.S. exchanges. There are eligibility criteria for being a member of the S&P 500 index. These criteria are detailed in the S&P U.S. Indices Methodology ("S&P U.S. Indices Methodology," 2019), but in essence the S&P 500 is comprised of large companies listed on stock exchanges in the U.S. The same document states "S&P Dow Jones Indices believes turnover in index membership should be avoided when possible. At times a stock may appear to temporarily violate one or more of the addition criteria. However, the addition criteria are for addition to an index, not for continued membership. As a result, an index constituent that appears to violate criteria for addition to that index is not deleted unless ongoing conditions warrant an index change."

10. Sometimes being acquired is voluntary and sometimes it is involuntary.

Perhaps going forward, with the increasing availability of data, computing power and better algorithms, the S&P 500 turnover rate will decrease? This seems unlikely. Looking out over time, independent analysts seem to be aligned on their views of an increasing rate of turnover for public companies. *“Public companies have a one in three chance of being delisted in the next five years. That’s six times the delisting rate of companies 40 years ago.”* (Reeves, Levin, & Ueda, 2016); *“About half of S&P 500 companies will be replaced over the next ten years.”* (Anthony, Viguerie, Schwartz, & van Landeghem, 2018); *“75% of S&P 500 companies will be removed from the index by 2027.”* (Minutemen, 2014); and *“Two out of three large companies will stall out, go bankrupt, be acquired or break into pieces in the next 15 years.”* (Allen, 2017).

From this empirical observation of public firms experiencing a high rate of involuntary turnover on major indices like the S&P 500, we considered the theoretical implications. A firm’s inability to sustain its leadership position implies an inability to sustain its competitive advantage. To sustain competitive advantage, top management need to make the strategic decisions that result in their firm remaining relevant to customers, differentiated from competitors, and economically viable (Eisenhardt & Tabrizi, 1995; Jansen, Van Den Bosch, & Volberda, 2006; Larrañeta, Zahra, & G., 2014; Nadkarni & Narayanan, 2007). This led us to wonder why, when the stakes are so high and the management teams of these leading organisations can typically muster the resources, like talent, data, algorithms, and computing power in the service of their vision and strategy, do we see the top management teams of public firms not making the strategic decisions that enable their firms to sustain their competitive advantage.

1.1 Context

To understand why the top management teams of public firms are not making the strategic decisions that enable their firms to sustain their competitive advantage, we considered the economic context in which these firms operate. In other words, we considered the market economy and its implications. The market economy is characterised by the private ownership of capital assets, which are deployed with a profit motive in a competitive market (Jahan & Mahmud, 2015).

The implications of these characteristics of the market economy were sharply articulated by Milton Friedman in his seminal work *“Capitalism and Freedom”* (Friedman, 1962) and a subsequent article (Friedman, 1970). When a firm is the private property of its shareholders, those shareholders have the prerogative, within the bounds of the law, to *“conduct the business in accordance with their desires”* (Friedman, 1970, p. 173).

If the owners choose to hire professional management, then the owner’s desires become the manager’s objectives which *“generally will be to make as much money as possible”* (Friedman, 1970, p. 173). Friedman’s shareholder theory has been challenged in many respects, such as the need to take a broader stakeholder view (Ferrero, Hoffman, & McNulty, 2014). Whether management have responsibilities to a broader group of stakeholders or not, the duty of management includes, at a minimum, delivering returns for shareholders.

Thus, managers make strategic decisions to direct their firm into the future with the aim of, amongst other things, delivering returns to shareholders. These decisions might include entering or exiting an industry, buying or selling a company, and so on. We considered the dynamics that managers face in their efforts to deliver shareholder returns.

According to Joseph Schumpeter (Schumpeter, 1942), the market economy is by necessity dynamic and driven by innovation. Schumpeter recognises innovative entry by entrepreneurs as a disruptive force that sustains economic growth, even as it destroys the value of established companies. Schumpeter sees managers’ actions in the pursuit of profit as the primary driver of capitalism: *“the fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumers, goods, the*

new methods of production or transportation, the new markets, the new forms of industrial organization that capitalist enterprise creates” (Schumpeter, 1942, p. 82-83).

Markets are dynamic not only because of innovation, but because of the entry and exit of competitors, especially so in this recent era where globalization waxes and wanes.

This pursuit of profit in a competitive context gives rise to “survival of the fittest” forces in a manner not dissimilar to Darwin’s evolutionary theory. The impact of these forces Schumpeter calls “creative destruction” and he describes it as *“a process of industrial mutation, that incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one” (Schumpeter, 1942, p. 83).*

Do we see “creative destruction” in practice? It appears so. The replacement of more than one third of the members of the S&P 500 over the last decade seems to provide antecedent evidence in support of Schumpeter’s claim. Firms that have dropped off the index because their performance has faltered because of disruptive industry changes are clear victims of creative destruction. But even firms that are still performing well, but have dropped off the index by virtue of being outcompeted, would have lost their relative share of value and this too is consistent with Schumpeter’s definition of creative destruction. Does the “perennial gale of creative destruction” imply the inevitable demise of incumbent S&P 500 member firms? While there is evidence that creative destruction is real and material, it does not present an unescapable reality for the incumbent.

If creative destruction does not necessarily imply the deletion of incumbents from the S&P 500, what else might explain this phenomenon? Why else might firms not be sustaining their competitive advantage?

In an unchanging world, firms would merrily continue to deliver the same products / services to the same customers under the same competitive pressure. And, as such, they would maintain their same level of performance. But firms operate in a dynamic context that includes a changing competitor landscape, emerging technologies, changing customer needs, as well as a changing regulatory environment, a changing geopolitical context, and more. It is these changes and how a firm responds to them, reactively and proactively, that drives changes in the firm’s absolute and relative performance.

1.2 Strategic decision making

How do firms respond to existing and expected changes? By strategizing. With an obligation to deliver returns to their shareholders, a firm’s management develops and executes strategies with the intent of mitigating threats and capitalising on opportunities in this changing world. These strategies are essentially a collection of strategic decisions. In fact, the decision is the only means available to managers to change the performance of their firm (Howard & Abbas, 2016). Thus, when aiming to deliver shareholder returns, decision making is not just an important lever for the executive, it is the **only** lever.

We followed Mintzberg, Raisinghani, and Theoret’s (1976) definition of strategy and Howard and Abbas’s (2016) definition of a decision to define a strategic decision as: **an important choice, in terms of the actions taken, the resources committed, or the precedents set, between two or more alternatives that involves an irrevocable allocation of resources.** Poor or failed strategic decisions might be one of the reasons for firms not being able to sustain their competitive advantage.

Since these are decisions about the future, which is inherently uncertain, strategic decision-making is decision making under uncertainty. This topic, decision making under uncertainty, has been examined by scholars in three broad categories: the descriptive, the normative, and the prescriptive (Bell, Raiffa, & Tversky, 1988). While there have been many examples in the descriptive decision making literature of how managers deviate from normative decision making, we considered two seminal bodies of work: Simon, Cyert, and March’s work on bounded rationality (Simon, 1955; Cyert, Simon, & Trow, 1956;

March & Simon, 1958; Cyert & March, 1963) and Kahneman and Tversky's work on heuristics, biases, and prospect theory (Tversky & Kahneman, 1974; Kahneman & Tversky, 1979; Tversky & Kahneman, 1986).

Our bounded rationality leads us to "satisfice" and to do so by applying heuristics or intuition. This, in turn, makes us vulnerable to cognitive biases that distort decision making (Tversky & Kahneman, 1974). Might management teams' vulnerability to cognitive biases help explain why firms struggle to sustain their competitive advantage. More specifically, might cognitive biases be undermining the quality of their strategic decisions thereby impacting the performance of their firms to the extent that those firms fail, are acquired, or are outcompeted by rivals?

1.3 Overconfidence bias

While numerous cognitive biases have been identified, for reasons that we explain below, we chose to specifically examine the impact of overconfidence bias on firm performance.

"Overconfidence is a belief about oneself or one's knowledge that is too extreme or too precise given a comparable, objective benchmark of reality" (Meikle, Tenney, & Moore, 2016)

Leading researchers have referred to overconfidence bias in these ways: "the most robust finding in the psychology of judgment" (De Bondt & Thaler, 1995), "the most significant of the cognitive biases" (Kahneman, 2011, p. 255), "no problem in judgment and decision making is more prevalent and more potentially catastrophic than overconfidence" (Plous, 1993, p. 217), and "the mother of all biases" (Moore & Bazerman, 2012a). Moore and Bazerman say this for two reasons: "overconfidence effects are some of the most potent, pervasive, and pernicious of any of the biases", and "overconfidence facilitates many of the other biases". Overconfidence bias was also worthy of our focus because, as will be described later, it has effects which have been demonstrated to impact firm performance.

Overconfidence is believed to have deep evolutionary roots (Johnson & Fowler, 2011) and is driven by cognitive, physiological, and motivational causes (Russo & Schoemaker, 1992). Thus it is not surprising that overconfidence is found to be pervasive (Griffin & Varey, 1996; Skąła, 2008; Moore & Bazerman, 2012b, Olsson, 2014¹¹).

Before theorising on the impact of overconfidence, we clarify our definition for this study because the concept of overconfidence is not consistent in the literature in two key respects.

Firstly, we found that most of the studies of the impact of overconfidence bias on firm performance focus on the overconfidence of CEO. However, strategic decisions in organisations are typically not made solely by the CEO or any single individual (Mukherjee, Dicks, Shackelford, Vira, & Sutherland, 2016). We therefore specifically focused our attention on the overconfidence bias exhibited by the group making the strategic decisions because "groups make most of the important decisions in organizations" (Tasa & Whyte, 2005).

Secondly, the literature is divided on what constitutes overconfidence. Moore and Healy (2008) suggest that there are three distinct types of overconfidence. Overestimating one's actual ability, performance, level of control, or chance of success they label as "overestimation", having excessive certainty regarding the accuracy of one's beliefs they call "overprecision", and falsely believing that we are better than others they call "overplacement".

11. Olsson's paper cites 10 papers that make statements about the pervasiveness of overconfidence, but Olsson challenges those claims on a methodological basis.

In the context of the impact on firm performance, we find that the body of literature is concentrated on overestimation and, to a lesser extent, overprecision. The omission of overplacement seems appropriate since overestimation and overprecision, but not overplacement, are most relevant in the context of the hard task of strategic decision making (Larrick, Burson, & Soll, 2007; Moore & Healy, 2008).

Thus, our study examined overconfidence as group-level overestimation and group-level overprecision.

Overestimation has been shown to manifest in four respects (Moore & Healy, 2008): Self-enhancement, where people view themselves positively, as opposed to accurately (Dunning, 2005); Illusion of control, where people think they have more control over circumstances than they actually do (Thompson, 1999); The planning fallacy, the common tendency to overestimate the speed at which we will complete projects (Buehler, Griffin, & Ross, 1994); and Unrealistic optimism, the tendency to overestimate the rosiness of our future (Sharot, Riccardi, Raio, & Phelps, 2007).

Overprecision is theorised to lead managers to overestimate and overreact to the precision of their knowledge (Goel & Thakor, 2008; Gervais et al., 2011) and to underestimate the riskiness of earnings and of projects (Gervais, Heaton, & Odean, 2002; Hackbarth, 2008).

These behavioural implications of overestimation and overprecision are antecedents of the impact that these types of overconfidence might have on firm performance. This led to our research question is **“what is the impact of group-level overestimation and overprecision biases on firm performance?”** and, in this respect, we found relevant theory and associated empirical studies that informed the development of our hypotheses.

1.4 Theory and hypotheses

Hubris theory, introduced by Richard Roll (1986) is the hypothesis that hubris explains why managers overinvest. This theory says that managers are subjected to strong pressures to maintain high performance and that this pressure, in the presence of hubris, drives risk-seeking behaviours. The predicted consequence is that in the context of mergers and acquisitions, bidding managers overestimate their ability to manage the target firm and hence overpay for it. Hubris applies not only to acquisitions, but more generally it pertains to risk taking in other respects, such as firm investing, financing, and in the case of banks, to lending standards. Hubris theory has been extended by other researchers (Hayward, Shepherd, & Griffin, 2006; Heaton, 2002b; Malmendier & Tate, 2005b, 2015) and Heaton (2002a) finds that hubris also leads to underinvestment. Underinvest occurs because optimistic managers might decline positive net present value projects when they require external financing because the optimistic manager believes that the cost of external finance is too high. In summary, overestimating managers overinvest and perhaps also underinvest, thus are not investing in shareholders' best interests as they are making investments that are value destructive and forgoing value creating investments. This theory has plenty of empirical support, all of it finding that overestimation has a negative relationship to firm performance (P.-H. Ho, Huang, Lin, & Yen, 2016; Hwang, Hyoseok, Kim, & Kim, 2020; Invernizzi, Menozzi, Passarani, Patton, & Viglia, 2017; J. B. Kim, Wang, & Zhang, 2016; Malmendier & Tate, 2008; Park, Kim, Chang, Lee, & Sung, 2018).

Hyper core self-evaluation theory is presented by Hiller and Hambrick (2005). Core self-evaluation (CSE) is a relatively enduring and fundamental evaluation of oneself as an individual. CSE is defined as the overlap of self-esteem, generalized self-efficacy, locus of control, and emotional stability. Hiller and Hambrick (2005) discuss hyper-CSE as extreme levels of the four aforementioned qualities, and mention that this closely aligns with hubris. However, their definition of overconfidence aligns to overprecision. Hyper-CSE theory predicts that the greater the CEO's CSE, the faster, more centralised, and less comprehensive will be the organisation's strategic decision-making process. This theory also predicts that for greater CSE of the CEO, the greater the number and scale of large-stakes initiatives undertaken

by the organization, the more the organisation's strategy will deviate from the central tendencies of the industry, the greater will be the organisation's persistence in pursuing strategies that were launched by the CEO, and, ultimately, the more extreme the organisation's performance will be. Hyper-CSE theory is referenced by and finds empirical support in two studies (M. C. Kim, Xiong, & Kim, 2017; Lai, Lin, & Chen, 2017), but in both cases it is unclear whether these empirical studies are measuring overprecision.

Capital structure theory has its origin with Hackbarth (2008) who theorises that optimistic and/or overconfident¹² managers choose higher debt levels and issue new debt more often. Hackbarth's theory is based on his assertion that optimistic managers overestimate the growth rate of earnings, which he calls growth perception bias, and overconfident managers underestimate the riskiness of earnings, which he calls risk perception bias. The consequence of growth perception bias and risk perception bias is that biased managers will prefer debt and, in fact, take on higher levels of debt than unbiased managers. In a similar vein, Deshmukh, et al. (2013) theorise that firms with overconfident¹³ CEOs generally pay out smaller dividends, because they believe their firm to be undervalued by the market. Capital structure theory finds empirical support in reduced dividends (Banerjee, Humphery-Jenner, & Nanda, 2018), higher leverage ratios (Barros & da Silveira, 2007), and greater debt issue (Malmendier, Tate, & Yan, 2011).

The central point of underinvestment mitigation theory is essentially a mirror image of hubris theory. The underinvestment mitigation theorists acknowledge many of the same points as the hubris theorists but find a positive impact on firm performance in respect of the tendency of overconfident managers to overinvest. Gervais, Heaton, and Odean (2002) theorise that moderately overconfident¹⁴ or optimistic managers make decisions that are in the better interest of shareholders than the decisions made by rational managers who are often too conservative. The basis of Gervais et al.'s argument is that overconfident or optimistic managers underestimate the risk of potential projects and overestimate the expected value of a risky project. Because of these beliefs they are less likely to postpone the decision to undertake, are more willing to undertake, and are quicker to undertake risky projects. Goel and Thakor (2008)'s theory is consistent with Gervais et al., but their definition of overconfidence only includes overprecision. Goel and Thakor (2008)'s theory is referenced and finds empirical support in Bharati et al. (2016)'s study, but is confused by Bharati et al. defining overconfidence in the overestimation way.

Innovation and R&D propensity theory has its origin in two papers (Galasso & Simcoe, 2011; Hirshleifer, Low, & Teoh, 2012) that appeared almost simultaneously. Galasso and Simcoe (2011) theorise that overconfident¹⁵ CEOs are more likely to take their firms in a new technological direction. The basis for their theory is that CEOs are aware that successful innovation is rewarded, and overconfidence encourages innovation by reducing a CEO's internal beliefs about the likelihood of failure. Hirshleifer et al.'s paper provides empirical support. For firms competing in innovative industries, they show that overconfident¹⁶ CEOs are more effective at exploiting growth opportunities and translating them into firm value. Tang et al. (2015)'s study provides empirical support in that they show a positive relationship between executive hubris¹⁷ and firm innovation. While numerous empirical studies support the theory that overconfident managers invest more in innovation and R&D, they do not always

12. Hackbarth uses optimism in the overestimation way and overconfidence in the overprecision way

13. Deshmukh et al. use overconfidence in the overestimation way.

14. Gervais et al. use overconfidence in the overprecision way and optimistic in the overestimation way.

15. Galasso and Simcoe use overconfidence in the overestimation way.

16. Hirshleifer et al. use overconfidence in the overestimation way.

17. Tang et al. define hubris as an exaggerated belief in one's own judgment that deviates from objective standards, which seems to imply overestimation.

agree that this produces favourable outcomes for shareholders, with some studies (Bharati et al., 2016; H. A. Kim, Choi, & Choi, 2019; Mundi & Kaur, 2019) showing a positive impact on firm performance, and others (S.-S. Chen et al., 2014) a negative impact on firm performance.

We aggregated related perspectives under the motivational theory theme, which considers the motivational value that a manager’s overconfidence confers on others as well as on themselves. Taylor and Brown (1988) explore the impact of positive self-illusions, namely exaggerated perceptions of control and unrealistic optimism, on mental health. They find a beneficial relationship in that overconfident¹⁸, optimistic people tend to be happier, more popular, more willing to help others, and more willing to persist in tasks. Gervais, Heaton, and Odean (2002, 2011) theorise that overconfident¹⁹ managers are motivated to expend more effort because they overestimate the value of their effort. And they apply this effort to gather information and learn such that they improve the success rate and value of the firm's investments. Ackert and Deaves (2009) take a similar view to Gervais et al. (2002, 2011) when they state that moderate level of overconfidence²⁰ could have a positive impact provided overconfidence gives rise to concentrated efforts of the CEO. Motivational theory finds empirical support (Hilary, Hsu, Segal, & Wang, 2016; Phua, Tham, & Wei, 2018) and experimental support (Shipman & Mumford, 2011), but is also confused by differing definitions of overconfidence.

From the theories discussed, we noted that Gervais, Heaton, and Odean (2002), Hackbarth (2008), and Goel and Thakor (2008) all theorise a non-monotonic relationship between overprecision and firm performance, with a moderate level of overprecision being most favourable. We also found a theoretical argument for a non-monotonic relationship to firm performance from Johnson et al. (2011) and Yu (2014) and we found partial empirical support in Hirshleifer et al. (2012)’s study where they show a non-monotonic relationship between overestimation and R&D spend. The absence of empirical support for non-monotonicity is unsurprising in that most empirical studies use a proxy for overestimation that is “blunt” in that it is either binary or trinary. Such a blunt instrument cannot resolve the subtlety of a non-monotonic relationship.

The potential non-monotonic nature of the relationship between both overestimation and firm performance and overprecision and firm performance suggests that there might be a “goldilocks” zone where just the right amount of overprecision and just the right amount of overestimation deliver the most favourable outcomes for shareholders. In other words, there might be a target spot or zone in the two-dimensional space illustrated below.

		Estimation	
		Under-	Over-
Precision	Over-	I know just how bad it will be	I know just how good it will be
	Under-	It will be bad, but I don't know how bad	It will be good, but I don't know how good

Figure 2: The space of overestimation and overprecision.

18. Used here in the sense of overprecision.

19. In their earlier paper, Gervais, Heaton, and Odean refer to both optimism and overconfidence, which implies overestimation and overprecision, but in their later paper they refer only to overconfidence in the form of overprecision.

20. Ackert and Deaves use overconfidence in the overestimation way in this context, but also recognise the alternative forms of overconfidence.

From theory and empirical evidence, it appears that overconfidence affects firm performance, however when quantifying its impact, we found the literature to be incomplete and inconsistent in twelve respects:

1. There appears to be no generally accepted best practices for strategic decision making.
2. There is a lack of clarity and consistency in the definition of overconfidence bias.
3. Researchers recognise the distinct types of overconfidence but have conflicting views on the nature of the relationship between overestimation and overprecision.
4. There is no unifying theory, which integrates discrete theories and related effects, of the impact of overconfidence on firm performance.
5. Most studies on the impact of overconfidence on firm performance, focus on the overconfidence of the CEO, with a paucity of studies that focus on the overconfidence of the group making the strategic decision.
6. Most studies derive a proxy for overestimation from the option-trading behaviour and/or the press characterisations of the CEO, with few studies deriving overconfidence proxies from group-level behaviour.
7. Researchers acknowledge that there is a “bright-side” and a “dark-side” to overconfidence but are divided in their view of the overall effect.
8. Of the studies that investigate the overall impact of overconfidence on firm performance, accounting measures are commonly used, but we have found no studies that use economic profit or its constituent drivers, spread and growth.
9. There is a theoretical argument for a non-monotonic relationship between overestimation and firm performance, but most empirical studies do not use a sufficiently granular proxy to locate the optimal level of overestimation.
10. Despite a theoretical basis for believing that there is a relationship between overprecision and firm performance, there is a gap in empirical support for this theory.
11. Furthermore, there is a gap in empirical studies on the combined impact of overestimation and overprecision on firm performance.
12. We have not found a study that claims a causal link between overconfidence, in any of its forms, and firm performance.

Since our research question was concerned with group-level overestimation and overprecision and the literature revealed issues 5 and 6 above, we needed to find proxies that could represent the underlying variables. We conceptualised proxies for overestimation and overprecision derived from management earnings guidance. Recognising that such proxies are subject to a variety of distorting forces, we conducted a theoretical assessment of the legitimacy of these proxies using latent variable theory (Borsboom, 2008). We found that our proxies were imperfect, with our overestimation proxy especially susceptible to managers’ desire to avoid a “negative earnings surprise”. Notwithstanding the imperfection, in at least the important respect of being a group-level measure, our overestimation proxy was superior to the options-trading proxy, and in other areas of weakness, it shared these with the options-trading proxy. We did not find a particular weakness in the use of earnings guidance for overprecision.

Armed with these proxies, in alignment with our research question, and to address some of the areas of incompleteness and inconsistency in the literature, we formulated five hypotheses:

When considering the relationship between overestimation and firm performance, hubris theory unambiguously predicts a negative relationship, underinvestment mitigation theory has both positive (mitigates underinvestment) and negative (invests in value destructive projects) aspects, and

innovation propensity theory and the broad body of empirical evidence is conflicting. We side with the consistency of hubris theory, its extensions, and its empirical support and accordingly hypothesize:

- *Hypothesis 1a. The relationship between overestimation and firm performance is negative.*

Further, recognizing the non-monotonicity predicted in the theories (Gervais et al., 2002; Hackbarth, 2008; Hirshleifer et al., 2012; Johnson & Fowler, 2011; Yu, 2014), we hypothesize:

- *Hypothesis 1b. The relationship between overestimation and firm performance is non-monotonic.*

The underinvestment mitigation theorists (Gervais et al., 2002, 2011; Goel & Thakor, 2008), acknowledge many of the same points as the hubris theorists, but find a positive impact on firm performance since moderately overconfident or optimistic managers make decisions that are better for shareholders since rational managers are often too conservative. While this theory predicts that the overestimating managers might go too far, it predicts that overprecise managers will expend more effort such that they improve the success rate and value of the firm's investments. With a paucity of empirical studies, we base our hypothesis on these theoretical predictions:

- *Hypothesis 2a. The relationship between overprecision and firm performance is positive.*

Further, recognizing the non-monotonicity predicted in the theories (Gervais et al., 2002; Goel & Thakor, 2008; Hackbarth, 2008), we hypothesize:

- *Hypothesis 2b. The relationship between overprecision and firm performance is non-monotonic.*

We build on hypotheses 1a, 1b, 2a, and 2b to hypothesize on the levels of overestimation and overprecision that maximise firm performance:

- *Hypothesis 3. Firm performance is maximised when there is moderate negative overestimation and moderate positive overprecision.*

1.5 Empirical strategy

For this study we followed the critical realist philosophy of science. Critical realism posits a realist ontology and a fallibilist epistemology, thus takes the position that truthful knowing might be attained, but human limitations mean that it cannot be claimed with certainty (K. D. Miller & Tsang, 2010).

There are many steps and many confounding factors between the “cause” (overconfidence bias in the forms of overestimation and overprecision) and the “effect” (firm performance). In addition, proxies are an imperfect abstraction of the variable we seek to measure. And overconfidence bias itself results in competing positive and negative effects. Consequently, the impact of overconfidence bias on firm performance is likely to be a small “signal” in a highly “noisy” context. For this reason, a large, high quality data set is required. The S&P 1500 is such a data set. In addition to the quality of the data, using data from the S&P 1500 also allows an understanding of the impact of overconfidence bias in some of the most sophisticated and largest firms in the world.

We analysed the performance of S&P 1500 firms in the period from 2009 to 2019 inclusive. This period avoids the Great Financial Crisis of 2007/2008 and the Covid-19 era that began in 2020. It also overlaps with the period that follows the SEC²¹'s implementation of Regulation Fair Disclosure in 2000, which led to greater prevalence of management earnings guidance data.

21. Securities and Exchange Commission

As a measure of firm performance, we selected a fundamental metric that is generally applied in studies of this nature. Accordingly, we used the accounting returns metric of industry-adjusted ROA (return on assets), as used by Park et al. (2018).

The impact of strategic decisions plays out over various time horizons. Some strategic decisions have short-term effects, e.g. share buybacks are “felt” within one year (Banerjee et al., 2018), others have medium to long-term effects, resulting in researchers lagging their dependent variables by two (Andreou, Cooper, de Olalla Lopez, & Louca, 2018), three (Billett & Qian, 2008) or five years (Rehm et al., 2012). Some studies, for example, S.-S. Chen et al. (2014), use multiple time horizons, which is the approach that we used.

Our treatment variables were the overestimation and overprecision biases of the management team making strategic decisions for their firm. As mentioned above, we had conceptualised and theoretically assessed proxies based on management earnings guidance. We operationalised these for use in our empirical analysis.

With our selected dependent and treatment variables, and a set of typically used control variables, we constructed our regression equation as displayed below:

$$adjROA_{i,t,n} = \beta_0 + \beta_1 \cdot oe_{i,t-n} + \beta_2 \cdot op_{i,t-n} + \beta_j \cdot C_{i,t-n} + \beta_k \cdot year_k \quad (1)$$

Where $adjROA_{i,t,n}$ is the sum of industry-adjusted return-on-assets over a period of n years for firm i at time t , oe and op are the treatment variables, C is a vector of control variables, $year$ is a vector of year dummies, all regressors were lagged by n years, and we considered n from one to five years to account for the delayed effect of decisions. We estimated our regression equation using a year and firm fixed-effects model.

1.6 Results

The analysis of our hypotheses yielded mixed findings, with hypotheses 1a and 2a finding unequivocal support, but hypotheses 1b and 2b not finding support, and hypothesis 3 finding partial support.

Hypothesis 1a showed a negative relationship with statistical significance at the 1% level for all 5 lags. Hypothesis 2a showed a positive relationship with statistical significance at the 1% level for the first 3 lags. Not only were these results statistically significant, but they were also practically consequential in the magnitude of the relationship that was found in the year following the guidance. Specifically, a one standard deviation increase in overestimation bias predicts a decline of 1.32 percentage points of industry-adjusted ROA, which amounts to an annual loss of \$26 million for the shareholders of the median-sized firm²². A sustained loss of this magnitude would cost shareholders \$260 million in present value terms²³. And, almost as a polar opposite, a one standard deviation increase in overprecision bias predicts an increase of 1.79 percentage points of industry-adjusted ROA, which amounts to an annual gain of \$36 million for the shareholders of the median-sized firm. A sustained gain of this magnitude would deliver \$360 million to shareholders in present value terms.

For hypotheses 1b, 2b, and 3, we converted our oe and op continuous variables into fine-grained categorical variables. We found that both hypotheses 1b and 2b were not supported in that we found a monotonic, rather than non-monotonic relationship in both cases. We found a negligible interaction effect between overestimation and overprecision and hence the findings of hypotheses 1a and 2a were

22. The median firm in our data set has an asset base of \$2 billion.

23. Assuming the loss is sustained in perpetuity and the weighted average cost of capital is 10%.

simply additive. As such, we found partial support for hypothesis 3. We found that firm performance is maximised not when overestimation and overprecision are moderately negative and positive, but rather when they are extremely negative and extremely positive, respectively. With our 7-point categorical scale, we found that the spread between the best firm performance, which occurs for the lowest overestimation and highest overprecision, and the worst firm performance, which occurs for the highest overestimation and lowest overprecision, was 7.0 percentage points of industry-adjusted ROA. If the median firm were to improve its industry-adjusted return on assets by 7.0% that would deliver an extra \$158 million annually to shareholders. On a present value basis, that represents value creation of a staggering \$1.58 billion for the median firm.

We acknowledged that this is almost the most extreme case in that it would entail the median firm migrating from being in the roughly two percent of worst performing firms to being in the two percent of best performing firms. A more conservative and standardised assessment of the value would consider the impact of a one standard deviation change of both overestimation and overprecision on industry-adjusted ROA. When overestimation decreases by one standard deviation and overprecision increases by one standard deviation, the resulting value creation for the median firm is \$62 million annually or \$622 million if this change is sustained. The opposite is also true in that \$622 million of value destruction awaits those that change from underestimation and overprecision to overestimation and no longer being overprecise.

We conducted supplementary analysis in an effort to explain our findings. This supplementary analysis, along with our initial findings, led us to conclude that hubris theory, capital structure theory, and underinvestment mitigation theory might provide parsimonious explanations of the negative relationship between overestimation and firm performance and the positive relationship between overprecision and firm performance. Furthermore, we found that the dynamic relationships between current and lagged versions of overestimation, overprecision, and firm performance suggests a self-limiting character of overestimation and overprecision.

Our conclusions from these results were that management teams that are specific pessimists deliver the highest firm performance and, correspondingly, the worst firm performance is associated with management teams that are vague optimists.

1.7 Contributions

This study makes theoretical contributions in six areas. We consider our most important contribution to be “a richer perspective on the impact of overconfidence on firm performance”, but for narrative purposes, we describe our contributions in the order below:

- An empirical motivation for treating overestimation and overprecision separately
- A justification for analysing the overestimation and overprecision of the top management team
- A validated set of proxies for group-level overestimation and overprecision
- A richer perspective on the impact of overconfidence on firm performance
- Speculative reasons explaining the observed impact
- An overarching framework to contextualise studies of this nature

Our empirical results demonstrated that overprecision and overestimation are indeed distinct, as argued by Moore and Healy (2008). Furthermore, we found a negligible interaction effect between overestimation and overprecision. For the field to advance, we agree that the term “overconfidence” can be confusing, leads to confounding of the distinct biases of overprecision and overestimation, and hence should be used sparingly and with caution.

While most of the literature on the impact of overconfidence bias on firm performance focuses exclusively on the overconfidence of the CEO, we add to the sparse literature on examining the impact of overestimation and overprecision biases expressed by the group making their firm's strategic decisions. We considered this a necessary perspective because "*groups make most of the important decisions in organizations*" (Tasa & Whyte, 2005).

Following from above, if we were to analyse the overestimation and overprecision of the top management team we required appropriate proxies. We provided a theoretical assessment of the validity of overconfidence proxies derived from management earnings guidance. We assessed our overestimation proxy and overprecision proxy, finding both to be imperfect proxies, but better than the alternatives, and having the important characteristic of serving as proxies for group-based overconfidence. In this regard, we make a methodological contribution.

We enrich the debate on whether the net effect of overconfidence on firm performance is bright or dark. Our study finds strongly in favour of the negative impact of overestimation. Our study finds this negative relationship, with a meaningful effect size and statistical significance for each of the five lag periods we examined. And, adding to the near vacuum of empirical overprecision studies, our analysis finds that overprecision is associated with a positive, meaningful effect size, and retains statistical significance for the first three time lags. Furthermore, we found that the combined impact of overestimation and overprecision has a negligible interaction effect, but each variable has a meaningful effect size with statistical significance for the first four time lags. We believe we are the first to show this combined effect. Using categorical variables, we located the combined level of overestimation and level of overprecision that maximises, and that which minimises, firm performance.

Our supplementary analysis leads to our contribution of two conjectures of the drivers of firm performance in the presence of overestimation and overprecision of the management team. In both of our conjectures we speculated that capital structure choices and the quality of investments are the key determining factors of firm performance that are associated with overestimation and overprecision. In saying this, we are also saying that, somewhat surprisingly, other candidate drivers of firm performance, like growth and R&D spend, show no meaningful relationship to overestimation and overprecision.

We saw a need for a unifying theory of overestimation and overprecision bias on firm performance because the existing theories predict discrete effects which might, or might not, be compatible with each other. Our contributions do not include a proposed unifying theory, but we contribute by defining an overarching framework that could accommodate a unifying theory.

We also make practical contributions in respect of corporate governance, recruitment and promotion of senior executives, and investment strategies. Some researchers and practitioners believe that it is impractical for people to address their own cognitive biases (Sibony, Lovallo, & Powell, 2017). Accordingly, we argue that our suggestions of practical contributions are indeed practical because they do not depend on some miraculous willpower of the individual, rather they are recommendations that can be applied by others.

1.8 Document layout

This thesis is organized as follows: Chapter 2 focuses on the theoretical context and the derivation of hypotheses; Chapter 3 explains the empirical strategy for testing the hypothesis; Chapter 4 discusses the findings of our analysis, and Chapter 5 concludes by describing the theoretical and practical contributions of this work. This is followed by references and Appendices.

2 Theoretical context and hypothesis development

*“For a man to achieve all that is demanded of him
he must regard himself as greater than he is”*

Goethe

The purpose of this chapter is threefold: First, to propose a conceptual model to explain, predict, and test firm performance resulting from overconfidence expressed in strategic decisions. Second, to review the literature in accordance with this conceptual model to identify gaps and inconsistencies, and to address the proxy issue we find. The third purpose is to derive a set of hypotheses that are grounded in the conceptual model and serve to address some of the identified gaps and inconsistencies.

This chapter is in four distinct, yet complementary parts. In the first part we develop a conceptual model to link firm performance and overconfidence bias based on this argument: Managers have an imperative to deliver firm performance. They strive to do so by strategizing for competitive advantage. In strategizing they make strategic decisions. Cognitive biases distort their strategic decisions. We choose to examine overconfidence and we read that it is an umbrella term for three distinct biases, namely overestimation, overprecision, and overplacement. We note that overestimation is more likely than overplacement to be present in a challenging decision context. We also note that strategic decisions are typically the product of a group of managers, rather than an individual. As such, we construct our conceptual model to consider the impact of group-level overestimation bias and overprecision bias on the decision quality of strategic decisions. Since we do not find a generally accepted metric for decision quality, we investigate the impact of these biases on firm performance.

In the second part we review the literature and find many theoretical and empirical issues. A non-exhaustive summary of these issues follows. There is a lack of clarity and consistency in the definition of overconfidence bias, leading to an inconsistent application in empirical work, making it difficult to make comparable interpretations of the research. Most studies on the impact of overconfidence on firm performance focus on the overconfidence of the CEO, with few that focus on the overconfidence of the group making the strategic decision. This leads us to develop and justify group-level overconfidence proxies to be used in this study, which, because of its complexity, we do in the fourth part of this chapter. We find that researchers acknowledge a “bright-side” and a “dark-side” to overconfidence but are divided in their view on the overall effect. We find a gap in empirical studies on the impact of overprecision on firm performance and, relatedly, a gap in empirical studies on the combined impact of overestimation and overprecision on firm performance.

Then, in the third part we develop our hypotheses. Notwithstanding the issues noted above, we find six theoretical themes on the impact of overconfidence on firm performance. In hubris theory, overestimating managers overinvest and perhaps also underinvest, thus are not investing in the best interests of shareholders. In hyper core self-evaluation theory, a CEO’s overprecision leads to a greater number and scale of large-stakes initiatives and, ultimately, more extreme performance. In capital structures theory, managers who overestimate and/or are overprecise will adopt capital structures with more debt leverage. In underinvestment mitigation theory, overprecise and/or overestimating managers are more willing to undertake, and quicker to undertake, risky projects. In innovation and R&D propensity theory, overestimating managers innovate more, but it is unclear whether the ROI on those innovations is positive or negative. And, lastly, in motivation theory, managers who overestimate and/or are overprecise improve the success rate and value of their firm’s investments.

It is from these six theoretical themes, along with their associated empirical support, that we base our hypotheses. Our hypotheses relate to the impact of group-level overestimation and group-level overprecision on firm performance, considered independently and jointly.

2.1 Context setting

2.1.1 Landscape

The focus of this study are for-profit, public firms that operate in competitive markets.

Generalising from the observation of the high involuntary rate of turnover of S&P 500 firms, we observed that for-profit, public firms are challenged in sustaining their leadership positions and, in fact, are even challenged in remaining viable for extended periods of time (Reeves et al., 2016). A firm's inability to sustain their leadership position is an inability to sustain their competitive advantage. What does it take to sustain competitive advantage? It takes an ability to make the strategic decisions that result in the firm remaining relevant to customers, differentiated from competitors, and economically viable (Eisenhardt & Tabrizi, 1995; Jansen et al., 2006; Larrañeta et al., 2014; Nadkarni & Narayanan, 2007).

This phenomenon of an inability to sustain firm performance exists to this day and is predicted to continue and probably intensify in the decades ahead (Allen, 2017; Anthony et al., 2018; Minutemen, 2014; Reeves et al., 2016). Why are these firms not able to sustain the performance necessary to sustain their leadership positions?

In this section we explore the strategic context in which firms compete, the performance that they strive for, the strategies that they employ, the decision making that they employ to arrive at those strategies, and why things so often go wrong. From this we derive this study's conceptual model and research question. These layers of context setting are illustrated in Figure 3.

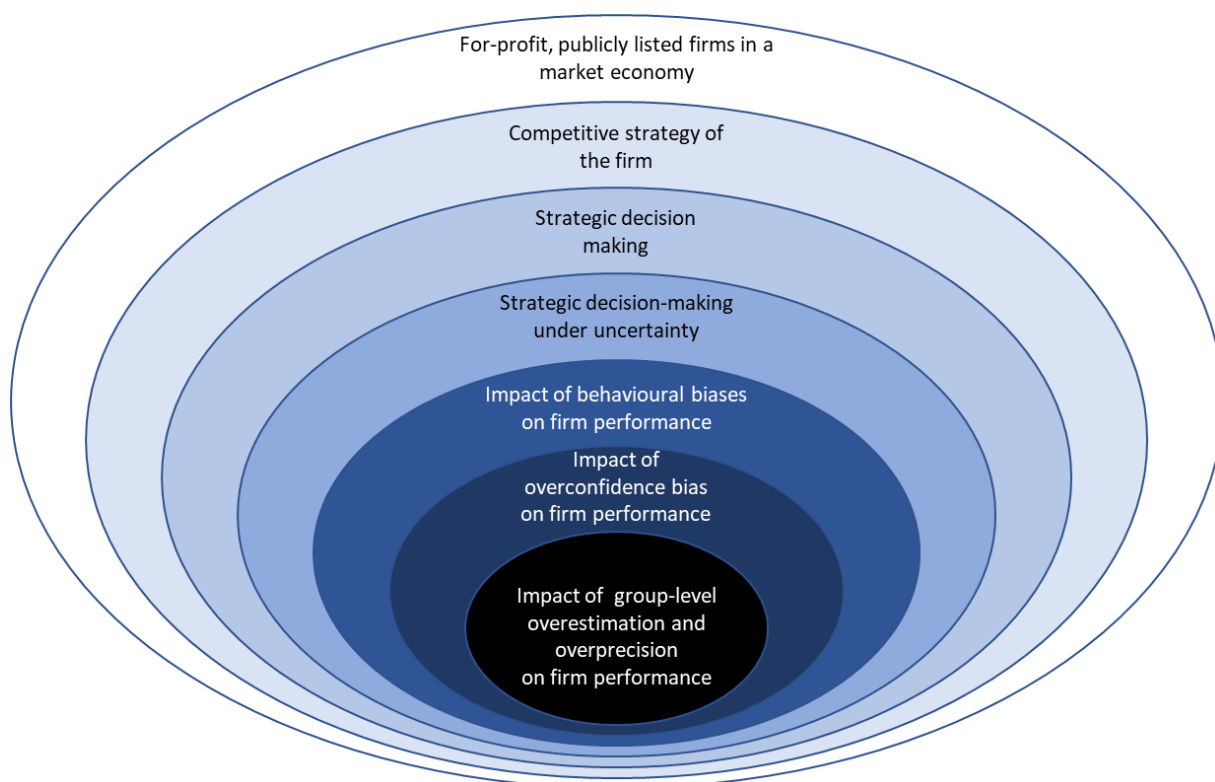


Figure 3: Context setting of research question.

2.1.1.1 Market economy

To understand why for-profit, public firms are not doing well at sustaining their performance, we considered the economic context in which these firms operate. In other words, we considered the market economy and its implications. The market economy is characterised by the private ownership

of capital assets, which are deployed with a profit motive in a competitive market (Jahan & Mahmud, 2015).

The implications of these characteristics of a market economy were sharply articulated by Milton Friedman in his seminal work "Capitalism and Freedom" (Friedman, 1962) and a subsequent article (Friedman, 1970). When a firm is the private property of its shareholders, those shareholders have the prerogative, within the bounds of the law, to "conduct the business in accordance with their desires" (Friedman, 1970, p. 173).

If the owners choose to hire professional management, then the owner's desires become the manager's objectives which "generally will be to make as much money as possible" (Friedman, 1970, p. 173). Friedman's shareholder theory has been challenged in many respects, such as the need to take a broader stakeholder view (Ferrero et al., 2014). Whether management have responsibilities to a broader group of stakeholders or not, the duty of management includes, at a minimum, delivering returns for shareholders.

Thus, managers make strategic decisions to direct their firm into the future with the aim of, amongst other things, delivering returns to shareholders. These decisions might include entering or exiting an industry, buying or selling a company, and so on. We considered the dynamics that managers face in their efforts to deliver shareholder returns.

2.1.1.2 Creative destruction

According to Joseph Schumpeter (1942), the market economy is by necessity dynamic and driven by innovation. Schumpeter recognises innovative entry by entrepreneurs as a disruptive force that sustains economic growth, even as it destroys the value of established companies. Schumpeter sees managers' actions in the pursuit of profit as the primary driver of capitalism: "the fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumers, goods, the new methods of production or transportation, the new markets, the new forms of industrial organization that capitalist enterprise creates" (1942, p. 82-83).

This pursuit of profit in a competitive context gives rise to "survival of the fittest" forces in a manner not dissimilar to Darwin's evolutionary theory. The impact of these forces Schumpeter calls "creative destruction" and he describes it as "a process of industrial mutation, that incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one" (1942, p. 83).

Do we see "creative destruction" in practice? It appears so. The replacement of more than one third of the members of the S&P 500 over the last decade seems to provide antecedent evidence in support of Schumpeter's claim. In fact, it is not just the S&P 500. Of the Fortune 500 firms in 1955, only 12% remained in 2016 (Perry, 2016) and after 30 years, only 19% of the FTSE 100 have consistently remained in the list (Clancy, 2014).

A firm's deletion from the S&P 500 index does not necessarily mean that it has failed, often the firm has simply been overtaken by more successful peers. In this case, the firm would have given up its relative share of value and this is consistent with Schumpeter's definition of creative destruction. Furthermore, if creative destruction is in play, then an early indication would be firms losing their relevance and being removed from major indices. When a dominant firm is overtaken or fails due to the introduction of a new technology this is considered to be "creative destruction in action" (Spencer & Kirchoff, 2006). In fact, Clayton Christensen refers to his theory of disruptive technology as a case study of creative destruction and argues that when technological progress intersects with customers' needs it "becomes disruptive and destructive to the leading firms in the industry that are based on the old technology" (Christensen, 2001). Christensen argues that "the ability to creatively destroy existing business models actually becomes the key to growth in the whole economy" (Christensen, 2001).

Despite the “perennial gale of creative destruction” some institutions have survived and thrived for very long periods. The history of the Catholic Church can be traced back 2,000 years (Stanford, 2011) and many universities are approaching 1,000 years old (Tucker, 2019). There are also more than a dozen companies that have been operating for more than 1,000 years (“List of oldest companies,” 2019). Even in the fast-changing world of information and communications technology (ICT), one finds companies that have celebrated their centenaries. This includes BT Group (BT), founded in 1846 as The Electric Telegraph Company, and IBM founded in 1911. BT and IBM have persisted while so many of their peers have gone bankrupt (remember Blockbuster, Compaq, NeXT, Palm?) by making strategic decisions that have favourably altered their trajectory. In fact, after more than six decades, 60 firms, including IBM, have retained their place in the Fortune 500 (Perry, 2017).

Across industries and geographies, we found that some firms survive and some of those thrive, while others do not. In all settings, from the Catholic Church to universities to ICT firms, institutions face change. While the transistor, the PC, the internet, and cloud computing might have been the downfall of IBM, somehow management evolved their business to continue to remain relevant and competitively advantaged. Thus, the demise of the incumbent is not inevitable. Even in times of disruptive technological change, some incumbents are capable of absorbing and integrating new technologies into their existing capabilities (Bergek, Berggren, Magnusson, & Hobday, 2013).

To conclude this section, we reiterate that there is evidence for creative destruction. However, the example of IBM’s reinvention through waves of fundamental technology change is testament to both the non-inevitability of value destruction and to the potential of the incumbent to innovate.

What determines whether an incumbent will sustain or improve its performance versus being absorbed, overtaken, or eliminated? Before answering that question, we need to be clear on what we mean by firm performance.

2.1.2 Firm performance

The owners of public firms either manage their firms themselves, e.g. Facebook, and/or employ professional managers to manage their firms. Owners might have altruistic or other interests beyond financial returns, but a minimum expectation that they place on the shoulders of managers is to deliver returns that exceed the owners’ cost of capital. Since ownership of public firms is generally spread amongst many entities, we will henceforth refer to shareholders rather than owners. And we will not differentiate between managers on whether they are founders, owners, or even on how much equity they hold.

Firm performance can be measured in multiple ways. Often managers will use income statement measures like operating profit or net profit. The issue with these income statement profit measures is that they do not take consideration of the investment required to deliver that profit. For example, if company A and company B both earned \$100 of profit in the same period, which would you prefer to invest in? It is obvious that this is a meaningless question without knowing what investment is required to deliver that \$100. The accounting response is to use a return-on-investment metric such as return on equity (ROE) or return on assets (ROA).

However, these metrics are problematic too. Both ROE and ROA use net income in their numerator and are thus susceptible to how expenses are classified. For example, an R&D²⁴ investment can be treated as an operating expense or a capital expense, with this classification affecting net income in a given period. ROE, defined as net income divided by the book value of equity, is also affected by its denominator in that it ignores the contribution of debt investors. Hence, a more heavily geared firm

24. R&D is the abbreviation for research and development.

will show a greater ROE. But a high gearing makes returns to shareholders less predictable and this raises the return expectations of the equity investor (Holland & Matthews, 2018). In fact, ROE is highly sensitive to a firm's debt-to-equity ratio. Consequently, firms cannot be compared in terms of their ROE performance unless they have identical risks and gearing, and if they trade in environments with similar inflation (Holland & Matthews, 2018).

ROA might be more robust than ROE because it removes the distorting effect of gearing. However, ROA measures the returns to equity investors relative to the investments made by both debt and equity investors (Holland & Matthews, 2018). This is problematic in that the numerator and denominator do not match as the returns to debt investors are not part of the metric. However, this can be adjusted for by including the interest paid to debt investors in the numerator. ROA is also problematic in that it treats operating liabilities, like vendors and employees, as debt investors. This necessitates a further adjustment. Accounts payable and non-interest bearing liabilities are thus typically removed to arrive at the invested capital (IC) of the firm (Holland & Matthews, 2018). Despite these issues with ROA, it is commonly used as a metric for the quality of earnings.

It is not just the denominator that needs attention, the numerator does too. Those accounting distortions that were mentioned earlier in this section are typically adjusted for by considering only the cash flow portion of income and subtracting taxes. This generates a numerator called net operating profit after taxes (NOPAT). The specifics of the adjustments to derive NOPAT and to derive IC are detailed in various textbooks, an example being McKinsey & Company's "Valuation: Measuring and managing the value of companies" (Koller, Goedhart, & Wessels, 2010). With NOPAT and IC defined, the measure ROIC, return on invested capital, can be generated. It is considered a superior metric to ROE and ROA for comparing the operating performance of firms (Holland & Matthews, 2018). We noted that Holland and Matthews go one step further in defining cash flow return on investment (CFROI), where they make further adjustments to ROIC to reverse inflationary and accounting distortions.

Would ROIC or CFROI provide an adequate measure of firm performance? Not quite. According to Damodaran (2013) there are four drivers of firm value: cashflow from existing assets, value added by growth assets, riskiness of cash flow from existing and growth assets, and the firm's timing to maturity. Rappaport (1986)'s seminal work²⁵ defines shareholder value added as NOPAT minus the capital charge, where the capital charge is calculated as the weighted average cost of capital (WACC) multiplied by invested capital. In a similar way, Koller et al. (2010) define economic profit as NOPAT²⁶ minus the capital charge.

In other words, the economic profit²⁷ or shareholder value added is the excess profit generated after meeting equity investor and debt investor expectations. At first glance it might seem that Rappaport (1986) and Koller et al. (2010) are not aligned to Damodaran (2013), but closer inspection reveals that they are. When we considered the time series of cash flows in the present and into the future, we saw that three of Damodaran (2013)'s four drivers describe the cash flow of the firm, with the fourth, riskiness of cash flow, being comparable to WACC. Similarly, ROIC or CFROI relate to the free cash flow generated by the firm or forecast to be generated. The free cash flow in the present is Damodaran (2013)'s first driver, while the future cash flows result from value added by incremental investments and the firm's timing to maturity. Damodaran (2013)'s last driver is relevant in the context of the sustainability of competitive advantage. Competitive advantage tends to erode over time either because competitors catch up or customer needs change or both. Robust modelling of future cash flows

25. Rappaport's book has been cited almost 2,000 times.

26. They use the term NOPLAT (not NOPAT), which is net operating profit less adjusted taxes, but with the same essential meaning.

27. Economic profit is also commonly called EVA, a registered trademark from Stern Stewart & Co.

requires recognition of the erosion of excess profits via ROIC or CFROI as competitive advantage fades. In fact, when Holland and Matthews (2018) model future cash flow, they define a term “fade” for just this purpose²⁸.

Another way of interpreting economic profit or shareholder value added is splitting the value of the firm into the value based on current performance and the value based on expected future performance. Both current and future performance need to be considered with respect to the firm’s cost of capital. The value created from the firm’s current performance is referred to as economic spread, which is defined as ROIC minus WACC. The value created from the firm’s future performance is growth. Damodaran (2013) does not demand how that value add from growth assets arises. For example, it could be from improved operating margin on the same size business, from the same operating margin on a larger business, or some combination of both.

This concept of value being created by economic spread²⁹ and growth was used by Varaiya, Kerin, and Weeks (1987). Varaiya et al. (1987) measured firm value using the market-to-book ratio. The market-to-book ratio³⁰ measures the ratio of the market value of the firm to the book value of the firm’s assets. The market value of the firm is a result of the capital market’s assessment of how effectively the firm is utilising its capital. If the market-to-book ratio exceeds one, then value is being created. If it is less than one then value is being destroyed. Varaiya et al. (1987) found that both economic spread³¹ and growth had a positive, predictive relationship to firm value. Notably, they found that spread was relatively more important in driving firm value than earnings growth³². Despite their use of ROE, their finding that spread and growth are drivers of firm value, and that spread is a stronger driver of value is consistent with the analysis of Koller et al. (2010) who use ROIC.

Koller et al. (2010) also define spread (based on ROIC and WACC) and growth as the drivers of shareholder value, but Koller et al. (2010) differ from Varaiya et al. (1987) not only in their definition of spread (ROIC versus ROE), but also in their definition of growth. Koller et al. (2010) refer to revenue growth (versus earnings growth). Holland and Matthews (2018) also see spread and growth as the drivers of shareholder value, but their growth is defined as growth in invested capital.

Why bother with all this alphabet soup of ROE, ROA, ROIC, CFROI, WACC, etc. when firm value can be measured using market-to-book ratio, market value added, total shareholder returns, or a similar metric? Ultimately, shareholders care about a return on their investment and this is measured in the value that the market attributes to the firm’s assets relative to the cost of those assets. However, this market value is not directly controllable by the firm’s management. What is controllable by the firm’s management are levers such as capital structures, corporate structures, legal entity domiciles, and, most importantly, the operating performance of the firm. In other words, Damodaran (2013)’s four drivers are within the control of management. As such, both the fundamental metrics and the market-based metrics have their place when assessing firm performance.

As mentioned previously, excess returns tend to fade unless a firm can reinvigorate its competitive advantage. Most firms seem unable to sustain their performance (section 2.1.1.2), yet investors desire firms that deliver returns in excess of their cost of capital on a sustained basis. Thus, in order to

28. An alternative, yet opposite, description of this effect is persistence. We might consider how persistent those excess profits are.

29. They defined spread as ROE minus cost of equity. The concept of spread is routinely used today to refer to ROIC minus WACC.

30. There are many definitions of market-to-book and similar ratios. The metrics differ in terms of their denominator. Market-to-book uses the book value of the firm’s assets, while Tobin’s Q, a commonly used metric, uses replacement value of the firm’s assets.

31. From here on we use the term “economic spread” and “spread” interchangeably.

32. They used growth in earnings per share.

recognise the firms that are sustaining their competitive advantage, we need to go beyond measuring firm performance at a point in time, we need to measure sustained firm performance. Such metrics have been devised, with eCAP³³ from Holland and Matthews (2018) being an example. A summary of the measures discussed in this section, with their pros and cons, are listed in Table 1 below.

Firm performance measures	Pros	Cons
Operating profit Net profit		No consideration of the investment required to deliver that profit
Return on equity (ROE)		Susceptible to how expenses are classified Ignores the contribution of debt investors and is highly sensitive to the debt-to-equity ratio
Return on assets (ROA)	Removes the distorting effect of gearing Commonly used in top-tier journals	Susceptible to how expenses are classified Requires some adjustments
Return on invested capital (ROIC)	Improves on ROA and ROE	Suffers some inflationary and accounting distortions
Cash flow return on investment (CFROI)	Improves on ROIC by reversing inflationary and accounting distortions	Proprietary in its implementation
Economic profit	Takes account of returns to debt and equity investors in excess of their cost of capital	Dependent on an accurate measure of WACC, which is not easily available
Sustainable economic profit (eCAP)	Measures returns in excess of cost of capital on a sustained basis	Proprietary in its implementation Dependent on an accurate measure of WACC, which is not easily available
Market-based measures	Measures the shareholder's actual return on their investment	Influenced by many factors beyond the manager's control

Table 1: Measures of firm performance.

In summary, firm performance from a shareholder perspective requires delivering returns in excess of the cost of capital and, ideally, sustaining those excess returns. One might consider metrics for measuring firm performance in fundamental terms, where management has direct control, and in market terms, because ultimately that is how shareholders earn their returns. Moreover, one might consider a metric for sustained firm performance.

We chose a fundamental metric because this is within the manager's control and, in keeping with the vast management strategy literature on firm performance, we selected industry-adjusted ROA. This is discussed further in section 3.3.

33. Empirical Competitive Advantage Period.

The challenge that managers face is that the markets in which they operate are dynamic, with customer expectations changing, competitors and their offerings changing, legislation changing, technologies emerging, and much more. Not only is their context changing, but often it is changing quickly and in complex and unpredictable ways. To deliver returns to their shareholders (and debt investors), managers must therefore anticipate and adapt to an unknown future in a way that creates or retains competitive advantage. This imperative of remaining relevant in a changing context is a key driver of a firm's competitive strategy. Whether explicitly defined or not, the firm's managers develop and execute a strategy in their pursuit of value creation for shareholders. It is in the development of strategy, and within that the making of strategic decisions, that cognitive biases like the overconfidence biases might their impact. We now explore what is strategy, what is strategic decision making, what is decision quality, and how might biases intrude on these concepts.

2.1.3 Strategy

What do we mean by strategy? There are multiple definitions of strategy from prominent researchers.

- "Strategy is the determination of the long-term goals and objectives of an enterprise, and the adoption of courses of action and the allocation of resources necessary for carrying out these goals." (Chandler, 1990)
- "Strategy is the way in which a corporation endeavours to differentiate itself positively from its competitors, using its relative strengths to better satisfy customer needs." (Ohmae, 1983)
- "Thinking strategically starts with reflection on the deepest nature of an undertaking and on the central challenges that it poses" (Senge, 1990)
- "Strategic management is a comprehensive procedure which starts with a strategic diagnosis and guides a firm through a series of additional steps which culminates in new products, markets and technologies, as well as new capabilities." (Ansoff, 1965)
- "Competitive strategy is concerned with the firm's position relative to its competitors in the markets which it has chosen." (Kay, 1995)
- "Developing a competitive strategy is developing a broad formula for how a business is going to compete, what its goals should be, and what policies will be needed to carry out those goals." (Porter, 2008)

From these definitions we inferred that, by some means³⁴, managers conduct five key activities in arriving at their competitive strategy: performing a diagnosis, setting a goal, determining their competitive positioning, choosing a course of action, and allocating resources for execution. They do this in the pursuit of competitive advantage for their firm.

Eisenhardt advises managers that competitive advantage is fleeting and that they should "focus on continually generating new sources of advantage" (Brown & Eisenhardt, 1998, p. 243). This message was endorsed more recently by Rita McGrath (2013) in her book "The End of Competitive Advantage". Failure to do so will lead to erosion of shareholder value and possibly the demise of the firm.

Thus, the fleeting nature of competitive advantage coupled with the unyielding pursuit of shareholder returns gives rise to a relentless pursuit of competitive advantage. The resource-based view (RBV) of

34. Not all strategies are deliberately formulated. In fact, Mintzberg (1977), delineates three ways that strategies arise: intended strategies that are executed, which he calls "deliberate" strategies; intended strategies that do not get executed, or "unrealized" strategies; and executed strategies that were never intended, or "retroactive" strategies. And often in practice, it is not just one of these, but some combination that plays out.

the firm (Barney, 1991) theorises how managers assemble resources to achieve competitive advantage, ideally sustainable competitive advantage.

According to RBV, sustainable competitive advantage depends on resource heterogeneity and immobility. For resources to be heterogenous and immobile they must be valuable, rare, imperfectly imitable, and non-substitutable. Because firms differ in their expertise and resources, they pursue innovation differently (Klepper, 1996) and hence have differing success. The more successful innovations will amount to competitive advantage, possibly even sustainable competitive advantage.

Competitive advantage is considered sustainable if it will not be competed away by the duplication efforts of other firms. The pursuit of competitive advantage is relentless because changes in the economic structure of the industry may mean that those resources that were valuable for competitive advantage are no longer valuable and might even become a weakness (Barney, 1991). At these times of structural change and in anticipation of such change³⁵, managers need to reconstitute their resources for competitive advantage.

Given the dynamic nature of markets, the resource-based view has been extended to include dynamic capabilities, which are existing internal or external firm-specific competences and resources that can be developed, deployed, and protected to address changing environments (Teece, Pisano, & Shuen, 1997). It should be noted that *“competitive advantage lies in the resource configurations that managers build using dynamic capabilities, not in the capabilities themselves”* (Eisenhardt & Martin, 2000).

More recent work by Rumult (2011) draws a sharp distinction between good and bad strategy, including as it pertains to competitive advantage. Unsurprisingly, Rumult identifies competitive advantage as one of the qualities of a good strategy³⁶. With respect to competitive advantage, Rumult advocates managers to focus their resources where they know they have the upper hand and avoid situations where they do not. He discusses how to strengthen competitive advantage, such as increasing demand for advantaged products and services, as well as how to prevent its erosion, such as blocking competitors' replication attempts.

Ultimately the competitive advantage that managers achieve is a result of the resource selection, development, deployment, and protection choices that they make. In other words, a firm's current performance and performance prospects are a consequence of the strategic decisions made by its management.

2.1.4 Strategic decision making

What are “strategic decisions”? We followed Mintzberg, Raisinghani, and Theoret's (1976) definition of “strategic” and Howard and Abbas's (2016) definition of a “decision” to define a strategic decision as: **“an important choice, in terms of the actions taken, the resources committed, or the precedents set, between two or more alternatives that involves an irrevocable allocation of resources”**.

Howard and Abbas (2016) state that the decision is the only means available to managers to change the performance of their firm. This claim might at first seem exaggerated, but on closer inspection it is irrefutable. However, just because the decision is all that is available to the manager, this does not mean that it is the only thing that determines the firm's performance. Factors beyond the manager's control or even beyond the manager's understanding might influence the firm's performance.

35. Intel Corporation, despite being a leader in their industry, famously coined the slogan “only the paranoid survive”, which nicely conveys the point that astute management are, or need to be, relentlessly on the lookout for industry changes and their next source of competitive advantage.

36. The other qualities are an understanding of competitors and what they might do, knowledge of industry dynamics and its implications for the company, and a recognition that every strategy is an hypothesis and is likely to need adjusting based on what is learned.

For example, if a manager chooses to setup the proverbial lemonade-stand on a day when it also happens to rain leading to no customer visits, the lemonade stand business will have performed poorly. The weather was beyond the manager's control. Perhaps the manager had not even considered that the weather might be a factor. The more capable manager might have considered the weather as a factor and might have assumed all would be good. The even more capable manager, rather than assuming all would be good, might have assessed the probability of rain, analysed customer behaviour under different weather conditions, determined break-even business volumes, and determined, with some confidence interval, the prospects of the lemonade business on that day. It might be that for the most competent manager, her analysis of her business' prospects revealed healthy profits in 90% of the cases, and losses in 10% of the cases. Further, she determined that the losses that she would incur 10% of the time, were losses that she could afford to bear, and the 90% chance of profits made this a deal worth making³⁷. In this case, the competent manager made the strategic decision to setup the lemonade-stand, yet that 1 in 10 event played out. Did the competent manager make a bad strategic decision?

Let us also consider an opposing scenario where a manager is faced with a 10% chance of profits, a 90% chance of a loss, and the loss would be problematic for the business. In this case, let us assume that an incompetent manager chooses to go ahead, and the 1 in 10 event plays out, this time in her favour and hence she delivered profits for the business. Did she make a good decision?

The purpose of the above story is to illustrate three important points. Firstly, when managers make strategic decisions, they are decisions about the future and the future is inherently uncertain. Consequently, strategic decision-making is decision making under uncertainty.

Secondly, managers can choose how thorough they wish to be when making a strategic decision. But, for strategic decisions, even the most thorough process and analysis will never produce certainty, due to the future's inherent uncertainties.

Thirdly, Howard and Abbas (2016) would argue that the competent manager did not make a bad decision and, similarly, that the incompetent manager did not make a good decision. In fact, they say that a good decision cannot go bad, nor can a bad decision become good. In other words, they draw a clear distinction between the decision and the outcome. The decision is the only thing that the manager has control over, they cannot control uncertainties like the weather. However, a manager can make a good decision by considering what the weather (and customers, etc.) might do, contrasting that to their goals, and choosing their course of action. Consequently, they define decision quality based on the process that was followed to the make the decision (Howard & Abbas, 2016, p. 18). Ron Howard summed it up when he said: *"you can't tell by the outcome whether you made a good decision"* (Fox, 2014).

The rationale for judging decision quality on process not on outcome is illustrated by Table 2 below (Russo & Schoemaker, 2002).

37. When the manager makes those assessments of the likelihood of profits versus losses, they can be distorted by biases. If she assumes her profits to be \$1m when an "objective" analysis would suggest \$0.5m, then she is overestimating her prospects. If asked to give a range where she is 80% confident that the profits will be in that range and she returns \$0.9m to \$1.1m, when in fact the levels of uncertainty would suggest a range of \$0.1m to \$3m, then she is being overprecise. Either or both overestimation and overprecision could undermine the quality of her decision making.

		Outcome	
		Good	Bad
Process used to make the decision	Good	Deserved success	Bad break
	Bad	Dumb luck	Poetic justice

Table 2: Decision process and outcome matrix.

With reference to the lemonade stand example above, the competent manager who suffered no sales due to the rain, which was an unlikely event, suffered a “bad break”³⁸. Considering the large, public firms that are the subject of this study, if the firm’s management do not appreciate this principle, they might punish good decision-making when it delivers a bad break, thus discouraging good behaviour. Equally, they might reward bad decision-making when it delivers dumb luck, thus encouraging bad behaviour. Furthermore, firms that do not appreciate this principle are more likely to underinvest in good strategic decision-making processes.

The lemonade stand example was a trivial case, but it lays the foundation for understanding decision-making under uncertainty. This matters because firms operate in a dynamic context that includes emerging technologies, a changing competitor landscape, a changing regulatory environment, changing customer needs, and more. This environmental dynamism means that firms face uncertainties when making strategic decisions. These uncertainties range from risk, or known chance, to Knightian uncertainty, where we cannot know all the information that we need to set accurate odds. The weather forecast described above is an example of Knightian uncertainty³⁹ (Knight, 1921). In practice, most uncertainties are Knightian in that their odds cannot be precisely known⁴⁰. When the odds of an uncertainty are not precisely known, then the concept of ambiguity (Ellsberg, 1961) is added to one’s assessment of that uncertainty. In other words, most uncertainties in business are defined by a set of three variables: the impact, the likelihood, and the ambiguity, where the ambiguity measures one’s degree of ‘confidence’ in the likelihood estimate.

Sometimes these uncertainties are “business-as-usual” in a world of creative destruction. But, sometimes, the uncertainties strike at firms from beyond the competitive landscape. We offer two examples of the impact of uncertainties, one from within and one from beyond the competitive arena.

An example within the competitive landscape is when the mobile phone sector’s leading firms Nokia, Ericsson, and RIM⁴¹ were replaced by Apple, Samsung and Huawei. In this case the uncertainties or the unpredictable events were classical forces of creative destruction like competitor action (Apple’s launch of the iPhone) and changing customer needs (desire for a touchscreen). We can infer that Nokia, Ericsson and RIM did not make the strategic decisions that allowed them to retain competitive advantage. In other words, being caught off guard by uncertainties or unpredictable events implies a shortcoming in the firm’s strategic decision making. Would a good strategic planning process⁴² have saved Nokia, Ericsson, and RIM? We can never know for sure, but there are examples where strategic

38. Often referred to as “shit happens”

39. We referred to the chance of rain as 10%, but in reality that 10% is an estimate emerging from an imperfect model. This differs from the role of a fair die, where the probability is precisely one sixth. The role of the die is a risk with known odds, whereas the weather forecast can never be precisely known.

40. An extreme case of Knightian uncertainty are “black swan” events. These are events that comes as a surprise, have a major effect, and are often inappropriately rationalised after the fact with the benefit of hindsight (Taleb, 2007).

41. RIM were the manufacturers of BlackBerry devices and have since been renamed to BlackBerry Ltd.

42. Strategic planning is used in this context to refer to the process followed to make a set of strategic decisions and ultimately arrive at a strategic plan that directs the firm’s investments.

planning has enabled firms to not only survive, but thrive, and to have done so when facing considerable uncertainty.

An example from beyond the competitive arena is when Royal Dutch Shell famously used scenario planning as part of their strategic planning. Scenario planning enabled Shell to navigate profound uncertainties and unpredictable events in their industry, namely the 1973 energy crisis, the more severe price shock of 1979, and the collapse of the oil market in 1986 (Kleiner, 2003). From the early 1970s to the late 1980s Shell's foresight gained through scenario planning helped propel them from worst position (7th) in their peer set to 1st (Stanford Strategic Decision and Risk Management, 2016) in terms of firm performance.

In summary, firms that employ good strategic planning processes have the possibility to navigate unpredictability and even gain competitive advantage in times of uncertainty and disruption, in other words to achieve their "deserved success". As per Table 2, a good process does not guarantee success, in some cases there will be a "bad break". But, without good process, "poetic justice" is more likely than "dumb luck". However, most managers don't follow this principle of judging decision quality by the process followed (Fox, 2014; Borchardt & Haas, 2016).

With consideration to Table 2, we can say that those 60 firms that have remained on the Fortune 500 list for more than six decades (Perry, 2017) have benefited from good outcomes and therefore have had "deserved success" or "dumb luck", or both. Since these firms would each have made multiple strategic decisions over the period of six decades, it is highly unlikely that any of the 60 have retained their position by repeated "dumb luck" alone. Hence a good decision-making process is a necessary ingredient for sustained leadership. Although a good decision-making process is necessary, it is not sufficient. Of the hundreds of S&P 500 members over the last six decades it is probable that some firms, despite having followed a good process, are no longer in the S&P 500 due to one or more "bad breaks". It is also likely that many firms are not still around due to making decisions poorly and hence suffering "poetic justice".

To understand whether a good decision-making process is being followed, or not, we considered how firms are performing where the unit of analysis is the decision itself. As mentioned in the introduction, strategic decisions have a poor track record with an estimated failure rate of above 40% (Cândido & Santos, 2015). These studies refer to failed decisions, but a firm does not need to fail in their strategic decisions to lose their leadership position, they simply need to perform less well than their competitors. And no doubt that failed decisions too are a contributing factor to being outperformed by competitors.

In today's world and looking to the future, top management will be compelled to make strategic decisions more quickly and more often and to do so in an increasingly dynamic, complex, and uncertain business environment. If they continue to make strategic decisions as they have, those predictions of an increasing rate of turnover on the S&P 500 (section 2.1.1.2) seem plausible. Yet, it does not need to be that way. If management follow a good strategic decision-making process, there will still be some "bad breaks", but "deserved success" is the more likely outcome and hence they can avoid value destruction and instead unlock value for their shareholders.

The implications of these strategic decisions are significant. Good decisions offer the prospects of substantial value creation for shareholders, while bad decisions can destroy shareholder value and sometimes even trigger the demise of the firm. This presents a paradox. When the stakes are so high and the management teams of these leading organisations can muster the resources, like talent, data, algorithms, and computing power in the service of their vision and strategy, why do strategic decisions fail so often?

We know that the outcome of a strategic decision is a product of that which is controllable and that which is not controllable (Table 2). The process that management follow to make the decision is controllable. This includes the information they choose to collect and analyse, their management of

key stakeholders, the insight and creativity they apply in developing strategic alternatives, their judgment of the executability of their alternatives, the logic that they apply to reach their decision, and everything else that is done that leads to their decision. The uncontrollable part is the uncertainty that they face. As mentioned before, a bet that is 90% certain, delivers an unfavourable outcome 1 out of 10 times. Since decisions are going badly⁴³ wrong at least 40% of the time and management would not make choices whose prospects were value destructive at that frequency, we infer that management are doing a poor job of the strategic decision-making process. The consequence of this poor process is an unnecessary susceptibility to the gale of creative destruction. How does the process of strategic decision-making go wrong?

To summarise to this point. We are considering top management teams of for-profit, public firms who pursue shareholder returns. This necessitates a fresh strategy that delivers competitive advantage. Formulating a competitive strategy requires making strategic decisions about the future. Since the future is inherently uncertain, these decisions are made in a context of uncertainty. The determinant of decision quality is the process followed to make the decision, not the outcome achieved, since the process is all that can be controlled by the manager. We now consider how managers are making strategic decisions and which approaches enhance or erode decision quality.

2.1.5 Decision quality

When seeking to improve the quality of strategic decision making, three options can be considered: (a) do the right stuff, (b) don't do the wrong stuff, and (c) do both (a) and (b). Stating this more formally, managers would deviate from decision quality if they did the wrong stuff, and this deviation would be a type I error. Similarly, if they did not do the right stuff, they would have committed a type II error. Due to the uncertain context in which strategic decisions are made, managers are susceptible to both type I errors (also called errors of commission) and type II errors (errors of omission). Either type can be devastating for a firm, for example an error of commission like the WHL acquisition mentioned earlier could destroy substantial shareholder value. Errors of omission are more difficult to identify, because, by definition, they did not happen, but Kodak, Blackberry, Blockbuster are all examples of firms that were industry leaders that were effectively destroyed by virtue of omitting to evolve their business models.

Investigating (a), which depended on the existence of generally accepted best practice for strategic decision making, has led to an inconclusive place in that it appears that there are no generally accepted best practices, in fact there are competing views in the literature in terms of the relative merits of the broad approaches that managers follow. These broad approaches are political, rational, intuitive, and heuristic, and combinations of these.

With respect to these different approaches, we inferred that there is no single correct solution as different approaches have their strengths and weaknesses in different contexts. Furthermore, researchers are divided in their views of the suitability of these different approaches as will be revealed in the following sections. A challenge in making an objective assessment of these different approaches is that "decision quality" is not a universally defined and accepted concept. In other words, researchers are measuring the decision-making approaches against different success criteria.

Despite the lack of a consistent measurement framework, our review of the literature yielded some summary perspectives on the different approaches to decision making in organizations. Political behaviour in strategic decision making was generally found to undermine decision quality. An analytical or rational approach was found to be well suited to big decisions with long investment horizons and

43. The use of "badly" is to emphasise that these 40% of decisions are those that "fail". The other 60% are not necessarily going "well" just because they did not fail. In many cases the non-failed decisions would still have "left money on the table".

reliable data. Its strengths are that it is consistent, logical, and teachable. Its weaknesses are that it does not always account for the limits of available time and data. In most studies the rational approach was found to deliver decision quality. Heuristics are rules of thumb that can be quickly applied, sometimes yielding good results, but sometimes causing errors. Intuition is often called “gut feel”. Like heuristics it can be very fast, can yield good results, but can cause errors. Heuristics differs from intuition in that the rule can be specified, whereas intuition remains a feeling. In most studies the intuitive approach does not deliver decision quality. Generally, the heuristic approach was found to be favourable when appropriate heuristics can be identified and applied. A more detailed account follows below and in [Table 25](#) and [Table 26](#) of the Appendix.

2.1.5.1 Political

Political behaviour was generally found to undermine decision quality. Specifically, it was found to be negatively related to decision effectiveness and organizational outcomes ([Dean & Sharfman, 1996](#); [Elbanna & Child, 2007](#)). A harsher assessment of a political approach was stated by Mueller, Mone, and Barker: “*Politicking slows down the decision process, distorts the information base, and wastes managerial effort*” ([2007](#)). However, in one study ([Nutt, 1998a](#)), it was found to be rarely used, but effective when used.

2.1.5.2 Rational

Findings regarding the relationship of a rational process on decision quality are discussed in three categories. Firstly, in a context of high environmental dynamism, secondly, in a context of low environmental dynamism, and lastly in a general context.

When the environment is highly dynamic, we noted one study ([Hough & White, 2003](#)) that found that the rational process provided little assistance to decision-makers and might actually slow the decision-making process and negatively impact performance. However, the other studies that we reviewed found a favourable relationship between a rational process and decision quality. Specifically, Walters and Bhuian ([2004](#)) found that analytical comprehensiveness was a favourable response to increased dynamism; Mueller et al. ([2007](#)) found that in dynamic environments, decision makers should use formal analysis for informational purposes; and, Miller ([2008](#)) found that procedural rationality is positive for performance under conditions of unpredictable change.

In a context of low environmental dynamism, we again found mixed results. In this setting Hough and White ([2003](#)) and Fox ([2015](#)) found in favour of the rational process. But, Miller ([2008](#)) found that procedural rationality was only favourable when at least a moderate extent of analysis was applied and too much analysis would erode performance.

When looking more generally at rational decision making, all the studies that we reviewed showed a favourable effect. A few examples follow. Paul Nutt, one of the most prolific researchers in this field, found that a rational, goal-directed, search approach and an analytic assessment of alternatives are more likely to produce good outcomes that increase the prospect of adoption and insure that good decision value and efficiency are realized ([Nutt, 1998b, 2005, 2008](#)). Other researchers also found that the rational decision process is positively related to decision effectiveness or firm performance ([Dean & Sharfman, 1996](#); [Elbanna & Child, 2007](#); [Goll & Rasheed, 2005](#); [Nooraie, 2008](#)). In addition, the practitioners argue that good analytical tools exist for a rational decision-making process ([Courtney, Lovallo, & Clarke, 2013](#); [Spetzler, Winter, & Meyer, 2016](#)).

2.1.5.3 Intuition

As with the rational approach, the intuitive approach is discussed in the three categories of high environmental dynamism, low environmental dynamism, and lastly in a general context.

With respect to environmental dynamism, Khatri and Ng ([2000](#)) find a positive relationship exists between intuition and firm performance in an unstable context, but find the relationship to be negative

in a stable context. Others suggest that in a volatile context managers build a collective intuition about strategic matters, which allows them to make strategic choices that are fast and of high quality (Mueller et al., 2007).

In the general context, we found conflicting views. On the positive side, we have Sadler-Smith (2004) reporting a positive finding in an early paper, but then later, with a co-author, finding that there is no relation between intuition and firm performance found (Sadler-Smith & Burke-Smalley, 2015). Elbanna and Child (2007) were also not able to confirm a negative relationship. Woiceshyn (2009) sees some value in intuition and hence proposes a model that integrates intuition and rational analysis. Multiple other researchers find a negative relationship between intuition and decision quality. For instance, Paul Nutt finds intuition to have a negative effect at many of the stages in the decision-making process (Nutt, 1998a, 2002, 2008) and Miller and Ireland (2005) find that intuition is capable of providing benefits, but only when firms are emphasizing exploration, yet even then there are many pitfalls. Kahneman and Klein (2009)'s landmark paper⁴⁴ attempts to clarify when intuition is or is not reliable in decision making. They find that for intuition to be reliable, there are two necessary conditions: a high validity⁴⁵ environment and adequate opportunities for learning in that environment, which amounts to prolonged practice and rapid and unequivocal feedback.

2.1.5.4 Heuristics

Heuristics received substantial attention in the academy following Tversky and Kahneman's paper (Tversky & Kahneman, 1974) which, at the time of this writing, has been cited almost 40,000 times. Tversky and Kahneman revealed how our judgments and decisions under uncertainty are predictably distorted by biases and heuristics.

Tversky and Kahneman's views have been robustly challenged, perhaps most vociferously by Gerd Gigerenzer. A landmark⁴⁶ work that champions the use of heuristics for decision making is Gigerenzer and Todd's book "Simple heuristics that make us smart" (1999) and it has been followed by numerous related papers. Gigerenzer and Todd argue that fast and frugal heuristics, simple rules of thumb for decision-making, are realistic, given our cognitive limitations, and enable smart choices that perform comparably to more complex algorithms. Gigerenzer and Todd are not alone. Bingham and Eisenhardt argue that heuristics are "rational" and are central to strategy, especially in unpredictable markets (Bingham & Eisenhardt, 2011). And, other researchers have also found heuristics that can be successfully applied (Nutt, 1998b; Woiceshyn, 2009).

While heuristics were found to be favourable for decision quality in the studies we reviewed, it suffers two notable drawbacks. Firstly, heuristics are susceptible to cognitive biases (Tversky & Kahneman, 1974), and secondly, it is not always clear which heuristic to use in a particular setting or even if an appropriate heuristic exists (Fox, 2015).

2.1.5.5 Conclusion

In conclusion, the four approaches (political, rational, intuition, heuristics) to strategic decision making appear to have strengths and weaknesses depending on the context, although in many cases researchers' views are still contested and hence there appears to be no generally accepted set of best practices for strategic decision making.

Since it cannot be expected that managers should follow best practices if best practices have not been defined, perhaps one can aim to avoid practices that undermine decision quality, namely option (b)

44. At the time of this writing, this paper was cited more than 1,900 times.

45. A high validity environment is one that is stable and linear.

46. At the time of this writing, this book was cited more than 6,500 times.

“don’t do the wrong stuff”. What might managers be doing wrong? To answer this question, we return to the topic of decision making under uncertainty, which was introduced in section 2.1.4.

2.1.6 Biases

When considering decision making under uncertainty, we established that the quality of a firm’s strategic decisions is all that management can control (section 2.1.4) and this directly relates to their firm’s performance. In this section, we explore the concept of cognitive biases as these are known to affect decision quality (Tversky & Kahneman, 1974).

Core to neo-classical economics is the concept of rational choice theory. In rational choice theory people are assumed to behave as rational agents. The rational agent is assumed to take account of all available information, probabilities of events, and potential costs and benefits in determining preferences, and to act consistently in choosing the self-determined best choice of action (Blume & Easley, 2008). However, this theory has been criticised as not being a realistic description of what people do in the real world. This criticism was initiated by Herbert Simon.

In 1955 Simon introduced the concept of “bounded rationality” where he showed that real people do not have the cognitive capabilities to live up to the requirements of rational choice expected by neo-classical economic theory (H. A. Simon, 1955). The concept of “boundedness” has been expanded to include bounded will-power and bounded self-interest (Mullainathan & Thaler, 2000). And it has been expanded further to include bounded reliability (Verbeke & Greidanus, 2009), bounded awareness and ethicality (Moore & Bazerman, 2012a).

Because of these bounded issues, people are not able to optimise and instead “satisfice” and do so by applying heuristics or intuition. This in turn, makes us vulnerable to cognitive biases that distort decision making (Tversky & Kahneman, 1974). Tversky and Kahneman’s work gave rise to the field of behavioural economics, for which Daniel Kahneman⁴⁷ won the Nobel Memorial Prize in Economic Sciences in 2002. Following Kahneman’s award, other researchers in behavioural economics, or its subfield behavioural finance, have also been awarded this prize. These include Robert Shiller (2013) and Richard Thaler (2017).

Numerous cognitive biases have been identified, many have been explored in various settings, and some have been shown to reliably demonstrate clear effects. For example, Richard Thaler said that overconfidence bias is “*the most robust finding in the psychology of judgment*” (De Bondt & Thaler, 1995). Lovallo and Sibony (2010) structured a typology of the biases that they consider to occur most frequently and have the largest impact on business decisions. Their typology included action-oriented biases, like competitor neglect, that drive us to take action less thoughtfully than we should; interest biases, such as inappropriate attachments, that arise in the presence of conflicting incentives; pattern recognition biases, like confirmation bias, that lead us to recognise patterns even when there are none; stability biases, for example loss aversion, which create a tendency towards inertia in the presence of uncertainty; and social biases, such as groupthink, that arise from the preference for harmony over conflict.

Might management teams’ vulnerability to cognitive biases help explain the inability of firms to sustain their performance? More specifically, might cognitive biases be undermining the quality of management teams’ strategic decisions thereby impacting the performance of their firms to the extent that those firms fail, are acquired, or are outcompeted by rivals?

47. Daniel Kahneman’s long-time collaborator Amos Tversky died before this award. It is generally believed that he would have shared the prize had he still been alive.

While numerous cognitive biases have been identified, for reasons that we explain below, we chose to specifically examine the impact of overconfidence bias on firm performance.

2.1.7 Overconfidence

Overconfidence bias is defined differently by different researchers, e.g. *“believing you are better than you are in reality”* (Johnson & Fowler, 2011) and *“the tendency to think that one knows more than one does”* (Tetlock, 1998). The reason for these differences will be explained later in this document. For now, an overarching definition of overconfidence that encompasses these differences is used:

“Overconfidence is a belief about oneself or one’s knowledge that is too extreme or too precise given a comparable, objective benchmark of reality” (Meikle et al., 2016)

There are several reasons to specifically investigate overconfidence bias as potentially being complicit in poor strategic decision making and the resulting impairment of firm performance.

- **The mother of all biases.** Overconfidence is believed to have deep evolutionary roots (Johnson & Fowler, 2011) and is driven by cognitive, physiological, and motivational causes (Russo & Schoemaker, 1992). Besides for De Bondt and Thaler (1995) calling overconfidence *“the most robust finding ...”*, other leading researchers have referred to overconfidence bias in these ways: *“the most significant of the cognitive biases”* (Kahneman, 2011, p. 255), *“no problem in judgment and decision making is more prevalent and more potentially catastrophic than overconfidence”* (Plous, 1993, p. 217), and *“the mother of all biases”* (Moore & Bazerman, 2012a, p. 14). Moore and Bazerman say this for two reasons: *“overconfidence effects are some of the most potent, pervasive, and pernicious of any of the biases”*, and *“overconfidence facilitates many of the other biases”*.
- **Effects that are theoretically consistent with shareholder value destruction.** The literature shows that CEO overconfidence has numerous effects on firm performance. From these effects, which are discussed in more detail later, it can be theorised that overconfidence bias could be a causal driver of decreased firm performance and, consequently, shareholder value destruction. This is because overconfidence could give rise to errors of commission (e.g. if we make that acquisition, it will deliver huge synergies for us) and it could give rise to errors of omission (e.g. we don’t need to be concerned about that technology, that competitor, etc.). Those errors of commission and errors of omission could result in poorer operational performance and/or could undermine investor sentiment. This would lead to investors bidding down the value of the firm.
- **Empirically demonstrated impairment of firm performance in certain cases.** While many of the papers reviewed show discrete effects on firm performance, a few papers show an overall effect on firm performance. For example, CEO overconfidence has been associated with greater drops in stock return performance and greater increases in expected default probability (P.-H. Ho et al., 2016), underperformance of Korean firms (Park et al., 2018), and an increased probability of bankruptcy (Leng et al., 2018). However, CEO overconfidence has also been shown to have a positive effect. An example is a study of Indian firms that shows a positive association between CEO overconfidence and return on assets (Mundi & Kaur, 2019). A more comprehensive account of these and other studies will be provided later in this document.

- **A call for further research on investor response to overconfidence bias.** Although there has been a significant growth in the number of papers⁴⁸ published on the topic of overconfidence bias, researchers are calling for further research on the consequences of mistaken judgment (Dunning et al., 2004), on how behavioural biases apply to managerial decision making (Goldfarb et al., 2012), and on whether investors take managerial overconfidence into consideration when determining a firm's stock price based on its forecasts (Hribar & Yang, 2016).

Many of the cognitive biases, including overconfidence bias, are well established at the individual level. However, strategic decisions in organisations are typically not made in isolation by the CEO or any single individual (Mukherjee et al., 2016). In fact, for the last few decades it has been noted that management teams play an important role in key organisational decisions (Hambrick & Mason, 1984) and the "modern" workplace embraces team-based decision making (Appelbaum & Batt, 2004; Cianni & Wnuck, 1997).

While it might not always be the top management team, invariably there exists a group of people that the CEO consults when making strategic decisions (Frisch, 2011). In other words, the strategic decision is a product of a group of people and those people, like all people, are vulnerable to cognitive biases. We therefore specifically focused our attention on the overconfidence bias exhibited by the group making the strategic decisions because "*groups make most of the important decisions in organizations*" (Tasa & Whyte, 2005). To what extent is the group that is making the strategic decision afflicted by cognitive biases? To answer this question, we first explored whether overconfidence persists in the organisation and then, if it did, how it impacts the quality of strategic decisions.

2.1.7.1 Overconfidence in organisations

Social psychology is concerned with the way people's feelings, thoughts, beliefs, intentions, and goals are cognitively constructed and how these mental representations, in turn, influence their interactions with others (Allport, 1985). A focus of social psychology is group dynamics. Group dynamics is concerned with the system of behaviours and psychological processes occurring within a social group or between social groups (Backstrom, Huttenlocher, Kleinberg, & Lan, 2006). Groups have the potential to be superior to individuals in terms of decision quality because they bring more cognitive resources (Kameda, Tindale, & Davis, 2003) and different perspectives (Eden & Ackermann, 2010) to bear on the decision task, they could catch each other's mistakes (Blanton et al., 2009; Vazire & Carlson, 2011), and there are social incentives to avoid making overconfident claims that could be discredited (Meikle et al., 2016).

But, groups are vulnerable to an array of biases and distorting effects that can undermine decision quality (Felfernig, Boratto, Stettinger, & Tkalčič, 2018). These include false consensus, groupthink, group polarization, social loafing, emotional contagion, and group escalation of commitment (Maccoun, Kerr, & Kramer, 1996; Jones & Roelofsma, 2000; Bjørnstad, 2002; Kameda et al., 2003; Yaniv, 2011; Mannion & Thompson, 2014; Felfernig et al., 2018). Furthermore, cognitive biases, including overconfidence bias, are present in the individuals that comprise the group. Do these cognitive biases persist during group decision making and, if so, are they attenuated or amplified by the group? It is plausible that overconfidence should persist in organisations because, according to Skala (2008), "*there*

48. In the last 15 years (2003-18), the number of papers published per year has increased by a factor of six. The papers have been published across many journals. The journals with the most papers on overconfidence are: Management Science, Organizational Behavior and Human Decision Processes, Journal of Economic Behavior and Organization, Journal of Behavioral Decision Making, and Journal of Economic Psychology. These five journals account for 115 papers, which is 9% of the papers published in this timeframe. Other notable journals accounting for the top 25% of the papers are Judgment and Decision Making and Strategic Management Journal.

is no critical mass of other, rational participants with the same degree of power that could cancel out overconfident managerial decisions”.

From the perspective of the behavioural theory of the firm, it is not just people that are bounded in their rationality, organisations are too, and hence the firm is also considered to “satisfice” (Cyert & March, 1963). Given that organisations satisfice, studies have attempted to determine whether cognitive biases persist during organisational decision making and, if so, what effect they have (Russo & Schoemaker, 1992, 2002; Houghton, Goldberg, Simon, & Aquino, 2000; Eden & Ackermann, 2010; Yaniv, 2011; Osmani, 2017; Felfernig, Boratto, Stettinger, & Tkalčič, 2018).

These studies have yielded mixed results where the impact of cognitive biases in group decision making is sometimes attenuated, sometimes amplified, and sometimes inconclusive (Maccoun et al., 1996; Yaniv, 2011; Osmani, 2017), while others (Houghton et al., 2000) found that the effect of biases that influenced their risk perception (e.g. illusion of control) was analogous for teams and individuals. And others (Johnson et al., 2011) found that individual level biases appear to be amplified at the group and organisational levels. Thus, it is known that cognitive biases play a role in organisational decisions, but there is not a straightforward mapping into how they impact the firm’s strategy (Sibony et al., 2017). With respect to overconfidence bias specifically, Meikle et al. (2016) studied the inhibitors and facilitators of overconfidence in organisations and found that “*overconfidence is present in and affects organizations*”, although they also noted that reports of overconfidence in organisations might be exaggerated. How does overconfidence manifest when strategic decisions are being made?

2.1.7.2 Overconfidence in strategic decision making

Despite (a) strategic decision making being the product of a team, and (b) the finding from Meikle et al. (2016) that overconfidence is present in and affects organisations, many researchers focus on the overconfidence of the CEO in the strategic decision making process.

For example, Sadler-Smith, Akstinaite, Robinson, and Wraet (2017) in their review of hubristic leadership acknowledge that their study is focused on hubris in individuals and they recognise that the study of “collective hubris” or “corporate hubris” is largely underdeveloped.

The fact that overconfidence has mostly been studied at the individual level is evident in the proxies used in empirical studies, which we will cover in detail later. For now, we mention one influential example. Malmendier and Tate (2005a) devised a proxy based on how the CEO trades their stock options. The authors justify their use of a proxy at the individual level by saying that they exploit the overexposure of typical CEOs to the idiosyncratic risk of their firms. They are not alone. Malmendier and Tate’s work has been extensively cited and their proxy adopted in many studies⁴⁹. Finkelstein, Hambrick, and Cannella (2009) recognise that although decision-making in organisations is often shaped by a dominant coalition of executives with their own perspectives, CEOs, due to their prominent positions, have considerable power over firm decisions and strategies. Schumacher et al. (2020) state that it is highly likely that the CEO will have a major influence on determining risk-taking decisions at the firm level. Earlier studies relating to acquisitions assert that they are individual decisions (Roll, 1986), that the acquiring CEO will be extensively involved (Haspeslagh & Jemison, 1991), and that they could not proceed without the CEO’s personal sponsorship (Hayward & Hambrick, 1997).

We do not dispute the disproportional influence of the CEO. Nor do we argue that developing a proxy for overconfidence in strategic decision making based on the CEO’s behaviour is incorrect. After all, all proxies are an abstraction of the underlying effect and, given the disproportionate power of the CEO’s role, a proxy based on the CEO’s behaviour might be adequate. However, given that the argument to

49. The paper in question has been cited more than 3,500 times and this proxy has been adopted in 18 of the 28 empirical studies that we reviewed.

proxy based on CEO behaviour does not negate the truth of points (a) and (b) above, we asserted that a proxy based on the management team, which includes the disproportionate impact of the CEO, that is making the strategic decision might bring more validity.

In summary, we have established that firms struggle to sustain their leadership position and that this amounts to a failure to sustain their competitive advantage. A firm’s competitive advantage is a product of its competitive strategy, which in turn is a result of the strategic decisions made by its management team. Strategic decisions are distorted by cognitive biases. We have chosen to specifically focus on the overconfidence bias of the management team making the strategic decision and the impact that it might have on decision quality and hence ultimately on firm performance.

2.1.8 Conceptual model

In this first part of the chapter, we contemplated the expectations that shareholders have of their management teams who compete in markets to meet or exceed those expectations. We have noted that management teams develop competitive strategies by making strategic decisions, but these are decisions made in a context of uncertainty. And decision making under uncertainty is known to be susceptible to a range of distorting factors, including cognitive biases, of which overconfidence is of particular interest to us. This study’s research question is: **what is the impact of group-level overestimation and overprecision biases on firm performance?** We illustrate how these concepts fit together in the conceptual model displayed below.

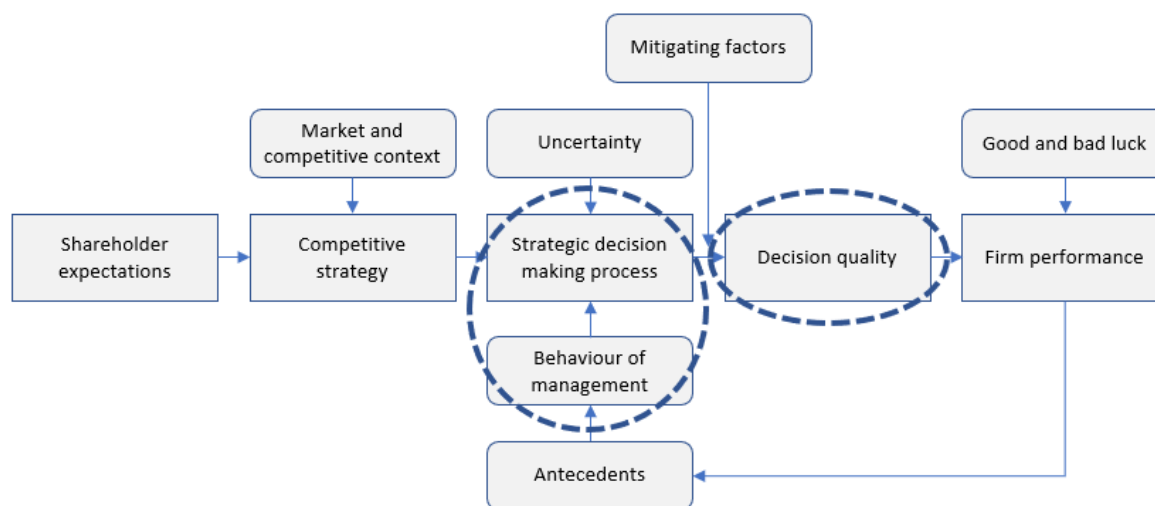


Figure 4: Conceptual model.

The dotted circles in the diagram represent the focus of this study. In the left circle we consider the impact of overconfidence on the firm’s strategic decision making in respect of how overconfident management teams behave and how this behaviour affects their strategic decision-making process. In the right circle we consider the decision quality that results. Since we have not found a generally accepted measure for decision quality, we use expected⁵⁰ firm performance as an indicator of decision quality. This is appropriate because, as mentioned before, it is only the decision quality that is within managers’ control and although for any single decision, firm performance might deviate from decision quality, for a sufficient number of decisions, firm performance approximates decision quality.

50. The adjective “expected” is deliberately used and is meant in line with the “expected value” terminology when considering probabilistic outcomes.

Using this model as a base, we explored the literature on the impact of overconfidence bias on decision quality and, ultimately, firm performance.

2.2 Literature review

We examined the literature regarding the impact of overconfidence bias, when groups make strategic decisions, on firm performance. We first strove for clarity on the definition of overconfidence, then we explored the antecedents and consequences of overconfidence. With that understanding of overconfidence, we made sense of theories regarding the implications of overconfidence and followed that with a review of experimental and empirical studies of the impact of overconfidence on firm performance.

We deliberately postponed the development of our hypotheses to follow the full account of our literature review because each of our hypotheses are dependent on a holistic consideration of several theories and their associated empirical support. We saw the need for this holistic consideration due to many of the theories bridging across two of the distinct forms of overconfidence, plus we found inconsistencies in these theories, and we found conflicts and gaps in the empirical studies. As such, our approach was to interpret the literature, with due recognition to the inconsistencies, conflicts, and gaps, and to use this as our basis for deriving hypotheses, which we do in section 2.3.

2.2.1 Defining overconfidence

To understand what the literature has to say about overconfidence bias we must be clear on its definition. Moore and Healy in their landmark paper⁵¹ (2008) suggest that overconfidence is a concept that embodies three distinct types, which are overestimation, overprecision, and overplacement. Moore and Schatz (2017) have more recently sharpened the definition of each type of overconfidence and we used these more recent definitions:

- **Overprecision** is the excessive faith that you know the truth.
- **Overestimation** is thinking that you are better than you are.
- **Overplacement** is the exaggerated belief that you are better than others.

In both of the above-mentioned papers (Moore & Healy, 2008; Moore & Schatz, 2017) the authors raise the concern that definitions of overconfidence and associated research have been vague and that this has undermined much of the research in this field. In our review of the literature, we found numerous examples to support their concern.

Many papers have been imprecise in their definitions and/or have combined two or three of the three types of overconfidence in their definition of overconfidence as a single concept. The vague definitions and combination of types into a single concept is problematic according to Moore and Healy (2008) because their analysis suggests that these three types are conceptually and empirically distinct. Not only do they argue that they are distinct concepts, but that they interact with each other, for example overprecision reduces overestimation. Moore and Healy (2008) and others (Larrick et al., 2007; Moore & Small, 2007) also find a negative relationship between overestimation and overplacement, whereby hard tasks produce the most overestimation and also produce the most underplacement, while easy tasks produce underestimation and overplacement.

We acknowledged that some definitions, for example (Malmendier & Tate, 2005b), precede Moore and Healy (2008)'s paper, which is the first paper that we have found where overestimation, overprecision,

51. At the time of this writing, this paper was cited more than 1,600 times.

and overplacement are all discussed. We further acknowledged that different researchers have their own preferences and rationale for the decisions that they have used. These points notwithstanding, the literature is challenging to make sense of because of the inconsistency in definitions.

Evidence for this problem of vague definitions and a combination of types of overconfidence is illustrated by the examples below of the definitions that the respective authors have used. We have preceded each definition with our interpretation using the Moore and Schatz (2017) definitions:

Overconfidence definitions that seem to confound overplacement and overestimation.

- “Overestimate their own skills relative to others and, as a result, are too optimistic about the outcomes of their decisions” (Malmendier & Tate, 2005b)
- “Hubristic individuals possess strong self-confidence and pride, perceive themselves as superior to their peers, and tend to overestimate their own abilities” (M. C. Kim et al., 2017)

Overconfidence definitions that seem to confound overestimation and overprecision.

- “Predict that favourable future events are more likely than they actually are, and they believe that they have more precise knowledge about future events than they actually have” (Hackbarth, 2008)
- “Underestimate risk and overestimate probability of success” (Li & Liu, 2012)
- “Overestimation of the mean and underestimation of the variance” (Hribar & Yang, 2016)
- “Overestimating their own ability and firms’ prospects, while under-estimating risks” (Banerjee et al., 2018)

Overconfidence definitions that seem to confound overplacement, overestimation, and overprecision.

- “Better-than-average abilities, judgment, or precision” (Lai et al., 2017)
- “Hubris can manifest itself in three specific ways: (1) overestimation of one’s own abilities, outcomes, and probability of success (2) overprecision in one’s own beliefs; and (3) overplacement of one’s own performance relative to that of others” (Picone, Dagnino, & Minà, 2014).

We also find numerous definitions that are consistent with the Moore and Schatz (2017) definitions. We mention some of these as they are useful in that they add “texture” to our understanding of these three concepts.

Overprecision.

- Hiller and Hambrick (2005) define overconfidence as an overestimation of certainty of being correct or producing a certain outcome.
- Ben-David, Graham, and Harvey (2013) use the term miscalibration and define it as “an underestimation of the range of potential outcomes”.
- G. Chen, Crossland, and Luo (2015) refer to overconfidence as “overestimate the accuracy of their knowledge and judgments”, which is similar to Gervais, Heaton, and Odean, (2011) who use “overestimates the precision of his signal”.

Overestimation.

- Hirshleifer, Low, and Teoh (2012) define overconfidence as the “tendency of individuals to think that they are better than they are in terms of characteristics such as ability, judgment, or successful life outcomes”.

- Ho, Huang, Lin, and Yen (2016) say that CEOs have overconfidence if they “generally think they are better than they are in terms of skill and judgment or in gauging the prospects of a successful outcome”.
- H. A. Kim, Choi, and Cho (2019) refer to overconfidence as “overestimate outcomes associated with their abilities and underestimate the probability of negative events”.
- Engelen, Neumann, and Schwens (2015) define overconfidence as “overestimation of one’s own abilities, performance, level of control, or chance of success.”
- Malmendier, Tate, and Yan (2011) define overconfidence as “overestimation of mean returns to investment”.

Overplacement.

- Hwang, Kim, and Kim (2018) define overconfident managers as those that “overstate their abilities relative to the average, resulting in the so-called “better-than-average” effect”.
- J. E. Lee (2016) defines people as overconfident when they “think of themselves as ‘above average’.”

In addition, many researchers use the terms optimism or hubris, but their definitions of these terms seem largely consistent with the Moore and Schatz (2017) definition of overestimation.

Hubris.

- Invernizzi, Menozzi, Passarani, Patton, and Viglia (2017) refer to hubris theory⁵² (Hayward et al., 2006) and define overconfidence as “overestimates the probability of a positive outcome to an event compared to the probability of experiencing a negative outcome from the same event”.
- Hayward and Hambrick (1997) refer to Roll’s hubris hypothesis (Roll, 1986) and define hubris as “exaggerated pride or self-confidence”. Park, Kim, Chang, Lee, & Sung (2018) follow Hayward and Hambrick (1997) in their definition.
- Picone et al. (2014) consider hubris to manifest as all three forms of overconfidence, namely overestimation, overprecision, and overplacement.

Optimism.

- J. B. Kim, Wang, and Zhang (2016) use overconfidence and overoptimism interchangeably and define this as “overestimate their own acumen, mastery, and prospects for positive future outcomes”.
- Billett and Qian (2008) refer to hubris theory (Roll, 1986) too, but define overconfidence as “overly optimistic opinion of their ability to create value”.
- Heaton (2002a) uses the term “managerial optimism” and defines it as “systematically overestimate the probability of good firm performance and underestimate the probability of bad firm performance.”
- Schrand and Zechman (2012) refer to an “optimistic bias” which they as “unrealistic (positive) beliefs about any aspect of the distribution of an uncertain outcome, such that the mean is overstated”.

52. More on hubris theory later.

It is interesting to note that Malmendier and Tate (Malmendier & Tate, 2005a, 2005b, 2008, 2015; Malmendier et al., 2011), two of the most cited researchers in the study of overconfidence (Costa, de Melo Carvalho, de Melo Moreira, & do Prado, 2017), base their theoretical argument (Malmendier & Tate, 2005b) on the “better than average” effect, which is overplacement, but in their other papers they define overconfidence in slightly different ways, sometimes implying overplacement, sometimes implying overestimation, and sometimes implying both overplacement and overestimation.

Moreover, the early work of Malmendier and Tate (2005a) establishes the options-based proxy of measuring CEO overconfidence and this approach has since been extensively adopted, mostly by other researchers studying what appears to be overestimation (Banerjee et al., 2018; Bharati, Doellman, & Fu, 2016; Engelen et al., 2015; Galasso & Simcoe, 2011; Hirshleifer et al., 2012; Ho et al., 2016; H. A. Kim et al., 2019; J. B. Kim et al., 2016; Mundi & Kaur, 2019; Phua, Tham, & Wei, 2018; Schrand & Zechman, 2012; Schumacher, Keck, & Tang, 2020), but also by some studying what appears to be overestimation and overprecision (Hilary, Hsu, Segal, & Wang, 2016; Hribar & Yang, 2016; J. M. Lee, Hwang, & Chen, 2017), another studying what appears to be overestimation and overplacement (S.-S. Chen, Ho, & Ho, 2014), yet another studying what appears to be overplacement (Hwang et al., 2018), and finally another that appears to be studying overestimation, overplacement and overprecision (Lai et al., 2017).

One of the issues with these confounded definitions of overconfidence is that it makes it challenging to interpret empirical studies. For example, Bharati, Doellman, and Fu (2016) rely on Goel and Thakor (2008)’s theory of overconfidence, which is based on overconfidence being of the overprecision type, but then use Malmendier and Tate (2005b)’s operationalisation, which is intended for overestimation (or overplacement, or both).

Unsurprisingly, not all researchers agree that these three types of overconfidence are distinct and should be treated as such. For example, Barros and da Silveira (2007) acknowledge that although some models treat overestimation and overprecision⁵³ separately for analytical purposes, they note psychological and behavioural research which suggests that these biases are closely related and are likely to appear jointly. As such, they define overconfidence in a manner that includes both overestimation and overprecision. A similar approach is taken by Hayward et al. (2006) who propose that both overestimation and overprecision⁵⁴ belong under the same overarching construct which they refer to as “optimistic overconfidence” in line with Kahneman and Tversky (2004). Barros, da Silveira, and Hayward et al. are not alone, as some of the examples earlier in this section illustrate. A recent paper makes this observation too: “... *the concept of hubris is elusive and contested, which has given rise to a variety of specific constructs in empirical research ...*” (Zeitoun, Nordberg, & Homberg, 2019). One last example that illustrates the confusion comes from (Tang et al., 2015) who define executive hubris as “*to overestimate the correctness of one’s own judgments*”, thereby effectively referring to overprecision, but calling it hubris.

Even the researchers that recognise the different types, do not always find the same relationships between these types. For example, three studies recognise that overprecision and overestimation are distinct, but Moore and Healy (2008) find a negative relationship, Merkle (2017) finds no relationship, and Hribar and Yang (2016) find a positive relationship.

In closing out this section on the definition of overconfidence, we found plenty of evidence in support of Moore and Healy (2008)’s concerns regarding a lack of clarity and consistency in definitions, leading

53. Just to make things even more confusing, they refer to “overprecision” as “overconfidence” and refer to “overestimation” as “optimism” in their paper.

54. They refer to “overestimation” and “overprecision” as “hubris” and “overconfidence” in their paper.

to an inconsistent application in empirical work, which makes it difficult to make comparable interpretations of much of the research.

We found that Moore and Healy (2008)'s assertion that overconfidence comprises of three distinct concepts (overprecision, overestimation, overplacement) is referenced and adopted by many, but not all, researchers. We also found that no researchers create definitions of overconfidence that are more granular than Moore and Healy (2008), but, as detailed at the beginning of this section, there are many that aggregate two or three of the concepts into their definition of overconfidence. Lastly, we found that some researchers define overconfidence in similar⁵⁵ ways to Moore and Healy (2008), but with different labels, such as hubris or overoptimism for overestimation, miscalibration or overconfidence for overprecision, and "better than average" for overplacement.

Since Moore and Healy (2008)'s conceptualisation of overconfidence is widely used, is the most granular we have found, and in the interest of building on the body of knowledge, we used these concepts of overprecision, overestimation, and overplacement for the remainder of this document. And, since Moore and Schatz (2017) created concise definitions of these concepts, we adopted these as our definitions for this document. Thus, for consistency and comparability, when we reviewed the work of other researchers, we related it back to these definitions.

With overconfidence defined we now venture into our conceptual model, starting with a light coverage of antecedents and behaviours, then delving into the implications of overconfidence in the strategic decision-making process, and lastly interpreting the literature regarding the impact of overconfidence on decision quality.

2.2.2 Antecedents of overconfidence

The antecedents of overconfidence have been extensively studied and numerous theories have been proposed. We do not offer a comprehensive account of these theories, instead provide a high-level summary of some of the influential work and useful frameworks.

Russo and Schoemaker (1992) define someone as overconfident if they are unjustifiably certain of their beliefs, which fits with Moore and Healy (2008)'s definition of overprecision. They present three categories of drivers of overconfidence, namely cognitive, physiological, and motivational. Russo and Schoemaker mention four cognitive biases that can give rise to overconfidence. The availability bias causes us to only consider what comes to mind, which is a limited set of possibilities, leading us to become unduly confident about predictions based on the possibilities we consider. The anchoring bias leads us to anchor on an initial idea and not adjust sufficiently from this starting point. Confirmation bias leads us to look for supporting evidence for our initial viewpoint and discount disconfirming evidence. And hindsight bias instils an illusion of omniscience. Russo and Schoemaker (1992) also argue that the elated feeling of well-being that commonly follows personal or professional success may cause overconfidence. This euphoric feeling is believed to have a biochemical basis, for example the endorphins that the body produces as a response to strong emotional reactions. Thirdly, they argue that there is a motivational basis for overconfidence. We distort reality because of a need to believe in our abilities else we would not take on risky projects and make progress.

Russo and Schoemaker (1992)'s motivational driver of overconfidence seems to be closely related to Johnson and Fowler (2011)'s theory of an evolutionary basis for overconfidence. Johnson and Fowler define overconfidence as "thinking you are better than you are" and detail this further in a manner that

55. We recognise that what one researcher might mean by "hubris" is not necessarily the same as what another might mean by "overoptimism" and that these might each also differ from "overestimation", but in order to make pragmatic use of the studies in this field, we have adopted this classification and mapping as described. Further, many researchers who use these different labels operationalise their studies using the same proxy, thus effectively nullifying any intended subtle differences.

encompasses overprecision, overestimation, and overplacement. In their theory, overconfidence maximises individual fitness, leading populations to become overconfident, if the benefits outweigh the costs. They find a relationship where the optimal level of overconfidence increases with the level of uncertainty. From this they predict that where the size of the prize exceeds the cost of competing, overconfidence will be especially prevalent in domains of inherently high uncertainty. Some examples of such domains are international relations and eras of novel business technologies like the internet bubble and modern financial instruments.

Lovalló and Kahneman (2003) argue that managers' overestimation⁵⁶ results from cognitive biases and organisational pressures. In their argument, they discuss what they term the "inside view" and the "outside view". They consider the inside view to arise spontaneously or intuitively. Unless the inside view is challenged, managers' forecasts are generally overly optimistic because people are inherently optimistic and because other biases, anchoring, competitor neglect, and political pressures to emphasise the positive and downplay the negative, amplify this optimism. They find that the outside view, also called reference-class forecasting, is more likely to produce accurate forecasts and much less likely to deliver overly optimistic ones.

Picone et al. (2014) provide a literature review of the antecedents of managerial hubris⁵⁷. And they define hubris, with reference to Moore and Healy (2008) to include overprecision, overestimation, and overplacement. They structure the antecedents of managerial hubris into two categories: personal dispositions and external stimuli. Personal dispositions include narcissism, gender⁵⁸, and educational background. We suggest that culture should be added to this list based on the work of Johnson and Tierney (2006, p.53). External stimuli include a firm's recent success, recent media praise, the manager's sense of self-importance, and the manager's sense of power based on how long they have held senior positions. We suggest that lack of corporate governance should be added to this list based on Paredes (2005)'s study that shows that CEOs become overconfident when they are highly paid and have extensive control.

We found many other theoretical explanations of the antecedents of overconfidence (Anderson, Brion, Moore, & Kennedy, 2012; Camerer & Lovalló, 1999; Kahneman & Lovalló, 1993; Moore & Healy, 2008; Van den Steen, 2004) and even an argument that challenges the very notion of overconfidence (Gigerenzer, Hoffrage, & Kleinbolting, 1991).

Despite the last citation (Gigerenzer et al., 1991), we followed the bulk of the literature and accepted that overconfidence, in its various forms, is a real phenomenon. Not only is it real, but it is highly prevalent. Earlier (section 2.1.7) we referenced Moore and Bazerman (2012a, p. 14)'s comments on overconfidence as: "*overconfidence effects are some of the most potent, pervasive, and pernicious of any of the biases*" and we referenced Plous (1993, p. 217) who wrote: "*no problem in judgment and decision making is more prevalent and more potentially catastrophic than overconfidence*". We also noted Ackert and Deaves (2009) who wrote that "*overconfidence is pandemic in society*". Besides for Ackert and Deaves, Plous, Moore and Bazerman, we read similar accounts of the prevalence and pervasiveness of overconfidence from many others (Anderson et al., 2012; Griffin & Varey, 1996; Johnson & Fowler, 2011; Radzevick & Moore, 2010; Skąła, 2008). However, we also noted some counterbalance from Meikle et al. (2016) where they offer reasons why overconfidence's prevalence might be exaggerated.

56. They use the term overoptimism.

57. Picone et al. define hubris as overconfidence plus pride.

58. Yes, sigh, various studies corroborate that men are more overconfident than women (Barber & Odean, 2001; Healy & Offenber, 2007).

Not only is overconfidence real and prevalent, multiple studies have found that it is also disproportionately present in top management (Graham, Harvey, & Puri, 2013; Moore & Healy, 2008; Taylor & Brown, 1988; Weinstein, 1980). In fact, Goel and Thakor (2008) theorise that overconfidence⁵⁹ will be more prevalent in CEOs than in the general population. This is because the competition for senior leadership positions drives managers to make riskier decisions that have prospects of delivering impressive results. Those that are overconfident are more likely to take such risks and hence some will achieve the results they sought. This theory finds empirical support in a recent paper (Banerjee, Dai, Humphery-Jenner, & Nanda, 2020).

Given that overconfidence arises for one or multiple reasons and is so prevalent, especially in top management, what beliefs and behaviours result?

2.2.3 Beliefs and behaviours resulting from overconfidence

Overestimation has been shown to manifest in four respects (Moore & Healy, 2008): self-enhancement, where people view themselves positively, as opposed to accurately (Dunning, 2005); illusion of control, where people think they have more control over circumstances than they actually do (Thompson, 1999); the planning fallacy, the common tendency to overestimate the speed at which we will complete projects (Buehler et al., 1994); and unrealistic optimism, the tendency to overestimate the rosiness of our future (Sharot et al., 2007).

The illusion of control is theorised to influence strategic decision making by leading managers to overestimate their efficacy and control in bringing about success (March & Shapira, 1987; Hayward & Hambrick, 1997; Malmendier & Tate, 2005; Hirshleifer, Low, & Teoh, 2012), underestimate their firm's or projects' likelihood of failure⁶⁰ (Galasso & Simcoe, 2011; Hackbarth, 2008; Malmendier & Tate, 2005b), and contribute to the hubris hypothesis, which is an overly optimistic opinion of one's ability to create value (Roll, 1986).

Unrealistic optimism is theorised to lead managers to believe the market undervalues their firm's or projects' current assets (Heaton, 2002; Malmendier & Tate, 2015), overestimate their chance of success (Gervais et al., 2002), and overestimate the returns or future cash flows of their firm or project (Gervais et al., 2002; Heaton, 2002; Malmendier & Tate, 2005, 2015; Hackbarth, 2008; Malmendier, Tate, & Yan, 2011).

Overprecision is theorised to lead managers to overestimate and overreact to the precision of their knowledge (Goel & Thakor, 2008; Gervais et al., 2011) and to underestimate the riskiness of earnings and of projects (Gervais et al., 2002; Hackbarth, 2008). Because they underestimate risk, overprecise investors are more risk-taking (Merkle, 2017) and overprecise managers are less likely to postpone the decision to undertake projects and are more willing to take on risky projects (Gervais et al., 2002). In so doing, they mitigate underinvestment, but this could lead to overinvestment (Goel & Thakor, 2008). Managers with overprecision are theorised to exert more effort to gather information that improves the success rate and value of their firm's investments (Gervais et al., 2011).

Overplacement has been found to work in the opposite direction to overestimation across task difficulty levels, with underplacement more typical in difficult tasks and overplacement more typical in easy tasks (Moore & Cain, 2007; Moore & Healy, 2008). Overplacement could lead to excessive market entry, but only in markets that are perceived to be "simple", the opposite might occur in markets perceived to be challenging (Moore & Cain, 2007). Investors expect their portfolios to deliver higher returns than

59. Goel and Thakor define overconfidence in the overprecision way.

60. Unrealistic optimism and the planning fallacy also lead managers to underestimating their firm's or projects' likelihood of failure.

the market and hence demonstrate overplacement bias (Merkle, 2017). Overplacement in investors results in increased risk taking and increased trading activity bias (Merkle, 2017).

2.2.4 Implications of overconfidence

Our review of the literature yielded six broad “themes” pertaining to the theoretical implications of overconfidence. Many of these themes are not single theories, rather they are our interpretation of how the theoretical work seems to cluster. For instance, we refer to “hubris theory” and “underinvestment mitigation” as two separate themes, although they both discuss the implications of overconfidence on the investment decision making. We have classified them separately because they are directionally distinct in that “hubris theory” predicts negative effects like overinvestment, while “underinvestment mitigation” predicts positive effects as implied by the label we have used. A summary of the six themes is provided in Table 3 below. The first three themes mostly predict negative impacts of overconfidence on firm performance, while the latter set of three themes mostly predict positive impacts.

Theoretical theme	Overprecision	Overestimation	Overplacement
Hubris theory		(Roll, 1986)	
		(Heaton, 2002)	
		(Malmendier & Tate, 2005b, 2015)	
		(Hayward et al., 2006)	
Hyper-CSE ⁶¹	(Hiller & Hambrick, 2005)		
Capital structures		(Hackbarth, 2008)	
		(Deshmukh, et al. 2013)	
Underinvestment mitigation		(Gervais et al., 2002)	
		(Hiller & Hambrick, 2005)	
		(Goel & Thakor, 2008)	
Innovation and R&D propensity		(Galasso & Simcoe, 2011)	
		(Yu, 2014)	
Motivation		(Gervais et al., 2002)	
		(Gervais et al., 2011)	
		(Shipman & Mumford, 2011)	

Table 3: Themes pertaining to the theoretical implications of overconfidence.

We now discuss each of these themes, describing, where available and appropriate, the background, the predictions, and the evidence for each.

2.2.4.1 Hubris theory

Hubris theory, introduced by Roll (1986) and subsequently cited and refined by a number of researchers (Hayward et al., 2006; Heaton, 2002a; Malmendier & Tate, 2005b, 2015), is the hypothesis that hubris explains why managers overinvest. Roll does not define hubris in his original paper, but considering the

61. CSE refers to core self-evaluation. Hyper-CSE is an extreme version of CSE and will be defined in the relevant section.

three types of overconfidence discussed in section 2.2.1 above, it seems that overestimation fits best, although he also makes the point that optimism in a competitive context may take the form of contempt for the capabilities of others, which would imply overplacement. Heaton (2002a) references Roll and refers to “managerial optimism”, which aligns with overestimation. Malmendier and Tate (2005b, 2015) define overconfident managers as those that “overestimate their own skills relative to others and, as a result, are too optimistic about the outcomes of their decisions”, which carries features of both overplacement and overestimation. Hayward et al. (2006) define hubris to include overconfidence in knowledge, overconfidence in prediction, and overconfidence in personal abilities. Consequently, their definition carries features of both overprecision and overestimation. Again we were challenged by the inconsistencies in definitions, but we noted that overestimation, although not stated explicitly, is common in the definition used by all researchers of hubris theory.

From Roll (1986) we read that managers are subjected to strong pressures to maintain high performance and that this pressure, in the presence of hubris, drives risk-seeking behaviours. The predicted consequence is that in the context of mergers and acquisitions, bidding managers overestimate their ability to manage the target firm and hence overpay for it. This theory has empirical support in the study of Hayward and Hambrick (1997) who find losses in acquiring firms’ shareholder wealth following an acquisition, and the greater the CEO hubris and acquisition premiums, the greater the shareholder losses. Park et al. (2018) build on Hayward and Hambrick (1997)’s work to provide further empirical support in their analysis of CEO hubris in Korean firms. Billet and Qian (2008)’s study also support Roll’s theory in that they find that CEOs tend to become overconfident after a successful acquisition, and, as a result, are more likely to follow it with acquisitions that negatively impact their firm’s stock. Malmendier and Tate (2005a, 2008) also find that overconfident CEOs overinvest. In fact, they find that overconfident CEOs are unambiguously more likely to make lower-quality acquisitions when their firm has abundant internal resources and hence, CEOs, prone to hubris, destroy value for their shareholders through acquisitions. Not only, do overconfident CEOs make value destructive acquisitions, they also tend to complete more deals (Hwang, Hyoseok et al., 2020)⁶² and hence the problem is amplified.

Hubris applies not only to acquisitions, but more generally it pertains to risk taking in other respects, such as firm investing, financing, and in the case of banks, to lending standards. From a firm investing and financing perspective, J. B. Kim et al. (2016) analysed S&P 1500 firms between 1993 and 2010 and found that firms with overconfident CEOs have a higher stock price crash risk. From a bank lending perspective, P.-H. Ho et al. (2016) analysed publicly listed U.S. banks from 1994 to 2009 and found that during crisis years, banks with overconfident⁶³ CEOs generally experienced more increases in loan defaults, greater drops in operating and stock return performance, greater increases in expected default probability, and higher likelihood of CEO turnover or failure than other banks.

Heaton (2002a) builds on Roll’s theory and reaches the finding that overconfident managers do not only overinvest, but underinvest too. Heaton arrives at this conclusion regarding underinvestment by arguing that optimistic managers might decline positive net present value projects when they require external financing because the optimistic manager believes that the cost of external finance is too high. The optimistic manager believes this because they believe that the capital markets undervalue their firm’s risky assets. The optimistic manager believes they overestimate the probability of good firm performance and underestimate the probability of bad firm performance. In summary, Heaton supports Roll’s idea that optimistic managers overinvest and that this is value destructive to

62. Hwang et al. define overconfidence as the “better than average” effect, which implies overplacement

63. Ho et al. use overconfidence in the overestimation way.

shareholders, but Heaton goes further to show that optimistic managers also forgo good projects, and this is costly⁶⁴ to shareholders too.

Malmendier and Tate (2005b) theorise that managers persistently overestimate their own skills relative to others and, as a result, are too optimistic about the outcomes of their decisions. The researchers arrive at this perspective by theorising that (a) the ‘better than average’ effect is particularly likely to apply to high-rank executives, and (b) that managers overestimate their abilities because they believe that they can control the outcome. Point (a), the ‘better than average’ effect, has its grounding in the work of Kruger (1999), Camerer and Lovallo (1999), and Moore and Kim (2003). Point (b) has its grounding in the work of Langer (1975), Weinstein (1980), Kunda (1987), and Weinstein and Klein (1995). Malmendier and Tate (2005b)’s theory finds empirical support in their own work (2005a, 2008), as well as Hribar and Yang’s study (2016) where they show that overconfidence⁶⁵ increases the likelihood of issuing a forecast, increases the amount of optimism in management forecasts, and increases the precision of the forecast.

Lastly, Hayward et al. (2006) theorise that managers who are overconfident, in the form of overestimation and overprecision, will create new ventures despite the high venture failure rates. Hayward et al.’s theory is empirically supported by Invernizzi et al. (2017) who find that overconfident⁶⁶ individuals are more likely to start and develop new ventures and such ventures are also more likely to fail.

We concluded that hubris theory leads overestimating managers to overinvest and perhaps also to underinvest. Over- or under-investment implies that managers are not investing in the shareholders’ best interests as they are making investments that are value destructive and forgoing investments that would have been value creating. This applies to investments such as company projects, acquisitions, or ventures. While this seems to be well demonstrated for overestimating managers, it is unclear whether the hubris theory applies to managers who display overplacement and/or overprecision.

2.2.4.2 Hyper core self-evaluation theory

Hyper core self-evaluation theory is presented by Hiller and Hambrick (2005). Core self-evaluation (CSE) is a relatively enduring and fundamental evaluation of oneself as an individual. CSE is defined as the overlap of four human qualities that have been extensively studied, namely self-esteem (“I am worthy”), generalized self-efficacy (“I succeed at tasks”), locus of control (“Life’s events are within my control”), and emotional stability (“I am free from anxiety”). Hiller and Hambrick (2005) discuss hyper-CSE, which they define as extreme levels of the four aforementioned qualities, and mention that this closely aligns with hubris. However, their definition of overconfidence as an overestimation of certainty of being correct or producing a certain outcome aligns to overprecision.

Hyper-CSE theory predicts that the greater the CEO’s CSE, the faster, more centralised, and less comprehensive will be the organisation’s strategic decision-making process. This theory also predicts that for greater CSE of the CEO, the greater the number and scale of large-stakes initiatives undertaken by the organization, the more the organisation’s strategy will deviate from the central tendencies of the industry, the greater will be the organisation’s persistence in pursuing strategies that were launched by the CEO, and, ultimately, the more extreme the organisation’s performance will be.

64. Costly in the form of an opportunity cost. In other words, if the optimistic manager has deprived the shareholder of what would have otherwise been value creation.

65. Hribar and Yang’s definition of overconfidence includes overestimation and overprecision.

66. Invernizzi et al. refer to hubris managers and seem to imply overestimation.

Hyper-CSE theory has empirical support in M. C. Kim et al. (2017)'s study⁶⁷ which finds that corporate managerial hubris predicts low strategic emphasis on advertising versus R&D, as well in Lai et al. (2017)'s study⁶⁸, which finds an increased propensity for full over shared ownership in foreign market entry.

Wang, Holmes, Oh, and Zhu (2016) define a similar measure to core self-evaluation, which they call "CEO positive self-concept". Individuals with positive self-concept hold favourable self-images and are more likely to view themselves as exceptional, potent, admirable, and important. Wang et al. (2016) found that CEO positive self-concept was positively associated with strategic actions and risk taking, but do not find a relationship between CEO positive self-concept and future firm performance.

2.2.4.3 Capital structures

Hackbarth (2008) theorises that optimistic and/or overconfident⁶⁹ managers choose higher debt levels and issue new debt more often. Hackbarth arrives at his theory using two building blocks. The first is his assertion that optimistic managers overestimate the growth rate of earnings, which he calls growth perception bias. The second is that overconfident managers underestimate the riskiness of earnings, which he calls risk perception bias. Growth perception bias leads managers to believe their firms will be more valuable and hence they view external finance as too costly, although if external finance is needed, they would choose debt before equity. Managers with a risk perception bias believe that their firm is less likely to be in financial distress because they believe it to be less risky than it actually is. The consequence of growth perception bias and risk perception bias is that biased managers will prefer debt and, in fact, take on higher levels of debt than unbiased managers. Hackbarth (2008)'s theoretical model shows a non-monotonic relationship between overconfidence and firm performance in that it predicts that a moderate level of overconfidence will result in a capital structure that is more favourable for shareholders than an unbiased manager, but a high level of overconfidence is detrimental to firm value because of the increased bankruptcy risk.

A related theory from Deshmukh, et al. (2013) who theorise that firms with overconfident⁷⁰ CEOs generally pay out smaller dividends. This view is consistent with overconfident CEOs viewing external financing as costly, because they believe their firm to be undervalued by the market and wishing to accumulate a financial buffer for future investments.

Banerjee et al. (2018) provides empirical support to Deshmukh, et al. (2013)'s theory when they find that overconfident⁷¹ managers are more likely to substitute repurchases for dividends or capital expenditure.

Hackbarth (2008) has empirical support in the work of Barros and da Silveira (2007), despite its earlier publication, in that they find a strong positive association between overconfidence, defined in terms of both overestimation and overprecision, and leverage ratios. Malmendier et al. (2011)'s empirical study also finds that overconfident⁷² managers are more likely to issue debt as they believe that their equity

67. M. C. Kim et al.'s study, despite referencing Hiller and Hambrick, uses overestimation, not overprecision, and hence the empirical support from their study is questionable.

68. Lai et al.'s study, despite referencing Hiller and Hambrick, uses a combination of overestimation, overprecision, and overplacement, and hence the empirical support from their study is questionable.

69. Hackbarth uses optimism in the overestimation way and overconfidence in the overprecision way

70. Deshmukh et al. use overconfidence in the overestimation way.

71. Banerjee et al. use overconfidence in the overestimation way.

72. Malmendier et al. use overconfidence in the overestimation way.

is undervalued. Further empirical support for Hackbarth (2008) comes from Leng et al. (2018) who find that overconfident⁷³ CEOs increase the likelihood of bankruptcy.

In conclusion, managers who overestimate and/or are overprecise will believe their firm to be undervalued and will consequently adopt capital structures with more debt leverage.

2.2.4.4 Underinvestment mitigation

The central point of the underinvestment mitigation theme is essentially a mirror image of hubris theory. The underinvestment mitigation theorists acknowledge many of the same points as the hubris theorists but find a positive impact on firm performance in respect of the tendency of overconfident managers to overinvest. We considered the work of three research groups that seem to arrive at theories that fit this theme.

Gervais, Heaton, and Odean (2002) theorise that moderately overconfident⁷⁴ or optimistic managers make decisions that are in the better interest of shareholders than the decisions made by rational managers who are often too conservative. The basis of Gervais et al.'s argument is that overconfident or optimistic managers underestimate the risk of potential projects and overestimate the expected value of a risky project. Because of these beliefs they are less likely to postpone the decision to undertake, are more willing to undertake, and are quicker to undertake risky projects. Gervais et al. (2002) recognise that overconfidence and optimism are valuable only at a moderate level. When managers have extreme overconfidence and/or optimism, they will perceive too little risk or too much value, leading them to take on value destructive projects.

Consistent with Gervais et al. (2002), Goel and Thakor (2008) also theorise that moderate overconfidence⁷⁵ mitigates the underinvestment problem. Goel and Thakor (2008) also find that overconfidence is disproportionately more prevalent in the top management team. Importantly, both research groups comment on the non-monotonic relationship between overconfidence (by their definition) and firm performance.

Hiller and Hambrick (2005) feature again because their hyper-CSE theory (section 2.2.4.2) predicts that the organisation's strategic decision-making process will be faster, more centralised, and less comprehensive under hubristic leadership. Strategic decision making of this "fast and frugal" type can be well suited to a context where information is unknown and information-processing capabilities are limited. That is the view, mentioned in section 2.1.5.4, of Gerd Gigerenzer and his colleagues (Gigerenzer & Gaissmaier, 2011; Gigerenzer & Todd, 1999; Goldstein & Gigerenzer, 1996)

The underinvestment mitigation theory is based on overprecision in that Gervais et al. (2002), Goel and Thakor (2008), and Hiller and Hambrick (2005) all specify overprecision in their definition of overconfidence. However, Gervais et al. (2002) also include optimism, hence overestimation, in their definition. Thus, we were challenged in interpreting whether the prediction of the non-monotonic relationship between overconfidence and firm performance applies to overestimation too. Bharati et al. (2016) base their empirical study on Goel and Thakor (2008)'s theory, which is based on overprecision, yet define overconfidence in the overestimation way. Bharati et al. (2016) find that overconfident⁷⁶ CEOs in their sample produce roughly higher annual stock returns than their non-overconfident counterparts.

73. Leng et al. use overconfidence in the overestimation way.

74. Gervais et al. use overconfidence in the overprecision way and optimistic in the overestimation way.

75. Goel and Thakor use overconfidence in the overprecision way.

76. Bharati et al. use overconfidence in the overestimation way.

In summary, although Gervais et al. (2002)'s definition of overconfidence includes optimism as well as overprecision, all three theoretical papers (Gervais et al., 2002; Goel & Thakor, 2008; Hiller & Hambrick, 2005) share the view that underinvestment is mitigated by moderate overprecision and hence moderate overprecision is favourable for shareholders.

2.2.4.5 Innovation and R&D propensity

This theme has its origin in two papers (Galasso & Simcoe, 2011; Hirshleifer et al., 2012) that appeared almost simultaneously and both of which were first published as working papers in 2010. Each of the final papers cited the working paper of the other. We based this theme off Galasso and Simcoe (2011)'s paper because it was published earlier and is theoretical, while Hirshleifer et al.'s is empirical. However, Hirshleifer et al.'s work is cited more often and seems to be the landmark paper when researchers mention this positive aspect of overconfidence.

Galasso and Simcoe (2011) theorise that overconfident⁷⁷ CEOs are more likely to take their firms in a new technological direction. The basis for their theory is that CEOs are aware that successful innovation is rewarded, and overconfidence encourages innovation by reducing a CEO's internal beliefs about the likelihood of failure. Hirshleifer et al.'s paper provides empirical support. For firms competing in innovative industries, they show that overconfident⁷⁸ CEOs are more effective at exploiting growth opportunities and translating them into firm value. Tang et al. (2015)'s study provides empirical support in that they show a positive relationship between executive hubris⁷⁹ and firm innovation. Hur, Kim and Cheung (2019) show a positive relationship between CEO overconfidence and R&D spend as a percentage of revenue in a context of declining sales.

Galasso and Simcoe (2011) and Hirshleifer et al. (2012) are cited extensively in the empirical literature. While the empirical studies support the theory that overconfident managers invest more in innovation and R&D, they do not always agree that this produces favourable outcomes for shareholders. We reference four studies here that all base their hypotheses of the relationship between overestimation and firm performance on the innovation and R&D propensity theory and cite Galasso and Simcoe (2011) and/or Hirshleifer et al. (2012). Three of the studies (Bharati et al., 2016; H. A. Kim et al., 2019; Mundi & Kaur, 2019) show a positive impact on firm performance, and one (S.-S. Chen et al., 2014) that shows a negative impact on firm performance. Bharati et al. (2016)'s favourable finding was mentioned in the previous section. H. A. Kim et al. (2019) shows that CEO overconfidence⁸⁰ is positively related with firm RONA⁸¹ and with stock performance. Mundi and Kaur (2019) find that firms with overconfident CEOs enjoy a higher return on assets and Tobin's Q. However, S.-S. Chen et al. (2014) show that, following an increase in R&D, stock performance is positive only for firms whose CEOs are not overconfident⁸² and, further, they find this to be the case even in high-tech industries. We also reviewed a study (M. Simon & Houghton, 2003) that was published well before Galasso and Simcoe's study, but nevertheless provides empirical support for their theory. M. Simon and Houghton find that overconfidence⁸³ was positively related to the degree to which new product introductions were pioneering. However, they

77. Galasso and Simcoe use overconfidence in the overestimation way.

78. Hirshleifer et al. use overconfidence in the overestimation way.

79. Tang et al. define hubris as an exaggerated belief in one's own judgment that deviates from objective standards, which seems to imply overestimation.

80. H. A. Kim et al. use overconfidence in the overestimation way.

81. Return on net assets.

82. S.S. Chen et al. define overconfidence in the overestimation and overplacement way, but measure it in the overestimation way only.

83. M. Simon and Houghton define overconfidence as "extreme certainty", which matches with overprecision.

also found that these products were less likely to achieve success, which conflicts with Hirshleifer et al.'s finding that overconfidence drives firm value.

What might explain these competing findings? Yu (2014) theorises that there is a trade-off between the strategic benefit of CEO overconfidence⁸⁴ leading to more R&D investment and the achievement of competitive advantage and overinvestment through the inefficient allocation of resources. Yu theorises that there is an inverse U-shape relationship, with moderate overconfidence delivering the most favourable results.

2.2.4.6 Motivation

The theoretical theme of motivation encompasses the motivational value that a manager's overconfidence confers on others as well as on themselves.

Taylor and Brown (1988) explore the impact of positive self-illusions, namely exaggerated perceptions of control and unrealistic optimism, on mental health. They find a beneficial relationship in that overconfident⁸⁵, optimistic people tend to be happier, more popular, more willing to help others, and more willing to persist in tasks. Gervais, Heaton, and Odean (2002, 2011) theorise that overconfident⁸⁶ managers are motivated to expend more effort because they overestimate the value of their effort. And they apply this effort to gather information and learn such that they improve the success rate and value of the firm's investments. Ackert and Deaves (2009) take a similar view to Gervais et al. when they state that moderate level of overconfidence⁸⁷ could have a positive impact provided overconfidence gives rise to concentrated efforts of the CEO.

This positive view presented by Taylor and Brown (1988), Gervais et al. (2002, 2011), and Ackert and Deaves (2009) contrasts with the views of other theorists. Goel and Thakor (2008) theorise that overconfidence leads to low information acquisition and hence less efficient investment decisions. And, as previously mentioned, Hiller and Hambrick (2005), theorise that overconfidence leads to faster and less comprehensive strategic decision-making.

Despite the theoretical inconsistency mentioned above, Gervais et al. (2002, 2011)'s effort expenditure theory appears to have some empirical support. From Phua et al. (2018) we read that the overconfident⁸⁸ manager believes the firm has valuable growth opportunities and therefore works harder. This work ethic is understood by employees and suppliers to translate into higher firm value, thus leading to better retention of talent and lower termination risk with suppliers. Further support comes from Hilary et al. (2016) who find that overconfident⁸⁹ managers appear to exert greater effort to meet their over-optimistic forecasts and in so doing increase firm value.

Shipman and Mumford (2011) define overconfidence in the overestimation way. They conceptualise and experimentally test two types of behaviours resulting from overestimating one's ability. The first is a failure to detect flaws and the second is holding overly optimistic beliefs. They find that the first behaviour is negative, but the second is positive for firm performance. Low levels of confidence, which is associated with seeing deficiencies, is critical to developing effective plans. However, they find that a positive impact on firm performance results from leaders holding overly optimistic beliefs in that

84. Yu uses overconfidence in the overestimation way.

85. Used here in the sense of overprecision.

86. In their earlier paper, Gervais, Heaton, and Odean refer to both optimism and overconfidence, which implies overestimation and overprecision, but in their later paper they refer only to overconfidence in the form of overprecision.

87. Ackert and Deaves use overconfidence in the overestimation way in this context, but also recognise the alternative forms of overconfidence.

88. Phua et al. uses overconfidence in the overestimation way.

89. Hilary et al. use overconfidence in the overestimation way.

expecting positive outcomes helps leaders to develop an inspirational vision that is appealing and motivating to followers.

2.2.4.7 Other

Since this section (2.2.4) reviews the implications of overconfidence, we would be amiss not to also reference the following studies. These studies do not fall neatly into any of our theoretical themes, but nonetheless demonstrate important effects of overconfidence.

Ben-David et al. (2013) find that managers who are miscalibrated, or have overprecision bias, about the stock market show similar miscalibration regarding their own firms' prospects. This finding suggests that overprecision in one domain transfers to another domain.

Schrand and Zechman (2012) find that overconfident⁹⁰ managers are more likely to intentionally misstate earnings. Schrand and Zechman find further empirical support in the studies conducted by Ahmed and Duellman (2013) and Bouwman (2014). J. E. Lee (2016) builds on Schrand and Zechman's study and finds that CEO overconfidence⁹¹ is positively associated with the existence of internal control weakness.

Schumacher et al. (2020) found that overconfident⁹² CEOs interpret information about their firm's performance more optimistically than non-overconfident CEOs. For positive feedback, they are more inclined to reduce their firm's risk taking, while for negative feedback, they are less inclined to increase risk taking, unless they are at risk of bankruptcy.

2.2.4.8 Conclusion

In conclusion, we saw that theories on the implications of overconfidence (overprecision and/or overestimation and/or overplacement) mostly predict discrete effects of overconfidence, for example the impact of overconfidence on capital structures or innovation. And we noted that sometimes these effects are positive for firm performance, sometimes negative, sometimes it is unclear whether the effect is positive or negative, and sometimes the effect is non-monotonic and hence might transition from positive to negative. These contrasting findings are true at the inter-theory level in that some theories are in opposition with each other, for example hubris theory and underinvestment mitigation theory. And, these contrasting findings are also true at the intra-theory level, for example the motivation theme includes researchers' theories that are in direct contrast with each other.

We recognised that it is possible, perhaps probable, that all these theories, despite their contrasting predictions, might have validity. How so? Firstly, context matters and hence a prediction might be true in one context, but not another and the context of each study differs in some ways to the other studies. Secondly, magnitude matters and hence the effect that a particular study finds might be real, but is swamped in the presence of a larger, opposing effect. Thirdly, metrics matter and certain effects might be more or less evident dependent on the metrics used. For example, different proxies would measure different effects.

This examination of theories on the implications of overconfidence (of each type) has revealed a set of theories that predict discrete effects which might, or might not, be compatible with each other. What appears to be missing is a unifying theory of the impact of overconfidence bias, in each of its forms, on firm performance. Such a unifying theory would ideally explain how these discrete predictions act together or in opposition to each other, it would potentially introduce other discrete effects, and it

90. Schrand and Zechman uses overconfidence in the overestimation way.

91. J. E. Lee defines overconfidence as the "better than average" effect, which implies overplacement.

92. Schumacher et al. use overconfidence in the overestimation way.

would describe the interactions and combined effects of the different types of overconfidence biases on firm performance. It might also explain the moderating and mediating factors between the overconfidence biases and firm performance. And it would describe any dynamic effects between the firm performance and the overconfidence biases, and between these biases. Arguably, a unifying theory could also incorporate other cognitive biases, such as confirmation bias, since we know that these biases can interact with each other (Moore & Bazerman, 2012b; Russo & Schoemaker, 1992).

When considering the theories from the perspectives of overprecision, overestimation, and overplacement, we noted that the theories are concentrated in overestimation, with some coverage in overprecision, and almost none in overplacement⁹³. From section 2.2.1 we learned that overestimation and overplacement have a negative relationship, whereby hard tasks produce the most overestimation and also produce the most underplacement, while easy tasks produce underestimation and overplacement. Since, as is evident from the definitions in section 2.1.3, strategy is a hard task, overestimation is more important to our study than overplacement. This, along with the lack of theory relating to overplacement and firm performance, led us to focus on overestimation and overprecision from this point on.

We are interested in the overall impact of overconfidence bias on decision quality and, ultimately, firm performance. We now consider the empirical and experimental literature in this regard.

2.2.5 Impact of overconfidence on firm performance

Since decision quality cannot easily be directly measured, we relied on firm performance as being representative of decision quality (see Figure 4). While this is improper for a single decision (as discussed in section 2.1.4), firm performance becomes a suitable proxy when enough decisions are being considered. We reviewed recent⁹⁴ studies that make an empirical or experimental assessment of the impact of overconfidence on firm performance.

Our research question is “what is the impact of group-level overestimation and overprecision biases on firm performance?” and, as discussed in section 2.1.7.2, we focused on the overconfidence of the management team making strategic decisions. Accordingly, we considered the impact of overconfidence bias on firm performance in these studies from four perspectives. First, is the overconfidence being studied that of an individual, typically the CEO, or is it the overconfidence of the group making the strategic decisions? Second, do the studies analyse a discrete or an overall impact of overconfidence bias? Third, which type, or types, of overconfidence are being assessed? Lastly, how is the possibility of reverse causality being addressed and what claims of causality of overconfidence on firm performance are these studies making?

Table 4 below summarises the studies that we discuss in this section. The studies are grouped into the type of impact on firm performance. Each study is summarised in terms of the type(s) of overconfidence⁹⁵ being studied, including overestimation (OE), overplacement (OL), and overprecision (OP); whether the CEO or group is demonstrating the overconfidence; and which dependent variable(s) is/are being analysed. See Appendix 7.2 for further detail of these studies.

93. We recognise that our searches related to overconfidence in the context of firm performance and hence we might have overlooked theories regarding overplacement if they were not related to firm performance. In fact, we see from Moore and Schatz (2017) that between 2008 and 2017, about 21% of the overconfidence studies have examined overplacement, although not necessarily in the context of firm performance. They found that the majority (60%) of the studies looked at overestimation and the balance (19%) examined overprecision.

94. Of the 31 empirical and experimental studies reviewed, one study was published in 1997, the other 30 were published in 2003 or later, with 26 of those published in the last decade.

95. When we encountered confusing definitions of overconfidence, we relied on the proxy(ies) of the study to classify the type(s) of overconfidence.

Study	OE	OL	OP	CEO / Group	Dependent variable(s)
Stock returns					
(Bharati, Doellman, & Fu, 2016)	x			CEO	Stock return performance
(Billett & Qian, 2008)	x			CEO	Buy and hold excess return
(Hayward & Hambrick, 1997)	x			CEO and Group	Cumulative abnormal returns
(H. A. Kim, Choi, & Choi, 2019)	x			CEO	RNOA ⁹⁶ , also ROE, ROI, ROA, <u>stock returns</u>
(Hilary, Hsu, Segal, & Wang, 2016)	x		x	CEO and Group	Buy-and-hold market-adjusted return
(Malmendier & Tate, 2008).	x			CEO	Merger frequency, merger value creation using <u>cumulative abnormal returns</u>
(S.-S. Chen, Ho, & Ho, 2014)	x			CEO	1, 3, and 5 year BHAR ⁹⁷
Price-to-book					
(Hirshleifer, Low, & Teoh, 2012)	x			CEO	Tobin's Q
(Li & Liu, 2012)	x			Group	Tobin's Q
(Mundi & Kaur, 2019)	x			CEO and Group	ROA and <u>Tobin's Q</u>
Accounting returns					
(Hilary, Hsu, Segal, & Wang, 2016)	x		x	CEO and Group	ROA
(H. A. Kim, Choi, & Choi, 2019)	x			CEO	<u>RNOA</u> , also ROE, ROI, <u>ROA</u> , stock returns
(Mundi & Kaur, 2019)	x			CEO and Group	<u>ROA</u> and Tobin's Q
(Park et al., 2018)	x			CEO	ROA in excess of the industry median ROA
Risk					
(Ho, Huang, Lin, & Yen, 2016)	x			CEO	Bank risk metrics
(Invernizzi et al., 2017)	x			Group	Risk of venture fail
(J. B. Kim, Wang, & Zhang, 2016)	x			CEO and Group	Stock price crash risk
(J. E. Lee, 2016)	x			CEO and Group	Internal control weakness
(Leng et al., 2018)	x			CEO	Bankruptcy risk
Other					
(Banerjee et al., 2018)	x			CEO	Stock repurchases
(Galasso & Simcoe, 2011)	x			CEO	Innovation measures

96. Return on net operating assets.

97. Buy-and-hold abnormal returns.

Study	OE	OL	OP	CEO / Group	Dependent variable(s)
(Hribar & Yang, 2016)	x		x	CEO	Likelihood of forecasting, optimism in forecasts, precision of the forecast
(Hwang, Kim, & Kim, 2018)	x			CEO	Deal completion, all cash offer
(M. C. Kim, Xiong, & Kim, 2017)	x			CEO	Spend on R&D, spend on advertising
(Lai, Lin, & Chen, 2017)	x			CEO	Full vs partial ownership
(Malmendier & Tate, 2005a)	x			CEO	Sensitivity of investment to cash flow
(Malmendier & Tate, 2015)	x			CEO	Corporate investment
(Malmendier, Tate, & Yan, 2011)	x			CEO	Debt vs equity funding
(Phua, Tham, & Wei, 2018)	x			CEO	Supplier and employee commitment
(Schrand & Zechman, 2012)	x			CEO and Group	Accounting, auditing enforcement releases
(Shipman & Mumford, 2011)	x			N/A	Inspiring vision
(M. Simon & Houghton, 2003)			x	CEO or 2IC	NPD success factors
(Tang, Li, & Yang, 2015)	x			CEO	Market performance of new products
(Zhao & Ziebart, 2017)	x			Group	Cost of borrowing

Table 4: Impact of overconfidence on firm performance.

2.2.5.1 Individual versus group overconfidence

As mentioned in sections 2.1.7.1 and 2.1.7.2, most strategic decisions are made by groups, rather than an individual. Thus, if we are interested in the impact of overconfidence on strategic decision making in firms, we need to consider the overconfidence expressed by the group making the strategic decision. We recognised that the CEO is often the most dominant individual in a group making strategic decisions, but ultimately it is the decision that emerges from the group that is of most relevance to this study.

We determined whether the study focuses on the overconfidence of the CEO, the group, or the CEO and the group. We made this determination by considering the proxies used for overconfidence. A common proxy is the options-trading behaviour of the CEO. This clearly measures the overconfidence of the CEO only. An example of a proxy measuring the group's behaviour is a management forecast. For a list of the proxies used and our characterisations of these, see Table 30 in Appendix 7.3.

Of these studies, most focus exclusively on the overconfidence of the CEO, while six studies (Hayward & Hambrick, 1997; Hilary et al., 2016; J. B. Kim et al., 2016; J. E. Lee, 2016; Mundi & Kaur, 2019; Schrand & Zechman, 2012) use proxies that represents both the CEO and the group's overconfidence, and three (Invernizzi et al., 2017; Li & Liu, 2012; Zhao & Ziebart, 2017) focus on the overconfidence of the group.

For our study, where we care about the overconfidence of the group making the strategic decision, we require proxies for group-level overestimation and group-level overprecision. The development and justification of these proxies is non-trivial and requires substantial analysis and argumentation. We dedicate a section (2.4) for this purpose.

2.2.5.2 Discrete versus overall impact

Discrete impact

We use the term "discrete" to refer to effects that we cannot easily translate into an overall impact on firm performance. Examples of discrete effects are the strength of internal controls, the emphasis on

advertising versus R&D, the propensity to acquire, and so on. Some discrete effect studies show a positive impact on firm performance, some show a negative effect, and others show an effect where it is unclear whether it is positive or negative for firm performance. The positive, negative, and unclear discrete effect studies that we reviewed are summarised below. Many of these studies have been previously referenced in section 2.2.4, but are repeated here for convenience.

The positive discrete effect studies are summarised below.

- Shipman and Mumford (2011) conducted an experiment where they found that excessive optimism helps a leader develop a vision that is appealing and motivating to followers.
- Phua et al. (2018) made 14,475 firm-year observations from the ExecuComp database between 1993 and 2011 and found that overconfident CEOs are better able to retain talent and have lower termination risk with suppliers.
- Tang et al. (2015) studied 2,820 Chinese manufacturing firms and 3,285 firm-year observations from US high-tech firms between 1995 and 2005 and show a positive relationship between executive hubris and firm innovation.

The unclear discrete effect studies are summarised below.

- Malmendier and Tate (2005a) studied 477 large publicly traded US firms from 1980 to 1994 and found that the investment behaviour of overconfident CEOs is more sensitive to cash flow than that of non-overconfident CEOs. The researchers went on to study firms in the Compustat database between 1996 and 2012 and made a similar finding regarding external financing costs (Malmendier & Tate, 2015).
- Galasso and Simcoe (2011) tested their own theory when they studied 450 US publicly traded companies and 627 CEOs from the years 1980 to 1994. They found a robust positive association between overconfidence and citation-weighted patent counts. Their results also suggested that overconfident CEOs are more likely to take their firms in a new technological direction.
- Hribar and Yang (2016) studied large U.S. firms covered by ExecuComp from 2001 to 2010 and found that overconfidence increases the likelihood of issuing a forecast, increases the amount of optimism in management forecasts, and increases the precision of the forecast.
- M. C. Kim et al. (2017) studied S&P 1500 firms between 1993 and 2007 and found that corporate managerial hubris predicts low strategic emphasis on advertising versus R&D.
- Lai et al. (2017) studied foreign market entries of U.S. firms between 2001 and 2014 and found that overconfidence drives an increased propensity for full over shared ownership in foreign market entry.
- Banerjee et al. (2018) constructed a firm-year panel dataset consisting of around 20,000 observations over the 1992–2011 period from the ExecuComp database and found that overconfident managers are more likely to substitute repurchases for dividends or capital expenditure.

The negative discrete effect studies are summarised below.

- J. E. Lee (2016) studied 8,933 firm-year observations from the Audit Analytics database, the ExecuComp database, and the Compustat database between 2004 and 2011 and found that CEO overconfidence is positively associated with the existence of internal control weakness.
- Hwang et al. (2018) made 13,754 U.S. firm-year observations over the 1996–2014 period and found that power-driven overconfident CEOs tend to complete more deals regardless of circumstances, do stock acquisitions, and make value-destroying acquisitions, relative to non-overconfident CEOs.

- Malmendier, Tate, and Yan (2011) inspected studied 477 large publicly traded U.S. firms from 1980 to 1994 and found that overconfident CEOs are less likely to issue equity than other CEOs.
- Schrand and Zechman (2012) reviewed 49 firms, from the 1990s and 2000s and found that overconfident executives are more likely to intentionally misstate earnings.
- M. Simon and Houghton (2003) studied 135 small computer firms that anticipated launching a product within the next 30 days and found that overconfidence was positively related to the degree to which new product introductions were pioneering. However, they also found that these products were less likely to achieve success.
- Zhao and Ziebart (2017) studied 708 firms that issued management earnings forecasts for the 14-year period beginning in 1996 and ending in 2009 and found that overconfidence increases the cost of debt.

These discrete studies largely align with the theoretical themes already discussed. They serve to illustrate many of the variety of effects that can result from overconfidence. However, what these studies cannot easily answer is: given this variety of effects, some of which are positive and some of which are negative for firm performance, what is the net or overall impact of overconfidence? To answer that question, we turn to the overall impact studies.

Overall impact

The positive overall effect studies are similar in many respects. All five investigate the impact of overestimation, with one study (Hilary et al., 2016) also considering overprecision as a mediating factor. As a measure of overestimation, all five of the studies use the options-trading behaviour of the CEO, four of them also use press characterisation, and two also use management forecast accuracy. They also differ in some important respects, specifically in their data set and their findings.

- Bharati et al. (2016) analysed ExecuComp's database from 1992 to 2010, used a binary proxy of overestimation based on options-trading behaviour of the CEO, and found that overconfident CEOs in their sample produce roughly 3.0% to 4.5% more stock return on an annual basis, depending on the return measure, relative to their non-overconfident counterparts.
- Hilary et al. (2016) analysed S&P 1500 firms between 1998 and 2010, measured overestimation using press characterisations and options-trading behaviour of the CEO, measured overprecision using the range width of the management forecast, and found that managers appear to exert greater effort to meet their over-optimistic forecasts and in so doing increase firm value.
- Hirshleifer et al. (2012) analysed 2,577 CEOs from 9,807 U.S. firm-year observations between 1993 and 2003, measured overestimation using press characterisations and options-trading behaviour of the CEO, and found that overconfident CEOs are more effective at exploiting growth opportunities and translating them into firm value, albeit only in innovative industries.
- H. A. Kim et al. (2019) analysed S&P 1000 firms between 1992 and 2010, measured overestimation using press characterisations and options-trading behaviour of the CEO, and found that CEO overconfidence is positively related to firm RONA and stock performance.
- Mundi and Kaur (2019) analysed Indian S&P BSE⁹⁸ 200 firms between 2000 and 2015, measured overestimation using press characterisations and options-trading behaviour of the CEO, as well

98. The BSE was formerly called the Bombay Stock Exchange. The S&P BSE 200 index is designed to measure the performance of the top 200 companies listed at BSE Ltd., based on size and liquidity across sectors.

as growth forecasts, and found that firms with overconfident CEOs enjoy a higher return on assets and Tobin's Q.

The negative overall effect studies are similar in that they all investigate the impact of overestimation. In addition, one study (Li & Liu, 2012) mentions overprecision and another (S.-S. Chen et al., 2014) mentions overplacement, but neither study operationalises these concepts. As a measure of overestimation, the ten studies are quite different in their use of proxies. They also differ in other important respects, specifically in their data set and their findings.

- Billett and Qian (2008) studied U.S. mergers and acquisitions announced between 1980 and 2002, resulting in 3,795 deals by 2,487 CEOs and found that CEOs tend to become overconfident after a successful acquisition, and, as a result, are more likely to follow it with acquisitions that negatively impact their firm's stock.
- Hayward and Hambrick (1997) studied U.S. public firms between 1989 and 1992 conducting 106 transactions and find losses in acquiring firms' shareholder wealth following an acquisition, and the greater the CEO hubris and acquisition premiums, the greater the shareholder losses.
- P.-H. Ho et al. (2016) analysed publicly listed U.S. banks from 1994 to 2009, measured overestimation using options-trading behaviour of the CEO, and found that during crisis years, banks with overconfident CEOs generally experienced more increases in loan defaults, greater drops in operating and stock return performance, greater increases in expected default probability, and higher likelihood of CEO turnover or failure than other banks.
- Invernizzi et al. (2017) analysed 203 micro and small firms operating in North West Italy, measured overestimation as the difference between budget estimates and actual results for EBITDA⁹⁹, equity, and borrowing costs, and found that overconfident individuals are more likely to start and develop new ventures and such ventures are also more likely to fail.
- J. B. Kim et al. (2016) analysed S&P 1500 firms between 1993 and 2010, measured overestimation using options-trading behaviour of the CEO along with firm investing and financing decisions, and found that firms with overconfident CEOs have a higher stock price crash risk.
- Leng et al. (2018) analysed 940 UK firms in sectors other than financial services in the 2000 to 2015 period, measured overestimation using stock-trading behaviour of the CEO, and found that CEO overconfidence increases the risk of bankruptcy, while moderate levels of confidence reduces it.
- Li and Liu (2012) analysed firms listed on the Shanghai and Shenzhen stock exchanges between 2007 and 2009, measured overestimation using management's performance prediction accuracy, and found that overconfidence and enterprise value are negatively correlated.
- Malmendier and Tate (2008) studied 477 large publicly traded U.S. firms from 1980 to 1994 and found that overconfident CEOs overpay for target companies and undertake value-destroying mergers.
- Park et al. (2018) analysed 200 largest firms listed on the Korea Stock Exchange for the years 2001 to 2008, measured overestimation using press coverage, award/certification records, and analysis of the CEO statement in annual report, and found that CEO hubris makes firms underperform in Korea.

99. Earnings before interest, tax, depreciation, and amortisation.

- S.-S. Chen et al (2014) analysed 477 large publicly traded US firms from 1980 to 1994, measured overestimation using options-trading behaviour of the CEO, and found that long-run stock performance is positive only for firms whose CEOs are not overconfident.

We see that the overall impact studies show opposing results. What might account for this inconsistency?

We considered whether the inconsistency might be due to the difference in the data sample (which firms in which years?) or in the methodology (what proxies and what estimating model?). This we could not answer conclusively. However, we found two studies (H. A. Kim et al., 2019; J. B. Kim et al., 2016) exploring the impact of overestimation using a similar data set (S&P 1000; S&P 1500), over a similar time period (1992-2010; 1993-2010), using similar proxies for overestimation (options-trading of the CEO; options-trading of the CEO plus firm investing and financing decisions). These studies are remarkable not just in their similarity¹⁰⁰, but in the fact that they found what appear to have opposing results. The first study (H. A. Kim et al., 2019) found that CEO overconfidence is positively related with firm RONA¹⁰¹ and with stock performance, while the second (J. B. Kim et al., 2016) found that firms with overconfident CEOs have a higher stock price crash risk. It is interesting to note that the second study reported its findings as “firms with overconfident CEOs” even though its proxy for overconfidence included investing and financing decisions which are typically not the exclusive decision of the CEO. Perhaps the different operationalisation of overconfidence by these two studies might explain the apparent opposition of their results. Notably, they differ on their dependent variable too (stock price crash risk is not the same as stock performance), so it is possible that the results are not truly opposing.

We have displayed numerous studies, some of them published in top-tier journals, with results that appear to be in direct contradiction. We examine this further in the next section.

2.2.5.3 Firm performance measures

In section 2.1.2 we discussed various measures of firm performance and their merits and demerits. We found that the overall impact studies measure firm performance in four categories, namely buy-and-hold and/or abnormal stock returns, Tobin’s Q, accounting returns¹⁰², and some form of risk measure¹⁰³. We noted that accounting returns are used by some of the studies, but none of the studies uses economic profit or its constituents like NOPAT, ROIC or CFROI. Table 5 below summarises the findings of the overall impact studies.

Performance measure	Positive relationship	Negative relationship
Stock returns	(Bharati et al., 2016) (H. A. Kim et al., 2019) (Hilary et al., 2016)	(Billett & Qian, 2008) (S.-S. Chen et al., 2014) (Malmendier & Tate, 2008) (Hayward & Hambrick, 1997)
Tobin’s Q	(Hirshleifer et al., 2012) (Mundi & Kaur, 2019)	(Li & Liu, 2012)

100. Right down to the last names of the lead authors!

101. Return on net assets

102. Measures used include return on assets and adjusted ROA, return on net operating assets.

103. Measures used include bank risk metrics, risk of venture failure, stock price crash risk, bankruptcy risk.

Performance measure	Positive relationship	Negative relationship
Accounting returns (industry-adjusted measures are shown with an *)	(Hilary et al., 2016) (H. A. Kim et al., 2019) (Mundi & Kaur, 2019)	(Park et al., 2018)*
Risk measure		(Ho et al., 2016) (Invernizzi et al., 2017) (J. B. Kim et al., 2016) (Leng et al., 2018)

Table 5: Firm performance measures used by overall impact studies.

Cross-referencing to Table 4, we saw all of these overall impact studies use the overestimation form of overconfidence, although Hilary et al. (2016) also considers overprecision, albeit as a mediating factor.

The key takeaway from this table is that, except for the studies that measure risk, for each measure of firm performance, there exist studies that show opposing results of the impact of overestimation on firm performance. It is perhaps unsurprising that there are opposing results. As discussed in the theoretical review of the impact of overconfidence (section 2.2.4) and in the empirical review of the discrete impacts (earlier in this section), overconfidence bias is a complex concept that drives both favourable and unfavourable effects.

That overconfidence has this dual nature, driving both favourable and unfavourable effects, has been recognised by researchers and referred to as the “bright-side” and “dark-side” (Burkhard, Siren, van Essen, & Grichnik, 2018; Hirshleifer et al., 2012; Malmendier & Tate, 2015; Phua et al., 2018; Picone et al., 2014; Resick, Whitman, Weingarden, & Hiller, 2009; Zeitoun et al., 2019).

As recently as 2018, the date of Burkhard et al. (2018)'s study, the net overall effect of the “bright-side” versus the “dark-side” was still recognised as an open question and even more recently, 2019, these terms were still in use regarding the implications of hubris (Zeitoun et al., 2019). Burkhard et al. (2018) claim to have answered the question using a meta-analytic technique and conclude that the relationship between CEO overconfidence and firm performance is positive. We challenged the relevance of this study's finding to our research question for two reasons. Firstly, the authors define overconfidence to be of the overestimation type, yet their meta-analytic approach appears to include not only overestimation studies, but overprecision and possibly overplacement¹⁰⁴ too. Secondly, their study focuses on the overconfidence of the CEO, which, as already mentioned (section 2.2.5.1), is somewhat displaced from our focus.

2.2.5.4 Type(s) of overconfidence impacting firm performance

Impact of overestimation

Considering Table 4 and Table 5, we noted that most of the experimental and empirical studies operationalised overconfidence exclusively in the overestimation way and that the overall effect of overestimation on firm performance remains an open question.

Impact of overprecision

Considering Table 4, we noted that Hilary et al. (2016) also considers overprecision, as does Hribar et al. (2016), but neither of these studies analyses the direct impact of overprecision on firm performance. Hilary et al. (2016)'s study considered overprecision as a mediating factor on overestimation, while

104. We cannot know for sure because the list of studies covered is not included in their paper. Some of the studies are referred to, giving evidence that at least overprecision studies are included in their analysis.

Hribar et al. (2016)'s study explored overprecision as the dependent variable in that they considered how overestimation drives a narrower management forecast range.

However, M. Simon and Houghton (2003) did consider the direct impact of overprecision. They found that overconfidence was positively related to the degree to which new product introductions were pioneering, but also found that these products were less likely to achieve success.

In summary, despite a theoretical basis for believing that moderate overprecision positively impacts firm performance, as described in section 2.2.4.4, we have not found empirical support for this theory.

Combined impact of overestimation and overprecision

Moore and Healy (2008) argue that the three types of overconfidence, namely overestimation, overplacement, and overprecision, are conceptually and empirically different. The claims that overestimation and overprecision are distinct concepts that interact finds empirical support in Hribar and Yang's study (2016) and in Merkle's study (2017).

With regard to the combined effects of overestimation and overprecision, we found one study (Moore & Healy, 2008) which theorises on the relationships between overestimation, overprecision, and overplacement, and then tests these theories experimentally. Their findings are that overprecision appears to be more persistent than either of the other two types of overconfidence, but its presence reduces the magnitude of both overestimation and overplacement.

Moore and Healy's (2008) findings suggest that there is likely an interaction effect between overestimation and overprecision. However, it is unclear what that effect will be, because different studies find different relationships. For example, three studies recognise that overprecision and overestimation are distinct, but Moore and Healy (2008) find a negative relationship, Merkle (2017) finds no relationship, and Hribar and Yang (2016) find a positive relationship. Furthermore, we have not found any study, the aforementioned three included, that examines the combined impact of overestimation and overprecision on firm performance.

Non-monotonic impact

From the theories discussed, we noted that Gervais, Heaton, and Odean (2002), Hackbarth (2008), and Goel and Thakor (2008) all theorise a non-monotonic relationship between overprecision and firm performance, with a moderate level of overprecision being most favourable. Gervais et al. (2002) recognize that overprecision motivates managers to expend more effort, but too much overprecision leads to the manager overlying on her imperfect information. Hackbarth (2008) predicts that a moderate level of overconfidence¹⁰⁵ will result in a capital structure that is more favourable for shareholders than an unbiased manager, but a high level of overconfidence is detrimental to firm value because of the increased bankruptcy risk. Goel and Thakor (2008) argue that moderate overprecision will mitigate underinvestment, but sufficiently high overprecision will lead to overinvestment. They also note that being overly diffident will not address the underinvestment risk and hence their theory suggests a "sweet spot" in the extent of overprecision.

As mentioned above, we have not found any empirical study other than M. Simon and Houghton (2003) that measures the relationship between overprecision and firm performance and this study measures a discrete effect, rather than an overall effect. As such, we saw a gap in the literature regarding an empirical analysis of the non-monotonic relationship between overprecision and firm performance.

Regarding overestimation, we found a theoretical argument for a non-monotonic relationship to outcomes from Johnson et al. (2011) and Yu (2014). In the context of war, Johnson et al. (2011) recognise limits to overestimation in that it improves outcomes, but only to the point when the costs

105. Hackbarth considers both overestimation and overprecision.

become too high. Consistent with Hirshleifer et al. (2012), Yu (2014) finds a trade-off between the benefits of overestimating, which leads to more R&D investment, and overinvesting, where too much investment results in an inefficient allocation of resources. This trade-off produces an inverse U-shaped relationship of what they refer to as strategic benefit and overconfidence. Gervais et al. (2002) and Hackbarth (2008) consider overconfidence in the overestimation and overprecision ways and they theorise on a non-monotonic relationship between overestimation (and overprecision as mentioned above) and firm performance. Gervais et al. (2002) note that optimism makes managers more willing to undertake risky projects and hence mitigates the underinvestment risk, but too much optimism results in the manager exaggerating her chances of success and hence sometimes undertaking negative NPV projects. Hackbarth (2008)'s argument is provided above.

Despite the theoretical arguments for non-monotonicity between overestimation and firm performance, we have not found empirical support for this argument. This might be because many of the empirical studies use a proxy for overestimation that is “blunt” in that it is either binary or trinary. A binary proxy takes on two values: overconfident or not. A trinary proxy takes on three values: overconfidence, justifiable confidence, diffidence. Such a blunt instrument cannot resolve the subtlety of a non-monotonic relationship.

It is possible to operationalise overestimation in a higher fidelity way¹⁰⁶. Three studies (Hilary et al., 2016; Invernizzi et al., 2017; Park et al., 2018) have done so. While these studies have commented on the impact of overestimation on firm performance, they have not attempted to offer a nuanced interpretation of the level of overestimation that delivers the best firm performance. It is also possible to operationalise overprecision in a high fidelity way, for example Hilary et al. (2016) use overprecision as a mediating factor and they operationalise it as a continuous variable.

The non-monotonic nature of the relationship between both overestimation and firm performance and overprecision and firm performance, along with the likely interaction effect between overprecision and overestimation suggests that there might be a “goldilocks” zone where just the right amount of overprecision and just the right amount of overestimation deliver the most favourable outcomes for shareholders. In other words, there might be a target spot or zone in the two-dimensional space illustrated below.

		Estimation	
		Under-	Over-
Precision	Over-	I know just how bad it will be	I know just how good it will be
	Under-	It will be bad, but I don't know how bad	It will be good, but I don't know how good

Figure 5: The space of overestimation and overprecision.

In summary, we have not found a study that provides a fine-grained analysis of the extent of overestimation that maximises firm performance. We have also not found a study with a fine-grained analysis of the impact of overprecision. And, by extension, we have not found a study that identifies the optimal point in the two-dimensional space of overestimation and overprecision to maximise firm performance.

106. To be discussed in the Method chapter.

2.2.5.5 Causality

Due to regression analyses expressing correlations, but not causality, we considered how the overall impact studies are addressing the question of a causal link between overconfidence (overestimation and overprecision) bias and firm performance.

Many of the studies (Bharati et al., 2016; S.-S. Chen et al., 2014; Hilary et al., 2016; J. B. Kim et al., 2016; Park et al., 2018) deal with the reverse causality risk by imposing time lags between the independent and dependent variables. The other studies control for possible endogeneity or simultaneity issues (P.-H. Ho et al., 2016; H. A. Kim et al., 2019) or propose alternative mechanisms (Hirshleifer et al., 2012; Leng et al., 2018) to explain the reverse causality and show that it is improbable.

While many of the studies address the risk of reverse causality, none of them make strong claims on the presence of forward causality.

2.2.6 Summary of issues in the literature

In developing our conceptual model and reviewing the related literature we found notable gaps and inconsistencies which are summarised below:

1. The four approaches (political, rational, intuition, heuristics) to strategic decision making appear to have strengths and weaknesses depending on the context, although in many cases researchers' views are still contested and hence there appears to be no generally accepted set of best practices.
2. There is a lack of clarity and consistency in the definition of overconfidence bias, leading to an inconsistent application in empirical work, which makes it difficult to make comparable interpretations of much of the research.
3. Following from above, some researchers recognise the distinct types of overconfidence, but have conflicting views on the nature of the relationship between overestimation and overprecision.
4. There is no unifying theory of the impact of overconfidence bias on firm performance. A unifying theory would ideally integrate the discrete theories, potentially introduce other discrete predictions, describe the interactions and combined effects of the different types of overconfidence biases, explain the moderating and mediating factors, and describe any dynamic relationships.
5. Most studies on the impact of overconfidence on firm performance, focus on the overconfidence of the CEO, with a paucity of studies that focus on the overconfidence of the group making the strategic decision.
6. Most studies derive a proxy for overestimation from the option-trading behaviour and/or the press characterisations of the CEO, with few studies deriving overconfidence proxies from group-level behaviour.
7. Researchers acknowledge that there is a "bright-side" and a "dark-side" to overconfidence, but the relative strengths of the two sides remains an open question as researchers are divided in their view of the overall effect.
8. Of the studies that investigate the overall impact of overconfidence on firm performance, we noted that accounting measures are commonly used, but we have found no studies that use economic profit or its constituent drivers, spread and growth.
9. We found a theoretical argument for a non-monotonic relationship between overestimation and firm performance, but most empirical studies do not use a sufficiently granular proxy to locate the optimal level of overestimation.

10. Despite a theoretical basis for believing that there is a relationship between overprecision and firm performance, there is a gap in empirical support for this theory.
11. Furthermore, there is a gap in empirical studies on the combined impact of overestimation and overprecision on firm performance.
12. We have not found a study that claims a causal link between overconfidence, in any of its forms, and firm performance.

From our review of theoretical, experimental, and empirical literature, we postulated that overconfidence bias, in the forms of overestimation and overprecision, will be present when groups are making strategic decision making, will affect the quality of those decisions, and hence will impact firm performance. Directed by our research question “what is the impact of group-level overestimation and overprecision biases on firm performance?” and the gaps and inconsistencies listed above, we now develop hypotheses in these respects.

2.3 Hypothesis development

Our overarching research question is: **What is the impact of group-level overestimation and overprecision biases on firm performance?** We illustrated this question in our conceptual model (see [Figure 4](#)) that shows how the overconfident behaviour of management teams influences their strategic decision-making process, which then impacts the quality of strategic decisions that are made, which ultimately impacts firm performance.

Using this conceptual model and with consideration to the gaps and inconsistencies in the literature, we decomposed our research question into three sub-questions to explore the independent and combined treatment of overestimation and overprecision.

What is the impact of group-level overestimation and overprecision biases on firm performance?

1. What is the impact of group-level overestimation bias on firm performance?
2. What is the impact of group-level overprecision on firm performance?
3. What is the combined impact of group-level overestimation bias and group-level overprecision bias on firm performance?

We drew on the theoretical themes of the implications of overconfidence (section 2.2.4) and the empirical studies of the impact of overconfidence on firm performance (section 2.2.5) to develop the hypotheses that will serve to answer these questions.

2.3.1 Presence

Given that overestimation and overprecision are pervasive ([Anderson, Brion, Moore, & Kennedy, 2012](#); [Griffin & Varey, 1996](#); [Johnson & Fowler, 2011](#); [Plous, 1993](#); [Radzevick & Moore, 2010](#); [Skafa, 2008](#)), are disproportionately more prevalent in the top management team ([Goel & Thakor, 2008](#)), and are likely to persist when groups are making strategic decisions ([Ben-David et al., 2013](#); [Finkelstein et al., 2009](#); [Meikle et al., 2016](#)), we assumed that we would find evidence of overestimation and overprecision in strategic decisions. We report on this in our descriptive statistics.

2.3.2 Impact

Given the assumed presence of overestimation and overprecision, we considered what impact it has on firm performance. For convenience, we summarise our findings of our review of theoretical (section 2.2.4) and empirical studies (section 2.2.5) that pertain to firm performance in [Table 6](#) below. The studies that describe a non-monotonic relationship are indicated with an asterisk.

Theory	Nature of study	Overestimation	Overprecision
Hubris theory	Theory	Overestimating managers overinvest and perhaps also underinvest, thus are not investing in shareholders' best interests as they are making investments that are value destructive and forgoing value creating investments (Hayward et al., 2006; Heaton, 2002; Malmendier & Tate, 2005b, 2015; Roll, 1986).	
	Empirical	Negative (P.-H. Ho et al., 2016) (Hwang, Hyoseok et al., 2020) (Invernizzi et al., 2017) (J. B. Kim et al., 2016) (Malmendier & Tate, 2008) (Park et al., 2018)	
Hyper-CSE	Theory		CEO's overprecision leads to a greater number and scale of large-stakes initiatives, more deviation of the organisation's strategy from the central tendencies of the industry, greater persistence in pursuing the CEO's strategy, and, ultimately, more extreme performance (Hiller & Hambrick, 2005).
Capital structures	Theory	Managers who overestimate and/or are overprecise will believe their firm to be undervalued and will consequently adopt capital structures with more debt leverage (Deshmukh et al., 2013),(Hackbarth, 2008)*.	
	Empirical	Negative (Leng et al., 2018) (Malmendier et al., 2011)	
Under-investment mitigation	Theory	Overprecise and overestimating managers will make them less likely to postpone the decision to undertake, more willing to undertake, and quicker to undertake, risky projects (Gervais et al., 2002).	
			Underinvestment is mitigated by moderate overprecision and hence moderate overprecision is favourable for shareholders (Goel & Thakor, 2008)*,(Hiller & Hambrick, 2005)
	Empirical	Positive (Bharati et al., 2016)	

Theory	Nature of study	Overestimation	Overprecision
Innovation and R&D propensity	Theory	Overestimating managers innovate more, but it is unclear whether the ROI is positive or negative (Galasso & Simcoe, 2011; Yu, 2014).	
	Empirical	Positive (Tang et al., 2015) Mixed (Hirshleifer et al., 2012)* Negative (S.-S. Chen et al., 2014)	Negative (M. Simon & Houghton, 2003)
Motivation	Theory	Managers who overestimate and/or are overprecise will expend more effort such that they improve the success rate and value of the firm's investments. They also improve talent retention and supplier relationships. (Gervais et al., 2002, 2011; Shipman & Mumford, 2011)	
	Empirical	Positive (Hilary et al., 2016) (Phua et al., 2018)	

Table 6: Theoretical and empirical summary of the impact of overconfidence on firm performance.

2.3.2.1 Impact of overestimation

Inspecting our summary of theoretical and empirical studies (Table 6), we noted that the relationship between firm performance and overestimation is predicted to be negative by hubris and capital structure theories, yet positive by underinvestment mitigation and motivation theories, and possibly positive by innovation and R&D propensity theory. The empirical evidence largely follows this pattern, although the innovation studies have conflicting positive and negative findings, and one study recognises a non-monotonic relationship.

Of these theories, only hubris theory and innovation and R&D propensity theory focus on overestimation exclusively. The other theories confound overestimation and overprecision or focus exclusively on overprecision. As such, we gave precedence to hubris theory and innovation and R&D propensity theory. From innovation and R&D propensity theory, we learned that overestimating managers innovate more, but it is unclear whether the ROI is positive or negative (Galasso & Simcoe, 2011; Yu, 2014). Moreover, the empirical studies in this respect show conflicting results. Thus, it is only hubris theory that provides an unambiguous prediction and is unambiguously supported by empirical studies. These unambiguous findings show a negative relationship between overestimation and firm performance¹⁰⁷. Consequently, we hypothesised a negative relationship:

Hypothesis 1a. The relationship between overestimation and firm performance is negative.

As mentioned in section 2.2.5.4 - **Non-monotonic impact**, we found a theoretical argument for a non-monotonic relationship to firm performance from Johnson et al. (2011) and Yu (2014) and we also found partial empirical support in Hirshleifer et al. (2012)'s study where they show a non-monotonic

107. We noted that, despite the confounding with overprecision, this negative relationship is consistent with capital structures theory.

relationship between overestimation and R&D spend. As such, we hypothesised that while the overall relationship will be negative, a more fine-grained analysis will reveal non-monotonicity.

Hypothesis 1b. The relationship between overestimation and firm performance is non-monotonic.

2.3.2.2 Impact of overprecision

Inspecting our summary of theoretical and empirical studies (Table 6), we noted a scarcity of empirical analysis on the relationship between firm performance measures and overprecision. In fact, the only such study we have found is on the relationship between overprecision and the introduction of pioneering products (M. Simon & Houghton, 2003). Although we had little empirical analysis to draw on, the theories allowed some inference for hypothesis setting.

The impact of overprecision on firm performance is theorised in hyper-CSE, capital structure, underinvestment mitigation, and motivation theories. However, like with overestimation, we faced the challenge of the confounding of overestimation and overprecision. Only the hyper-CSE and underinvestment mitigation themes offered theories that are exclusively focused on overprecision. Hyper-CSE predicts more extreme performance but does not offer a prediction on whether overprecision will have a positive or negative relationship to firm performance. Underinvestment mitigation theory predicts that moderate overprecision is favourable for shareholders. With no other theory to lean on, we developed our overprecision hypotheses as below:

Hypothesis 2a. The relationship between overprecision and firm performance is positive.

Hypothesis 2b. The relationship between overprecision and firm performance is non-monotonic.

2.3.2.3 Combined impact of overestimation and overprecision on firm performance

In order to hypothesise on the combined impact of overestimation and overprecision on firm performance, we first considered the relationship between overestimation and overprecision. We saw that researchers are divided on the relationship between overestimation and overprecision, with Moore and Healy (2008) finding a negative relationship, Merkle (2017) finding no relationship, and Hribar and Yang (2016) finding a positive relationship. Gervais et al. (2002) also take the view of a positive relationship as they state that “these two traits will often go hand in hand”. We will report on the relationship between overestimation and overprecision in our descriptive statistics.

Theorists who define overconfidence to include both overestimation and overprecision are found in hubris theory (Hayward et al., 2006), in capital structure theory (Hackbarth, 2008), in underinvestment mitigation theory and in motivation theory, where Gervais et al. (2002) features in both. While Hayward et al. (2006) does not predict overall firm performance, the other theorists do, and they are consistent in their prediction that moderate overestimation and moderate overprecision is most favourable for firm performance.

This theoretical prediction is partly inconsistent with our hypotheses to date since, although we anticipated a non-monotonic aspect, we expected firm performance to be maximised for negative, or moderately negative, overestimation. As mentioned, we had not found any empirical study that examines the combined impact of overestimation and overprecision on firm performance, so our hypothesis was based on the above-mentioned theoretical prediction and our hypotheses 1a, 1b, 2a, and 2b. While hypotheses 1b, 2a, and 2b are all consistent with the theoretical prediction of moderate overestimation and moderate overprecision being best, hypothesis 1a is in conflict. We chose to retain internal consistency with our hypotheses and hence hypothesised as:

Hypothesis 3. Firm performance is maximised when there is moderate negative overestimation and moderate positive overprecision.

Before we progress into chapter 3, where we will discuss our methods for testing these hypotheses, we return to the topic of proxy development. We noted in section 2.2.5.1 that we require proxies for group-level overestimation and group-level overprecision. The following section is dedicated to the theoretical aspects of proxy development, while the operationalisation of the proxies will be covered in chapter 3.

2.4 Proxy conceptualisation

As mentioned in section 2.2.5.1, most studies of the impact of overconfidence on firm performance focus exclusively on the overconfidence of the CEO. Our interest is in the overconfidence of the management team making strategic decisions for their firm. More specifically, the constructs we sought to measure are the overestimation and the overprecision expressed by the group making their firm's strategic decisions.

To characterise this in more detail, we recognised that strategic decisions are the product of a group of people interacting over a period of time in some process that results in decisions being made. The people involved in this process might be as few as a single individual, but is often a dominant coalition of executives (Finkelstein et al., 2009), and might extend to individuals beyond the top management team, for example independent auditors, external counsel, audit committee, disclosure committee, and the board of directors. The respective contribution from individuals will be dependent on their role in the decision-making process and their political power in that context. The process that is followed and the level of effort applied will differ for different decisions and might have political, rational, intuitive, and heuristic elements (section 2.1.5).

The latent variables of overestimation and overprecision bias are innately present, to a lesser or greater extent, in the individuals involved in the strategic decision-making process and they might manifest at the group-level. How these biases manifest at the group-level and how they impact the strategic decision-making process is largely opaque. In sections 2.1.7.1 and 2.1.7.2, we discussed the literature that has attempted to answer this question. In summary, there is no clear answer, in fact there are mixed results with some studies showing that cognitive biases are sometimes attenuated and sometimes amplified in group decision making. However, Meikle et al. (2016) found that *"overconfidence is present in and affects organizations"*. Thus, it is unsurprising that there have been more than one hundred studies of overconfidence bias in organisational settings where effects have been reported. Given the elusiveness of the concept, it is also unsurprising that findings of the overall effects of overconfidence on firm performance have yielded mixed results (see Table 5).

To have a perfect measure of overestimation and overprecision would be practically impossible. It would require measuring the contribution of everyone involved in the decision-making process at every point of their involvement. It would then require revising each of those contributions to the perfectly calibrated contribution that the same person would have made if they had displayed no overestimation and no overprecision. Since there are dynamic relationships between contributions, with one person's contribution influencing another person's contribution, the counterfactual of the perfectly calibrated contributions and their interactions would need to be modelled. Then, in theory, this model would give rise to the perfectly calibrated decision, which can be contrasted to the actual decision that was made. This comparison could yield a measure of the overestimation and a measure of the overprecision resulting from the group's decision-making process.

Clearly, achieving such a measure cannot be operationalised today and perhaps will never be possible. An alternative might be interviewing managers, but this suffers validity and reliability issues due to memory fallibility and attribution bias. Since we cannot directly observe cognitive biases like overconfidence, we need to rely on a measurable artefact that represents the effect of the bias (Sibony et al., 2017). As such, we needed to find proxies or observed variables that can represent the underlying variables.

There have been many studies of overconfidence, mostly of overestimation and some of overprecision, and they have used a variety of proxy variables, which we will now describe. Following this, we will introduce our overestimation and overprecision proxies. Then, we will assess whether our definitions meet the theoretical and empirical requirements of a good proxy.

2.4.1 Proxies used in overconfidence studies

When reviewing how overestimation and overprecision has been operationalised in other empirical studies, we noted that numerous proxies have been used. Broadly, we grouped proxies into those that measure overconfidence at the level of the individual, typically the CEO, and those that measure overconfidence at the level of the firm. We also characterised the proxy as being based on objective or subjective data and on whether the underlying data is publicly available. The proxies and their characteristics are summarised in Table 7. Some of the studies we reviewed used a single proxy, but others used more than one proxy, and they sometimes used a combination of individual-level and firm-level proxies.

Overconfidence bias proxy	OE ¹⁰⁸	OP ¹⁰⁹	Group- or individual-level	Objective or subjective	Public or non-public data
Stock trading	x		Individual	Objective	Public
Options trading	x	x	Individual	Objective	Public
Press coverage	x	x	Individual	Subjective	Public
Market predictions ¹¹⁰		x	Individual	Objective	Non-public
CEO relative compensation	x	x	Individual	Objective	Public
CEO tone in calls, reports, tweets	x		Individual	Subjective	Public
Recent firm performance / awards	x	x	Group	Objective	Public
Investment and capital decisions	x		Group	Objective	Public
Management budget / forecast ¹¹¹	x	x	Group	Objective	Public / non-public

Table 7: Characteristics of overconfidence bias proxies.

The individual-level proxies are the stock trading behaviour of the CEO (Barros & da Silveira, 2007; Leng et al., 2018; Malmendier & Tate, 2008), the option-trading behaviour of the CEO (Banerjee et al., 2018; Hwang, Hyoseok et al., 2020; H. A. Kim et al., 2019; Phua et al., 2018), how press coverage characterises the CEO (Banerjee et al., 2018; H. A. Kim et al., 2019; Mundi & Kaur, 2019; Park et al., 2018; Phua et al., 2018), the market predictions made by senior executives (Ben-David et al., 2013; Merkle, 2017), the CEO's compensation relative to others (G. Chen et al., 2015; Hayward & Hambrick, 1997), and the CEO's tone in calls, reports and tweets (J. M. Lee et al., 2017; Park et al., 2018).

108. OE = overestimation

109. OP = overprecision

110. Individual investors at a large bank in the United Kingdom were asked for their return expectations and risk perceptions regarding the UK stock market and their own portfolios (Merkle, 2017). The proxy was based on actual market returns versus CFOs predicted 80% confidence intervals of market returns (Ben-David et al., 2013).

111. In some cases this is public data, but in other cases it is not public data, e.g. budget estimates and actual results for EBITDA, owner equity and borrowing costs that were gathered from small and micro private firms (Invernizzi et al., 2017).

Group-level proxies are less commonly used. Of the empirical studies that we reviewed, we found overconfidence proxies based on recent firm performance or awards (G. Chen et al., 2015; Hayward & Hambrick, 1997; Park et al., 2018), the investment and capital decisions made (J. B. Kim et al., 2016; J. E. Lee, 2016; Schrand & Zechman, 2012), and management budgets or forecasts (G. Chen et al., 2015; Hayward & Fitzg, 2017; Hilary et al., 2016; Hribar & Yang, 2016; Invernizzi et al., 2017; J. M. Lee et al., 2017; Li & Liu, 2012; Mundi & Kaur, 2019).

2.4.2 Our proxies

In our study we sought proxies for overestimation and overprecision for the group making the firm’s strategic decisions. We chose to explore the use of management earnings forecasts for the derivation of our proxies. Management earnings forecasts are group-level, objective, and publicly available. Conveniently, they can also serve as a basis for both overestimation and overprecision bias.

Figure 6 provides a conceptual illustration of overestimation and overprecision with respect to management earnings forecasts. The actuals are depicted by a dotted line that is intended to represent the position and range of the actuals that an objective assessment would yield assuming that it was possible to make such an objective assessment. In other words, the dotted line is intended to serve as a pseudo-confidence interval.

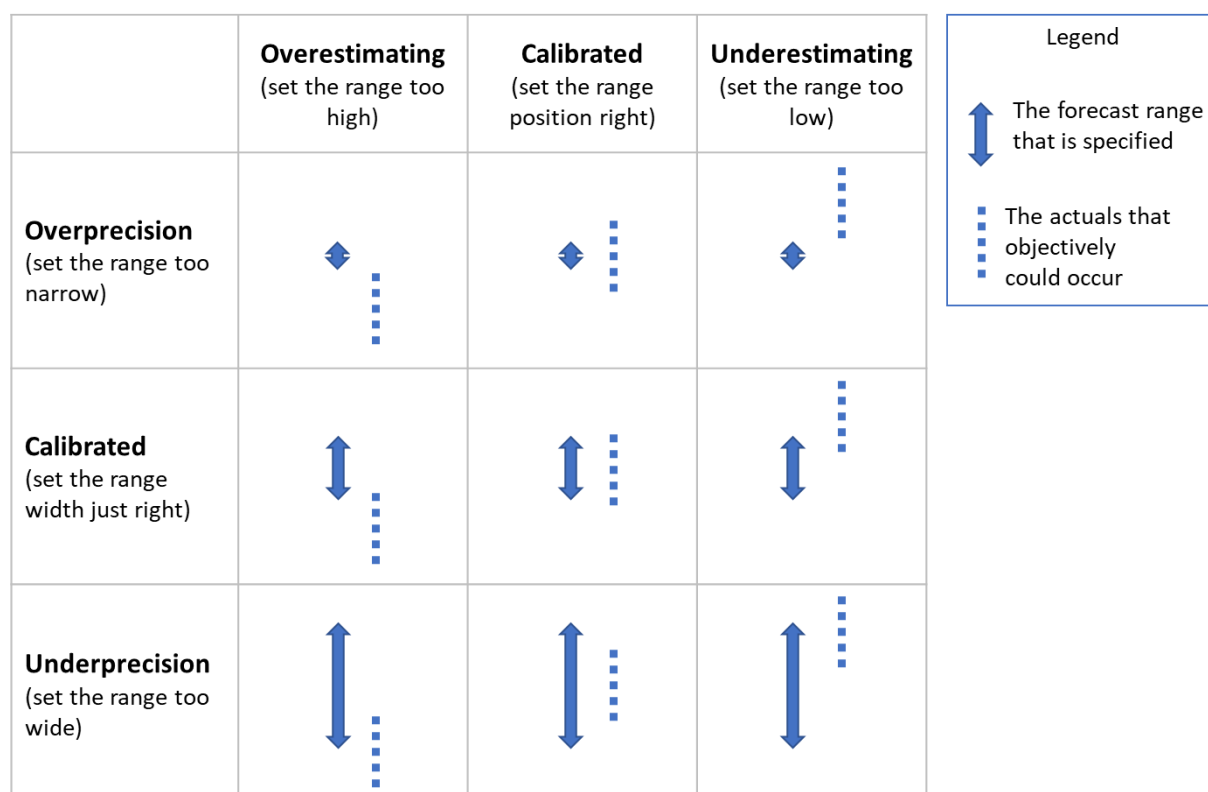


Figure 6: Conceptual illustration of overestimation and overprecision using earnings forecasts.

Overestimation occurs when the forecast range is set too high in comparison to the expected actuals. Underestimation might also occur; this is when the forecast range is set too low. The forecaster is “calibrated” when the forecast range is positioned correctly, such that actuals are equally likely to fall above or below the forecast range. We developed a group-level overestimation proxy by contrasting management earnings forecasts to actuals. The specific operationalisation is discussed in section 3.4.1.

Overprecision occurs when the forecast range is too narrow given the degree of uncertainty of the actuals. The forecaster is “calibrated” when the width of the forecast range matches the expected variance of the actuals. As Figure 6 illustrates, underprecision is also theoretically possible and this

occurs when the forecaster creates a forecast range that is too wide for the expected variance of the actuals. The conventional approach of computing overprecision¹¹² is not possible because management do not provide confidence intervals when issuing a range forecast. Yet, a proxy for overprecision can be calculated from management earnings forecasts by considering the width of the forecast range that management issue. We developed a group-level overprecision proxy by using the forecast range width. The specific operationalisation is discussed in section 3.4.2.

Given that our results will have a critical dependency on these proxies, that we are deviating from the most used overconfidence proxies, and that the concept of earnings forecasts is readily criticised for gaming, we are compelled to justify our choice. To do so, we applied the criteria of latent variable theory (Borsboom, 2008) to perform a quality assessment of our proxies. We also performed a quality assessment on the most used overestimation proxy, the options-trading behaviour of the CEO, to contrast how it performs relative to our overestimation proxy.

2.4.3 Theoretical requirements of a good proxy

From latent variable theory, we noted that proxies are observed variables that aim to represent latent variables (Borsboom, 2008). Borsboom (2008) distinguishes between observed and latent variables based on their epistemic accessibility: “*observed variables are somehow epistemically accessible to the researcher, whereas latent variables are not epistemically accessible*”. This means that the measurement of an observed variable can be inferred with certainty from the data, while measurement of a latent variable cannot be made with certainty. According to Borsboom (2008), three requirements must be met in order to treat a data structure as an observed variable of an underlying latent variable.

Firstly, the data structure must have a deterministic dependence. This means that the latent variable must have a causal relationship to the observations in the data structure. Secondly, the latent variable should be the only causally relevant structure at work producing variation in the data structure. Lastly, the number of distinct data patterns of the observed variable should be the same as the number of distinct positions of the latent objects. These three requirements are labelled by Borsboom (2008) as determination, causal isolation, and equivalent cardinality.

In addition to Borsboom (2008)’s three requirements, we also considered the relationship between our proxy and a proven, commonly used proxy.

2.4.4 Quality assessment of our proxies

From the above section, we noted the three theoretical criteria for a good proxy as determination, causal isolation, and equivalent cardinality. And, given the volume of literature on overconfidence based on other proxies, we considered the relationship between a proxy derived from management earnings forecasts and a well-established proxy. To test whether our overestimation and overprecision proxies fulfil these criteria we considered these four questions:

112. Overprecision is typically computed by an objective probabilistic analysis, i.e. determining the number of times that actuals fall within a confidence interval range, e.g. for an 80% confidence interval an estimator is considered to be well calibrated if 8 of her 10 estimates fall within the range, and considered to be overprecise if less than 8 fall within that range (Moore & Healy, 2008). Since management are not formally defining their range as a confidence interval, it is not possible to do an objective probabilistic analysis. However, it seems reasonable that the absolute difference from the point estimate or the closest bounds of the range offers a measure of overprecision. So, by necessity, we will use a different method, and this is noted as a limitation.

- Does overconfidence¹¹³ in the group's strategic decision-making cause overconfidence in management earnings forecasts?
- Are there any other structures at work that produce variation in the management earnings forecasts?
- Is there equivalence in the cardinality of group's strategic decision-making overconfidence and management earnings forecast overconfidence?
- Does an overestimation proxy derived from management earnings forecast correlate with another measure that has been shown to be a suitable measure of the latent effect?

2.4.4.1 Determination

We do not claim that overconfidence in the group's strategic decision-making causes overconfidence in management earnings forecasts, but we do argue that overconfidence is likely to be present and persistent in those making strategic decisions and if it is present in that domain, it is also likely to be present in the domain of developing and issuing earnings guidance. The substantiation for this argument is provided below.

Moore and Bazerman refer to overconfidence as "the mother of all biases" (2012a, p. 14) for two reasons: "overconfidence effects are some of the most potent, pervasive, and pernicious of any of the biases", and "overconfidence facilitates many of the other biases". Besides for potent, pervasive, and pernicious, it seems that we can add "persistent" for both overprecision and overestimation. Ben-David et al. (2013) find persistence in short-term and long-term overprecision and also in short-term and long-term optimism (or overestimation). Hence, we inferred that overprecision and overestimation are likely persistently present in both earnings guidance and strategic decision making.

Furthermore, overprecision has been shown to transfer across domains. Ben-David et al. (2013) also show that executives who are miscalibrated about the stock market show similar miscalibration regarding their own firms' prospects.

Several studies have empirically and experimentally demonstrated relationships between earnings guidance and overconfidence.

- Hribar and Yang (2016) found that overconfidence¹¹⁴ increases the likelihood of issuing a forecast, increases the amount of optimism in management forecasts, and increases the precision of the forecast.
- Kramer and Liao (2016) found that firms with overconfident¹¹⁵ CEOs are more likely to have analysts issue earnings forecasts that are optimistic relative to actual earnings; that is, the earnings forecasts more frequently exceed the actual realized earnings than the reverse.
- Libby and Rennekamp (2012) conducted an experiment and find that both overoptimism about firm performance and overconfidence in their ability to predict future firm performance contribute to issuance of earnings forecasts.

113. We use the shorthand of overconfidence for both overestimation and overprecision, yet each form of overconfidence will be separately assessed.

114. Hribar and Yang define overconfidence in the overestimation way and measure it using the options-trading and press characterisations proxies.

115. Kramer and Liao define overconfidence in the overestimation and overprecision way, but use proxies for overconfidence (options-trading and press characterisations) that are typically associated with overestimation.

- Wei and Zhang (2018) found that overconfident¹¹⁶ CEOs are less likely to announce earnings that positively surprises the market relative to the analyst consensus forecast.
- Hilary and Hsu (2011) showed that a recent history of forecast accuracy drives overconfidence¹¹⁷ which leads to less accuracy in subsequent earnings predictions.

We recognise two shortcomings in our argument. Firstly, we have found evidence for the transfer of overprecision, but not overestimation, from one domain to another. Secondly, while the presence and persistence of overconfidence in individuals is well established, this is not the case for overconfidence in groups. The studies of the impact of cognitive biases in group decision making have yielded mixed results. These studies show that the impact of cognitive biases are sometimes attenuated, sometimes amplified, and sometimes inconclusive (Maccoun et al., 1996; Yaniv, 2011; Osmani, 2017), while others (Houghton et al., 2000) found that the effect of biases that influenced their risk perception (e.g. illusion of control) was analogous for teams and individuals. And others (Johnson et al., 2011) found that individual level biases appear to be amplified at the group and organisational levels. With respect to overconfidence bias specifically, Meikle et al. (2016) studied the inhibitors and facilitators of overconfidence¹¹⁸ in organisations and found that “*overconfidence is present in and affects organizations*”, although they also noted that reports of overconfidence in organisations might be exaggerated.

2.4.4.2 Causal isolation

We considered that causal isolation in our context requires three requirements to be met and we examined each in turn. A violation of any of the criteria would undermine causal isolation.

- The same or similar people and their respective power are at play when making strategic decisions and when doing what the proxy is measuring.
- The same or similar process and related effort is applied when making strategic decisions and when doing what the proxy is measuring.
- The biases at play are the same or similar when making strategic decisions and when doing what the proxy is measuring, or if there are additional biases, they can be controlled for.

Same or similar people and their respective power are at play

Those involved in earnings guidance are typically people from investor relations, senior management, such as the CEO, CFO, and business unit heads, independent auditors, in-house and external counsel, audit committee, disclosure committee, and the board of directors (Diamond & Yevmenenko, 2015). While the senior management individuals involved in strategic decision making might differ from one strategic decision to the next, it seems reasonable to assume a significant overlap in the set of individuals responsible for earnings guidance and for strategic decision making. It also seems reasonable to assume that the respective power dynamics are similar in both settings.

But this first requirement for causal isolation is not without its weaknesses. A challenge to the above might be that the CFO is the dominant player when developing and issuing earnings guidance, while the CEO is the dominant player when making strategic decisions. A second challenge could be that earnings guidance is the product of an aggregation of estimates from senior managers across the full

116. Wei and Zhang define overconfidence in the overestimation and measure it using the options-trading proxy.

117. Hilary and Hsu do not define overconfidence in terms of overestimation and overprecision but refer to other researchers who use both of those constructs.

118. The Meikle et al. (2016) paper is co-authored with Don Moore. Moore wrote the landmark paper that showed the three distinct types of overconfidence. The Meikle et al. (2016) paper refers to overestimation, overprecision, and overplacement, but is not specific in which type of overconfidence they refer to in the extracted sentence.

breadth of the firm, while strategic decisions are the responsibility of the top management team (TMT) or a division or function of the firm in conjunction with TMT members.

Same or similar process and related effort is applied

As previously mentioned (section 2.1.5), the strategic decision making process that is followed might have political, rational, intuitive, and heuristic elements. And, since strategic decisions differ in their scale and complexity, they are likely to differ in the degree of rigour and effort applied. In contrast, earnings guidance follows a more consistent process from one guidance cycle to the next.

Setting earnings guidance and making strategic decisions might also differ due to the agency problem (Ross, 1973), especially in businesses where projects outlast decision makers as in mining and pharmaceuticals, since decision makers might act differently where the consequences of their decisions are not fully realised during their period of accountability.

Although the process for the development and issuance of earnings guidance likely differs from that of strategic decision making, both processes consume considerable effort of managers and other stakeholders. Based on these process differences and possible effort differences, this second requirement for causal isolation also has its weaknesses.

The biases at play are the same or similar

An analysis of the biases acting on managers when issuing earnings forecasts suggests that there is a strong motivation to deliver accuracy and precision in their forecasts because the punishment for not doing so could be severe. These punishments might include a substantial drop in share price, a reduction in a manager's bonus, and an increased risk of litigation and job security (Heflin, Kross, & Suk, 2016). However, there are cognitive and motivational biases that undermine forecast quality. A summary of the biases driving and undermining forecast quality are illustrated in Figure 7 and then described in further detail in this section.

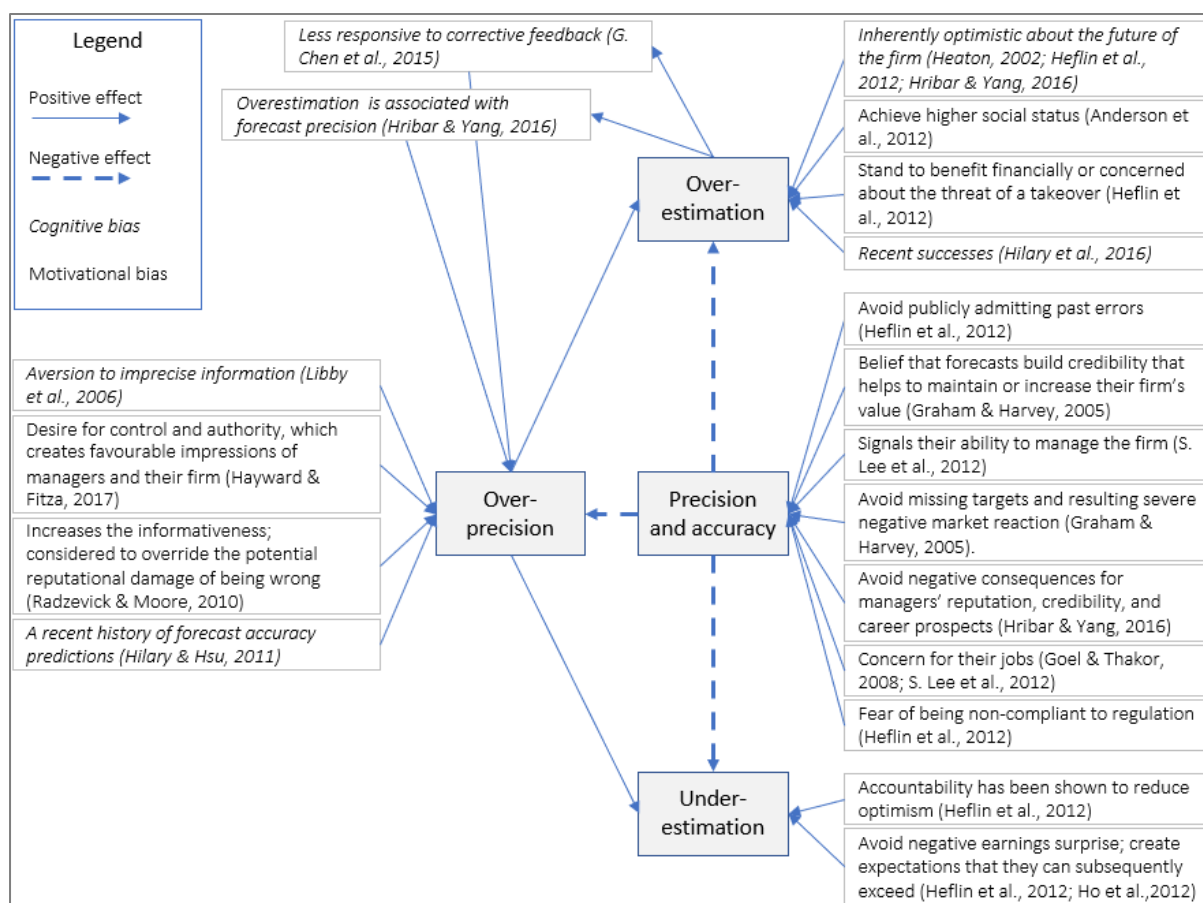


Figure 7: Biases driving and undermining forecast quality.

From a psychological perspective, people are inherently overly optimistic about the future of the firm, they overestimate their ability to influence earnings and they underestimate the probability of uncertain, negative events (Heaton, 2002; Heflin, Kross, & Suk, 2012; Hribar & Yang, 2016). As such, we expected overprecision from managers who overestimate and this is borne out by Hribar and Yang (2016) who show that overconfidence¹¹⁹ is associated with forecast precision, with overconfident CEOs issuing narrower range forecasts. Furthermore, when CEOs are overconfident¹²⁰, they are less responsive to corrective feedback in improving management forecast accuracy (G. Chen et al., 2015). Overprecision in forecasts also arises because managers have an aversion to imprecise information, prefer to be precise, and hence issue narrow forecast ranges (Libby, Tan, & Hunton, 2006). And, a recent history of forecast accuracy drives overconfidence¹²¹ which leads to less accuracy in subsequent earnings predictions (Hilary & Hsu, 2011).

In addition to cognitive biases driving precision, there are also motivational biases that drive precision. Being more precise conveys control and authority, which creates favourable impressions of managers and their firm, and their prospects (Hayward & Fitza, 2017). Managers express precision, often at the

119. Hribar and Yang refer to the overestimation form of overconfidence and measure it using the options-trading and press portrayal proxies.

120. G. Chen et al. recognise the different types of overconfidence and define their overconfidence measure in the overestimation way.

121. Hilary and Hsu do not define overconfidence in terms of overestimation and overprecision, but refer to other researchers who use both of those constructs.

cost of being wrong, because precision increases the informativeness¹²² of what they say and this is considered to override the potential reputational damage of being wrong (Radzevick & Moore, 2010).

An obvious consequence of overprecision is forecast inaccuracy. If the forecast is inaccurate, it is either too high (overestimation) or too low (underestimation).

As mentioned above, people are inherently overly optimistic (Heaton, 2002; Heflin et al., 2012; Hribar & Yang, 2016). Also, managers of firms that have experienced recent successes are more likely to subsequently issue forecasts that are more optimistic than they would have been absent this bias (Hilary et al., 2016). Managers are also motivated to overestimate their forecasts. Managers might overestimate their forecast to achieve higher social status (Anderson et al., 2012) or when they personally stand to benefit financially or when they are concerned about the threat of a takeover (Heflin et al., 2012).

Overestimating guidance creates a risk that management fails to meet the expectation of those earnings, creating a negative earnings surprise. This event “decreases share price, reduces managers’ bonus compensation and job security, and increases litigation risk” (Heflin et al., 2016). Managers are aware that if targets are missed that could indicate that a firm is poorly managed and could result in severe negative market reaction (Graham & Harvey, 2005). Consequently, in fear of a negative earnings surprise, managers might underestimate just to be safe. In fact, management are driven to pessimistically bias their forecasts to create expectations that they can subsequently exceed (Heflin et al., 2012; L. C. J. Ho, Liu, & Ouyang, 2012).

Overestimation is also reduced when managers feel accountable. This claim is based on the finding of Tetlock and Kim (1987) who show that accountability improves forecast calibration, and Jensen (2006) who finds that accountability to “important audiences” triggers status anxiety. Because of this, Heflin et al. (2012) predict that managers who might need to publicly justify a previous forecast will put more effort into constraining their optimistic tendencies, resulting in less optimistic forecasts.

In addition to the avoidance of a negative earnings surprise, managers experience other motivational forces that drive forecast accuracy. Managers strive for accuracy in their forecasts because it builds credibility for their organisation and out of concern for themselves. Managers believe that accurate forecasts build credibility in the market that helps to maintain or increase their firm’s value (Graham & Harvey, 2005) and signals their ability to manage the firm (S. Lee, Matsunaga, & Park, 2012). Inaccurate forecasts could have significant consequences for managers’ reputation, credibility, and career prospects (Hribar & Yang, 2016). In fact, managers strive for accuracy because of a concern for their jobs as forecast error has been positively associated with CEO turnover (Goel & Thakor, 2008; S. Lee et al., 2012). Managers might strive for high quality forecasting because they want to avoid publicly admitting past errors (Heflin et al., 2012). Lastly, managers fear being non-compliant to regulation. Since the Securities and Exchange Commission’s (SEC) promulgation of Regulation Fair Disclosure in October, optimism in forecasts has reduced without an increase in pessimism and there have been improvements in forecast accuracy and informativeness (Heflin et al., 2012).

If managers make a sincere effort to be accurate and precise, then resulting inaccuracies could be due to luck (good or bad) or could be due to biases that they are not conscious of. A summary follows in two parts, the first part in support of causal isolation and the second part in opposition to causal isolation.

122. As an example, borrowing from (Hayward & Fitzg, 2017), a management forecast for EPS of \$1.10 to \$1.15 is considered to more informative and more authoritative than a forecast of \$0.90 to \$1.30.

In support of causal isolation

Since earnings guidance and strategic decision making are pursued in a context of high uncertainty, luck will certainly play out, but its effect should be random and hence there should be no systematic bias that explains higher or lower forecasts.

Overestimation and overprecision are likely to be persistently present in both the processes of earnings guidance and strategic decision making. Evidence of overprecision in earnings guidance might be indicative of overprecision in strategic decision making, as Ben-David et al. (2013) showed that miscalibration¹²³ transfers across domains. Note that we have not found theoretical or empirical evidence that overestimation transfers across domains.

The motivational biases for control, authority, and expression of informativeness also drive managers to be overprecise. It seems reasonable to assume that these biases would also play out in strategic decision making.

In opposition to causal isolation

Both cognitive biases and motivational biases drive overprecision in forecasts. As such, if overprecision is found in earnings guidance, it will be unclear whether this is due to overprecision or a motivational bias or both. It is also unclear whether the motivational biases to create favourable impressions of their firm and/or to increase informativeness would play out in strategic decision making.

Managers have a strong motivation to guide low on expected earnings, but managers are inherently optimistic and systematically overestimate the probability of good firm performance and underestimate the probability of bad firm performance (Heaton, 2002), hence we might expect the biases driving earnings guidance and strategic decision making to act in opposite directions.

In summary, as with the other two requirements, there is no clear-cut case that other causal factors might be at play. Thus, we concluded that the causal isolation criterion, when considered from the perspectives of people, process, and biases, is challenged.

2.4.4.3 Equivalent cardinality

The third criterion for a quality proxy is an equivalence in cardinality between the group's strategic decision-making overconfidence and management earnings forecast overconfidence. While many researchers have operationalised their overconfidence proxies in a binary or trinary way, some have operationalised their proxy as a continuous variable. Our proxy specifications for overestimation and overprecision are as continuous variables¹²⁴. Our overestimation proxy is unbounded in its negative extent and unbounded in its positive extent. It seems reasonable to assume that the latent phenomenon of group overestimation in strategic decisions is also continuous and unbounded in both the positive and negative directions. Our proxy specification for overprecision is also as a continuous variable, but can only take the state of not overprecision or positive and unbounded overprecision. As illustrated in Figure 6, it is theoretically possible to have negative overprecision, in other words underprecision, but our proxy does not allow for this state. We considered this limitation a minor weakness in our model.

Recognising the imperfection of our proxy specifications, we assessed the most used proxy for overestimation, namely the options-trading behaviour of the CEO, as devised by Malmendier and Tate (2005a). If we could show that despite the imperfections of our proxies, if they perform better than the best alternative, then there would be merit in using them.

123. Miscalibration is their term for overprecision.

124. Later, we also derive categorical variables from these continuous variables.

2.4.4.4 Relationship to a proven proxy

A review of the literature reveals that an overestimation proxy derived from management earnings forecasts has been shown to correlate with Malmendier and Tate (2005a)'s commonly used options-trading proxy.

- Otto (2014) defined a proxy for overestimation based on the frequency that the low bound of a range forecast exceeds the actuals and find that this correlates at the 1% significance level with the options-trading proxy.
- Hribar and Yang (2016) defined an overestimation variable, OptBias, which has a positive correlation with the options-trading proxy at the 1% significance level.
- Zhao and Ziebart (2017) used management earnings forecast as their overestimation proxy, but also conducted a sensitivity test and showed that their results were robust to the options-trading proxy.
- Mundi and Kaur (2019) showed that their forecasting error metric for overestimation correlates with the options-trading proxy at the 10% significance level.

While Malmendier and Tate (2005a)'s options-trading proxy was developed to measure overestimation, Hribar and Yang (2016)'s overprecision variable, Range, was also found to correlate with it, at the 1% significance level.

2.4.5 **Quality assessment of the options-trading proxy**

Malmendier and Tate (2005a) studied the effect of overconfidence¹²⁵ on corporate investment decisions and constructed three proxies of overconfidence based on the personal portfolio decisions of CEOs: Holder67, Longholder, and Net Buyer. The first two measures, Holder67 and Longholder, are based on when the CEO exercises their options. With this measure, a CEO is considered overconfident if they purchase additional company stock despite their already high exposure to company risk (Malmendier & Tate, 2005a).

It is these first two measures that have since been extensively used. Of the studies we have reviewed, Holder67 has been used in the following papers: (Ahmed & Duellman, 2013; Banerjee et al., 2020, 2018; Bharati et al., 2016; S.-S. Chen et al., 2014; Deshmukh, Goel, & Howe, 2009; Deshmukh et al., 2013; Galasso & Simcoe, 2011; Hribar & Yang, 2016; H. A. Kim et al., 2019; Kramer & Liao, 2016). And Longholder has been used in these studies: (Andreou et al., 2018; Bouwman, 2014; S.-S. Chen et al., 2014; Deshmukh et al., 2009, 2013; Kramer & Liao, 2016; Lai et al., 2017; Malmendier & Tate, 2008, 2015; Malmendier et al., 2011; Otto, 2014).

Malmendier and Tate (2005a) recognise that CEO compensation contracts often include large quantities of stock and option grants. They derive their Holder67 metric by considering the status of each individual option package at the end of its vesting period and then calculate the proportion of packages that are in-the-money. Because of risk aversion and a desire for diversification, they predict that CEOs should exercise their options immediately after the vesting period if the amount in-the-money exceeds a rational benchmark. They classify a CEO as overconfident if, at least three times during their tenure as CEO, they have held options that are more than 67% in-the-money after they have vested (Malmendier & Tate, 2005a).

For their calculation of the Longholder metric, Malmendier and Tate (2005a) focus on the expiration date of option packages. They classify a CEO as overconfident if they ever hold an option until its

125. We interpret Malmendier and Tate (2005a)'s overconfidence as overestimation.

expiration year. Malmendier and Tate (2005a) argue that Holder67 and Longholder demonstrate a habitual failure to diversify and thus indicate a personality, rather than a time-varying, overconfidence effect.

How do Holder67 and Longholder, or collectively options-trading, perform against the quality criteria for a good proxy?

- Does overconfidence¹²⁶ in corporate investment decisions cause overconfidence in the CEO's options-trading?
- Are there any other structures at work that produce variation in the CEO's options-trading?
- Is there equivalence in the cardinality of overconfidence in corporate investment decision-making overconfidence and the CEO's options-trading?

2.4.5.1 Determination

Just as we did not claim that overconfidence in the group's strategic decision-making causes overconfidence in management earnings forecasts, we believe that Malmendier and Tate (2005a) would not claim that the CEO's overconfidence in corporate investment policy making causes the CEO's overconfidence in their options-trading behaviour.

However, in the same vein as our argument, we speculate that Malmendier and Tate (2005a) would argue that the same overconfident behaviour that CEOs exhibit when making corporate investment decisions is displayed in their options-trading behaviour. This speculation is supported by their opening sentences: "... we argue that the personal characteristics of CEOs in large corporations lead to distortions in corporate investment policies" and "... we study the investment decisions of CEOs who overestimate the future returns of their companies, measured by a failure to divest company-specific risk on their personal accounts".

How do we know that the overestimation expressed by the CEO when corporate investment policy decisions will manifest as the overestimation in the CEO's options-trading behaviour? Malmendier and Tate (2005a) refer to the "better-than-average" effect and argue that CEOs will overstate their acumen relative to the average. They then cite Camerer and Lovo (1999) to argue that this behaviour extends to economic decision making and, in so doing, create the determination link.

Furthermore, the use of options-trading for a proxy of the CEO's overestimation behaviour has been empirically demonstrated in numerous settings, as referenced in the introduction of this section.

2.4.5.2 Causal isolation

As we did when we assessed the quality of our proxies (section 2.4.4), we considered that causal isolation requires three requirements to be met and we examined each in turn. A violation of any criterion would undermine causal isolation.

- The same or similar people and their respective power are at play when making strategic decisions and when doing what the proxy is measuring.
- The same or similar process and related effort is applied when making strategic decisions and when doing what the proxy is measuring.
- The biases at play are the same or similar when making strategic decisions and when doing what the proxy is measuring, or if there are additional biases, they can be controlled for.

126. We use the shorthand of overconfidence for both overestimation and overprecision, yet each form of overconfidence will be separately assessed.

Same or similar people and their respective power are at play

Malmendier and Tate (2005a) justify their use of overconfidence proxies at the individual level by saying that they exploit the overexposure of typical CEOs to the idiosyncratic risk of their firms. And, they are not alone. Malmendier and Tate's work has been extensively cited and their proxy adopted in many studies¹²⁷. Finkelstein, Hambrick, and Cannella (2009) recognise that although decision-making in organisations is often shaped by a dominant coalition of executives with their own perspectives, CEOs, due to their prominent positions, have considerable power over firm decisions and strategies. Schumacher et al. (2020) state that is highly likely that the CEO will have a major influence on determining risk-taking decisions at the firm level. Earlier studies relating to acquisitions assert that they are individual decisions (Roll, 1986), that the acquiring CEO will be extensively involved (Haspeslagh & Jemison, 1991), and that they could not proceed without the CEO's personal sponsorship (Hayward & Hambrick, 1997).

Despite Malmendier and Tate (2005a)'s justification and the endorsement from others, we saw the measurement of an individual's behaviour as a proxy for the firm's corporate investment policies as a shortcoming. We do not dispute Malmendier and Tate (2005a)'s argument about the disproportional influence of the CEO. Nor do we argue that developing a proxy for overconfidence in the firm's decision making based on the CEO's behaviour is incorrect. After all, all proxies are an abstraction of the underlying effect and, given the disproportionate power of the CEO's role, a proxy based on the CEO's behaviour might be adequate. However, we called this a shortcoming because, as mentioned in section 2.1.7, "groups make most of the important decisions in organizations" (Tasa & Whyte, 2005). Even if the CEO as acting independently of her management team, which seems unlikely, corporate investment policies would need to be approved by the board of directors.

Same or similar process and related effort is applied

Even if the CEO were solely responsible for the firm's corporate investment policies, would she follow the same process and apply the same effort in making corporate investment policy decisions? Again, this seems unlikely, both in terms of process and related effort.

The biases at play are the same or similar

When considering the biases at play when a CEO makes options-trading decisions and makes corporate investment policy decisions, we noted two points of potential misalignment. The first is that the CEO's personal circumstances most likely will not mirror those of the firm, and hence the context for decision making is different. For example, the firm might be in a cash-flush position, while the CEO might have unexpected expenses to discharge, or vice versa. The second point of misalignment is a consequence of principal-agent theory.

As explained by principal-agent theory (Meckling & Jensen, 1976), managers make choices in their interest that do not necessarily align with the interests of shareholders. Despite efforts, such as the Sarbanes-Oxley Act, to address the agency problem, recent studies still demonstrate that it is in play (Al Mamun, Balachandran, & Duong, 2020; Gul, Krishnamurti, Shams, & Chowdhury, 2020; Pan, Liu, & Wang, 2019). For example, Gul et al. (2020) find that overconfident CEOs have the tendency to use their firm's CSR engagement to extract private benefits through empire building activities. Thus, if the agency problem still applies, the decisions of the CEO acting in her individual capacity is not necessarily a good model for the CEO acting on behalf of her firm. In fact, an overconfident CEO might be inclined, due to the agency problem, to take greater risks with the firm's capital than they would with their own capital.

127. The paper in question has been cited more than 3,500 times.

2.4.5.3 Equivalent cardinality

We have no challenge to the cardinality equivalence between Malmendier and Tate (2005a)'s measures for options-trading decisions and corporate investment policy decisions.

2.4.6 Conclusion

Based on our assessment of the quality of our overestimation proxy and that of the commonly used overestimation proxy, we reached the following conclusion: Our proxy is imperfect, but in at least one important respect it is superior to the options-trading proxy, and in terms of its other areas of weakness, it shares these with the options-trading proxy.

The primary weakness of our overestimation proxy is that it is susceptible to gaming and hence our proxy might be negatively biased toward underestimation. However, if this negative bias is consistent, then the relative extent of over- or underestimation would still be a useful indicator. The primary weakness of the options-trading proxy is that it measures an individual's behaviour while the latent effect that we wished to measure is the product of group behaviour. This individual versus group distinction brings at least three distortions that might be material to the measurement, namely it captures the behaviour of an individual rather than a group, it does not control for how the personal circumstances of that individual might differ from the firm's context, and it is vulnerable to the misalignment predicted by principal-agent theory.

There are two further weaknesses of our overestimation proxy and they are shared with the options-trading proxy. The first of these is that it is unlikely that the same or similar people and their respective power are at play when making strategic decisions and issuing earnings guidance and, similarly, it is that it is unlikely that the same or similar people and their respective power are at play when making investment decisions and trading the CEO's options. The second weakness is that it is unlikely that the same or similar process and related effort is applied when making strategic decisions and issuing earnings guidance and the same can be said for the options-trading proxy.

A decade after they first developed the options-trading proxy that has been extensively used in studies of overconfidence (Costa et al., 2017), Malmendier and Tate (2015) wrote that there is "a clear foundation for exploring earnings forecasts as a measure of overconfidence". Their justification was not related to the concerns mentioned above, but instead due to the changing nature of options-based compensation. In their recognition of the need for a new proxy, they call out management earnings forecasts as a good candidate (Malmendier & Tate, 2015).

Since Malmendier and Tate (2005a)'s options-trading proxy is so widely used, we took comfort from the fact that an overestimation proxy derived from earnings guidance correlates to the options-trading proxy. And, an overestimation proxy based on management forecasts has been used in at least three studies (Invernizzi et al., 2017; Li & Liu, 2012; Mundi & Kaur, 2019) of the impact on overconfidence on firm performance.

We do not find a weakness in the use of earnings forecasts for overprecision, other than that the conventional approach of computing overprecision is not possible because management do not provide confidence intervals when issuing a range forecast. We also noted that, given the dearth of overprecision empirical studies, there is no commonly used overprecision proxy to compare against.

Having developed a conceptual model to explain, predict, and test firm performance resulting from various types of overconfidence bias expressed in strategic decisions, reviewed the literature and identified gaps and inconsistencies, derived a set of hypotheses based on the theoretical and empirical body of knowledge, and theoretically justified our proxies for this study, we now move to chapter 3 where we will define our empirical strategy.

3 Empirical strategy

*“It is unwise to be too sure of one's own wisdom.
It is healthy to be reminded that the strongest might weaken and the wisest might err.”*

Gandhi

The overarching purpose of this chapter is to convert our conceptual model into a research model and estimation approach that can be used to test the hypotheses that we developed in the previous chapter. Our hypotheses relate to the impact of overconfidence on firm performance and, broadly speaking, we have hypothesised that overestimation will have a negative impact, overprecision will have a positive impact, and both of overestimation's and overprecision's impact will be non-monotonic and hence firm performance will be maximised for some moderately negative amount of overestimation and some moderately positive amount of overprecision.

To achieve our purpose of developing an approach for testing these hypotheses, we firstly state our philosophical standpoint. Then, we describe the data that we used in testing our hypotheses and we describe our dependent, treatment, and control variables. Using these variables and our conceptual model we develop a research model that forms the basis for our quantitative analysis. Lastly, we explain how we select an estimation approach. With our research model and estimation approach we have the platform for executing our analysis, the results of which will be presented in the next chapter.

3.1 Philosophical standpoint

For this study we followed the critical realist philosophy of science. Critical realism posits a realist ontology, which assumes the existence of a world independent of the researchers' knowledge of it and considers the researchers' knowledge of the world to be socially produced (K. D. Miller & Tsang, 2010). Like Karl Popper's falsificationism (Popper, 1959), critical realism supports the critical evaluation of theories on the basis of empirical data and seeks to advance knowledge by falsifying theories¹²⁸. However, diverging from falsificationism, critical realism posits a fallibilist epistemology (K. D. Miller & Tsang, 2010), where it acknowledges the potential fallibility of all knowledge claims and encourages modesty regarding both verification and falsification (K. D. Miller & Tsang, 2010). Rather than a binary claim of false or not false, critical realism aims to offer a judgment of the superiority or inferiority of a theory. Accordingly, from the viewpoint of the critical realist, truthful knowing might be attained, but human limitations mean that it cannot be claimed with certainty (K. D. Miller & Tsang, 2010).

This philosophical standpoint is suited to social science studies in general, and management studies in particular, for a number of reasons. First, organisations are complex and dynamic, making it difficult to precisely define the required empirical context for testing a particular theory (K. D. Miller & Tsang, 2010). Second, unlike in the natural science setting, in a management study the subjects of interest are people who have some freedom of choice. In fact, not only are strategic choices non-deterministic, they can be intentionally unpredictable for competitive reasons (K. D. Miller & Tsang, 2010). Third,

128. The motivation for falsification results from the problem of induction, which was formalised by David Hume in 1739. The problem of induction is that even in the presence of an abundance of supporting evidence, a single observation of contrary evidence can disprove a hypothesis. This concept is delightfully illustrated by Taleb (2007). Taleb tells the story of a turkey that is fed every day. And every feeding strengthens the turkey's belief that people are looking after its best interest. This continues until one day, which happens to be the day before Thanksgiving, when the turkey has an abrupt revision of its belief.

again unlike in the natural science setting, the researchers' act of observing management behaviour might influence that behaviour¹²⁹ (K. D. Miller & Tsang, 2010).

Since critical realism relies on the principle of falsification, we employed the classical approach of null hypothesis testing. We formulated a null hypothesis which states that the effect we are hypothesising does not exist and then we sought to reject the null hypothesis. If we were able to reject the null hypothesis, this provided indirect, probabilistic support for our hypothesis of interest (Bhattacharjee, 2012).

Given the probabilistic nature of the inferences we intend to make when testing our hypotheses, how will we decide whether a relationship exists or is a matter of chance? A conventional approach is to consider a result to be significant if the probability of it being rejected due to chance is 5% or less (Bhattacharjee, 2012). This probability is referred to as the p-value and we considered a relationship to be significant when the p-value is less than 5%. We also noted relationships that are more or less significant when they produce a p-value of 1% or 10%, respectively. Accordingly, *ceteris paribus*, we judged a hypothesis to be superior if the p-value is lower.

What we have described is the classical approach to accepting or rejecting a hypothesis when the data that is being assessed is a sample from a population. In our case, our data set is a population and not a sample. We used all the available data from our universe of interest and hence our statistics are population statistics. However, we continued to follow the classical p-value approach for a few reasons: 1. It produces results that are easily understood and compared to other studies, 2. Our unit of analysis is firm-years, but data is not available for all firm-years and hence we have a sample, albeit not a randomly extracted sample, and 3. Our universe is S&P 1500 firms (discussed in more detail in the next section), which might itself be a sample for all public firms, or even all firms. We discuss point 2 and 3 in more detail when we consider the limitations (section 5.4) of this study.

3.2 Empirical context

In answering the research question “**what is the impact of group-level overestimation and overprecision biases on firm performance?**”, we are concerned with why for-profit, public firms are not able to sustain the performance necessary to maintain their leadership positions.

With reference to our conceptual model, Figure 4, we discuss in the following sections how we quantified the “cause” represented by our dotted circle on the left and the “effect” represented by the dotted oval on the right. The “cause” is the overconfidence (overestimation and/or overprecision) demonstrated by the management team when making strategic decisions. We used proxies based on management earnings guidance to measure this overconfidence. The “effect” is the decision quality that results from this decision-making process and, as mentioned in section 2.1.8, since decision quality cannot easily be directly measured, we relied on firm performance as being representative of decision quality. Our conceptual model was translated into a research model, incorporating our five hypotheses (1a, 1b, 2a, 2b, and 3), as displayed in Figure 8 below.

129. The astute reader might challenge this claim due to the “observer effect” that occurs in certain experiments in physics, most notably in quantum mechanics.

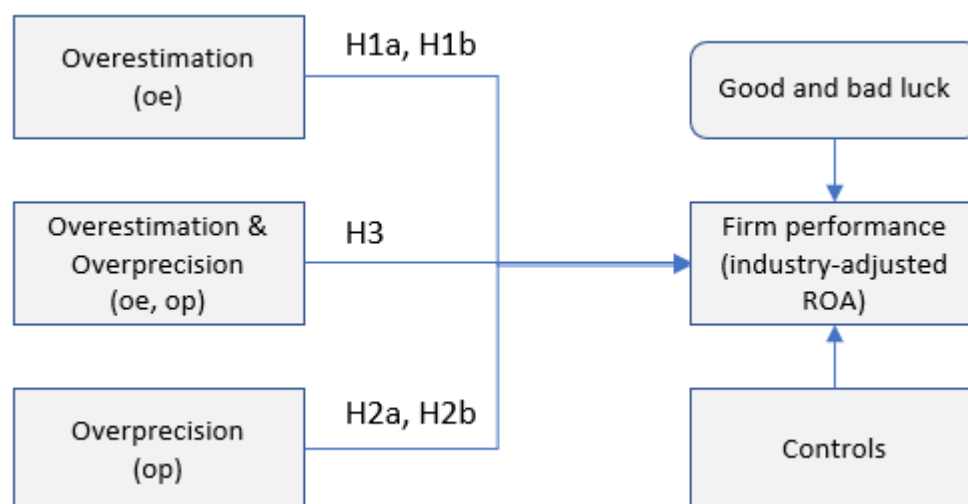


Figure 8: Research model.

We recognised that we have an imperfect model, with many steps and many confounding factors between the “cause” (overestimation and/or overprecision) and the “effect” (decision quality as measured by firm performance). In addition, proxies are an imperfect abstraction of the variable we sought to measure. And overconfidence bias itself results in competing positive and negative effects. Consequently, the impact of overconfidence bias on firm performance was likely to be a small “signal” in a highly “noisy” context. For this reason, a large, high quality data set was required. The S&P 1500 is such a data set. The S&P 1500 is a stock market index of U.S. stocks created by Standard & Poor’s (“S&P 1500,” 2020). This index covers approximately 90% of the market capitalisation of U.S. stocks. The market cap of the S&P 1500 was \$31 trillion in January 2020. For comparison purposes, the global GDP in 2019 was \$88 trillion (“GDP (current US\$)”). The S&P 500 are the 500 largest stocks within the S&P 1500.

The apocryphal story has it that when bank robber Willie Sutton was asked why he robbed banks, he answered “because that’s where the money is” (Sutton & Linn, 1976). Continuing in that vein, in this study we chose to focus on the S&P 1500 “because that’s where the data is”¹³⁰. In fact, given the \$31 trillion mentioned above, we could have also answered “because that’s where the money is”.

In addition to the quality of the data, using data from the S&P 1500 also allows an understanding of the impact of overconfidence bias in some of the most sophisticated and largest firms in the world. If a significant and material effect were found in the S&P 1500, then it is likely that this effect will also be present in less sophisticated companies.

The set of firms to be analysed will be all firms that have appeared in the S&P 1500 between 2003 and 2020. We started with 2003 because this was the earliest year in which it was possible to extract S&P 1500 membership data on a Bloomberg terminal¹³¹. There are 2,952 firms meeting this requirement. All firms were looked at longitudinally for the full period of analysis to avoid survivorship bias¹³². Once

130. Credit for that wonderful answer goes to Jim Collins when discussing why he focused on public companies when he wrote “Good to Great” (Buchanan, 2019).

131. We used a Bloomberg LP terminal, accessed with UCT Libraries’ subscription.

132. In other words, irrespective of whether a firm was an S&P 1500 member every January 1st during these years, or only on one of the January 1sts, our requirement is a minimum of a single appearance and that firm becomes a member of our data set.

the firm is a member of our data set, all available data for that firm for the full period of analysis was collected. Our unit of analysis was a firm-year.

Not all firms provide management earnings guidance. Those that do provide guidance typically provide it at the beginning of their fiscal year and/or when they provide quarterly updates and/or at their last quarterly update before their fiscal year-end. Since we were seeking earnings guidance as a proxy for strategic decision making, which is typically long term in nature, we opted to gather the guidance provided at the beginning of the fiscal year. In other words, this guidance is made with a roughly 12-month forecasting horizon. Specifically, we collected annual guidance if it was provided in the time window three months before and three months after the beginning of the fiscal year.

We restricted our data set to the period from 2009 to 2019 inclusive for three reasons. The first reason was to avoid the Great Financial Crisis of 2007/2008, which caused turmoil in the equity markets. The second reason was the availability of management earning guidance. Consistent with the SEC's implementation of Regulation Fair Disclosure in October 2000, we found that management earnings guidance data in the S&P 1500 effectively becomes available¹³³ from 2001. Considering the S&P 1500, we found guidance data for at least 500 of the 2,952 S&P 1500 firms in each year from 2009 to 2019 inclusive¹³⁴. The third reason was to avoid the impact of the Covid-19 era that became effective from about February 2020.

We found 6,618 firm-years which have guidance data in the period 2009 to 2019 inclusive. This includes range guidance, point guidance, floor guidance, and ceiling guidance. Range guidance is where the firm communicates its earnings guidance as a range from low to high, implying that they expect their actual earnings to fall within that range. Point, floor, and ceiling guidance is where a single number is provided, but with floor and ceiling guidance the management are saying they expect at least this much (floor) or at most this much (ceiling). We constructed our overestimation and overprecision variables from the range guidance, for which we had 6,008 observations. The balance (610 observations) was due to point guidance, floor guidance, ceiling guidance, missing actuals, or calendar misalignment¹³⁵.

Consistent with similar studies (Lovallo, Brown, Teece, & Bardolet, 2020; Malmendier & Tate, 2005a; Park et al., 2018), we excluded Financial Services firms because, due to their use of leverage, they do not deliver comparable ROA or even comparable industry-adjusted ROA. This left us with 5,116 observations of our overestimation and overprecision variables. Our sample selection process is displayed in Table 8 below.

133. From the Bloomberg terminal we can identify S&P 1500 members from 2003, and S&P 500 members, the largest firms of the S&P 1500, from many years earlier. In 2001 there were 184 management earnings guidance data points for the S&P 500. Before that, guidance was scarcely available: 1998 (9 observations), 1999 (34 observations), 2000 (76 observations). After 2001, it scales steadily to reach 300 or more observations per year from 2005 until 2019.

134. There are at least 600 guidance observations in each from 2011 to 2018 inclusive, with 2009, 2010, and 2019 having between 500 and 600 observations each.

135. Our overestimation operationalisation allows point guidance, but since there were relatively few data points (351 or 5% of the total guidance is point guidance) we chose to use only the range guidance for overestimation. This forced the overestimation and overprecision variables to be based on the identical firm years. Calendar misalignment refers to firms with financial years that overlap for less than six months in the calendar year of interest.

Number of firms that appear in the S&P 1500 between 2003 and 2020	2,952
Theoretical maximum firm-years between 2009 and 2019 (=11 years x 2,952 firms)	32,472
Firm-years (2009-2019) for which there were earnings reported	20,460
Firm-years (2009-2019) which have any guidance data	6,618
Of those above, which have matching actuals and range guidance data	6,008
Of those above, excluding Financial Services firms	5,116

Table 8: Sample selection process.

All our data, except for the earnings guidance and actuals data, was extracted using a Bloomberg terminal. The earnings guidance and actuals were extracted using FactSet's data service¹³⁶. Therefore, we adopted Bloomberg's and FactSet's definition for our variables, respectively. These definitions are provided in Table 31 in Appendix 7.4.

3.3 Dependent variables

The purpose of this study is to determine the net effect of the management team's overconfidence on firm performance. The management team's overconfidence can affect their strategic decisions and it can affect investor sentiments of the firm. As such, both fundamental and market-based measures of firm performance could be driven by the management team's overconfidence. The use of both a fundamental measure and a market-based measure is indeed used by some studies (H. A. Kim et al., 2019; Mundi & Kaur, 2019) that have examined the impact of overconfidence on firm performance. However, since our study's objective is to understand the impact of overconfidence on the decision quality resulting from the management team's strategic decision making, as illustrated in our conceptual model (Figure 4), we chose to focus on what is within management's control and hence a fundamental measure of firm performance was more appropriate.

Since there is no perfect metric and each has advantages and disadvantages, we selected a fundamental metric that is generally applied in studies of this nature (see Table 5). Accordingly, we used the accounting returns metric of ROA (return on assets). More specifically, we used industry-adjusted ROA as used by Park et al. (2018). We computed industry-adjusted ROA (adjROA) as:

$$adjROA_{firm,t} = ROA_{firm,t} - \overline{ROA}_{industry,t} \quad (2)$$

Where $\overline{ROA}_{industry,t}$ is the industry median of ROA in year t . Since the objective of industry-adjusting the variable is to allow comparison across industries, we are cognizant that a single large outlier in a particular industry in any year could drive a positive (or negative) bias into that industry's data if the industry mean were used. Thus, the median, versus mean, is chosen to minimize the effect of large outliers. We used Bloomberg's ROA variable which is defined as Net Income / Average Total Assets. Bloomberg's definition of ROA is provided in Table 31 in the Appendix 7.4.

3.3.1 Timing

The impact of strategic decisions plays out over various time horizons. Some strategic decisions have short-term effects, e.g. share buybacks are "felt" within one year (Banerjee et al., 2018), others have medium to long-term effects, resulting in researchers lagging their dependent variables by two

136. FactSet data was accessed via a free trial during May 2020. Thank you to Nikita Chandiramani in this regard.

(Andreou et al., 2018), three (Billett & Qian, 2008) or five years (Rehm et al., 2012). Some studies, for example, S.-S. Chen et al. (2014), use multiple time horizons, which is the approach that we used.

S.-S. Chen et al. (2014) studied the impact of an increase in R&D expenditure on firm performance when the CEO is overconfident¹³⁷ and not overconfident. They recognise that profits (or losses) may take years to be fully realised and hence considered the impact on firm performance after 1, 2, 3, 4, and 5 years.

3.3.2 Operationalisation

With consideration to the time lag between overconfidence being expressed and the effect of overconfidence being realised in the dependent variable, we considered our dependent variable with lags of one, two, three, four, and five years. The operationalisation of these lags is detailed below.

For *adjROA* we computed a cumulative metric over the period of interest, which ranges from one to five years. For the lagged versions, we defined cumulative *adjROA* over *n* time periods as below.

$$adjROA_{firm,n} = \sum_{t=n-1}^0 adjROA_{firm,t} \tag{3}$$

We recognise that using the sum is imperfect because some of the returns are reinvested for growth, which would suggest that compounding the returns might be appropriate. However, a compound measure is imperfect too because firms use their returns to issue dividends and buyback shares. Since a blend of summing and compounding is impractical, we elect to sum, but also check our sensitivity to compounding in our robustness tests.

Overconfidence expressed *n* years ago would impact *adjROA* as measured by *adjROA_{c_n}*. For example, to measure the impact on *adjROA* of overconfidence expressed 2 years ago, we calculated *adjROA_{c2}* as *adjROA* 1 year ago added to *adjROA* in this year. Figure 9 shows this example when *n=2* and the current year is 2013 and overconfidence is measured using the metric *oe*.

Year	2011	2012	2013	Resulting variables for analysis
Industry-adjusted ROA		<i>adjROA</i> ₂₀₁₂	<i>adjROA</i> ₂₀₁₃	<i>adjROA</i> _{c2} = <i>adjROA</i> ₂₀₁₂ + <i>adjROA</i> ₂₀₁₃
Overconfidence	<i>oe</i> ₂₀₁₁			<i>oe</i> ₂₀₁₁

Figure 9: Example showing time lag between overestimation and *adjROA*.

3.4 Treatment variables

Our independent variable or treatment variable is the overconfidence of the management team making strategic decisions for their firm. More specifically, the constructs we sought to measure are the overestimation and the overprecision expressed by the group making their firm’s strategic decisions. We have argued (section 2.4) that management earnings guidance, although imperfect, can be used as the basis for deriving our overestimation and overprecision proxies. We now discuss how we operationalised each of these proxies.

137. S.-S. Chen et al. define overconfidence in the overestimating and overplacement way, but measure it in the overestimation way only.

3.4.1 Overestimation

Overestimation occurs when the forecast range is set too high in comparison to the expected actuals. Underestimation might also occur; this is when the forecast range is set too low. The forecaster is “calibrated” when the forecast range is positioned correctly, such that actuals are equally likely to fall above or below the forecast range.

Overestimation can be calculated by contrasting management earnings forecasts to actuals. This approach to deriving an overestimation proxy from budgets or earnings forecasts has been applied by several researchers (Hilary et al., 2016; Hribar & Yang, 2016; Invernizzi et al., 2017; J. M. Lee et al., 2017; Li & Liu, 2012; Mundi & Kaur, 2019; Otto, 2014; Zhao & Ziebart, 2017). These researchers have applied different calculations to derive their proxy, where the differences lie in whether the variable is referenced to the midpoint, the actuals, or boundaries of the range, whether it is a binary, trinary, or continuous variable and, if continuous, how it is scaled.

- Hilary et al. (2016) showed a series of links that go from past performance to overconfidence¹³⁸, from overconfidence to over-optimism¹³⁹, from over-optimism to effort, and from effort to performance. They measured overestimation using the signed difference between the management earnings forecast and the consensus analyst forecast, scaled by the absolute value of the analyst forecast. For robustness they also used press characterisations and the options-trading behaviour of the CEO. They found that managers appear to exert greater effort to meet their over-optimistic forecasts and in so doing increase firm value.
- Hribar and Yang (2016) examined how overconfidence affects the properties of management forecasts. They measured overprecision using range, which they defined as the difference between the upper and lower bound of the range forecast, scaled by logged assets per share. They also measured the optimism (or overestimation) of the forecast, which they define OptBias and measured as the management forecast minus actual earnings, scaled by logged assets per share. Note that OptBias is a dependent variable in this analysis.
- Invernizzi et al. (2017) explored the relationship between overestimation and venture failure rate. They measure overestimation as the difference between budget estimates and actual results for EBITDA, equity, and borrowing costs, scaled by the actuals.
- J. M. Lee et al. (2017) studied whether founder CEOs of large S&P 1500 companies are more overconfident¹⁴⁰ than their non-founder counterparts. They defined overconfidence using CEO tweets, earnings calls, options-trading behaviour, and management earnings forecasts. From the earnings forecasts they created the variable “misguidance” as the difference between forecasted quarterly EPS and actual quarterly EPS, scaled by lagged price-per-share.
- Li and Liu (2012) explored the relationship between overestimation and firm performance. They define overestimation using what they call the “performance prediction deviation method”, whereby they assign the binary variable overconfidence to one if forecast earnings are 50% or more than actual earnings.
- Mundi and Kaur (2019) explored the relationship between overestimation and firm performance. They measure overestimation using a variety of proxies, namely options-trading, stock-trading, press characterisations, and forecast growth rate of their company or any macro-economic factor. They

138. Hilary et al. use overconfidence in the overprecision way.

139. Hilary et al. use over-optimism in the overestimation way.

140. J. M. Lee et al. define overconfidence as the tendency of individuals to think that they are better than they truly are with respect to their abilities, judgments, or future prospects, and to underestimate risk. As such their definition includes overestimation and overprecision.

assign a binary value of one to forecast error if their forecast is greater than the actual, else forecast error is zero.

- Otto (2014) studied the effect of CEO optimism¹⁴¹ on CEO compensation. Otto used the conventional measure of CEO overestimation, options-trading behaviour, as well as a measure based on earnings forecast. Where the management forecast exceeds the actual earnings or the analyst consensus forecast, it is classified as optimistic. The fraction of optimistic forecasts is then used as a proxy for the CEO’s optimism. Otto found that optimistic CEOs earn less total compensation.
- Zhao and Ziebart (2017) measured CEO overconfidence based on the degree of optimism in management earnings forecasts and use this to determine a relationship to the cost of borrowing. They operationalise their overestimation metric as the difference between the management earnings forecast and actual EPS for point forecasts and as the difference between the midpoint of the forecast range and actual EPS for range forecasts.

Borrowing from these constructs, we operationalised overestimation (oe) as specified below:

$$oe = \begin{cases} \frac{(Guidance_L - Actual)}{|Midpoint|} \text{ if } Actual < Guidance_L \\ \frac{(Guidance_H - Actual)}{|Midpoint|} \text{ if } Actual > Guidance_H \\ 0 \text{ if } Actual \geq Guidance_L \text{ AND } Actual \leq Guidance_H \end{cases} \quad (4)$$

Where $Guidance_H$ and $Guidance_L$ refer to the upper or lower bound of the guidance range. $Midpoint$ is the average value of the guidance range, calculated as the high-end plus the low-end of the guidance range divided by two. $Actual$ is the actual earnings delivered at the fiscal year end. Note that when the actual is greater than the high-end of the guidance range, oe will take on a negative value and hence this is negative overestimation or what might be called underestimation.

The above operationalisation of overestimation, oe, is as a continuous variable. We also derived a categorical variable for oe, where we divided oe into seven parts using percentiles such that we have roughly equal number of observations in each part. Since oe includes “calibrated” observations where actuals fall within the guidance range and hence the oe value is zero, the categorical divisions are not of equal size, but using percentiles, we strove for roughly similar number of observations in each of the seven parts.

Our measures for overestimation and overprecision are graphically represented in Figure 10 below. In this illustration a_1 would represent an underestimation situation and oe would be calculated as $(g_H - a_1)/g_M$, which would be negative. Similarly, a_2 would represent an overestimation and since g_L is greater than a_2 , oe would have a positive sign. An actual that fell between g_L and g_H would be calculated as an oe of zero, or we might say that the guidance was calibrated.

Our oe variable is “calendarized” to align with our other variables. This means that oe, which is originally aligned to fiscal years, is adjusted to align to calendar years. The calendarization process is described in section 7.4.3 of Appendix 7.4.

141. Otto uses optimism in the overestimation way.

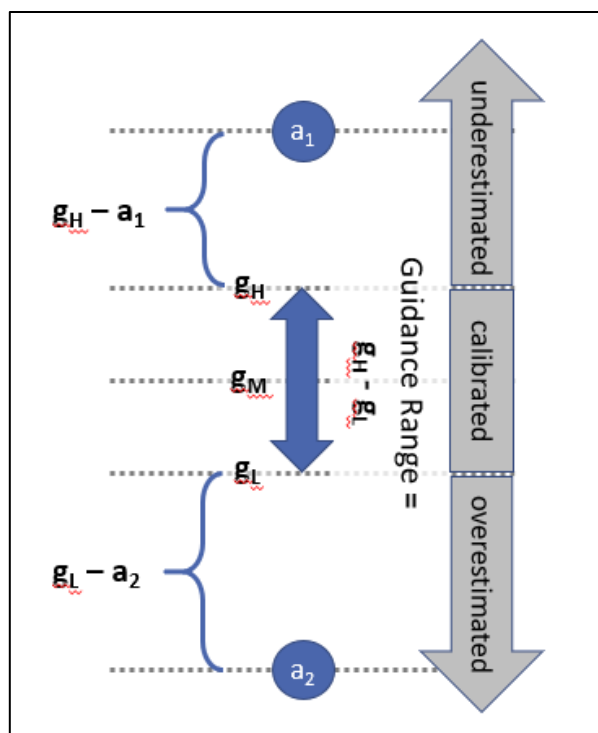


Figure 10: Derivation of overestimation and overprecision from earnings guidance.

3.4.2 Overprecision

Overprecision occurs when the forecast range is too narrow given the degree of uncertainty of the actuals. The forecaster is “calibrated” when the width of the forecast range matches the expected variance of the actuals. As Figure 6 illustrates, underprecision is also theoretically possible and this occurs when the forecaster creates a forecast range that is too wide for the expected variance of the actuals.

The conventional approach of computing overprecision¹⁴² is not possible because management do not provide confidence intervals when issuing a range forecast. Yet, a proxy for overprecision can be calculated from management earnings forecasts by considering the width of the forecast range that management issue. We found four cases (Hayward & Fitza, 2017; Hilary et al., 2016; Hribar & Yang, 2016; Otto, 2014) where researchers have derived an overprecision proxy from earnings forecast data. Each of these formulations uses the range width as a measure of precision, with a narrower width meaning greater precision. These cases are described below.

- Hayward and Fitza (2017) studied earnings guidance to determine whether managers use precision in guidance as a means of managing how their organisation is perceived. They defined a forecast as accurate if the actual result fell within their guidance range. They defined precision as the spread (in cents) with which a forecast is given. Since earnings per share (EPS) differs between firms, a 5-cent range on 50c EPS is less precise than a 5c range of \$5 EPS, they

142. Overprecision is typically computed by an objective probabilistic analysis, i.e. determining the number of times that actuals fall within a confidence interval range, e.g. for an 80% confidence interval an estimator is considered to be well calibrated if 8 of her 10 estimates fall within the range, and considered to be overprecise if less than 8 fall within that range (Moore & Healy, 2008). Since management are not formally defining their range as a confidence interval, it is not possible to do an objective probabilistic analysis. However, it seems reasonable that the absolute difference from the point estimate or the closest bounds of the range offers a measure of overprecision. So, by necessity, we will use a different method and this is noted as a limitation.

include the midpoint of the guidance range a control variable. Since larger guidance ranges represent lower precision, they multiplied their precision variable by -1 such that a higher number represents greater precision.

- Hilary et al. (2016)'s study was discussed in the previous section. They considered both overestimation and overprecision. Overprecision was calculated as the difference between the upper and lower bound of the forecast, divided by the absolute value of the mid-point forecast.
- As mentioned in the previous section, Hribar and Yang (2016) measured overprecision using range, which they defined as the difference between the upper and lower bound of the range forecast, scaled by logged assets per share.
- As mentioned in the previous section, Otto (2014) studied the effect of CEO optimism¹⁴³ on CEO compensation. Otto also defined a variable, ForecastWidth, which was calculated as the difference between the upper and the lower bound of the forecast, divided by the midpoint of the range.

Borrowing from these constructs, we operationalised overprecision (op) as specified below:

$$op = \frac{-Range}{|Midpoint|} \quad \text{if } oe \neq 0 \quad (5)$$

Where:

- $Range = Guidance_{high} - Guidance_{low}$
- $Guidance_{high}$ and $Guidance_{low}$ are the high-end and low-end of the guidance range.
- $Midpoint$ is the average value of the guidance range, calculated as the high-end plus the low-end of the guidance range divided by two.

This is also illustrated in Figure 10 where, in that setting, the overprecision metric op would be calculated as $-1 * range / |midpoint|$ or $(g_H - g_L) / |g_M|$. It should be noted that the definition in equation (5) multiplies range by -1 and hence op is always negative and is more negative if more uncertainty is expressed and less negative if more precision is expressed.

The above operationalisation of overprecision, op, is as a continuous variable. As with overestimation, we also derived a categorical variable for op, where we divided op into seven parts using percentiles such that we have roughly equal number of observations in each part. And, as with oe, we also calendarized op.

3.5 Control variables

Recognising that many factors other than our treatment independent variables of overestimation and overprecision might influence firm performance, we identified the factors that we needed to control for. Our approach to identifying control variables was to ground our thinking using our conceptual model (section 2.1.8), refer to corporate finance theory, consider what similar studies had done, and then inspect the effect of our controls in the model. We ensured that the bivariate result of each control matched the behaviour of the same variable in the multivariate model. We discarded control variables that did not match in coefficient sign with the multivariate and we also discarded control variables that did not improve model fit. The results of the bivariate and multivariate analysis are provided in Appendices 7.5.1 and 7.5.2.

143. Otto uses optimism in the overestimation way.

Our analysis of control factors yielded industry controls, year controls, and firm-level controls. Since our dependent variable is an industry-adjusted variable, we have effectively controlled for the industry effect. For the effects of particular years, we used year dummies for each year under consideration, as is commonly done in similar studies (Bharati et al., 2016; Lovallo et al., 2020; Phua et al., 2018).

For controls at the firm-level, we considered control variable candidates in the categories of firm size, investment, capital structure, managerial discretion (buybacks and dividend pay-outs), market premium, and board attributes. Within each of these categories we selected zero or one variable, based on the criteria of bivariate matching and contribution to model fit. This is detailed below.

We considered controls for firm size because larger firms might use their abundant resources more efficiently (Hall & Weiss, 1967) and opted for the natural log of the number of employees (Petrenko, Aime, Recendes, & Chandler, 2019). Alternative controls for firm size included revenue and invested capital, and the logarithm of those. The log of employee count was selected because it made the best contribution to model fit.

We evaluated controls for investment, considering R&D¹⁴⁴ expenditure and investment intensity¹⁴⁵ because these investments are made to increase firm value (Lev & Sougiannis, 1996; McConnell & Muscarella, 1985) and selected R&D expenditure (Huang & Chen, 2010), scaled by revenue, and then transformed this into a binary variable, with zero for those firms that did not make R&D investments.

We evaluated controls for capital structures because managerial discretion and growth opportunities are affected by leverage and debt-to-equity ratio (Iyengar & Zampelli, 2009) and selected leverage (Hilary et al., 2016), which we log transformed.

We included a control for share buybacks, because we recognised that management teams use buybacks to manage their earnings (Banerjee et al., 2018). We transformed buybacks into a binary variable, with zero for those who did no buybacks.

We included a control for market premium, using Tobin's Q (Iyengar & Zampelli, 2009), which is the book value of equity divided by the market value of equity, since market premium affects growth opportunities available to the firm's management (Bamber & Cheon, 1998).

We considered dividend pay-out ratio but found that this did not contribute to our model. We also considered board attributes like board size and composition, as well as CEO attributes like age, gender, tenure, but for these variables the availability of data from our data source was inadequate before 2013 and hence they weakened our data set.

3.6 Regression equation

Given the selections of dependent variable, treatment variables, and control variables, we converted our research model (Figure 8) into a regression equation as shown below.

$$adjROA_{i,t,n} = \beta_0 + \beta_1 \cdot oe_{i,t-n} + \beta_2 \cdot op_{i,t-n} + \beta_3 \cdot EE_{i,t-n} + \beta_4 \cdot RD_{i,t-n} + \beta_5 \cdot LEV_{i,t-n} + \beta_6 \cdot BB_{i,t-n} + \beta_7 \cdot tq_{i,t-n} + \beta_k \cdot year_k \quad (6)$$

Where:

- $adjROA_{i,t,n}$ = sum of industry-adjusted return on assets for firm i over a period of n years (Hilary et al., 2016; Mundi & Kaur, 2019);

144. Research and Development.

145. We calculated investment intensity as capital expenditure plus R&D expenditure divided by revenue.

- *oe* and *op* are the treatment variables, applied as continuous variables or as categorical variables;
- *EE* is a transformed variable for number of employees that controls for firm size;
- *RD* is a transformed variable for R&D investment that controls for growth opportunities;
- *LEV* is a transformed variable for the leverage ratio that controls for capital structure;
- *BB* is a transformed variable for share buybacks that controls for earnings management;
- *tq* is Tobin's Q that controls for management discretion based on market premium;
- *year* is for the year dummies;
- All regressors are lagged by *n* years; and
- We consider $n = 1, 2, \dots, 5$ to account for the delayed effect of decisions.

This regression equation was modified slightly for each of our hypotheses. For hypotheses 1a and 2a, we dropped the *op* and *oe* terms, respectively. For hypotheses 1b, 2b, and 3, we used the *oe* and *op* terms in their categorical form to allow a finer-grained analysis of the character of the relationship. In our efforts to find non-monotonicity we chose to create categorical variables as we did not have a preconceived notion of the character of the relationship. This is because theory did not provide us with sufficient a priori insight to assume a particular mathematical function.

With this regression equation specified, we now discuss the estimation technique to be applied.

3.7 Estimation technique

We required an estimation technique that was appropriate for our research question “what is the impact of group-level overestimation and overprecision biases on firm performance?” and our associated hypotheses. The estimation technique must be appropriate for our data, which, as described in section 3.2, is a panel of some three thousand firms over an 11-year period. In other words, we had a large *N*, small *T* panel.

Given the nature of our data and our research question, we saw three valid approaches to estimation. They are static panel data analysis using random-effects, static panel data analysis using fixed-effects, and dynamic panel data analysis such as Generalised Method of Moments.

To select one of these estimating models, we considered their relevance for our needs. The first consideration is whether a dynamic or static panel data analysis is more appropriate. In contemplating the dynamic versus static question, we recognised the importance of having clarity of our objectives. Specifically, did we seek to estimate the impact of our treatment variables on the dependent variable or did we seek to predict the dependent variable as accurately as possible? This is a subtle, but essential distinction.

An estimation model can serve to explain or predict (Shmueli, 2010). When one seeks to test causal hypotheses, one is applying an explanatory model to obtain the most accurate representation of the underlying theory (Shmueli, 2010). When one seeks to predict the dependent variable as accurately as possible, one seeks to minimise bias and estimation variance, including possibly sacrificing theoretical accuracy, to achieve empirical precision (Shmueli, 2010).

Our dependent variable, industry-adjusted ROA, has a high level of persistence and hence a lagged version of industry-adjusted ROA is a strong predictor of future industry-adjusted ROA. Thus, if we were seeking to predict industry-adjusted ROA as accurately as possible, we would want to include the lagged dependent variable. In that case, a technique such as the Generalised Method of Moments would be suitable. However, that was not our primary objective. Since we were interested in the time-delayed effect of overestimation and overprecision on firm performance, our requirement was for explanation

rather than prediction. Accordingly, we sought an explanatory model and hence a static panel data analysis model was more suitable.

That meant that we should pick between random-effects and fixed-effects. Fixed effects models are generally considered to be a more convincing tool for estimating ceteris paribus effects (Wooldrige, 2014, p. 398), because fixed-effects controls for all time-invariant differences between firms, so the estimated coefficients cannot be biased because of omitted time-invariant characteristics¹⁴⁶. At the same time, fixed-effects controls for differences in firm performance due to economic cycles.

Based on the above, a fixed-effects model was our clear choice. We found support for this choice by reviewing what other similar studies have done and by confirming that we met the technical requirements for a fixed-effects model.

As shown in Table 5, we found four studies that had large N, small T panels and examined the impact of overconfidence on accounting returns. We noted that between them they have used the same three estimating models, namely static panel data analysis using random-effects (Park et al., 2018), static panel data analysis using fixed-effects (Hilary et al., 2016; Mundi & Kaur, 2019), and dynamic panel data analysis using Generalised Method of Moments (H. A. Kim et al., 2019). Park et al. (2018) recognised that fixed-effects is preferred, but they were precluded from using fixed-effects because some of their variables of interest were stable across time.

Before launching into using this model, we needed to validate that our data and fixed-effects estimation model meet the required assumptions. These assumptions are the classical linear model (CLM) assumptions (Wooldrige, 2014), which includes the five Gauss-Markov assumptions plus the assumption of a normally distributed error term (Wooldrige, 2014). In addition to the CLM assumptions, we will also consider the effect of serial correlation and autocorrelation. We find that we adequately meet these requirements and display our results in section 4.5.4. We also need to meet the technical requirements of a negative Hausman test. We found that it did so convincingly, and the results are shown in Appendix 7.5.2.2.

146. Also commonly referred to as unobserved heterogeneity.

4 Results

“Overconfidence will drown you in the sea of reality”

Norain

The purpose of this chapter is to present the results of our analysis. Our results are a product of applying our research model using our estimation approach to test our hypotheses.

This chapter is structured as follows: we first present the descriptive statistics, then we present the main results of our hypotheses testing, this is followed by supplementary analysis where we sought to explain why we saw what we saw, and lastly we pre-empt potential concerns with a series of robustness tests. With our results presented and concerns addressed, we are positioned to conclude, which we do in the next and final chapter.

4.1 Nomenclature

In this chapter and in various sections of the Appendix we apply nomenclature to our statistical analyses for reading convenience. The following nomenclature applies:

- *****, **, *** reflect statistical significance at the 1%, 5%, and 10% levels, respectively.
- Robust standard errors are shown in parentheses below coefficients.
- **“N”, “min”, “p5”, “p50”, “p95”, “max”, “mean”, “sd”** refer to the number of observations, the minimum, 5th percentile, 50th percentile, 95th percentile, and maximum value observation, the mean, and the standard deviation, respectively.
- Pink cells reflect negative values and green cells reflect positive values.
- In many of the analyses displayed, regressors are lagged. Lagged regressors are depicted by the actual lag number, such as **“L3.”** for a 3-year lag, or using **“L(n).”** where the **“(n)”** matches the dependent variable in the column, for example a column with **“adjROA_c3”** will imply that **“L(n).”** of the regressor equates to **“L3.”**

4.2 Descriptive statistics

Our dependent, treatment, and control variables were specified in sections 3.3, 3.4, and 3.5. We report the descriptive statistics of these variables in Table 9. We also include our supplementary analysis variables, which we will discuss in section 4.4. In this table, N refers to the observation count, min and max to the smallest and largest observations for that variable, p5, p50, and p90 to the 5th, 50th, and 90th percentiles, and mean and sd are mean and the standard deviation for the variable. These descriptive statistics follow the winsorisation and transformation processes that have been applied to the variables. The winsorisation and transformation that we applied is shown in Table 33 of the Appendix.

stats	N	min	p5	p50	p95	max	mean	sd
Dependent variables								
adjROA_c1	17 048	-41.87	-16.70	0.00	13.04	26.31	-0.49	9.48
adjROA_c2	15 070	-70.67	-29.81	0.04	24.57	45.89	-0.73	16.91

stats	N	min	p5	p50	p95	max	mean	sd
adjROA_c3	13 198	-99.02	-41.34	0.01	35.03	64.77	-0.94	23.77
adjROA_c4	11 404	-122.27	-51.03	0.07	45.39	83.41	-0.99	30.03
adjROA_c5	9 683	-148.55	-59.49	-0.01	54.63	98.52	-1.03	36.00
Treatment variables								
oe	5 116	-84.21	-27.62	0.00	27.45	99.01	-1.14	20.45
op	3 866	-66.67	-22.53	-5.44	-1.84	-0.02	-8.09	9.22
oexop	3 866	-2953.02	-352.73	8.20	359.18	2962.96	14.41	529.29
Control variables								
BB	12 891	0.00	0.00	1.00	1.00	1.00	0.66	0.47
EE	15 425	-58.19	-19.42	0.48	19.29	41.81	0.00	11.87
LEV	16 932	-59.23	-20.59	1.98	13.07	40.77	0.00	10.29
RD	15 704	0.00	0.00	1.00	1.00	1.00	0.51	0.50
tq	15 547	-23.26	-14.54	-5.40	35.05	76.74	0.00	16.82
Supplementary analysis variables								
adjrev_g1	16 154	-112.03	-21.97	0.00	36.17	114.59	2.73	21.59
adja_g1	15 021	-105.80	-21.11	0.00	50.18	166.47	5.53	28.21
adjrd	15 704	-12.76	-7.98	0.00	14.23	57.85	1.65	8.64
adjii	15 537	-0.14	-0.06	0.00	0.15	0.32	0.02	0.07
adjde	16 161	-118.99	-53.12	0.00	290.86	1 366.68	48.62	188.71
adjlev	16 932	-0.63	-0.34	0.00	0.45	0.95	0.02	0.25
adjopm	18 792	-119.58	-23.83	0.00	21.60	36.51	-1.21	18.98

Table 9: Descriptive statistics of dependent and independent variables.

Our dependent variable, industry-adjusted return on assets (adjROA), was considered over five lag periods, as discussed in section 3.3. It is interesting to note that the mean and median of adjROA is close to zero in all cases. The widening of the distribution curve, noted by an increasing standard deviation, as we move from adjROA_c1 to adjROA_c2, and so on, is a consequence of some firms having repeated positive or negative outlier returns.

Consistent with the views that overestimation and overprecision are pervasive (Anderson, Brion, Moore, & Kennedy, 2012; Griffin & Varey, 1996; Johnson & Fowler, 2011; Plous, 1993; Radzevick & Moore, 2010; Skała, 2008), are disproportionately more prevalent in the top management team (Goel & Thakor, 2008), and are likely to persist when groups are making strategic decisions (Ben-David et al., 2013; Finkelstein et al., 2009; Meikle et al., 2016), we found evidence of overestimation (oe) and overprecision (op) in our sample.

We have 5,116 observations of range guidance across all firm-years. Of these range guidance observations, actuals fall within the guidance range in 1,250 (24%) cases and hence these guidance range observations are considered to not be overprecise, while actuals fall outside of the guidance range in the other 3,866 (76%) cases and hence these are overprecise observations. The overprecision observations are either over- or under-estimated. We found that 1,385 (27%) are above the actuals

and hence represent overestimation, while 2,481 (48%) are below the actuals and hence represent underestimation.

The finding that underestimation (48% of observations) is almost twice as prevalent as overestimation (27%) is not unexpected given the pressure to avoid a negative earnings surprise as discussed in section 2.4.4.2. The effect of accountability (Heflin et al., 2012) might also be driving managers to underestimate.

We present a pairwise correlation matrix in Table 10. The correlation between **oe** (overestimation) and **op** (overprecision) of 0.015 is notably low. From section 2.3.2.3 we noted that researchers differed in their view on the relationship between overestimation and overprecision. Our findings of a positive relationship are consistent with Hribar and Yang (2016)'s expectation, but given the low value perhaps our finding aligns best with Merkle (2017)'s view that there is no relationship.

Except for the correlation between LEV (leverage) and EE (employees), which is moderate at 0.36, there is relatively low correlation between the other regressors. The correlations between the regressors do not distort our regression model nor pose a collinearity risk. More detail on this point is provided in the robustness analysis (section 4.5.4).

	oe	op	BB	EE	LEV	RD
op	0.015					
BB	-0.011	0.185***				
EE	0.036**	0.211***	0.221***			
LEV	0.050***	0.126***	0.007	0.360***		
RD	-0.032**	-0.002	0.012	-0.085***	-0.197***	
tq	-0.186***	0.171***	0.094***	-0.100***	-0.136***	0.183***

Table 10: Pairwise correlation matrix of regressors of our estimation model.

Note: ***, **, * reflect statistical significance at the 1%, 5%, and 10% levels, respectively

4.3 Main results

For convenience, our research model (equation (6)) from section 3.6 is repeated below.

$$adjROA_{i,t,n} = \beta_0 + \beta_1 \cdot oe_{i,t-n} + \beta_2 \cdot op_{i,t-n} + \beta_3 \cdot EE_{i,t-n} + \beta_4 \cdot RD_{i,t-n} + \beta_5 \cdot LEV_{i,t-n} + \beta_6 \cdot BB_{i,t-n} + \beta_7 \cdot tq_{i,t-n} + \beta_k \cdot year_k$$

Our results from using this model are presented as bivariate analysis, which provides insights into the signs and strengths of each regressor, and then as multivariate analysis, where our hypotheses are tested.

4.3.1 Bivariate analysis

The bivariate analysis for each lag of our dependent variable on the model regressors is displayed in Table 11. We ran our bivariate analysis on the same sample as our multivariate analysis by restricting the bivariate analysis to the data that would be available for the multivariate analysis. The full results with standard errors are provided in Table 34, Table 35, and Table 36 of the Appendix.

For example, the regression of adjROA_c2 on oe of -0.132 refers to the overestimation variable that was computed in year t-2, while adjROA_c2 is the sum of adjROA in year t and t-1. Thus together, adjROA_c2 regressed on oe spans a 3-year period.

Year	t-2	t-1	t
Dependent variable		adjROA	adjROA
Independent variable	oe		

Figure 11: Example illustrating the temporal position of independent and dependent variables in bivariate analysis of adjROA_c2 regressed against oe.

The bivariate analysis shows that adjROA on oe is negative and significant at the 1% level for all 5 lags of adjROA. This is consistent with hypothesis 1a from a sign perspective and will be discussed in more detail later. The analysis shows a positive relationship between adjROA and op, but the statistical significance fades after 3 years and the coefficient switches to negative in the fifth lag. The positive relationship is consistent with hypothesis 2a. The control variables are largely consistent in their sign for all lags of the dependent variable, except for BB (buybacks) that has a sign change in the latter lags for reasons that are not understood.

VARIABLES	adjROA_c1	adjROA_c2	adjROA_c3	adjROA_c4	adjROA_c5
L(n).oe	-0.0758*** (0.00942)	-0.139*** (0.0172)	-0.180*** (0.0254)	-0.191*** (0.0319)	-0.186*** (0.0364)
L(n).op	0.205*** (0.0321)	0.202*** (0.0554)	0.133* (0.0791)	0.0827 (0.0823)	-0.0454 (0.0874)
L(n).BB	1.175*** (0.437)	1.243 (0.812)	0.872 (1.085)	-0.418 (1.279)	-1.405 (1.488)
L(n).EE	-0.384*** (0.0787)	-0.829*** (0.155)	-1.259*** (0.225)	-1.596*** (0.298)	-1.798*** (0.405)
L(n).LEV	-0.396*** (0.0483)	-0.417*** (0.0907)	-0.460*** (0.146)	-0.490*** (0.178)	-0.574** (0.231)
L(n).RD	-1.511 (1.581)	-3.823 (3.769)	-6.009 (6.423)	-6.678 (8.512)	-8.710 (8.965)
L(n).tq	0.185*** (0.0175)	0.377*** (0.0344)	0.498*** (0.0504)	0.519*** (0.0682)	0.430*** (0.0907)

Table 11: Bivariate analysis.

Notes regarding the table:

- ***, **, * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.
- Robust standard errors are shown in parentheses below coefficients.
- Pink cells reflect negative values and green cells reflect positive values.
- In many of the analyses displayed, regressors are lagged. Lagged regressors are depicted by the actual lag number, such as "L3." for a 3-year lag, or using "L(n)." where the "(n)" matches the dependent variable in the column, for example a column with "adjROA_c3" will imply that "L(n)." of the regressor equates to "L3."

4.3.2 Multivariate analysis

4.3.2.1 Findings

We subjected our research model to multivariate analysis using a firm and year fixed-effects model. The results of the multivariate analysis are displayed in Table 12. These results are presented in five blocks, one each for adjROA_c1, adjROA_c2, ... adjROA_c5. For each dependent variable, the treatment variables and control variables are lagged to occur before the first year of the dependent variable. For example, adjROA_c3 sums the industry-adjusted ROA in years t, t-1, t-2, and the regressors all occur in year t-3. Within each block there are four models. The models in the first column are baseline models that include the controls, but not the treatment variables. The second column introduces the treatment variable oe, while the third column introduces the treatment variable op. The last column includes both oe and op as treatment variables.

The last row of each block illustrates the improvement in R² due to the inclusion of the treatment variables. The cells with black borders indicate where there is a difference to the bivariate analysis. The results for all five lags are provided in Appendix 7.5.2.

VARIABLES	adjROA_c1	adjROA_c1	adjROA_c1	adjROA_c1
L.EE	0.0373 (0.0703)	-0.129* (0.0684)	-0.190** (0.0774)	-0.155** (0.0714)
L.LEV	-0.426*** (0.0420)	-0.365*** (0.0429)	-0.321*** (0.0412)	-0.315*** (0.0414)
L.RD	-1.642 (1.194)	-1.083 (0.980)	-0.108 (1.023)	-0.00345 (0.837)
L.BB	1.183*** (0.249)	1.200*** (0.382)	1.272*** (0.438)	1.303*** (0.393)
L.tq	0.218*** (0.0139)	0.169*** (0.0203)	0.184*** (0.0204)	0.154*** (0.0200)
L.oe		-0.0596*** (0.00837)		-0.0638*** (0.00787)
L.op			0.163*** (0.0275)	0.191*** (0.0249)
Year fixed effects	Y	Y	Y	Y
Constant	-0.112 (0.683)	2.141** (0.868)	2.983*** (0.995)	3.069*** (0.876)
Observations	9,838	3,060	2,443	2,443
R-squared	0.163	0.253	0.261	0.321
Number of uid	1,423	580	557	557

VARIABLES	adjROA_c3	adjROA_c3	adjROA_c3	adjROA_c3
L3.EE	-0.551** (0.277)	-0.604*** (0.184)	-0.766*** (0.235)	-0.663*** (0.215)
L3.LEV	-0.193** (0.0848)	-0.201* (0.105)	-0.168 (0.108)	-0.151 (0.0993)
L3.RD	-3.184 (2.998)	-5.480 (4.198)	-6.445 (5.456)	-5.970 (4.771)
L3.BB	1.653*** (0.568)	1.923** (0.902)	2.769** (1.140)	2.641*** (1.016)
L3.tq	0.680*** (0.0474)	0.491*** (0.0569)	0.554*** (0.0608)	0.478*** (0.0586)
L3.oe		-0.128*** (0.0251)		-0.136*** (0.0267)
L3.op			0.0913 (0.0589)	0.175*** (0.0595)
Year fixed effects	Y	Y	Y	Y
Constant	-1.372 (1.743)	4.635* (2.774)	5.324 (3.765)	5.387 (3.354)
Observations	7,840	2,424	1,935	1,935
R-squared	0.186	0.311	0.288	0.355
Number of uid	1,333	522	505	505

VARIABLES	adjROA_c5	adjROA_c5	adjROA_c5	adjROA_c5
L5.EE	-1.396** (0.578)	-1.132*** (0.338)	-1.396*** (0.461)	-1.279*** (0.417)
L5.LEV	0.0121 (0.154)	-0.205 (0.179)	-0.212 (0.206)	-0.185 (0.191)
L5.RD	-7.904* (4.061)	-9.464 (6.880)	-7.068 (6.197)	-7.012 (6.095)
L5.BB	0.461 (0.764)	1.031 (1.362)	1.472 (1.709)	1.846 (1.691)
L5.tq	0.657*** (0.0755)	0.454*** (0.0969)	0.526*** (0.108)	0.455*** (0.107)
L5.oe		-0.145*** (0.0375)		-0.152*** (0.0407)
L5.op			0.0134 (0.0871)	0.172* (0.0914)
Year fixed effects	Y	Y	Y	Y
Constant	6.003** (2.364)	14.82*** (4.688)	14.41*** (4.968)	14.73*** (4.769)
Observations	5,757	1,743	1,392	1,392
R-squared	0.128	0.213	0.176	0.231
Number of uid	1,225	458	437	437

Table 12: Multivariate analysis of research model showing lags 1, 3, and 5. Each lag shows the baseline model without treatment variables, plus the additional effect of the treatment variables independently and together.

Notes regarding the table:

- ***, **, * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.
- Robust standard errors are shown in parentheses below coefficients.
- Pink cells reflect negative values and green cells reflect positive values.
- In many of the analyses displayed, regressors are lagged. Lagged regressors are depicted by the actual lag number, such as “L3.” for a 3-year lag, or using “L(n).” where the “(n)” matches the dependent variable in the column, for example a column with “adjROA_c3” will imply that “L(n).” of the regressor equates to “L3.”.

We observed the following from these results. First, a high degree of consistency of coefficient sign with the bivariate analysis for all regressors. Second, the treatment variables are sign consistent with the bivariate analysis in all cases, except op in the fifth lag of the dependent variable. Third, the overestimation variable (oe) is negative and significant at the 1% level for all five versions of the dependent variable, while the overprecision variable (op) is positive and significant for the first two lags of the dependent variable, but thereafter fades in significance. Fourth, the effect of the treatment variables is to drive up the model fit (R^2) in all cases, with oe having more impact than op, except for the first lag. Fifth, op has more impact on the impact on firm performance (adjROA) than oe in the first lag, but this impact is relatively short-lived and fades faster than oe’s impact. We measured impact by calculating the effect of a one standard deviation (sd) change of the treatment variable on one standard deviation of adjROA. Sixth, the impact of both oe and op is greatest in the first lag of adjROA but fades thereafter. This is illustrated in Table 13 below.

	adjROA_c1	adjROA_c2	adjROA_c3	adjROA_c4	adjROA_c5
sd of adjROA	9.48	16.91	23.77	30.03	36.00
oe 1 unit impact	-0.0638***	-0.112***	-0.136***	-0.151***	-0.152***
op 1 unit impact	0.191***	0.210***	0.175***	0.216***	0.172*
sd of oe	20.62	20.53	20.27	20.41	20.55
sd of op	9.37	9.47	9.40	9.29	9.49
oe sd impact	-1.32	-2.30	-2.76	-3.08	-3.12
op sd impact	1.79	1.99	1.64	2.01	1.63
oe sd impact as % of adjROA sd	-14%	-14%	-12%	-10%	-9%
op sd impact as % of adjROA sd	19%	12%	7%	7%	5%

Table 13: Impact of a 1 standard deviation change of oe and op on adjROA in each lag period.

4.3.2.2 Interaction between overestimation and overprecision

We introduced a variable (oexop) to assess the interaction effect between overestimation and overprecision. The results of this analysis are shown in Table 14. We found that this variable’s coefficient in our model was small and not statistically significant. It had a negligible impact on model fit (R^2), it had a small effect on the magnitude of the overestimation and overprecision coefficients, and it had no effect on overestimation and overprecision’s significance levels. From this, we concluded that overestimation and overprecision do not interact in any meaningful way. Consequently, we did not include the interaction variable in our estimating model.

VARIABLES	without adjROA_c1	with oexop adjROA_c1	without adjROA_c3	with oexop adjROA_c3	without adjROA_c5	with oexop adjROA_c5
L(n).oe	-0.0638*** (0.00787)	-0.0471*** (0.0119)	-0.136*** (0.0267)	-0.131*** (0.0292)	-0.152*** (0.0407)	-0.129*** (0.0459)
L(n).op	0.191*** (0.0249)	0.196*** (0.0263)	0.175*** (0.0595)	0.176*** (0.0631)	0.172* (0.0914)	0.190* (0.0987)

L(n).EE	-0.155** (0.0714)	-0.152** (0.0716)	-0.663*** (0.215)	-0.660*** (0.214)	-1.279*** (0.417)	-1.252*** (0.410)
L(n).LEV	-0.315*** (0.0414)	-0.314*** (0.0414)	-0.151 (0.0993)	-0.151 (0.0989)	-0.185 (0.191)	-0.188 (0.189)
L(n).RD	-0.00345 (0.837)	0.0452 (0.805)	-5.970 (4.771)	-5.950 (4.742)	-7.012 (6.095)	-7.004 (6.113)
L(n).BB	1.303*** (0.393)	1.302*** (0.395)	2.641*** (1.016)	2.638*** (1.013)	1.846 (1.691)	1.847 (1.692)
L(n).tq	0.154*** (0.0200)	0.156*** (0.0201)	0.478*** (0.0586)	0.479*** (0.0585)	0.455*** (0.107)	0.458*** (0.107)
L(n).oexop		0.000891 (0.000563)		0.000228 (0.00163)		0.00119 (0.00233)
Year fixed effects	Y	Y	Y	Y	Y	Y
Constant	3.069*** (0.876)	3.050*** (0.864)	5.387 (3.354)	5.374 (3.334)	14.73*** (4.769)	14.66*** (4.764)
Observations	2,443	2,443	1,935	1,935	1,392	1,392
R-squared	0.321	0.323	0.355	0.355	0.231	0.232
Number of uid	557	557	505	505	437	437

Table 14: Effect of an overestimation and overprecision interaction variable.

Notes regarding the table:

- ***, **, * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.
- Robust standard errors are shown in parentheses below coefficients.
- Pink cells reflect negative values and green cells reflect positive values.
- In many of the analyses displayed, regressors are lagged. Lagged regressors are depicted by the actual lag number, such as “L3.” for a 3-year lag, or using “L(n).” where the “(n)” matches the dependent variable in the column, for example a column with “adjROA_c3” will imply that “L(n).” of the regressor equates to “L3.”

4.3.2.3 Hypothesis evaluation

The multivariate analysis allowed us to evaluate hypotheses 1a and 2a.

Hypothesis 1a. The relationship between overestimation and firm performance is negative.

Our results of the impact of overestimation (shown as the second of the four results columns in Table 12) showed a negative relationship at the 1% significance level for oe and firm performance for all five lags of the dependent variable. Thus, we could confidently reject the null hypothesis and hence hypothesis 1a found support. In the full model (last column of Table 12), the coefficient for oe is negative and ranges between -0.064 and -0.152, with a steady growth in magnitude with increasing lags. With reference to Table 13 and considering lag 1 of the dependent variable (adjROA_c1), a coefficient of -0.064 means that a standard deviation of change in oe is associated with -1.32 percentage points of change in industry-adjusted ROA, which is -14% of industry-adjusted ROA's standard deviation.

What does a decline of 1.32 percentage points of industry-adjusted ROA mean for the shareholder? The median¹⁴⁷ asset base of our data set across our period of interest¹⁴⁸ was \$2 billion. If the median

147. The mean asset base is \$10 billion.

148. Our period of interest was 2009 to 2019, and this was the period used in our analysis. However, if we look at the median firm size in 2019, it is \$3.3 billion.

firm’s industry-adjusted return on assets declined by 1.32% that would destroy \$26 million of shareholder value. And, assuming a 10% WACC, the present value of a sustained annual loss of \$26 million is a value loss of \$260 million.

Hypothesis 2a. The relationship between overprecision and firm performance is positive.

Our results (shown as the third of the four results columns in Table 12) showed a positive relationship at the 1% significance level for op and firm performance for the first two lags of the dependent variable. For lags 3, 4 and 5, there is no statistical significance for op on its own, although when included in a model with oe (rightmost column of Table 12) op retains statistical significance at the 1% level for lag 4 and at the 10% level for lag 5.

Thus, when considering lags 1 to 2, we could confidently reject the null hypothesis and hence hypothesis 2a found support. In the full model (last column of Table 12), the coefficient for op is positive and ranges between 0.172 and 0.216. Considering lag 1 of the dependent variable (adjROA_c1), a coefficient of 0.191 means that a standard deviation of change in op is associated with +1.79 percentage points of change in industry-adjusted ROA, which is 19% of industry-adjusted ROA’s standard deviation.

What does a gain of 1.79 percentage points of industry-adjusted ROA mean for the shareholder? Using the same logic as above, the annual value to shareholders of the median firm would be \$36 million and in present value terms this would amount to a value gain \$360 million.

To explore the hypothesised non-monotonic aspect, hypotheses 1b and 2b, as well as in our quest to find the “goldilocks” zone, hypothesis 3, finer grained analysis was required. This finer grained analysis could be achieved using a higher order continuous function, like a quadratic or cubic, or using categorical analysis, which is the approach that we took. We chose to create categorical variables as we did not have a preconceived notion of the character of the relationship. This is because theory did not provide us with sufficient a priori insight to assume a particular mathematical function.

4.3.3 Heatmaps

4.3.3.1 Findings

We converted our oe and op continuous variables into fine-grained categorical variables, which we called soecat and sopcat¹⁴⁹, respectively. We used a 7-part¹⁵⁰ categorical variable thus allowing visibility of the “shape” of the curve of industry-adjusted ROA with respect to overestimation and overprecision.

As mentioned in section 4.2, we found that 24% of our observations were “calibrated” in that the actuals fell within the guidance range. In these cases, we recorded our overestimation continuous variable (oe) as zero and we treated these observations as not exhibiting overprecision and hence they did not feature in our continuous variable (op) as defined in section 3.4.2 and repeated below for convenience.

$$op = \frac{-Range}{|Midpoint|} \text{ if } oe \neq 0$$

149. The reason for the naming starting with “s” is for the division into seven or septiles.

150. The choice of 7-parts was informed by the desire to have roughly equal number of observations in each category, while dividing into several categories to allow fine-grained analysis. Since 24% of our observations are calibrated, we feel that a sensible division is to divide the 27% of overestimation observations in two and our 48% of underestimations into four.

Due to the absence of overprecision data in the case of our calibrated observations, we would not have been able to plot a heatmap across the full two-dimensional space from underestimation to calibration to overestimation on one axis and from low overprecision to high overprecision on the other axis. The current definition would have resulted in a gap on the overestimation dimension at the categorical position for calibration as illustrated in Figure 12 below.

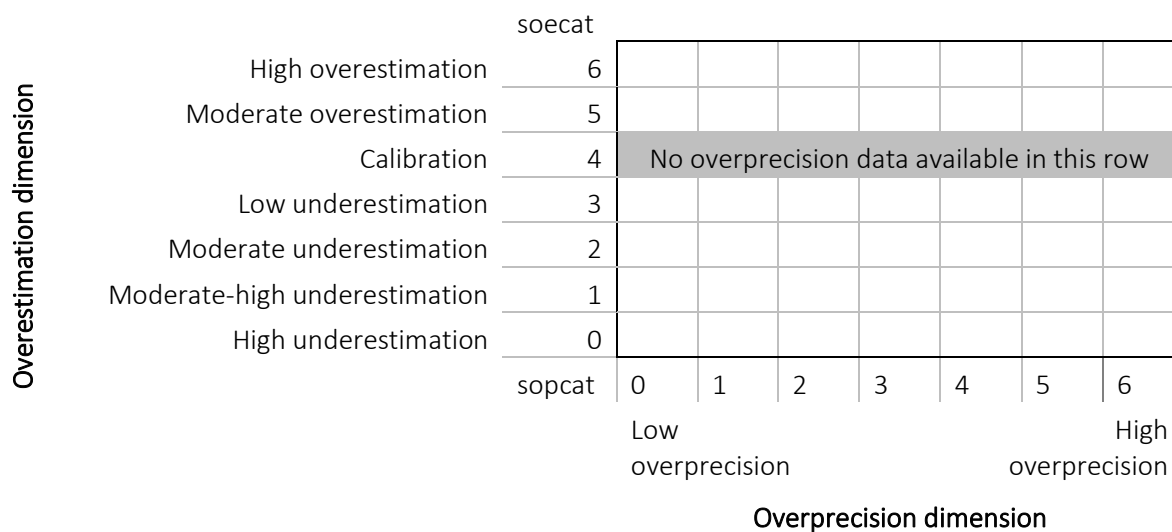


Figure 12: Heatmap showing the gap in overprecision data.

To enable the development of the heatmap across the full two-dimensional space, we modified our definition of the overprecision variable. We removed the “if $oe \neq 0$ ” constraint and hence we measured the scaled guidance range, irrespective of whether the actuals were in range or not.

$$sopcat = \frac{- Range}{|Midpoint|}$$

Thus, our sopcat variable measures the level of precision expressed by the management team, ranging from low precision to high precision on the calibration, and from low overprecision to high overprecision on all other rows.

The multivariate analysis using categorical treatment variables, soecat and sopcat, is shown in Table 15. This analysis showed that, with one exception, sopcat 1 for lag 1, the categorical variables are sign consistent with the multivariate analysis using the continuous variables. Moreover, the statistical significance was largely retained in all lags for overestimation and for the first three to four lags for overprecision.

VARIABLES	adjROA_c1	adjROA_c2	adjROA_c3	adjROA_c4	adjROA_c5
0bL.soecat	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
1L.soecat	0.205 (0.366)	-1.136* (0.656)	-1.090 (0.966)	-1.410 (1.263)	-0.387 (1.612)
2L.soecat	-0.871** (0.364)	-2.446*** (0.688)	-2.326** (0.972)	-2.113* (1.251)	-2.328 (1.545)
3L.soecat	-0.690* (0.370)	-2.151*** (0.646)	-2.579*** (0.935)	-3.435*** (1.223)	-4.174*** (1.573)
4L.soecat	-0.714* (0.373)	-2.254*** (0.714)	-2.350** (1.023)	-3.440*** (1.294)	-4.302*** (1.638)
5L.soecat	-0.831** (0.414)	-2.981*** (0.741)	-3.675*** (1.038)	-4.058*** (1.317)	-4.765*** (1.657)
6L.soecat	-3.133*** (0.507)	-6.452*** (0.954)	-8.131*** (1.468)	-9.364*** (1.802)	-10.28*** (2.151)
0bL.sopcat	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
1L.sopcat	1.840*** (0.448)	1.603** (0.712)	1.272 (0.957)	0.190 (1.142)	-0.285 (1.550)
2L.sopcat	2.662*** (0.482)	2.664*** (0.857)	2.285* (1.270)	1.419 (1.419)	1.423 (1.755)
3L.sopcat	3.082*** (0.516)	4.402*** (0.939)	4.041*** (1.303)	3.603** (1.454)	3.222* (1.908)
4L.sopcat	3.497*** (0.546)	4.588*** (0.943)	3.877*** (1.347)	2.587* (1.520)	1.228 (1.972)
5L.sopcat	3.546*** (0.612)	4.920*** (1.092)	4.944*** (1.650)	4.258** (1.743)	2.725 (2.013)
6L.sopcat	3.877*** (0.649)	5.151*** (1.130)	4.905*** (1.666)	4.800** (1.932)	5.034** (2.483)
L.EE	-0.157** (0.0672)	-0.432*** (0.126)	-0.656*** (0.182)	-0.970*** (0.243)	-1.226*** (0.337)
L.LEV	-0.333*** (0.0411)	-0.213*** (0.0710)	-0.138 (0.105)	-0.0792 (0.129)	-0.156 (0.186)
L.RD	-1.330 (0.965)	-4.068* (2.182)	-5.946 (4.144)	-6.929 (5.995)	-9.629 (6.730)
L.BB	0.840** (0.382)	1.385** (0.705)	1.612* (0.942)	1.179 (1.151)	0.395 (1.348)
L.tq	0.161*** (0.0180)	0.348*** (0.0354)	0.468*** (0.0531)	0.483*** (0.0701)	0.413*** (0.0934)
Year fixed effects	Y	Y	Y	Y	Y
Constant	0.812 (0.930)	3.210* (1.699)	5.088* (2.938)	10.53** (4.234)	18.09*** (5.328)
Observations	3,060	2,762	2,424	2,080	1,743
R-squared	0.263	0.309	0.312	0.277	0.228
Number of uid	580	555	522	493	458

Table 15: Multivariate analysis using categorical treatment variables.

Notes regarding the table:

- ***, **, * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.
- Robust standard errors are shown in parentheses below coefficients.
- Pink cells reflect negative values and green cells reflect positive values.

From this categorical analysis we developed heatmaps for each of the adjROA lags. The heatmaps for adjROA_c1, adjROA_c3, and adjROA_c5 are shown in Figure 13, Figure 14, and Figure 15 below. The profiles show the effect on industry-adjusted ROA for each of the 7 steps in the categorical variables, while the heatmap shows the combined effect. Note that the adjROA_c3 and adjROA_c5 heatmaps were annualised by dividing all values by three and five, respectively.

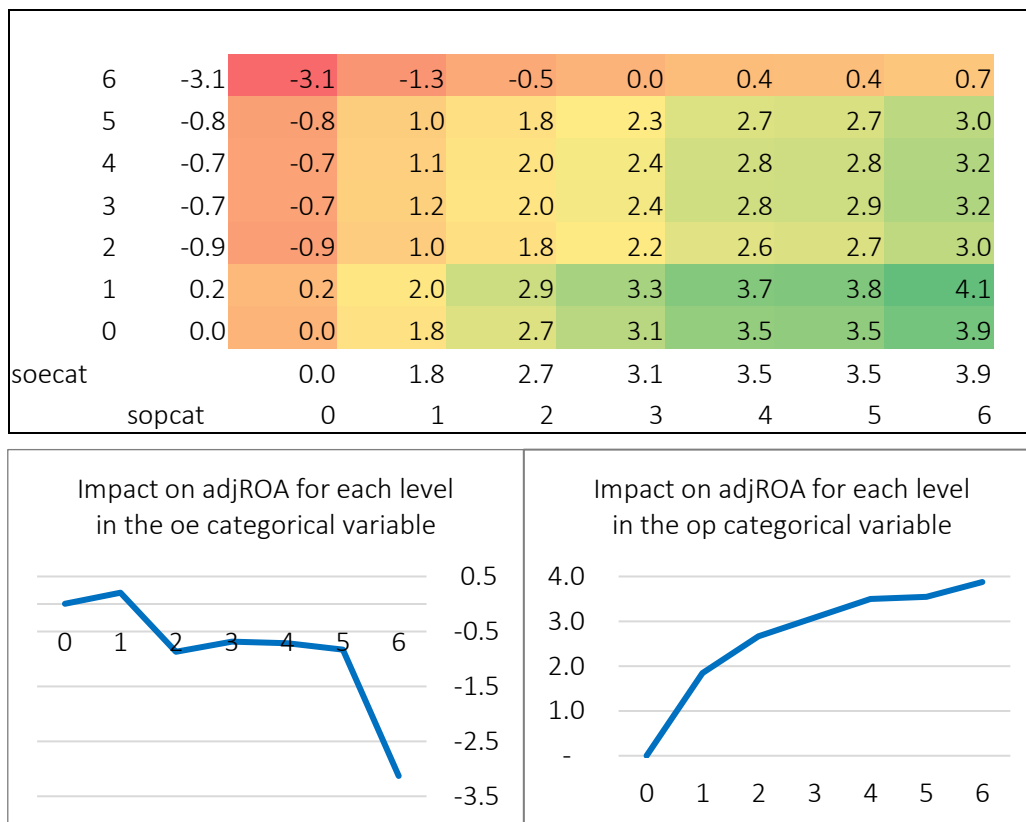
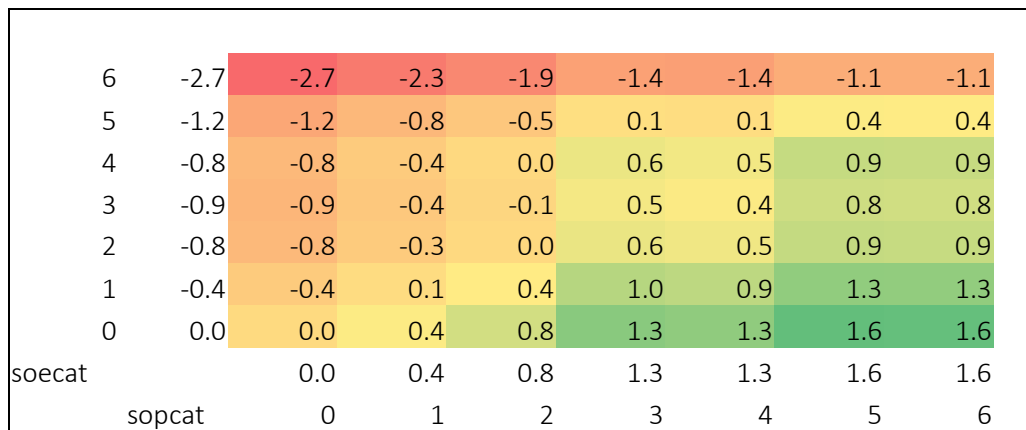


Figure 13: Heatmap and profiles of adjROA_c1 with respect to overestimation and overprecision.



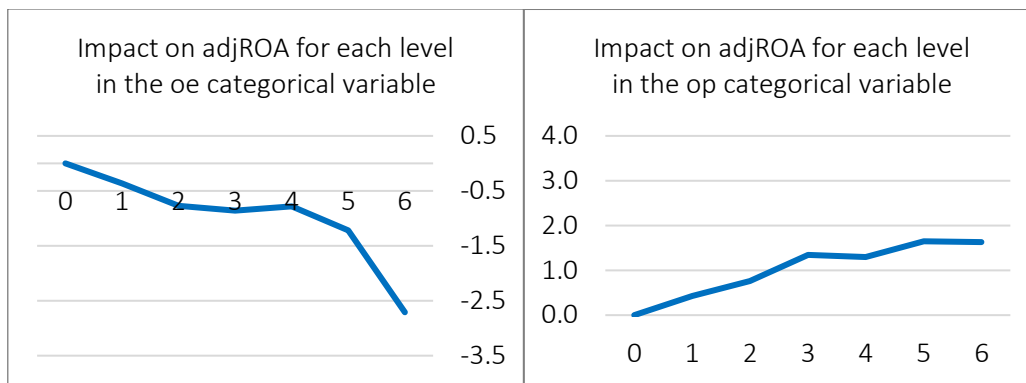


Figure 14: Heatmap and profiles of annualised adjROA_c3 with respect to overestimation and overprecision

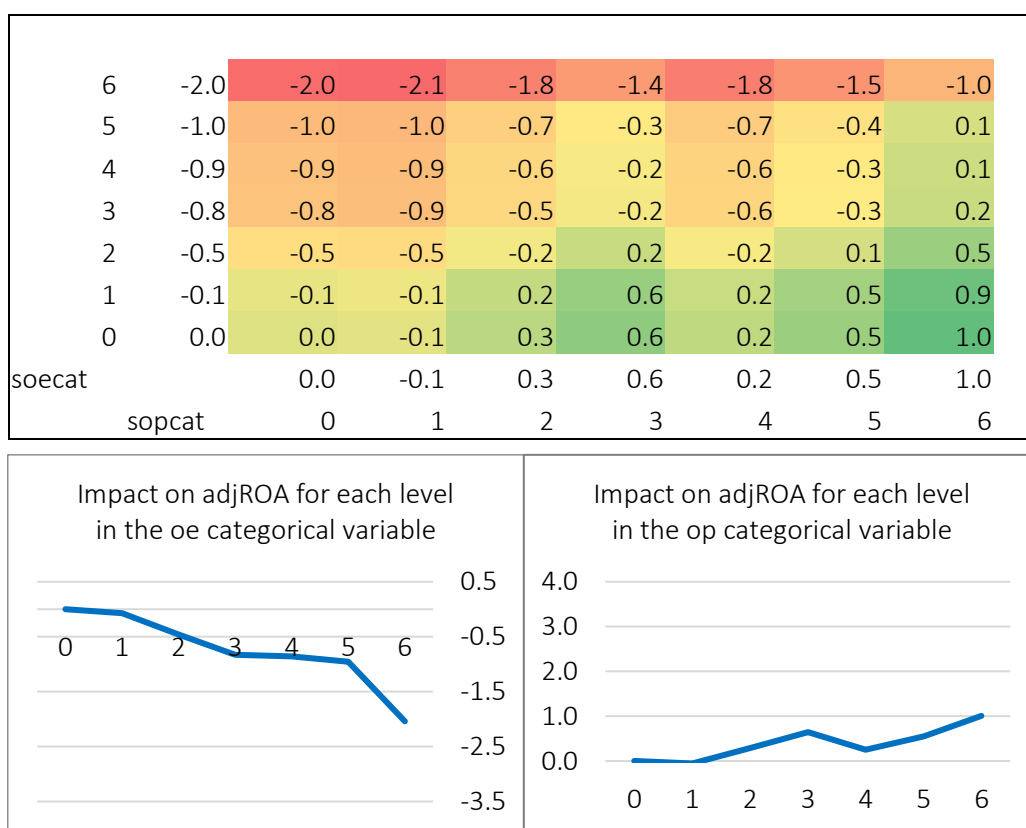


Figure 15: Heatmap and profiles of annualised adjROA_c5 with respect to overestimation and overprecision.

The heatmap for adjROA_c1 showed that the highest firm performance is 3.9 percentage points of industry-adjusted ROA and it occurs when overprecision is at its highest and overestimation is at its lowest. The lowest firm performance is -3.1 percentage points and occurs at the opposite extreme, namely the lowest level of overprecision and highest level of overestimation. Consequently, the spread in firm performance between these best and worst categories is 7.0 percentage points, a substantial effect size given that the standard deviation for adjROA_c1 is 9.5 percentage points.

We considered what 7.0 percentage points of industry-adjusted ROA means for the shareholder. If the median S&P 1500 firm, with an asset base of \$2 billion, were to improve its industry-adjusted return on assets by 7.0% that would deliver an extra \$140 million annually to shareholders. On a present value

basis, assuming a 10% WACC, that represents value creation of a staggering \$1.4 billion for the median firm.

The total and annualised spread between best and worst performers for each dependent variable is displayed in Table 16 below. This table shows that although the total spread ramps up with each successive year, the annualised effect decreases since the standard deviation of the dependent variable increases faster. We compared the total spread to the standard deviation of adjROA to determine the impact of a change from worst to best (or vice versa) performer. For lag 1, as mentioned above, moving from best to worst performer amounts to 7 percentage points of adjROA and this is three quarters of the standard deviation of adjROA. This impact shows a steady decline with increasing lags and by lag 5 the total spread’s impact on adjROA has decreased to 42% of the standard deviation of adjROA.

	adjROA_c1	adjROA_c2	adjROA_c3	adjROA_c4	adjROA_c5
Total spread [%]	7.0	11.6	13.0	14.2	15.2
Annualised spread [%]	7.0	5.8	4.3	3.5	3.0
Standard deviation of adjROA	9.5	16.9	23.8	30.0	36.0
Total spread to stdev(adjROA)	74%	69%	55%	47%	42%

Table 16: Impact of spread between best and worst performers on the standard deviation of industry-adjusted ROA.

We acknowledged that this is almost the most extreme case in that it would entail the median firm migrating from being in the roughly two percent of worst performing firms to being in the two percent of best performing firms. A more conservative and standardised assessment of the value would consider the impact of a one standard deviation change of both overestimation and overprecision on industry-adjusted ROA. Since overestimation and overprecision have opposite effects, we considered the four permutations of a standard deviation change of each. We used the calculations in Table 13 to produce the combined impact table shown below. When overestimation decreases by one standard deviation and overprecision increases by one standard deviation, the resulting value creation for the median firm is \$62 million annually or \$622 million if this change is sustained. The opposite is also true in that \$622 million of value destruction awaits those that change from underestimation and overprecision to overestimation and no longer being overprecise.

sd of oe	+1	-1	+1	-1
sd of op	+1	+1	-1	-1
ROA impact of sd change in oe and op [%]	0.47	3.11	-3.11	-0.47
ROA impact on median firm [\$ million]	9.4	62.2	-62.2	-9.4
Firm value change [\$ million]	94	622	-622	-94

Table 17: Combined impact of a one standard deviation change in overestimation and overprecision.

4.3.3.2 Hypothesis evaluation

In addition to the effects over time, from adjROA_c1 to adjROA_c5, with the granularity afforded by the categorical variables, we were able to inspect the character of the overestimation and overprecision effect within a particular time period. We saw that the profile of the overestimation categorical variable (soecat) showed a dramatic fall-off between the last two categories. This is especially true for

adjROA_c1, but still noticeable in adjROA_c3 and adjROA_c5. Despite this non-linear behaviour, soecat is still largely monotonic. The overprecision categorical variable (sopcat) is smoother in character and clearly monotonic, although with some moderate non-monotonicity in adjROA_c5.

With these findings, we were able to evaluate hypotheses 1b, 2b, and 3, which we repeat again for convenience:

- *Hypothesis 1b. The relationship between overestimation and firm performance is non-monotonic.*
- *Hypothesis 2b. The relationship between overprecision and firm performance is non-monotonic.*
- *Hypothesis 3. Firm performance is maximised when there is moderate negative overestimation and moderate positive overprecision.*

We found that both hypotheses 1b and 2b are not supported. In considering why these hypotheses have not found support, we noted that both hypotheses were founded on theory only, with no empirical studies yet found that demonstrate this effect. The absence of this effect from empirical studies might be due to the “bluntness” of the proxies used, as previously mentioned. It might also be due to the resolution of the time period, for example perhaps non-monotonicity plays out in weeks or months, rather than years, or even in decades, rather than years. Another possible explanation is that the effect exists but is “drowned out” by other factors. And yet another explanation is that the theoretical basis is simply incorrect.

Due to the monotonic, rather than non-monotonic finding, we found partial support for hypothesis 3. We found that firm performance is maximised not when overestimation and overprecision are moderately negative and positive, but rather when they are extremely negative and extremely positive, respectively.

Although we did not find non-monotonicity in our results, we believe this case is not closed. An alternative specification of the model, for example using differently designed proxies or different time horizons, might yet yield a non-monotonic relationship. As such, we suggest this as an area for further research.

4.4 Supplementary analysis

Why do we see what we see? In seeking to explain our results, specifically the negative relationship between overestimation and firm performance and the positive relationship between overprecision and firm performance, we conducted supplementary analysis using our data set. We considered the interaction effect between overestimation and overprecision, the effect of firm past performance on overestimation and overprecision, the effect of past overestimation and overprecision on future overestimation and overprecision, and lastly, we considered the effect of overestimation and overprecision on mediating variables that are related to firm performance.

This analysis was conducted with the intent to elicit insights that could inform future research. The summary findings are presented below, and the full results of this analysis is in Appendix 7.5.2.

4.4.1 Effect of firm past performance on overestimation and overprecision

We regressed our overestimation variable on the lagged versions of our firm performance metric, industry-adjusted ROA. We did the same with our overprecision variable. The results of this analysis are provided in Table 45 of the Appendix.

We found, consistent with Hilary et al. (2016), that past firm performance increases overestimation, albeit not in a statistically significant way. We also found that past firm performance increases overprecision and with a one-year lag this was statistically significant. In other words, when the firm

does well, management's overconfidence increases, both in terms of overestimating and being overprecise.

That overestimation and overprecision are enhanced by recent firm performance is not surprising in that prior research finds that past success drives a plethora of individual and social biases, including executive hubris, delusional optimism, overconfidence, competition neglect, learning myopia, groupthink, corporate inertia, and cultural stagnation (Powell, 2017).

4.4.2 Effect of past overestimation and overprecision on current overestimation and overprecision

We regressed our overestimation and overprecision variables on their lagged versions and lagged versions of the other. The results of this analysis are provided in Table 46 of the Appendix.

With a one-year lag, we found that overestimation had a positive, but non-significant relationship with current overestimation, but a negative relationship with current overprecision, that was statistically significant. Adding a two-year lag to the one-year lag, showed two-year lagged overestimation to have a negative and significant relationship to current overestimation, while in the case of overprecision, lagged overestimation for one- and two-year lags was consistently negative and significant. The relationship between lagged overestimation and itself is difficult to make sense of, but lagged overestimation was unambiguously related to a decrease in overprecision. In other words, it seems that following optimism, one becomes less precise.

When considering the lag of overprecision, we found that a one-year lag had a positive and significant relationship with both overestimation and overprecision. That lagged overprecision is related to increased overestimation is consistent with the findings of Hilary et al. (2016). Adding a two-year lag to the one-year lag did not materially change the results.

Thus, there appears to be a dynamic, self-limiting nature to the interplay between overestimation and overprecision. Overestimation might result in less overprecision, which in turn might result in less overestimation. Similarly, overprecision might be self-limiting via overestimation.

4.4.3 Effect of overestimation and overprecision on mediating variables that are related to adjROA

We considered mediating variables that might influence industry-adjusted ROA. For each of those mediating variables we calculated an industry-adjusted measure in the same way that we calculated adjROA. For example, for revenue growth, we calculated industry-adjusted revenue growth as the firm's revenue growth minus the industry median revenue growth in each year. Our variables of interest were grouped in four categories: growth, investments, capital structure, and operating margin.

We executed a multivariate regression of each of these mediating variables against lagged overestimation and lagged overprecision as continuous variables and as categorical variables. We considered the relation between lagged overestimation and lagged overprecision on each of these mediating variables along with the bivariate analysis of each of these mediating variables on the firm performance measure, adjROA. The summary of this analysis is presented in Table 18 (detailed results can be found in Table 49 and Table 50 of the Appendix) and is discussed below. We use "NS" to indicate that no statistically significant relationship was found.

Industry-adjusted ...		Bivariate of mediating variable to adjROA	Multivariate of mediating variable to lagged treatment variables			
			oe coeff significance	oe sd impact as % of adjROA sd	op coeff significance	op sd impact as % of adjROA sd
Growth	Revenue growth	- ***	**	-4.9%	**	6.0%
	Asset growth	+ ***	**	-4.3%	NS	2.1%
Investments	R&D to revenue	- ***	NS	0.4%	NS	-3.4%
	Investment intensity	+ NS	NS	0.6%	NS	-3.2%
Capital structure	Debt-to-equity	- ***	NS	0.0%	NS	-0.2%
	Leverage	- ***	NS	0.2%	NS	-0.9%
Operating margin	Operating margin	+ ***	***	-4.6%	NS ¹⁵¹	3.6%

Table 18: Relationships between industry-adjusted mediating variables to adjROA and to the lagged treatment variables.

Notes regarding the table: ***, **, * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.

With consideration to one standard deviation of the treatment variables’ impact as a percentage of industry-adjusted ROA’s standard deviation, we noted that three of the mediating variables have substantially greater impact than the other variables. These are revenue growth, asset growth, and operating profit margin. We also noted that only these variables delivered statistically significant results.

From the growth analysis, we found that industry-adjusted revenue growth has a negative relationship to industry-adjusted ROA. We found that overestimation has a negative relationship and overprecision has a positive relationship to industry-adjusted revenue growth, both at the 5% significance level. We also found a negative and statistically significant relationship between industry-adjusted asset growth and overestimation. That overestimation has a negative relationship to industry-adjusted revenue growth and that industry-adjusted revenue growth, in turn, has a negative relationship to industry-adjusted ROA, suggests that, ceteris paribus, overestimation should have a positive relationship to industry-adjusted ROA, which we have found is not the case. And, a similar argument, but with opposite signs, applies for overprecision. This inconsistent finding suggests that other relationships, such as industry-adjusted operating margin, have a dominant effect over industry-adjusted revenue growth.

From the investments analysis, we found that there is no statistically significant effect of overestimation or overprecision on industry-adjusted R&D or on overall industry-adjusted investment intensity. However, we noted that the positive relationship between overestimation and R&D was consistent with the findings of Hur et al. (2019). Our take-away was that the overconfidence (overestimation or overprecision) of management teams does not lead to them making more or less investments. This

151. Although the continuous variable does not show statistical significance, the categorical variable analysis (Table 50 in the Appendix) shows significance at the 5% level in 4 of its 7 categories.

finding is not inconsistent with our conclusion in section 2.2.4.1 that hubris theory leads overestimating managers to overinvest and perhaps also to underinvest. Given the lack of statistical significance in these findings, we concluded that overestimation and overprecision's impact on industry-adjusted ROA is not likely to be through a mediating effect of the scale of R&D and/or capital investments.

Considering industry-adjusted debt/equity and industry-adjusted leverage, we did not find any statistically significant relationships with overestimation or overprecision. Although not statistically significant, the positive relationship with overestimation is consistent with capital structure theory (section 2.2.4.3), but the negative relationship with overprecision is not consistent with capital structure theory. Given the lack of statistical significance in these findings, we concluded that overestimation and overprecision's impact on industry-adjusted ROA is not likely to be through a mediating effect of the firm's capital structure.

From the operating margin analysis, we found a significant and negative relationship between overestimation, especially in the higher categories of the categorical variable, and industry-adjusted operating margin. We found a positive, but not statistically significant relationship between overprecision and industry-adjusted operating margin, when considering the continuous variable. However, when considering the categorical variable analysis, we see that overprecision has a positive relationship with significance at the 5% level in four of its seven categories. Our take-away from this analysis was that less (more) operating margin leads to a lower (higher) quality of earnings, which we speculated arises from lower (higher) quality investments. Less (more) operating margin will reduce (increase) industry-adjusted ROA and hence, ceteris paribus, overestimation, acting via operating margin, should have a negative effect on industry-adjusted ROA, while overprecision, acting via operating margin, should have a positive effect on industry-adjusted ROA.

That overestimation should influence the quality of the firm's investments is consistent with the ways in which overestimation has been shown to manifest. As previously mentioned (section 2.2.3), overestimation is believed to manifest as self-enhancement, where people view themselves positively, as opposed to accurately (Dunning, 2005); illusion of control, where people think they have more control over circumstances than they actually do (Thompson, 1999); the planning fallacy, the common tendency to overestimate the speed at which we will complete projects (Buehler et al., 1994); and unrealistic optimism, the tendency to overestimate the rosiness of our future (Sharot et al., 2007).

Overestimation's unfavourable impact on investment quality is also consistent with our examination of hubris theory (section 2.2.4.1), where we read that over- or under-investment implies that managers are not investing in the shareholders' best interests as they are making investments that are value destructive and forgoing investments that would have been value creating.

Overprecision's favourable impact on investment quality is consistent with our review of underinvestment mitigation theory (section 2.2.4.4), where we noted the management teams that were overprecise would underestimate risk and hence would be less likely to postpone the decision to undertake projects and more willing to take on risky projects (Gervais et al., 2002). In addition, management teams with overprecision were theorised to exert more effort to gather information that improves the success rate and value of their firm's investments (Gervais et al., 2011). This theory's prediction of possible overinvestment is not borne out as shown by the investments analysis earlier in this section.

We also speculate that management teams that offer more precise forecasts know their business better and hence are more likely to deliver better performance.

4.4.4 Conjectures on how overestimation and overprecision impact firm performance

From this set of supplementary analyses, we arrived at two conjectures. We call these conjectures because they are preliminary perspectives on the relationships between overestimation and

overprecision on firm performance. Further, more rigorous work is required to derive and test the hypotheses implied by these conjectures. We suggest this as an area for further research.

Conjecture 1: The negative relationship between overestimation and firm performance is at least partly a result of overestimation being associated with negatively impacting the quality (as measured by operating margin), but not the quantity, of investments (as measured by R&D or investment intensity). That overestimation shows a negative association to investment quality is consistent with Kahneman and Lovallo (2003)'s view that the competitive jockeying to secure funding for projects results in projects with overoptimistic forecasts being funded. The dynamics of overestimation, overprecision, and firm performance appear to be self-limiting.

Conjecture 2: The positive relationship between overprecision and firm performance is at least partly a result of overprecision being associated with positively impacting the quality, but not the quantity, of investments. The same self-limiting dynamics mentioned in conjecture 1 seem to apply.

Before concluding on the findings of our main and supplementary results, we considered the robustness of these results and of our argument in general.

4.5 Robustness tests

Most studies of this nature contain argumentation and/or analysis that readers might disagree with. In our study we have attempted to pre-empt likely objections and offer our response to these. The list of objections are summarised below and are followed by a response in each case.

1. **Questionable example case.** Woolworths' value destruction with David Jones was due to bad luck, not overconfidence.
2. **Stakeholders versus shareholders.** Firms exist to deliver returns to stakeholders, not just shareholders.
3. **Questionable proxy.** Earnings guidance is not valid data for deriving proxies because of managers' deliberate manipulation.
4. **Fixed-effects estimation model.** The estimation model is not consistent with the assumptions required for an unbiased, consistent, and efficient fixed-effects estimation.
5. **Dynamic versus static panel data analysis.** The nature of this analysis lends itself better to dynamic panel data analysis.
6. **Sensitivity to data sample.** The results are a product of outlier treatment and/or the data sample analysed and would differ if a different extract of the data was used.

4.5.1 Questionable example case

Objection: Woolworths' value destruction with David Jones was due to bad luck, not overconfidence.

Response: While it is true that good strategic decisions can sometimes produce bad outcomes, as described in section 2.1.4 as a "bad break", at best this might account for the acquisition premium being justified and hence the avoidance of some proportion of the impairments. However, it would not account for the repeated overestimation and overprecision of the EBIT margin guidance.

Further, the reader might object that this case is not representative of the S&P 1500 data set in that it is not a member of the S&P 1500 and the metric (EBIT margin) is not the same as the proxies that this study uses to measure overestimation and overprecision. And that is a legitimate objection in all those respects. The reason for the use of this case is that the author of this study had direct exposure to the case and, in fact, it was these events, along with a few similar cases that the author also had exposure to, that prompted this study.

4.5.2 Stakeholders versus shareholders

Objection: Firms exist to deliver returns to stakeholders, not just shareholders.

Response: We do not disagree with the importance of firms taking a broad stakeholder perspective. However, a broad stakeholder does not negate the importance of meeting shareholder expectations, rather it is in addition to. Thus, whether management have responsibilities to a broader group of stakeholders or not, the duty of management includes, at a minimum, delivering returns for shareholders.

4.5.3 Questionable proxy

Objection: Earnings guidance is not valid data for deriving proxies because of managers' deliberate manipulation.

Response: We acknowledge that proxies derived from earnings guidance is flawed because managers manage their earnings! However, in seeking proxies of the overconfidence (overestimation and overprecision) expressed by the group making the firm's strategic decisions, we had little to choose from. In section 3.4 we offered a theoretical analysis of the validity and reliability of our proxies. From this analysis we identified that the primary weakness of our overestimation proxy is that it is susceptible to deliberate downward bias to avoid negative earnings surprises. However, we have found no reason to believe that this downward bias is not systematic. In other words, it might be that all management teams are subjected to the same downward bias and hence the proxy still contains useful information in terms of its relative position. In addition, we found that the most commonly used proxy, based on the options-trading behaviour of the CEO, brings its own weaknesses, predominantly that the overconfident behaviour of the CEO in her personal capacity might differ from the management team's overconfidence in strategic decision making, even if the CEO is dominant in those decisions.

As mentioned in section 3.4, we did not find a weakness in the use of earnings guidance for overprecision, other than that the conventional approach of computing overprecision is not possible because management do not provide confidence intervals when issuing a range forecast.

4.5.4 Fixed-effects estimation model

Objection: The estimation model is not consistent with the assumptions required for an unbiased, consistent, and efficient fixed-effects estimation.

Response: We found that the assumptions that matter are met. These assumptions are the classical linear model (CLM) assumptions (Wooldridge, 2014). The CLM assumptions contain the five Gauss-Markov assumptions plus the assumption of a normally distributed error term (Wooldridge, 2014). In addition to the CLM assumptions, we also considered the effect of serial correlation and autocorrelation. All seven assumptions are listed below along with our findings and commentary.

1. **Linear in parameters.** We specified our model such that it is in line with the standard form.
2. **Random sampling.** Since we used all data that meets our requirements for this analysis (discussed in section 3.2), we have a population data set, so this assumption does not apply. Later in this document (section 5.4.1), we explored whether we might, by chance, meet the random sample assumption, but found that we do not.
3. **No perfect collinearity.** When regressors are highly correlated, the model's coefficients might become biased and hence estimation will be compromised. A conventional approach is to consider the pairwise correlations of the regressors and/or to assess the variable inflation factors (VIF) of the regressors. If the correlations are high and/or the VIFs are above 5 or, to be less conservative above 10 (Craney & Surles, 2002), then remedial measures might be necessary. Our pairwise correlations of the regressors are shown in Table 10 and this revealed

that the highest pairwise correlation was EE and LEV with a value of 0.36 and the next highest value is 0.22. We ran a VIF analysis (Table 19) on our model using our midpoint dependent variable adjROA_c3 and found that our regressor with the highest VIF was L3.BB with a VIF of 3.93, which was comfortably within the guidelines. Thus, we concluded that our model did not have a collinearity problem and hence no remedial action was warranted.

Our VIF test is conducted after we have executed our regression and yields the results shown in Table 19.

Variable	VIF	1/VIF
L3.BB	3.93	0.254757
L3.RD	2.33	0.429824
L3.op	1.75	0.571379
L3.EE	1.65	0.606339
y_18	1.51	0.661453
y_17	1.50	0.667766
y_16	1.48	0.674045
y_19	1.48	0.674112
y_15	1.45	0.690390
y_14	1.42	0.704637
y_13	1.38	0.722418
y_12	1.36	0.733724
L3.LEV	1.28	0.781969
L3.tq	1.20	0.831924
L3.oe	1.08	0.928369
Mean VIF	1.65	

Table 19: Variable inflation factor analysis of the regressors of our adjROA_c3 model.

4. **Zero conditional mean.** This assumption is expressed as

$$E(u_{it}|X_{i1}, X_{i2}, \dots, X_{iT}) = 0$$

and is tested by inspecting the fitted and error plot of the residuals. We used the model from our midpoint dependent variable, adjROA_c3, to generate this plot, which we display below as Figure 16. Inspection of this plot shows that our assumption of zero conditional mean is satisfied.

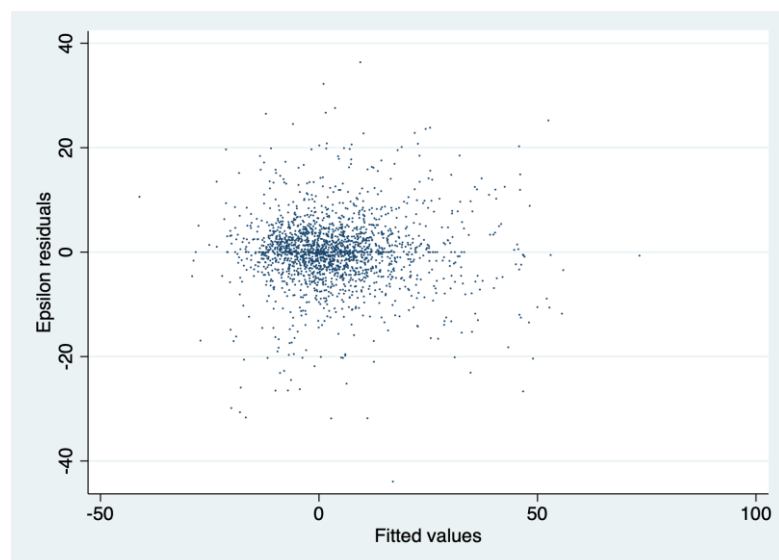


Figure 16: Fitted and error plot of the residuals.

5. **Homoscedasticity.** With reference to Figure 16, we observed an increase in variation of the data as fitted values increase from -25 to 0, as well as a reduction in variation between 0 and 50. This is suggestive of the presence of heteroskedasticity. We used robust standard errors to correct for heteroskedasticity.
6. **Normality of residuals.** We tested for the normality of residuals after we have executed our regression. We found that the residuals are not normally distributed. This assumption is considered stronger than the other assumptions and often does not need to be met in practice (Wooldrige, 2014). We applied the practice guidelines and hence continue with our model despite this assumption not being met.
7. **Serial correlation and autocorrelation.** We anticipated autocorrelation and serial correlation because adjROA is highly persistent. In the presence of autocorrelation and serial correlation the estimate coefficients will not be biased, but the standard errors will be incorrect. However, the standard errors can be corrected for using “robust”, which we did.

4.5.5 Reverse causality concern

Objection: The results could arise from a potential reverse causality problem between management’s overconfidence and firm performance.

Response: To address the concern of possible reverse causality we offer two explanations.

Firstly, like many similar studies (Bharati et al., 2016; J. B. Kim et al., 2016; M. C. Kim et al., 2017; Park et al., 2018; Tang et al., 2015), our analysis uses a time offset between the independent variables and the dependent variables. This is recognised as partially addressing the endogeneity concern (J. B. Kim et al., 2016).

Secondly, we consider the alternative explanation and show that it is unlikely. The alternative explanation is that rather than overconfidence causing firm performance, firm performance causes overconfidence. In the case of overestimation, based on our findings of a negative relationship, this would require an improvement in firm performance to lead to a reduction in overestimation. In other words, management’s optimism would decrease as firm performance increased. It seems unlikely that improving performance would lead a management team to reduce their optimism of their prospects. As discussed in section 4.4.1, we found that recent past firm performance increases overestimation, albeit not in a statistically significant way, thus lending empirical support to the logical argument that a management team’s optimism would not decrease when firm performance improved.

In terms of overprecision, where we found a positive relationship, a reverse causal argument would require that improvement in firm performance would lead to greater overprecision. This seems more plausible. To empirically test these reverse causality possibilities, we reverse our estimating models.

The reverse causality risk is not easily dismissed in the case of overprecision as a positive relationship between firm performance and overprecision is found in both directions. However, the empirical results are materially stronger for the forward causality argument as displayed in Table 20 below. The magnitude of the coefficient is greater in the forward causality model than in the reverse causality model for the both the bivariate and multivariate analysis. Statistical significance is at the 1% level for the multivariate forward causality model versus no statistical significance for the multivariate reverse causality model. Model fit R² is greater in the bivariate and multivariate cases for forward causality. Model fit improves with the inclusion of the treatment variable in the forward causality model but worsens for the reverse causality model. Based on this analysis, we concluded that reverse causality is a less likely explanation than forward causality.

	Forward causality: Firm performance is the dependent variable		Reverse causality: overprecision is the dependent variable	
	Bivariate ¹⁵²	Multivariate ¹⁵³	Bivariate	Multivariate
Treatment variable coefficient	0.208***	0.163***	0.184***	0.081
R ²	0.076	0.261	0.028	0.052
R ² without treatment variable	N/A	0.163	N/A	0.060
Improvement in R ²		0.098		-0.008

Table 20: Comparison of forward and reverse causality analysis for overprecision (op) and adjROA_c1.

Notes regarding the table: ***, **, * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.

4.5.6 Dynamic versus static panel analysis

Objection: The nature of this analysis lends itself better to dynamic panel data analysis.

Response: We offer four reasons as to the suitability of our static panel analysis.

4.5.6.1 Our focus is on the time delayed effect of the treatment variables

As discussed in section 3.7, we noted the distinction between estimating for explanation and estimating for prediction purposes. Since, we are estimating to explain a theoretical effect, we opted for an explanatory model that is suited to explaining, rather than predicting. This led us to choose a static panel data analysis method, namely firm fixed-effects.

4.5.6.2 Endogeneity concerns have been partly addressed in other ways

Endogeneity is a concern for studies of this nature. Endogeneity might arise due to omitted variable bias, measurement error, or simultaneity bias. Omitted variable bias for time invariant variables is directly addressed by a fixed-effects model. In addition, any bias due to serial correlation resulting from the removal of the lagged dependent variable is corrected for by using robust standard errors in the

152. The bivariate analysis for both the forward and reverse causality models also includes year dummies, so it is not truly bivariate.

153. The multivariate analysis for both the forward and reverse causality models uses a single treatment variable (oe or op) and all of the controls in the research model (section 3.6).

static model specification. Measurement error is still not solved by either a static or dynamic panel analysis. Lastly, we have addressed simultaneity bias by virtue of the time offset between the dependent and treatment variables, and the related issue of reverse causality has been addressed by our discussion in section 4.5.5.

4.5.6.3 Dynamic panel specification is consistent with our static panel data analysis

Although our focus is on the time delayed effect of the treatment variables, we elected to develop a dynamic panel model for robustness test purposes.

We developed a Generalised Method of Moments panel model (Blundell & Bond, 1998) using Stata’s xtabond2 (Roodman, 2009) function. We applied this model to estimate adjROA_c3, since this is the midpoint of our set of dependent variables. The results are presented in Table 21 below. Our model is considered dependable because it met all the diagnostic requirements of the Hansen J test, the AR(2) test, instruments less than groups, and a positive coefficient on the lagged dependent variable (Piper, 2014). We contrasted the static and dynamic panel estimations and found sign consistency on all, but one, of the coefficients, but this coefficient (L3.BB) was not statistically significant in either case. We also found that overestimation remained significant at the 1% level, but overprecision did not. With the exceptions of the coefficient for overprecision, we found that the regressor coefficients were all reduced in the dynamic panel specification. This is not surprising since the lagged dependent variable, which was significant at the 1% level, becomes the primary predictor of adjROA_c3.

VARIABLES	xtreg	xtabond2
	adjROA_c3	adjROA_c3
L.adjROA_c3		0.285*
		(0.172)
L3.EE	-0.663***	-2.071**
	(0.215)	(0.844)
L3.LEV	-0.151	-0.388
	(0.0993)	(0.340)
L3.RD	-5.970	11.09
	(4.771)	(12.23)
L3.BB	2.641***	1.433
	(1.016)	(1.446)
L3.tq	0.478***	0.00329
	(0.0586)	(0.119)
L3.oe	-0.136***	-0.0945***
	(0.0267)	(0.0319)
L3.op	0.175***	0.120
	(0.0595)	(0.111)
Year fixed effects	Y	Y
Constant	5.387	
	(3.354)	
Observations	1,935	1,007
R-squared	0.355	
Number of uid	505	342
Hansen J test		0.515
AR(2) test		0.134
Instruments		60

Table 21: Comparison of coefficients between static and dynamic panel estimators for adjROA_c3.

Notes regarding the table: ***, **, * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.

4.5.6.4 There is a precedent for static panel data analysis for studies of this kind

As previously mentioned (Table 5), other studies of the impact of overconfidence on firm performance have used ROA or adjROA as their measure of firm performance. Besides for these studies, we also reviewed two papers in FT50 journals¹⁵⁴ that measure firm performance using ROA or adjROA. We found that static panel data analysis is used in a number of these studies (see Table 22). Those that used static panel data analysis applied fixed-effects estimation in all cases, except Park et al. (2018), who recognise that fixed-effects would have been preferable, but are precluded from using it because some of their variables were stable across time for their sample.

Author	Journal	Firm performance measure	Estimation technique
(Aral & Weill, 2007)	Organization Science	ROA	Static panel analysis using firm fixed-effects and OLS
(Hilary et al., 2016)	Journal of Accounting and Economics	ROA	Static panel analysis using CEO fixed-effects
(H. A. Kim et al., 2019)	Asia-Pacific Journal of Accounting and Economics	RNOA (return on net operating assets)	Dynamic panel analysis using Generalised Method of Moments
(Lovallo et al., 2020)	Strategic Management Journal	Industry-adjusted ROA	Static panel analysis using firm fixed-effects
(Mundi & Kaur, 2019)	Vision	ROA	Static panel analysis using firm fixed-effects
(Park et al., 2018)	Journal of Business Ethics	Industry-adjusted ROA	Static panel analysis using random effects

Table 22: Estimation technique when firm performance is ROA or industry-adjusted ROA.

4.5.7 Sensitivity to data sample

Objection: The results are a product of outlier treatment and/or the data sample analysed and would differ if a different extract of the data was used.

Response: We tested the robustness of our analysis to different extracts of our data set in various ways. We tested robustness to outlier treatment, to analysis by industry, to analysis by year, and to whether the firm was an S&P 500 member or not. We also tested our model's sensitivity to inclusion (or not) of a substantial control variable and its sensitivity to an alternative operationalisation of the dependent variable for firm performance. Overall, we found our model and our analysis to be robust to different extracts of the full data set, but fragile to small extracts such as a single industry. We also found our analysis to be robust to changes in our model specification. A summary of these analyses follows and the detail can be found in section 7.5.2.1 of the Appendix.

154. FT50 journals are the 50 journals used by the Financial Times in compiling the FT Research rank, included in the Global MBA, EMBA and Online MBA rankings.

4.5.7.1 Outlier treatment

We sought to preserve as much data as possible and therefore treated outliers sparingly. We dropped two ROA observations because they are greater than a million and hence were almost certainly errors in the data. The remainder of our data was winsorised at p1 and p99¹⁵⁵, or just p99, or just p1, or not at all. Our winsorisation approach can be found in [Table 33](#) of the Appendix.

Our outlier treatment robustness tests ([Table 39](#)) compared the results of four different treatments of outliers and scaling to our baseline model ([Table 38](#)): 1. We dropped outliers at p1 and p99, rather than winsorising. This had no material effect on our model; 2. We scaled our variables but did not winsorise nor dropped any outliers. This resulted in some degradation in model fit and some loss of significance in our treatment variables, but all regressors remained sign consistent with our baseline model; 3. We ran a robustness test where we made no changes to the data. In this case, as per the previous test, we saw a drop in model fit and also many of our treatment variables lost statistical significance but remained sign consistent; 4. We also winsorised at p5 and p95. This had no material effect on our model. In all these robustness tests, our control variables remained sign consistent with our baseline model, with only three minor exceptions (L1.RD in the second test; L1.RD and L4.LEV in the fourth test).

From these tests, we concluded that our results were robust to these alternative methods of outlier treatment.

4.5.7.2 Analysis by year

We estimated our model for our midpoint dependent variable, adjROA_c3, for each of the years 2012 to 2019. The results are displayed in [Table 40](#) of the Appendix.

We found, for reasons not yet understood, a sign reversal on one of our controls (L3.EE), but other than that we found entirely consistent estimates. It should be noted that this analysis by year differed in an important way, in that it was not a panel data regression, from the baseline model. We found that the treatment variables were sign consistent in every year and the overprecision variable differed in significance with some years not resulting in significance, but the overestimation variable was significant at the 5% or 1% level in all years.

4.5.7.3 Analysis by industry

We estimated our model for our midpoint dependent variable, adjROA_c3, for each of the nine BICS1¹⁵⁶ industry groups. The results are displayed in [Table 41](#) of the Appendix.

We found that our model estimated with perfect sign consistency for some industry groups, but not for all industry groups. In four of the industry groups we saw sign reversal on one or both of our treatment variables. These industry groups each had relatively few observations and collectively accounted for 19% of our observations and 115 of our 505 firms or 23% of our firms. For the other five industry groups, the estimates were sign consistent for treatment variables and mostly sign consistent for the controls.

4.5.7.4 Analysis by S&P 500 members

We estimated our model for firms that were at any point during our period of interest were a member of the S&P 500 and those that were not. The results are displayed in [Table 42](#) of the Appendix.

With 557 firms providing guidance, we found that 259 were S&P 500 members, and 298 were not. We estimated our model over each of the 5 lag periods for these two subsets of our data. We found that

155. P1 and p99 refers to the first and ninety-ninth percentiles, respectively.

156. Bloomberg Industry Classification System at level 1.

the model fit was better for the non-S&P 500 firms than for the S&P 500 firms or for the full data set. Despite the difference in model fit, we found that our overestimation and overprecision variables have the same sign, similar magnitude, and perform at the same significance level in all three cases, namely the full data set, the S&P 500 data set, and non-S&P 500 data set.

4.5.7.5 Sensitivity to control variables

As shown in our bivariate analysis, [Table 36](#), Tobin's Q is the control variable with the most substantial contribution to our model fit. While we have found this control variable being used in firm performance models in top-tier journals ([Iyengar & Zampelli, 2009](#)), we also recognised that it is not commonly used. As such, we felt the need to test the robustness of our model to the absence of this control variable. The results of this robustness test are shown in [Table 43](#) of the Appendix. From these results we saw that, as expected, the model fit decreases substantially in that R^2 drops from 0.36 to 0.22 in lag 3 (and has a similar drop for other lags), the magnitude of the oe and op coefficients increased by about 25%, and the control variables all remained sign consistent with the base model. We concluded from this that Tobin's Q helps with model fit and does not have a distorting effect of concern on the treatment and control variables.

4.5.7.6 Sensitivity to an alternative operationalisation of the dependent variable

Since the return on assets has a different dynamic range for different industries and this is only partially addressed by median differencing, there is an argument for also scaling the variable by the industry's median ROA. In other words, instead of operationalising as given by the equation defined in section [3.3.2](#), we might operationalise by this equation below.

$$zROA_{firm,t} = \frac{ROA_{firm,t} - \overline{ROA}_{industry,t}}{\overline{ROA}_{industry,t}} \quad (7)$$

Where $\overline{ROA}_{industry,t}$ is the industry median of ROA in year t and $zROA_{firm,t}$ is the scaled version of the dependent variable.

How would our model and our analysis perform with this alternative operationalisation? We ran this analysis using our multivariate model with the dependent variable being the only change and we found no differences in the signs of the coefficients and only slight differences in the significance levels in some cases. The detailed results are displayed in [Table 44](#) of the Appendix. We concluded that our model and analysis were robust to this alternative operationalisation, yet we chose to stay with industry-adjusted ROA in its original formulation because it allows easy comparisons with other studies.

4.6 Results conclusion

In conclusion, our main results showed a clear negative relationship between overestimation and firm performance and a positive relationship between overprecision and firm performance. These results showed meaningful effect sizes, were statistically significant¹⁵⁷, and showed that the treatment variables have predictive power in all years, from one to five, following the year that earnings guidance was communicated. Furthermore, these results were robust to all samples of the data that we considered, except in some cases where the observation count is low.

When combining our main results and the results of our supplementary analysis we found that hubris theory, capital structure theory, and underinvestment mitigation theory might be parsimonious

157. Since we are analysing all data in the population of S&P 1500 firms that provide guidance, statistical significance is not required when claiming an observed effect. We continue to use statistical significance measures, however, because this data might be considered a sample of the S&P 1500 and we consider its generalisability in the next chapter.

explanations of the negative relationship between overestimation and firm performance and the positive relationship between overprecision and firm performance. Furthermore, we found that the dynamic relationships between current and lagged versions of overestimation, overprecision, and firm performance suggests a self-limiting character of overestimation and overprecision.

Contrary to our expectations, we found monotonicity rather than non-monotonicity in the relationships between overestimation and firm performance and overprecision and firm performance. This monotonic relationship yields greatest firm performance for extreme negative overestimation (management teams that are highly pessimistic) and extreme positive overprecision (management teams that are highly specific). The opposite is also true in that the worst firm performance occurs for extreme positive overestimation (management teams that are highly optimistic) and extreme negative overprecision (management teams that are highly vague).

When considering the optimism pessimism dimension, we might wonder why the pessimists perform better. One explanation might be that the optimists believe that things will turn out well, so they do not anticipate obstacles, hence they do not plan for how they might eliminate or mitigate those obstacles, and then, because business and life in general are often more complex and/or more unpredictable than we recognise, unexpected obstacles emerge, and the optimist's plans are derailed. Or, to state this point from the perspective of the pessimist, we reference Annie Duke's comments from her interview with Katy Milkman ([Milkman, 2020](#)).

"You should have positive goals, no question. But the way to succeed is actually to think negatively. Imagine the ways in which you might fail along the way to that positive goal. [...] It's thinking negatively, in the sense of seeing where all the obstacles are going to be and then helping you route yourself around those so that you can get to that positive goal, the destination that you ultimately want to achieve."

So, when picking your management team, the specific pessimists are your best bet. And beware of the vague optimists!

5 Conclusions

*“It ain’t what you don’t know that gets you into trouble.
It’s what you know for sure that just ain’t so”*

Mark Twain¹⁵⁸

In this final chapter, we provide a summary of our discussion to this point, summarise our findings, discuss our theoretical and practical contributions, acknowledge the limitations, consider the generalisability, and suggest areas for further research. We conclude with some personal reflections.

5.1 Discussion

We began our journey into the world of overconfidence and firm performance triggered by the Woolworths / David Jones debacle¹⁵⁹, our observation that this event of value destruction was not an anomaly, and the suspicion that cognitive biases, overconfidence bias specifically, might be complicit in undermining the quality of strategic decisions.

This led us to examine the context in which strategic decisions are made in for-profit, public firms. We saw that Schumpeter’s “creative destruction” (Schumpeter, 1942) is ever present and is forecast to persist, perhaps intensify, yet it is not an unescapable reality. We have seen that some firms reinvent themselves and sustain their performance through decades and through disruptive industry changes. In fact, the management of public firms are compelled to strive for performance because, although they might have responsibilities to multiple stakeholders, they must, at a minimum, deliver returns to the firm’s shareholders. To navigate change and sustain or improve their performance, they formulate and execute competitive strategies.

Ultimately the competitive advantage that managers achieve is a result of the resource selection, development, deployment, and protection choices that they make. In other words, a firm’s current performance and performance prospects are a consequence of the strategic decisions made by its management. Since the future is inherently uncertain, these strategic decisions are made in a context of uncertainty. We recognised that the determinant of decision quality is the process followed to make the decision, not the outcome achieved, since the process is all that can be controlled by the manager. We found that there are four broad approaches (political, rational, intuition, heuristics) to strategic decision making and they each appear to have strengths and weaknesses depending on the context, but researchers’ views on their merits are still divided and there appears to be no generally accepted set of best practices (section 2.1.5). Since it cannot be expected that managers should follow best practices if best practices have not been defined, we explored instead what managers might be doing that undermines decision quality and this led us into the world of cognitive biases.

158. Like so many Mark Twain quotes, the origin of this one is contested.

159. While Woolworths / David Jones brought the issue of overconfidence into stark relief for us, it was not our first experience observing senior executives in public firms demonstrating hubris. In 2013, this author had the first-hand experience of interviewing the head of strategy at a JSE-listed retailer and witnessing his unmistakable display of hubris. A few weeks following that interview, the strategy executive and the CEO of that firm were fired by their board. As is often the case, the true reasons were not communicated, but the firm’s poor performance under their leadership was surely a factor. And this author speculates that the firm’s poor performance was at least partly explained by these influential executives having delusional optimism or, in cruder terms, they seemed to have lost touch with reality and were “believing their own bullshit”.

It has been recognised for decades that as people we have “bounded rationality” (H. A. Simon, 1955), along with bounded will-power, self-interest, awareness, and ethicality (Moore & Bazerman, 2012a; Mullainathan & Thaler, 2000), and this leads us to “satisfice” rather than optimise. When we satisfice, we do so by applying heuristics or intuition, and this, in turn, makes us vulnerable to cognitive biases that distort our decision making (Tversky & Kahneman, 1974). We chose to specifically examine one of these cognitive biases, overconfidence. We chose overconfidence because leading researchers have called it out as the most significant of the cognitive biases (De Bondt & Thaler, 1995; Kahneman, 2011; Moore & Bazerman, 2012a; Plous, 1993), it has effects that are theoretically consistent with shareholder value destruction, it has been empirically demonstrated to impair firm performance (P.-H. Ho et al., 2016; Leng et al., 2018; Mundi & Kaur, 2019; Park et al., 2018), and there has been a call for further research into overconfidence bias (Dunning et al., 2004; Goldfarb et al., 2012; Hribar & Yang, 2016).

Our review of the literature showed that despite the CEO having disproportionate power, strategic decisions are generally the product of a group of people (Frisch, 2011; Tasa & Whyte, 2005). The literature also revealed that overconfidence is present in and affects organisations, but how overconfidence affects group-based decision making is not well understood. This was our key interest: what impact does overconfidence have on the quality of the strategic decisions made by the firm’s management?

Given our interest in the overconfidence of the group making strategic decisions, we needed to be explicit on what we meant by overconfidence. This aspect of the literature review yielded three important findings. First, some leading researchers consider overconfidence to be an overarching term that comprises three distinct biases, namely overestimation, overprecision, and overplacement (Moore & Healy, 2008; Moore & Schatz, 2017). Second, there is a lack of clarity and consistency of overconfidence definitions in the literature (section 2.2.1), making it challenging to interpret and compare some studies. Third, although some researchers recognise the distinct types of overconfidence, they have conflicting views on the nature of the relationship between overestimation and overprecision (Hribar & Yang, 2016; Merkle, 2017; Moore & Healy, 2008). We elected to use the terms overestimation, overprecision, and overplacement, and this served as a frame for our review of the theoretical and empirical literature.

In the theoretical literature we found and categorised six broad themes that predicted the impact of the various types of overconfidence on firm performance. In hubris theory we found that overestimating managers overinvest and perhaps also underinvest, thus are not investing in shareholders’ best interests as they are making investments that are value destructive and forgoing value creating investment (Hayward et al., 2006; Heaton, 2002; Malmendier & Tate, 2005b, 2015; Roll, 1986). In hyper-CSE theory we found that a CEO’s overprecision leads to a greater number and scale of large-stakes initiatives, more deviation of the organisation’s strategy from the central tendencies of the industry, greater persistence in pursuing the CEO’s strategy, and, ultimately, more extreme performance (Hiller & Hambrick, 2005). In capital structures theory we found that managers who overestimate and/or are overprecise will believe their firm to be undervalued and will consequently adopt capital structures with more debt leverage (Deshmukh et al., 2013; Hackbarth, 2008). In underinvestment mitigation theory we found that managers who are overprecise and who overestimate are less likely to postpone the decision to undertake, more willing to undertake, and quicker to undertake, risky projects (Gervais et al., 2002; Goel & Thakor, 2008; Hiller & Hambrick, 2005). In innovation and R&D propensity theory we found that overestimating managers innovate more, but it is unclear whether the ROI on those innovations is positive or negative (Galasso & Simcoe, 2011; Yu, 2014). And, lastly, in motivation theory we found that managers who overestimate and/or are overprecise will expend more effort such that they improve the success rate and value of their firm’s investments (Gervais et al., 2002, 2011; Shipman & Mumford, 2011). They also improve talent retention and supplier relationships.

We found that the theories related to firm performance were concentrated in overestimation, with some coverage in overprecision, and almost none in overplacement. Because of this, and because overestimation is associated with hard tasks and overplacement with easy tasks, and strategic decision making is a hard task, we chose to focus our study on overprecision and overestimation. The concentration of studies on overestimation was also the case in the empirical literature where we found very few studies on overprecision.

In addition to the three issues in the literature already mentioned, we found a further nine issues in the studies of overconfidence. For convenience, we list all twelve issues below and will refer to these when we discuss our contributions (section 5.3):

1. There appears to be no generally accepted best practices for strategic decision making.
2. There is a lack of clarity and consistency in the definition of overconfidence bias.
3. Researchers recognise the distinct types of overconfidence but have conflicting views on the nature of the relationship between overestimation and overprecision.
4. There is no unifying theory, which integrates discrete theories and related effects, of the impact of overconfidence on firm performance.
5. Most studies on the impact of overconfidence on firm performance, focus on the overconfidence of the CEO, with a paucity of studies that focus on the overconfidence of the group making the strategic decision.
6. Most studies derive a proxy for overestimation from the option-trading behaviour and/or the press characterisations of the CEO, with few studies deriving overconfidence proxies from group-level behaviour.
7. Researchers acknowledge that there is a “bright-side” and a “dark-side” to overconfidence but are divided in their view of the overall effect.
8. Of the studies that investigate the overall impact of overconfidence on firm performance, accounting measures are commonly used, but we have found no studies that use economic profit or its constituent drivers, spread and growth.
9. There is a theoretical argument for a non-monotonic relationship between overestimation and firm performance, but most empirical studies do not use a sufficiently granular proxy to locate the optimal level of overestimation.
10. Despite a theoretical basis for believing that there is a relationship between overprecision and firm performance, there is a gap in empirical support for this theory.
11. Furthermore, there is a gap in empirical studies on the combined impact of overestimation and overprecision on firm performance.
12. We have not found a study that claims a causal link between overconfidence, in any of its forms, and firm performance.

With these literature issues in mind, we cascaded our research question into an inquiry into the impact of overestimation, overprecision, and the combined impact of both, on firm performance. This led to five hypotheses relating to the impact of overestimation and/or overprecision on firm performance.

We formulated an empirical strategy to test these hypotheses. This began with taking an epistemological standpoint of objectivity and an ontological standpoint of critical realism in that we believe there is an external reality, but it cannot be known with certainty. Given the probabilistic nature of the inferences we make when testing our hypotheses, we chose to apply the conventional approach of considering a result to be significant if the probability of it being rejected due to chance is 5% or less.

With the expectation of a small “signal” in a “noisy” context, we selected a high-quality data set, that being the public financials of the S&P 1500. We restricted our sample to the period from 2009 to 2019 inclusive, to avoid the Great Financial Crisis of 2007/8 and the Covid-19 era that began in 2020 and to overlap with the period when management earnings guidance became more readily available. We ascertained which firms were present in the S&P 1500 at any time in the period 1998 to 2020 and, if so, we extracted data for those firms for the entire period of interest, irrespective of whether they retained their presence in the S&P 1500. This resulted in a total of 2,952 firms. We found that about 16% of the available firm-years had data that met all our requirements and we ended up with a data sample of 5,116 firm-years of data.

As a measure of firm performance, we selected a fundamental metric, industry-adjusted return-on-assets (adjROA), which is commonly applied in studies of this nature (Hilary et al., 2016; H. A. Kim et al., 2019; Mundi & Kaur, 2019; Park et al., 2018). We excluded financial services firms. Since, the impact of strategic decisions plays out over various time horizons, we chose to use lagged versions of adjROA to capture impacts from one year to five years following the year of the strategic decision.

As mentioned, our treatment variables were the overestimation and the overprecision expressed by the group making their firm’s strategic decisions. We recognised that a perfect measure of group-level overestimation and overprecision would be practically impossible. As such, we needed to find proxies or observed variables that could represent these underlying variables. We reviewed the proxies used in similar studies (section 2.4.1) and chose to diverge from the most used proxies for overestimation, which were based on the options-trading behaviour and/or press characterisations of the CEO, because these are attempting to represent CEO, rather than group, overconfidence. Instead, we opted for proxies for overestimation and overprecision derived from management earnings guidance. Recognising that such proxies are subject to a variety of distorting forces, we conducted a theoretical assessment of the legitimacy of these proxies using latent variable theory (Borsboom, 2008). We found that our proxies are imperfect, with our overestimation proxy especially susceptible to managers’ desire to avoid a “negative earnings surprise”. Notwithstanding the imperfection, in at least the important respect of being a group-level measure, we found our overestimation proxy to be superior to the options-trading and press characterisations proxies, and in other areas of weakness, it shares these with those proxies. We did not find a weakness in the use of earnings guidance for overprecision.

With our selected dependent and treatment variables, and a set of typically used control variables, we constructed our regression equation, which we estimated using a year and firm fixed-effects model. Our summary results are presented in the next section.

5.2 Results summary

The analysis of our hypotheses yielded mixed findings as detailed in sections 0 and 4.3.3, and summarised in Table 23 below.

Hypothesis	Supported?	Comments
1a. The relationship between overestimation and firm performance is negative.	Yes	Relationship is negative and significant at the 1% level for all 5 lags.
1b. The relationship between overestimation and firm performance is non-monotonic.	No	With only minor fluctuations, the relationship is monotonically negative.

Hypothesis	Supported?	Comments
2a. The relationship between overprecision and firm performance is positive.	Yes	The relationship is positive and significant at the 1% level for lags 1 and 2, and at the 5% level for lag 3, and non-significant thereafter.
2b. The relationship between overprecision and firm performance is non-monotonic.	No	With only minor fluctuations, the relationship is monotonically positive
3. Firm performance is maximised when there is moderate negative overestimation and moderate positive overprecision.	Partially	Firm performance is maximised at the extremes of negative overestimation and positive overprecision

Table 23: Summary evaluation of hypotheses.

We conducted supplementary analysis in an effort to explain our findings. This supplementary analysis, along with our initial findings, led us to conclude that hubris theory, capital structure theory, and underinvestment mitigation theory are potentially parsimonious explanations of the negative relationship between overestimation and firm performance and the positive relationship between overprecision and firm performance. Specifically, we found a negative relationship between overestimation and the quality (measured by industry-adjusted operating margin), but not the quantity (measured by industry-adjusted R&D or investment intensity), of investments made by the firm. And we found a positive relationship between overprecision and investment quality, but not quantity. We also found that overestimation was related to greater industry-adjusted leverage, while overprecision was related to less industry-adjusted leverage. Furthermore, we found that the dynamic relationships between current and lagged versions of overestimation, overprecision, and firm performance suggests a self-limiting character of overestimation and overprecision.

Contrary to our expectations, we found monotonicity, rather than non-monotonicity, in the relationships between overestimation and firm performance and overprecision and firm performance. This monotonic relationship yields the greatest firm performance for management teams that are specific pessimists in that they exhibit extremely negative overestimation and extremely positive overprecision. The opposite is also true in that the worst firm performance occurs for management teams that are vague optimists in that they exhibit extremely positive overestimation and extremely negative overprecision.

Our findings were not only statistically significant, but also indicated a substantial effect size. When overestimation decreases by one standard deviation and overprecision increases by one standard deviation, the resulting value creation for the median firm is \$62 million annually or \$622 million if this change is sustained. The opposite also applies and hence there is the risk of \$622 million of value destruction.

In other words, overconfidence, in the forms of overestimation and overprecision, predicts a magnitude of change in firm performance that should matter to shareholders, boards, and management teams.

5.3 Contributions

In this section we discuss the theoretical and practical contributions of this study. Our contributions are based on addressing the issues that we found in the body of literature (section 2.2.6) and we go further in three respects: (a) we use our supplementary analysis to speculate on the possible reasons

underlying our findings; (b) we introduce a framework to contextualise our study and future theoretical and empirical work in this domain, and (c) we offer a starter for an eclectic theory. Our study also makes practical contributions, which we discuss in the last portion of this section.

We discuss our theoretical contributions in six areas. We consider “a richer perspective on the impact of overconfidence on firm performance” to be our most important contribution, followed by “a justification for analysing the overestimation and overprecision of the top management team” and “an empirical motivation for treating overestimation and overprecision separately”, but for narrative purposes, we describe our contributions in the order below:

- An empirical motivation for treating overestimation and overprecision separately
- A justification for analysing the overestimation and overprecision of the top management team
- A validated set of proxies for group-level overestimation and overprecision
- A richer perspective on the impact of overconfidence on firm performance
- Speculative reasons explaining the observed impact
- An overarching framework to contextualise studies of this nature

5.3.1 An empirical motivation for treating overestimation and overprecision separately

As mentioned in literature issue #2, there is a lack of clarity and consistency in the definition of overconfidence bias, leading to an inconsistent application in empirical work, which makes it difficult to make comparable interpretations of much of the research.

Based on our literature review, we shared Moore and Healy (2008)’s concern about the confounding of overprecision and overestimation (section 2.2.1). In the interests of clarity and consistency, we followed Moore and Healy (2008)’s definitions of overprecision and overestimation and operationalised proxy variables accordingly. Our empirical results demonstrated that overprecision and overestimation are indeed distinct, as argued by Moore and Healy (2008).

Moreover, researchers are divided on whether overestimation and overprecision have a positive, negative, or no relationship with each other. We performed an analysis of the combined impact of overestimation and overprecision. Consistent with Merkle (2017), we found close to no relationship between overestimation and overprecision and a correspondingly negligible interaction effect. This finding adds to the debate referred to in literature issue #3 on the relationship between overestimation and overprecision.

For the field to advance, we advocate that the term “overconfidence” should be used sparingly and with caution.

5.3.2 A justification for analysing the overestimation and overprecision of the top management team

Most strategic decisions are made by groups, typically the top management team, rather than by an individual (section 2.1.7). Thus, if we are interested in the impact of overconfidence on strategic decision making in firms, we needed to consider the overconfidence expressed by the group making the strategic decision. We recognised that the CEO is often the most dominant individual in a group making strategic decisions, but ultimately it is the decision that emerges from the group that is of most relevance to this study. Of the overconfidence studies we reviewed, as per literature issue #5, most focus exclusively on the overconfidence of the CEO, while some studies (Hayward & Hambrick, 1997; Hilary et al., 2016; J. B. Kim et al., 2016; J. E. Lee, 2016; Mundi & Kaur, 2019; Schrand & Zechman, 2012) use proxies that represents both the CEO and the group’s overconfidence, and three (Invernizzi et al., 2017; Li & Liu, 2012; Zhao & Ziebart, 2017) focus on the overconfidence of the group. We add to the

sparse literature on examining the impact of overestimation and overprecision biases expressed by the group making their firm's strategic decisions.

5.3.3 A validated set of proxies for group-level overestimation and overprecision

As mentioned in literature issue #6, if we were to analyse the overestimation and overprecision of the top management team we required appropriate proxies.

Most studies derive a proxy for overestimation from the option-trading behaviour and/or the press characterisations of the CEO, with only a few studies using other sources for their proxies, including deriving overestimation proxies from management earnings guidance. We provided a theoretical assessment of the validity of overconfidence proxies derived from management earnings guidance. We assessed our overestimation proxy and overprecision proxy, finding both to be imperfect proxies, but better than the alternatives, and having the important characteristic of serving as proxies for group-based overconfidence. In this regard, we make a methodological contribution.

There is also practical value to management earnings guidance as a source for proxies in that it is a cost-effective metric to gather at scale, as the underlying data already exists in the databases of Bloomberg, FactSet, and other service providers. This practicality allows this study's methodology to be applied in various other settings, for example in the assessment of the impact of overconfidence expressed by management of public companies listed on other stock exchanges.

Using these proxies, we provide empirical support for the impact of overestimation and overprecision of the group making the firm's strategic decisions, rather than just the overconfidence of the CEO.

5.3.4 A richer perspective on the impact of overconfidence on firm performance

We enrich the debate on whether the net effect of overconfidence on firm performance is bright or dark. As mentioned in literature issue #7 and section (2.2.5.3), researchers are divided on this topic as it pertains to overestimation, with some (Bharati et al., 2016; Hilary et al., 2016; Hirshleifer et al., 2012; H. A. Kim et al., 2019; Mundi & Kaur, 2019) showing a positive impact, but others (Billett & Qian, 2008; S.-S. Chen et al., 2014; Hayward & Hambrick, 1997; P.-H. Ho et al., 2016; Invernizzi et al., 2017; J. B. Kim et al., 2016; Leng et al., 2018; Li & Liu, 2012; Malmendier & Tate, 2008; Park et al., 2018) showing a negative impact. Our study finds strongly in favour of the negative impact of overestimation. Our study finds this negative relationship, with a meaningful effect size and statistical significance at the 1% level, for each of the five lag periods we examined. For the median firm a one standard deviation increase in overestimation in the year following the guidance is associated with a decrease of \$26 million in that year, or a \$260 million decrease in firm value if sustained, and is statistically significant at the 1% level.

We contribute further in that we have not found a study that examines the impact of overestimation on overall firm performance over five time horizons, just one overestimation study (S.-S. Chen et al., 2014) that examines the multi-time horizon impact, but that study analyses a discrete effect, namely R&D spend.

With the exception of one study (M. Simon & Houghton, 2003), we have found no empirical studies on the impact of overprecision on firm performance. Our study interprets the theoretical literature of underinvestment mitigation theory (section 2.2.4.4) and motivation theory (section 2.2.4.6) to hypothesise a positive relationship. Our empirical analysis finds support for that relationship. Our finding is that overprecision is associated with a positive, meaningful effect size and retains statistical significance for the first two lags of the dependent variable. We thus address literature issue #10. For the median firm a one standard deviation increase in the overprecision variable in the year following the guidance is associated with an increase of \$36 million in that year, or a \$360 million increase in firm value if sustained, and is statistically significant at the 1% level.

Since there is a paucity of empirical overprecision studies, there are unsurprisingly no studies (that we have found) on the combined impact of overestimation and overprecision on firm performance, as mentioned in literature issue #11. We modelled the impact of overestimation and overprecision separately and together. We found that the combined impact of overestimation and overprecision has a meaningful effect size: a sustained one standard deviation decrease in overestimation combined with one standard deviation increase in overprecision is associated with a \$620 million increase in value for the median firm. This effect applies to the year following the guidance and is statistically significant at the 1% level. In fact, we found the same effect, albeit with declining effect size, with statistical significance at the 1% level for both biases for the first four lags of the dependent variable. We believe we are the first to show this combined effect.

We create categorical variables of our overestimation and overprecision continuous variables to provide a fine-grained perspective in search of the optimal level of each to maximise firm performance. As mentioned in literature issue #9, we had anticipated non-monotonic relationships based on our review of the literature, but we found essentially monotonic relationships. And we were able to locate the combined level of overestimation and level of overprecision that maximises, and that which minimises, firm performance. Again, we believe that we are the first to present such results. We found that the best firm performance occurs for the “specific pessimists” and worst for the “vague optimists”, with a considerable spread (7.0 percentage points of industry-adjusted ROA) between them.

5.3.5 Speculative reasons explaining the observed impact

Our supplementary analysis examined the potential drivers underlying the empirical results that we observed. From this analysis we speculated on the reasons that overestimation is associated with a negative impact and overprecision with a positive impact on firm performance.

This speculation leads to our contribution of two conjectures of the drivers of firm performance in the presence of overestimation and overprecision of the management team. In both of our conjectures we speculated that the quality of investments is a key determining factor of firm performance that is associated with overestimation and overprecision. In saying this, we were also saying that, somewhat surprisingly, other candidate drivers of firm performance, like growth, investment intensity, and capital structure choices, show no meaningful relationship to overestimation and overprecision.

Conjecture 1: The negative relationship between overestimation and firm performance is at least partly a result of overestimation being associated with negatively impacting the quality (as measured by operating margin), but not the quantity, of investments (as measured by R&D or investment intensity). The dynamics of overestimation, overprecision, and firm performance appear to be self-limiting.

Conjecture 2: The positive relationship between overprecision and firm performance is at least partly a result of overprecision being associated with positively impacting the quality, but not the quantity, of investments. The same self-limiting dynamics mentioned in conjecture 1 seem to apply.

5.3.6 An overarching framework to contextualise studies of this nature

As mentioned in literature issue #4, we noted that there is no unifying theory of the impact of overconfidence on firm performance. We saw a need for a unifying theory because the existing theories predict discrete effects which might, or might not, be compatible with each other (section 2.2.4.8). A unifying theory would potentially explain how these discrete predictions act together or in opposition to each other, it might introduce other discrete effects, and it would describe the interactions and combined effects of the different types of overconfidence biases on firm performance. It might also explain the moderating and mediating factors between the overconfidence biases and firm performance. And it would describe any dynamic effects between the firm performance and the overconfidence biases, and between these biases.

Our contributions do not include a proposed unifying theory, but we contribute by defining an overarching framework that could accommodate a unifying theory. We have designed this overarching framework to accommodate all, but one¹⁶⁰, of the literature issues we identified, as well as to accommodate our speculation on the reasons explaining the observed impact reported in this study, and to accommodate the impact of other biases on firm performance. This framework also serves to contextualise our study and to reveal the gaps that would need to be closed to achieve a comprehensive account of the impact of cognitive biases on the quality of a top management team’s strategic decisions, and hence on firm performance.

We introduce an overarching framework as shown in [Figure 17](#) below. In this overarching framework, our context would be all firms and we would see the impact of the cognitive biases of the top management team impacting, via mediating and moderating factors, firm performance, measured in fundamental and market-based terms, with dynamic effects between the firm performance and the biases and also within the biases.

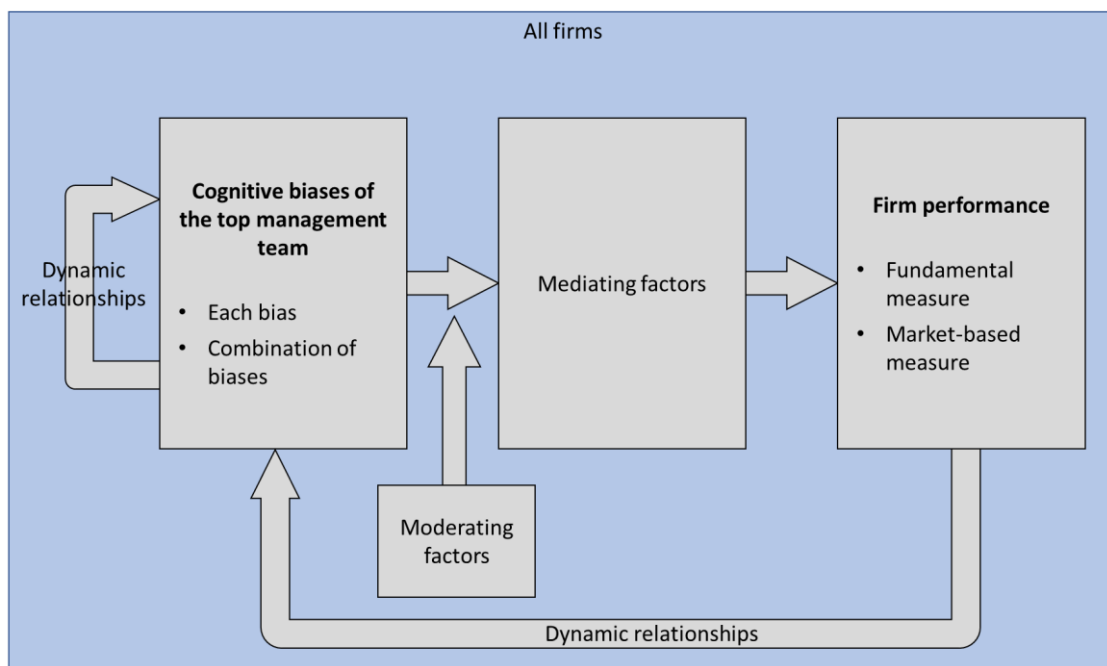


Figure 17: Overarching framework for considering the impact of cognitive biases of the top management team on firm performance.

In considering the key dimensions of this overarching framework, we show [Table 24](#). In this table, the blue shaded cells indicate the overarching framework’s target position in each of the four dimensions of: the biases that are covered (which biases?), the entity making the strategic decision and expressing these biases (expressed by whom?), the measurement of the impact that these biases are having on firm performance (with what impact?), and for which firms this framework applies (for which firms?). Our study has not achieved all these target positions, but what we have done is shown in this table using yellow cells. Our view of the “centre of gravity” of the body of literature is shown in italics.

160. We do not address issue #1: best practice approaches to strategic decision making.

Scope of overarching framework	Least comprehensive				Most comprehensive
Which biases?	<i>Overestimation only</i>	Overestimation and over-precision and combined effects	All types of overconfidence and their combined effects	All cognitive biases and their combined effects	All biases (cognitive and other) and their combined effects
	Overprecision only				
	Overplacement only				
	Other cognitive biases				
	Other biases, e.g. motivational biases				
Expressed by whom?	<i>Top management team and/or CEO</i>		Top management team		
			Top management team		
			CEO		
With what impact?	Empirical study based on theory predicting an overall impact		Overall impact measured	Fundamental	Fundamental and market-based measure
				Market-based	
	<i>Empirical study based on theory predicting a discrete impact</i>		<i>Overall impact measured</i>	<i>Fundamental</i>	<i>Fundamental and market-based measure</i>
				<i>Market-based</i>	
		<i>Discrete impact measured</i>	<i>Fundamental</i>		
			<i>Market-based</i>		
For which firms?	<i>S&P 1500 firms with guidance data</i>		All S&P 1500 firms	All publicly-listed firms	All firms
	Other S&P 1500 firms				
	<i>Other publicly-listed firms</i>				

Table 24: Scope of the overarching framework. Blue cells represent the target position, yellow cells represent what our study delivered, and the italics represent the body of literature.

5.3.6.1 Which biases?

When considering the phenomena of the challenge of sustaining a leadership position, as evidenced by turnover on indices like the S&P 500, we wondered whether cognitive biases might be an explanatory factor. We chose to specifically investigate overconfidence bias, and this study focused on the impact of overestimation and overprecision bias on firm performance. But it is not only overestimation and overprecision that we should be concerned about. We noted before that when management teams are making strategic decisions, they become vulnerable to “satisficing” and thus might be affected by a plethora of cognitive biases. With the findings of this study that just two cognitive biases are associated with a material impact on firm performance, plus recognising that many other cognitive biases might also be at play when management teams are making strategic decisions, we believe that an overarching framework of the impact of all cognitive biases on firm performance is warranted. We might even consider that the framework should extend beyond cognitive biases, since the management team’s strategic decision making might be further compounded by social forces like organisational politics, along with personal agendas and other motivational biases.

5.3.6.2 Expressed by whom?

As we have previously argued, strategic decisions are not solely the product of the CEO, but of the top management team. Accordingly, our overarching framework accommodates studies that are concerned with the cognitive biases of the top management team.

5.3.6.3 With what impact?

Despite our desire for theoretical and empirical studies to examine all biases, or at least all cognitive biases, or, failing that, all three forms of overconfidence bias, our review of the literature shows that almost all empirical studies on the impact of overconfidence bias on firm performance, examine overestimation only (Table 24). We noted that Hilary et al. (2016) also considers overprecision, as does Hribar et al. (2016), but neither of these studies analyses the direct impact of overprecision on firm performance. Hilary et al. (2016)'s study considered overprecision as a mediating factor on overestimation, while Hribar et al. (2016)'s study explored overprecision as the dependent variable in that they considered how overestimation drives a narrower management forecast range. However, M. Simon and Houghton (2003) do consider the direct impact of overprecision, but this is the only form of overconfidence that they examine. Thus, we have not found any study that theorises or empirically examines the overall impact of overestimation and overprecision on firm performance, and consequently no study that examines the overall impact of all cognitive biases on the management team's strategic decision making. Our overarching framework would accommodate all cognitive biases and their combined effects. And this impact would be measured using fundamental and market-based measures of firm performance.

5.3.6.4 For which firms?

The studies that we reviewed use data sets from data service providers like ExecuComp, Compustat, Bloomberg, FactSet, and they examined firms on stock exchanges in countries including the U.S., the UK, China, Korea, and India. In our study we found that we were not able to generalise our findings from those S&P 1500 firms that provided guidance to the broader S&P 1500, let alone to all U.S. firms, or beyond. Our overarching framework would accommodate the top management team's strategic decision making in all firms, public and non-public, and for all countries.

In addition to the four dimensions shown in Table 24, the overarching framework would also accommodate the mediating and moderating variables, and the dynamic effects between the firm performance and the biases and also within the biases. While these are not shown in the table above, we demonstrated, using our study, in Figure 18, how a study could be mapped to this framework such that all of the above-mentioned dimensions can be displayed.

Our study's areas of coverage of the framework are in dark grey, we have also partially addressed some mediating factors and some dynamic relationships, and we recognise in light grey the factors that we have not covered at all. In addition, we have not studied all firms, but S&P 1500 firms in the period 2009 to 2019.

In summary, while we have not developed a comprehensive theory of the impact of the management team's cognitive biases on firm performance, we have designed an overarching framework to accommodate this theory or theories and associated empirical studies, and we have made some progress in populating a portion of this framework in a manner that can inform the generation of theory.

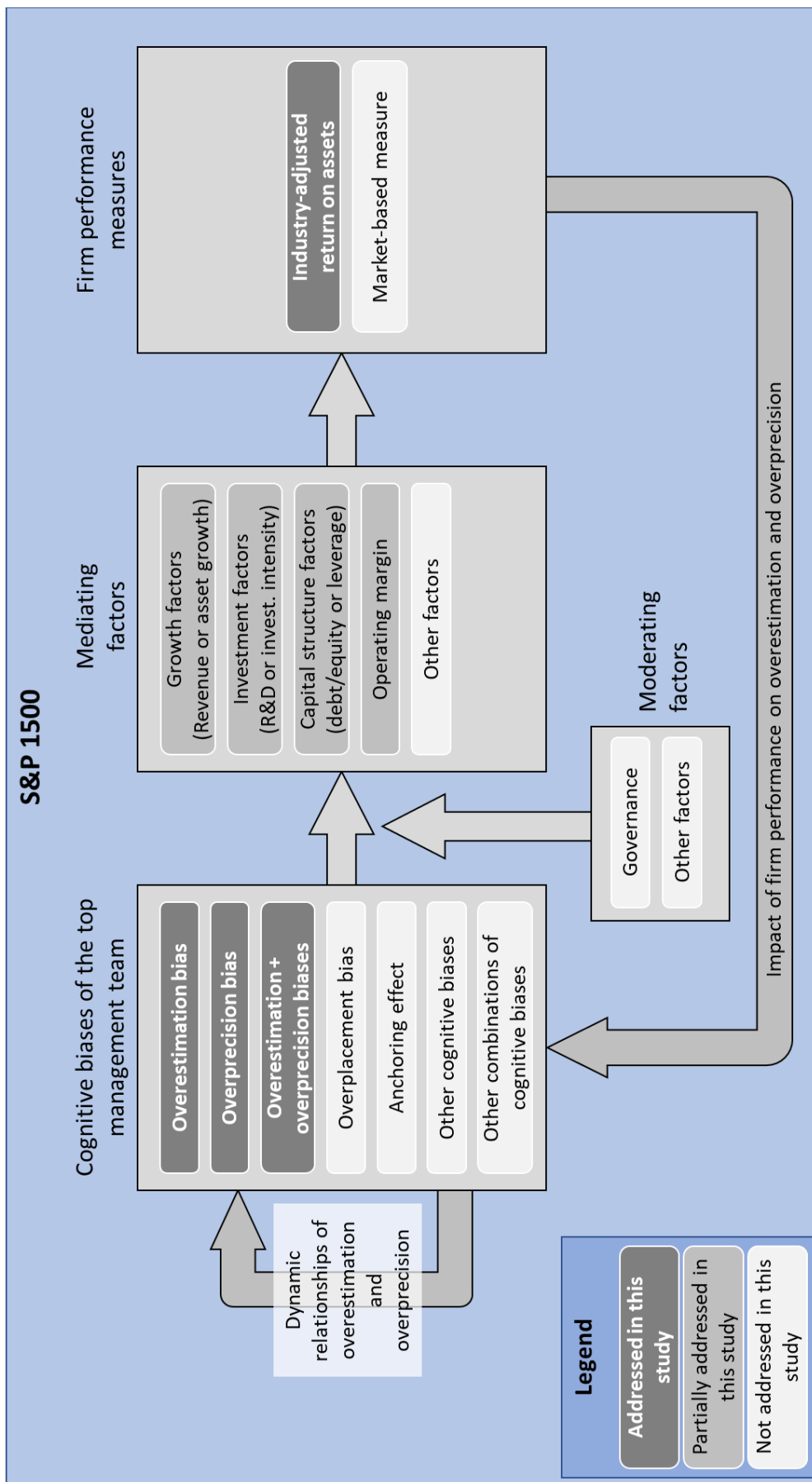


Figure 18: Our study mapped against the overarching framework.

5.3.7 A starter for an eclectic theory

We discussed that shareholder value destruction was driven by errors of commission and errors of omission (section 2.1.5) and that these errors would arise from managers' decision making, because that was all that managers could do (section 1.2). We considered six theoretical themes when developing our hypotheses of the impact of overestimation and overprecision on firm performance: hubris, hyper core self-evaluation, capital structure, underinvestment mitigation, innovation and R&D propensity, and motivation theory. We made passing reference to the relationship between overestimation and narcissism (section 2.2.2) and intentional bad behaviours like misstating earnings (section 2.2.4.7). And, our empirical analysis (section 4.3) found a negative relationship between overestimation and firm performance, a positive relationship between overprecision and firm performance, no correlation between overestimation and overprecision, and hence firm performance being maximised (minimised) when overestimation is negative (positive) and overprecision positive (negative). We also found that investment quality was likely an important mechanism in explaining these relationships (section 4.4.4).

From these points, we offer a "starter" for an eclectic theory that explains the impact of group-level overestimation and overprecision on firm performance. In essence, our theory rests on what we term "the 3Ms of shareholder value destruction". Shareholder value destruction occurs for three reasons: misses, mistakes, and malice. And group-level overestimation and overprecision explains how and why misses (errors of omission), mistakes (errors of commission), and malice (deliberate bad behaviour) arise in a firm's management team. Although we have noted that there is inconsistency in some of the empirical studies that we reviewed (section 2.3.2), our eclectic theory below retains consistency with the six theoretical themes that were considered.

Misses might arise, according to hubris theory, because overestimation leads managers to underinvest. According to Heaton (2002a), overestimating managers might decline positive net present value projects when they require external financing because they believe that the cost of external finance is too high. They believe this because they believe that the capital markets undervalue their firm's risky assets. Misses might, however, be avoided as hyper-CSE theory predicts that overprecision leads to a greater number and scale of large-stakes initiatives and, by underinvestment mitigation theory, since pursuing these initiatives mitigates the risk of misses.

Mistakes might arise for many reasons. Hubris theory argues that in the context of mergers and acquisitions, bidding managers overestimate their ability to manage the target firm and hence overpay for it. Hubris applies not only to acquisitions, but more generally it pertains to risk taking in other respects, such as firm investing, financing, and in the case of banks, to lending standards. Since capital structure predicts that overestimating managers take on more debt and pay out smaller dividends, they generate the "fuel" to make the mistakes that hubris theory predicts. And, underinvestment mitigation theory, supports the view that this could happen because too much overestimation results in the manager exaggerating her chances of success and hence sometimes undertaking negative NPV projects. Innovation and R&D propensity theory unambiguously predicts that overestimation leads to more investments and while the empirical studies show conflicting results, our supplementary analysis shows a negative relationship between overestimation and investment quality. Motivation theory suggests that the overprecise manager might be avoiding mistakes by expending more effort.

Malice differs from misses and mistakes in that it is deliberate. This study has not given specific focus to deliberate behaviour, but we have noted narcissism as an antecedent to hubris and we also see that overestimating managers are more likely to intentionally misstate earnings (Schrand & Zechman, 2012). Taken together, this suggests that overestimation's negative relationship to firm performance might partly be explained by malice.

In short, overestimation is consistent with all three drivers of shareholder value destruction, misses, mistakes, and malice, while overprecision is consistent with the avoidance of both misses and mistakes.

5.3.8 Practical contributions

From a practical perspective, we have found a material and significant overconfidence effect on firm performance. We argue that this should have implications in areas such as corporate governance, recruitment and promotion of senior executives, and investment strategies. Each of these are discussed below.

Before we discuss each of these areas, we comment on a general point regarding practical contributions related to cognitive biases. Some researchers and practitioners believe that it is impractical for people to address their own cognitive biases (Sibony et al., 2017). Accordingly, we argue that our suggestions of practical contributions are indeed practical because they do not depend on some miraculous willpower of the individual, rather they are recommendations that can be applied by others. For instance, the board can introduce measurement systems for key strategic outcomes to ascertain the level of bias in the management team (Sibony et al., 2017). If the bias needs to be addressed, then the board could go further by developing and insisting that management follow strategic decision processes (Sibony et al., 2017) that prevent these biases from undermining decision quality when strategic investments are being considered.

5.3.8.1 Corporate governance

We see opportunities for corporate governance interventions in respect of large-scale investments. Given that investment quality (measured by operating margin) is likely a substantial driver of firm performance and seems to be materially affected by management's overestimation in a negative way, boards should impose requirements, like the need to display at least two viable, yet diverse, strategic alternatives (Spetzler et al., 2016), that management must meet before investments are approved. German electric utility RWE is an example of a firm that recognised its investment decisions were being undermined by cognitive biases and successfully overhauled its decision-making processes to debias its investment decisions (Günther, 2017).

5.3.8.2 Recruitment and promotion

With regard to the recruitment and promotions of senior executives into the top management team, the board can favour the selection of managers that are more likely to contribute to group-level strategic decision making that is specific and pessimistic, and should disfavour the opposite, namely vague and optimistic strategic decision making. This would necessitate finding or developing assessments, probably at group- and individual-level, that could demonstrate these biases with reliability and validity. This suggests an opportunity for the organisations that provide psychometric assessments.

5.3.8.3 Investment strategies

Lastly, taking the perspective of the asset manager or investor, the findings of this study suggest that investment strategies might be revised in the light of this differential firm performance emerging from management teams that are "specific pessimists" and "vague optimists".

5.4 Limitations

In this section we discuss the limitations of our study. We identify three limitations, a limitation on generalisability, a limitation on causality claims, and a limitation on our proxies, which we detail below.

5.4.1 Generalisability

We consider whether our findings, which were the result of analysis of a subset of the S&P 1500, are generalisable. Specifically, can these findings be generalised to all members of the S&P 1500? And, if

that is true, could the findings be generalised further from the S&P 1500 to all public companies, for example those listed on other exchanges like the Hang Seng, the FTSE, etc? And, if that is true, could the findings potentially even generalise to apply for all firms, both public and private?

To make the first claim of generalisability we required that our sample be a representative sample of the S&P 1500. One way to ensure representativeness is to sample at random. We did not have the privilege of sampling at random, instead we gathered all the data that met our requirements. Our most limiting requirement was that there should be earnings guidance data available. Since issuing guidance data is voluntary, not all firms do so. As previously mentioned, we were able to gather 16% of the theoretical maximum number of observations. Might that 16% be representative by luck? This is unlikely as Hribar and Yang (2016) found that overconfidence¹⁶¹ increases the likelihood of issuing a forecast.

Nevertheless, we hoped for the best and conducted a “missing completely at random” test. Unsurprisingly, we found that we do not have a true random sample. As such, we cannot generalise our findings with statistical legitimacy.

We chose to examine our sample in relation to the full data set a bit further to see if there were any observable biases. We mapped (see Figure 19) the median, 80% confidence interval, and 90% confidence interval of our firm performance measure for the full data set (dark blue), the data set where there was no range guidance (orange), the data set where there was range guidance and hence overestimation and overprecision variables (grey), and for the range guidance, where there was overestimation (yellow), calibration (blue), and underestimation (green). We did this exercise for each lag of the dependent variable and the chart below shows the first lag of the dependent variable and the guidance in the preceding year.

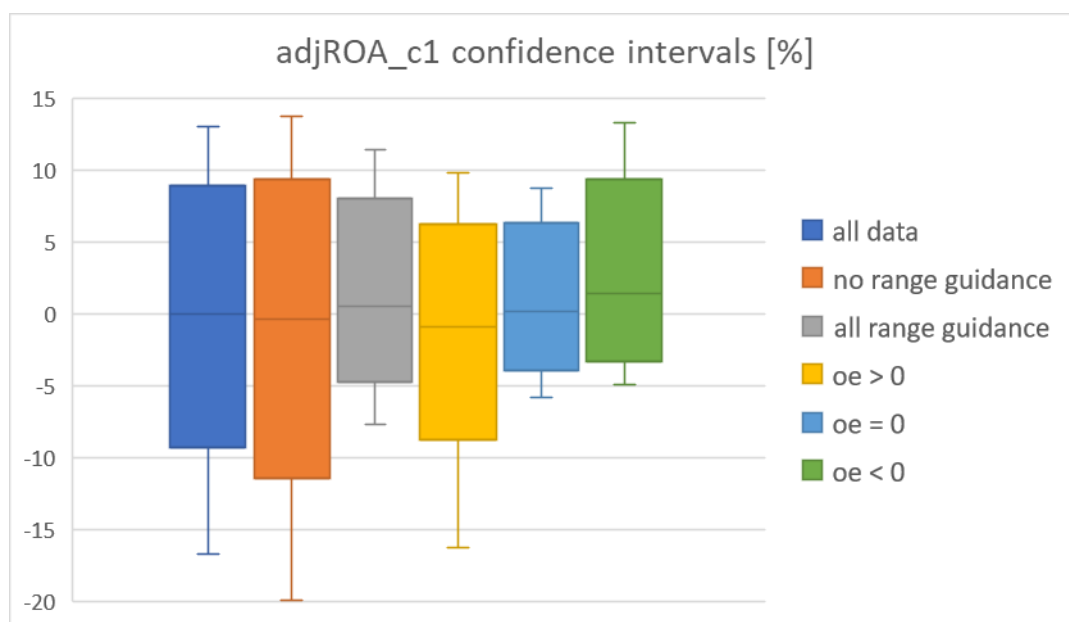


Figure 19: *adjROA_c1 confidence intervals (box is the 80% CI, whiskers are the 90% CI) for our data with and without range guidance data.*

From this analysis, which looked very similar under all lags, we noted that the data set excluding those that provide range guidance (orange bar) has a slightly lower median and a much lower left tail than those who guide (grey bar). In other words, those that guide deliver better performance and notably

161. Hribar and Yang use overconfidence in the overprecision way.

deliver less poor performance. Examining those that provide range guidance revealed that the overestimators (yellow bar) performed similarly to those that do not provide range guidance. However, in comparison to those that do provide range guidance, those that are calibrated (blue bar) and those that underestimate (green bar) showed similar median values, slightly lower 90th and 95th percentile values, but substantially greater 5th and 10th percentile values. In other words, the overestimators bring along substantial downside risk.

Notwithstanding the statistical test that limits our ability to claim generalisability, we have not found a reason to believe that the biased strategic decision-making behaviour of the management teams of S&P 1500 firms that provide guidance is meaningfully different from the strategic decision making behaviour of management teams of other public firms. Thus, we see merit in replicating this study in other markets and we include this as an area for further research.

5.4.2 Causality

Since our treatment and dependent variables are offset in time, we do not risk simultaneity bias, but we might still be subject to reverse causality. In section 4.5.5 we feel that we made a reasonable argument against the risk of reverse causality. So, with simultaneity and reverse causality issues addressed, can we claim that we have described a causal relationship between overconfidence and firm performance? Unfortunately not. We recognise that to claim true causality requires a randomised controlled experiment. As such, we recognise our inability to claim true causality as a limitation of this study.

However, Granger causality (Granger, 1969) might be within the grasp of our data and estimation technique. We note this as an area for further research.

5.4.3 Proxy imperfections

As discussed in section 2.4.4, our proxies are imperfect. The consequence of imperfect proxies is that we are not measuring what we are seeking to measure. There might be ways to improve the quality of our proxies. We consider four additional ways that management guidance might be useful in deriving better proxies for overestimation and overprecision bias: using guidance metrics other than earnings; we using the dynamic and persistent aspects of earnings guidance behaviour over years; using the behaviour of earnings guidance revisions within a fiscal year; and extending Malmendier and Tate (2005a)'s option trading proxy to the entire top management team. We consider each of these as areas for further research.

5.4.4 Leadership changes

The character and behaviour of the CEO and other senior managers influence the firm's strategic decisions. Leadership changes, such as a change of CEO, could alter the extent to which overconfidence bias manifests in the team making the strategic decisions. Our study did not control for leadership changes and we recognise this as a limitation.

5.5 Further research

Our study has, directly and indirectly, revealed numerous areas for further research. The direct areas emerge from the learnings of our hypotheses that did not find empirical support and from our limitations. The indirect areas result from observations that have emerged in the course of this work. These research areas are discussed below.

5.5.1 Market-based firm performance

We elected to measure firm performance using a fundamental metric, namely industry-adjusted return on assets. Since the management team's overconfidence can affect their strategic decisions and it can affect investor sentiments of the firm, there is merit in considering the relationship between overestimation and overprecision on the market-based performance of the firm.

5.5.2 Proxy assessment through experimentation

Our study assumes that the overconfidence (overestimation and overprecision) expressed in management earnings guidance is representative of the overestimation and overprecision that a firm's management demonstrates in their strategic decision making. While we have strived to theoretically validate this assumption, we recognised (section 4.5.3) that there is still fragility in this assumption. One way to strengthen this claim would be to conduct an experiment whereby executives make a series of strategic and non-strategic decisions, then set earnings guidance, and then the hypothesis of correlation of the overconfidence in strategic decisions and the overconfidence in earnings guidance would be tested.

5.5.3 Alternative proxies

Continuing the theme of the imperfection of the proxy, we consider how else group-level overestimation and overprecision might be measured. Since earnings is perhaps the most carefully managed by the management team, we might do better using other guidance metrics. Although earnings guidance is the guidance most issued, management teams guide on other metrics too. This includes revenue, revenue growth, capital expenditure, operating margin, tax rate, and others.

From our supplementary analysis (section 4.4.2) we found an indication that past overestimation might affect both current overestimation and current overprecision, and similarly that past overprecision also might have an effect, albeit shorter lasting. This leads us to wonder whether a history of overestimation and/or overprecision might be used to develop a better proxy. In fact, we noted that Malmendier and Tate (2015) believe that a series of optimistic forecasts are required to separate overconfidence bias from mistakes or bad luck.

Yet another approach to group-level proxy development is to extend Malmendier and Tate (2005a)'s commonly-used proxy based on CEO options-trading behaviour beyond the CEO to the entire top management team.

Further research might construct group-level overestimation and overprecision proxies using one, or a combination, of these metrics.

5.5.4 CEO fixed effects

We argued in section 2.1.7 that strategic decisions are the product of a group of people, typically the top management team, rather than the sole product of the CEO. Although we have made a logical argument, we have not substantiated this analytically.

There would be merit in determining to what extent this argument is valid. If it were shown that strategic decisions are indeed the product of the top management team in a manner that is materially different to the CEO alone, then overconfidence (overestimation and overprecision) proxies based on the behaviour of the CEO would need to be reconsidered. An approach to this research might be through developing a CEO fixed-effects model and contrasting that somehow to the firm fixed-effects model. This would also address the limitation noted in section 5.4.4.

5.5.5 Non-monotonicity

As discussed in section 4.3.3.2, we consider the case on non-monotonicity still open. We mentioned that our inability to find non-monotonicity of overestimation and overprecision might be due to the “bluntness” of the proxies used, or the resolution of the time period, or the possibility that the effect exists but is “drowned out” by other factors, or lastly because the theoretical basis is simply incorrect.

Further research might attempt alternative specifications of the model, for example using differently designed proxies or different time horizons, to search for non-monotonicity of overestimation and overprecision on firm performance.

5.5.6 Granger causality

In our study we have made no strong claims of a causal relationship between overestimation or overprecision on firm performance. However, we have shown a substantial effect of these biases on firm performance with respect to the baseline model. And we have addressed the simultaneity risk and, to some extent, reverse causality. As such, we believe we have a good case for showing that the relationships we have found demonstrate Granger causality (Granger, 1969) and recommend that this analysis should be done.

5.5.7 Conjecture analysis

Our supplementary analysis (section 4.4) resulted in two conjectures, one for overestimation and one for overprecision. These conjectures seek to provide an explanation of the underlying drivers that give rise to the firm performance we witnessed in the presence of overestimation and overprecision. Further research could be done to formulate and test the hypotheses implied by these conjectures. This would lead to a more substantiated understanding of the underlying mechanisms by which overestimation and overprecision influence each other, influence intermediate metrics like operating profit margin, and ultimately influence firm performance.

5.5.8 Generalisability

As mentioned in the limitations (section 5.4.1), research is warranted to determine the generalisability of these findings. We would like to see this study replicated for the major indices of public firms on other exchanges like the Hang Seng, DAX, CAC, FTSE.

5.5.9 Anchoring and overconfidence

We note that earnings guidance is often provided at the beginning of the financial year and then revised and communicated each quarter when results are presented. Consequently, there is often a series of guidance communicated in each financial year. We know from behavioural science that anchoring with insufficient adjustment is another common cognitive bias (Kahneman, 2011). We wonder whether the first guidance might serve as an anchor that influences subsequent guidance. We wonder too whether the extent to which managers adjust their guidance is somehow informative of their overconfidence, for example an unwillingness to adjust might be an indicator of overconfidence. G. Chen, Crossland, and Luo (2015) find that corporate resistance to corrective feedback is related to CEO overprecision. This finding suggests that a series of intra-year guidance might allow for a more nuanced and perhaps more accurate proxy for overprecision. And perhaps there is something in intra-year guidance that improves overestimation too.

5.5.10 Scale invariance

In our analysis of the data, we observed a “scale invariance” behaviour in the earnings guidance. One might expect that, ceteris paribus, a management team with lower expected earnings per share would

communicate a tighter guidance range than a management team with higher expected earnings per share. In other words, one might expect that the ratio of the guidance range to the magnitude of the expected earnings would be roughly constant. However, what we observe is a clear hyperbolic, versus uniform, pattern when plotting our overprecision variable, which is the ratio of range to midpoint, against the midpoint (Figure 20). The strong hyperbolic lines are a result of a dominance of certain guidance ranges, like 10c, 15c, 20c, 25c, 30c, 40c, and 50c, as is evident in Figure 21. To be clear, the issue is not that management teams use these “convenient” range widths, but rather why they do not adjust to higher (or lower) range widths when their expected earnings are higher (or lower).

A cursory examination of this characteristic reveals a positive relationship at the 1% significance level between the guidance midpoint and the extent of overprecision. In fact, using the midpoint as an additional control variable seems to improve our main model, but a more careful assessment would be required.

This observation suggests further research might be warranted in understanding why management teams are scale invariant and whether there is predictive value in this demonstrated scale invariance. There are two related concepts that should be explored in conjunction with this research topic – they are “ratio bias” and “denominator neglect”.

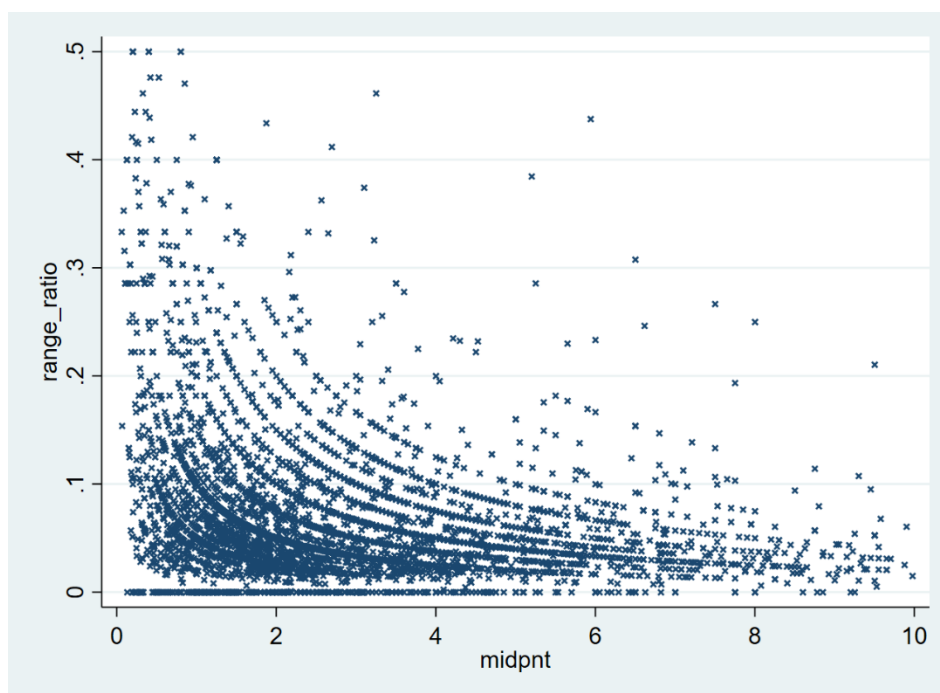


Figure 20: Ratio of overprecision (guidance range to guidance midpoint) to guidance midpoint.

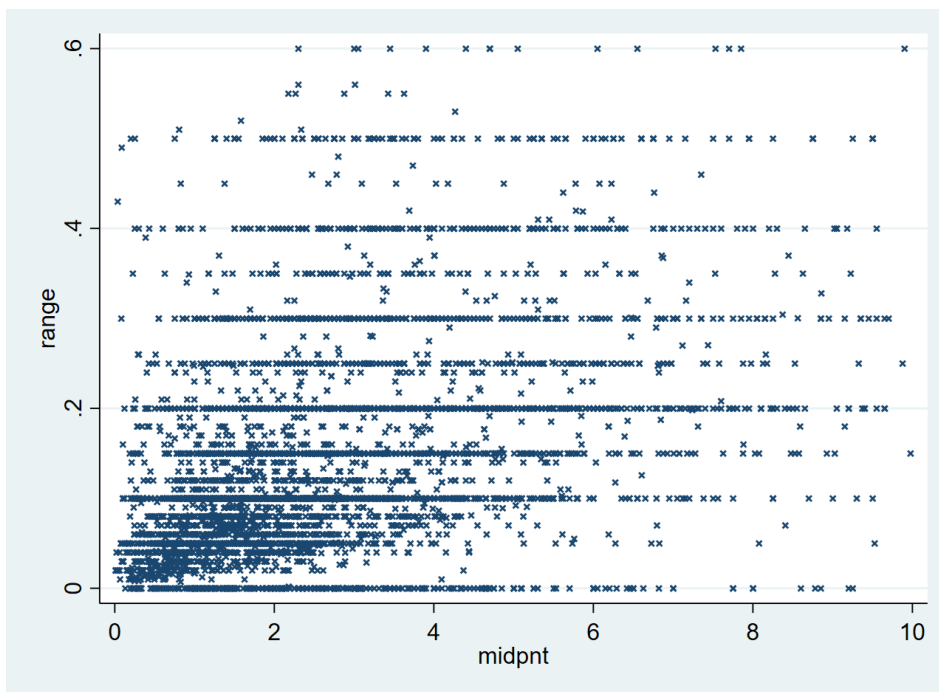


Figure 21: Guidance range width for each guidance midpoint.

5.6 Reflections

Had we been asked what we expected the impact of overconfidence on firm performance would be before our research efforts began, our response would have been fundamentally different to this study’s findings. Specifically, we would have thought that a management team that was well calibrated, both in terms of their level of certainty of what they knew and their expectation of how well they expected to do, would deliver the best firm performance because they were better “grounded in reality”. In cases where they were miscalibrated and hence saw the world more or less favourably than would be objectively justified, our initial thoughts were that erring on the side of optimism would be more beneficial than pessimism. This was because we expected that optimistic management teams were more likely to be less risk averse and thus take bold actions and that this tendency for action would confer strategic advantage in a dynamic competitive context. Hence, we would have thought that calibrated optimists would drive the highest firm performance. As a testament to the scientific method, the data has spoken, and our views have now changed.

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7 Appendices

“The problem with the world is that the intelligent people are full of doubts, while the stupid ones are full of confidence.”

Charles Bukowski

7.1 Crude meta-analysis of approaches to strategic decision making

This Appendix shows the results of a literature scan that focused on the effect on decision quality of broad strategic decision-making approaches.

The key take-aways from this literature scan are listed below:

- Note: Some papers refer to decision outcomes and some to decision quality. For a large enough data set, I assume that decision outcomes and decision quality are synonymous.
- Key take-aways: The literature contains numerous inconsistencies on how strategic decision-making approaches relate to decision quality, although it seems to reasonable to offer this guidance:
 - Avoid Politics
 - Use Rational approach with some caution
 - Use Intuitive approach with high caution
 - Use Heuristics

The simple legend below is used to characterise the effect:

- [+] = demonstrated positive effect
- [-] = demonstrated negative effect
- [0] = demonstrated neutral effect
- [?] = unclear result
- [~] = more complicated relationship

7.1.1 Summary literature findings

Context		Political	Rational	Intuitive	Heuristics
Environmental dynamism	H	[-]	Mostly [+]	Mostly [+]	[+]
Environmental dynamism	L	No papers	Mostly [+]	[-]	No papers
Context independent		Mostly [-]	[++]	Mostly [-]	[+]

Table 25: Summary findings of the impact of strategic decision-making approaches on firm performance.

7.1.2 Detailed literature findings

Context	Political	Rational	Intuitive	Heuristics
High environmental dynamism	[-] formal analysis for communications and persuasion (Mueller et al., 2007)	[-] rational processes (Hough & White, 2003) [+] analytical comprehensiveness (Walters & Bhuian, 2004) [+] formal analysis for informational purposes (Mueller et al., 2007) [+] comprehensiveness (C. C. Miller, 2008)	[+] intuition (Khatri & Ng, 2000) [+] build a collective intuition (Mueller et al., 2007) [-] intuition (Fox, 2015)	[+] when data is unreliable (Fox, 2015)
Low environmental dynamism		[+] rational processes (Hough & White, 2003) [0] analytical comprehensiveness (Walters & Bhuian, 2004) [~] comprehensiveness (C. C. Miller, 2008) [+] decision analysis (Fox, 2015)	[-] intuition (Khatri & Ng, 2000) [-] intuition (Fox, 2015)	
Context independent	[-] political behaviour (Dean & Sharfman, 1996)	[+] procedural rationality (Dean & Sharfman, 1996) [+] evaluation: analytical assessment (Nutt, 1998a) [+] “thinking first” (Mintzberg & Westley, 2001) [+] discovery-driven (Nutt, 2002)	[-] evaluation: judgmental tactics (Nutt, 1998a) [-] idea-driven (Nutt, 2002)	[+] evaluation: subjective that drew on performance records or user views (Nutt, 1998a)

	<p>[+] evaluation: bargaining (Nutt, 1998a)</p> <p>[-] political behaviour (Elbanna & Child, 2007)</p>	<p>[+] rational, goal-directed, search approach (Nutt, 2005)</p> <p>[+] rationality, only when environment is munificent (Goll & Rasheed, 2005)</p> <p>[+] rationality (Elbanna & Child, 2007)</p> <p>[+] rational process (Nooraie, 2008)</p> <p>[+] discovery: logical and political rationality (Nutt, 2008)</p> <p>[+] CEOs use intuition, analysis and guiding principles (Woiceshyn, 2009)</p> <p>[+] best practice: using an objective, searching with either benchmarking or innovation, using analytical or participation evaluation tactics, and implementing with participation (Nutt, 2010a)</p> <p>[+] good analytic tools for all contexts (Courtney et al., 2013)</p> <p>[+] rational process using Decision Quality and Dialog Decision Process (Spetzler et al., 2016)</p>	<p>[+] intuitive style (Sadler-Smith, 2004)</p> <p>[?] intuition (Elbanna & Child, 2007)</p> <p>[-] intuition (C. C. Miller & Ireland, 2005)</p> <p>[-] idea imposition: pragmatics and sense-making (Nutt, 2008)</p> <p>[-] intuition (Kahneman & Klein, 2009)</p> <p>[+] CEOs use intuition, analysis and guiding principles (Woiceshyn, 2009)</p> <p>[0] intuition (Sadler-Smith & Burke-Smalley, 2015)</p>	<p>[+] “doing first” (Mintzberg & Westley, 2001)</p> <p>[+] CEOs use intuition, analysis and guiding principles (Woiceshyn, 2009)</p> <p>[+] heuristics (Bingham & Eisenhardt, 2011)</p> <p>[+] structured analogies (Lovallo et al., 2012)</p>
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Table 26: Detailed findings of the impact of strategic decision-making approaches on firm performance

7.2 Impact of overconfidence bias on firm performance

This Appendix contains three tables that summarise empirical and experimental studies that show the impact of overconfidence on firm performance. Table 27 summarises studies that show the overall impact of overconfidence, Table 28 summarises studies of the discrete impacts of overconfidence, and Table 29 shows the same studies, but groups by type of firm performance measure, and indicates the journal, the type of overconfidence, and the dependent variable. Some of the column headings warrant explanation. “OE”, “OL”, and “OP” are abbreviations for overestimation, overplacement, and overprecision, respectively. These are the three types of overconfidence as defined by Moore and Healy (2008). The column “Group / CEO” refers to whether the study considered the overconfidence of a group of people making the strategic decision or the overconfidence of the CEO only.

Study	Data set	OE	OL	OP	CEO / Group	Overconfidence proxy	Description of the effect
Negative overall effect							
(Li & Liu, 2012)	Firms listed on Shanghai or Shenzhen SE between 2007 and 2009	x			Group	Performance prediction	Overconfidence and enterprise value are negatively correlated.
(S.-S. Chen et al., 2014)	477 large publicly traded US firms from 1980 to 1994	x			CEO	Options-based	Long-run stock performance is positive only for firms whose CEOs are not overconfident.
(P.-H. Ho et al., 2016)	Publicly listed US banks over 1994–2009	x			CEO	Options-based	Firms led by overconfident CEOs had greater increases in loan defaults, greater drops in operating and stock return performance, greater increases in expected default probability.
(J. B. Kim et al., 2016)	S&P 1500 companies between 1993 and 2010	x			CEO and Group	Options-based, firm investing and financing decisions	Firms with overconfident CEOs have a higher stock price crash risk.
(Invernizzi et al., 2017)	203 micro and small firms operating in North West Italy	x			Group	Difference between budget estimates and actual results for EBITDA	Overconfident individuals are more likely to start and develop new ventures and such ventures are also more likely to fail.
(Leng et al., 2018)	940 UK firms in non-FS over 2000-2015 period	x			CEO	Stock purchases	CEO overconfidence increases the risk of bankruptcy while moderate levels of confidence reduce it.
(Hayward & Hambrick, 1997)	US public firms between 1989 and 1992 conducting 106 transactions	x			CEO	Recent organisational success, press-coverage, CEO compensation to the next highest paid	Losses in acquiring firms' shareholder wealth following an acquisition, and the greater the CEO hubris and acquisition premiums, the greater the shareholder losses
(Malmendier & Tate, 2008)	477 large publicly traded US firms from 1980 to 1994	x			CEO	Options-based, press coverage	Overconfident CEOs overpay for target companies and undertake value-destroying mergers.

Study	Data set	OE	OL	OP	CEO / Group	Overconfidence proxy	Description of the effect
(Billett & Qian, 2008)	US mergers and acquisitions announced between 1980 and 2002, resulting in 3,795 deals by 2,487 CEOs	x			CEO	N/A	CEOs tend to become overconfident after a successful acquisition, and, as a result, are more likely to follow it with acquisitions that negatively impact their firm's stock.
(Park et al., 2018)	200 largest firms listed on the Korea Stock Exchange for the years 2001–2008.	x			CEO	Press coverage, award / certification records, and CEO statement in annual report	CEO hubris makes firms underperform in Korea.
Positive overall effect							
(Hirshleifer et al., 2012)	2,577 CEOs from 9,807 US firm-year observations between 1993 and 2003	x			CEO	Options-based, press coverage	Overconfident CEOs are more effective at exploiting growth opportunities and translating them into firm value (only in innovative industries).
(Hilary et al., 2016)	S&P 1500 firms between 1998 and 2010	x			CEO and Group	Management earnings forecast relative to consensus forecast	Managers appear to exert greater effort to meet their over-optimistic forecasts and in so doing increase firm value.
(Bharati et al., 2016)	ExecuComp's database from 1992 to 2010	x			CEO	Options-based	Overconfident CEOs produce roughly 3.0%–4.5% more stock return on an annual basis, depending on the return measure, relative to their non-overconfident counterparts.
(H. A. Kim et al., 2019)	S&P 1000 companies between 1992 and 2010	x			CEO	Options-based	CEO overconfidence is positively related with firm RONA and with stock performance.
(Mundi & Kaur, 2019)	Indian S&P BSE 200 firms between 2000 and 2015	x			CEO and Group	Options-based, press coverage, growth forecasts	Firms with overconfident CEOs enjoy a higher return on assets and Tobin's Q

Table 27: Empirical and experimental studies of overconfidence bias that show an overall impact on firm performance.

Study	Data set	OE	OL	OP	CEO / Group	Overconfidence proxy	Description of the effect
Negative discrete effect							
(Malmendier et al., 2011)	477 large publicly traded US firms from 1980 to 1994	x			CEO	Options-based	Overconfident CEOs are less likely to issue equity than other CEOs. Per dollar of financing required, they issue about 33 cents more debt than their peers; results are more loan defaults, larger drops in stock returns, and poorer operating performance.
(Schrand & Zechman, 2012)	49 firms, from the 1990s and 2000s	x			CEO and Group	A composite measure based on excess investment, net acquisition, debt-to-equity ratio, risk debt, and dividend policy	Overconfident executives are more likely to intentionally misstate earnings.
(J. E. Lee, 2016)	8,933 firm-year observations from Audit Analytics database, the Execucomp database, and the Compustat database between 2004 and 2011		x		CEO and Group	A composite measure based on excess investment, net acquisition, debt-to-equity ratio, risk debt, and dividend policy	CEO overconfidence is positively associated with the existence of internal control weakness.
(Hwang, Hyoseok et al., 2020)	13,754 U.S. firm-year observations over the 1996-2014 period		x		CEO	Options-based	Power-driven overconfident CEOs tend to complete more deals regardless of circumstances, do stock acquisitions, and make value-destroying acquisitions, relative to non-overconfident CEOs.
Unclear discrete effect							
(Malmendier & Tate, 2005a)	477 large publicly traded US firms from 1980 to 1994.	x	x		CEO	Options-based	A strong positive relation between the sensitivity of investment to cash flow and executive overconfidence

Study	Data set	OE	OL	OP	CEO / Group	Overconfidence proxy	Description of the effect
(Galasso & Simcoe, 2011)	450 US publicly traded companies and 627 CEOs from the years 1980 to 1994	x			CEO	Options-based	A robust positive association between overconfidence and citation-weighted patent counts. Results suggest that overconfident CEOs are more likely to take their firms in a new technological direction
(Malmendier & Tate, 2015)	Firms in the Compustat database between 1996 and 2012	x			CEO	Options-based	Investment of overconfident CEOs is more sensitive to external financing costs than is the investment of rational CEOs
(Hribar & Yang, 2016)	Large U.S. firms covered by ExecuComp from 2001 to 2010	x		x	CEO	Options-based, press coverage	Overconfidence increases the likelihood of issuing a forecast. Overconfidence increases the amount of optimism in management forecasts. Overconfidence increases the precision of the forecast.
(M. C. Kim et al., 2017)	S&P 1500 firms between 1993 and 2007	x			CEO	Press coverage	Corporate managerial hubris predicts low strategic emphasis on advertising vs R&D.
(Lai et al., 2017)	Foreign market entries of US firms between 2001 and 2014	x	x	x	CEO	Options-based, press coverage	Overconfidence gives an increased propensity for full over shared ownership in foreign market entry.
(Banerjee et al., 2018)	From Execucomp database, a firm-year panel dataset consisting of around 20,000 observations over the 1992–2011 period	x			CEO	Press-based, options-based	Overconfident managers repurchase stock at lower levels of cash holdings and respond more to stock-price declines. Overconfident CEOs are also more likely to substitute repurchases for dividends or capital expenditure.
Positive discrete effect							
(Shipman & Mumford, 2011)	Lab experiment	x			N/A	Survey-based multi-factor variable	Excessive optimism helps a leader develop a vision that is appealing and motivating to followers.

Study	Data set	OE	OL	OP	CEO / Group	Overconfidence proxy	Description of the effect
(Phua et al., 2018)	14,475 firm-year observations from the Execucomp database between 1993 and 2011	x			CEO	Options-based, press coverage	Overconfident CEOs are better able to retain talent, particularly in industries where human capital is more valuable; The supplier relationships of overconfident CEOs have lower termination risk.

Table 28: Empirical and experimental studies of overconfidence bias that show a discrete impact on firm performance.

Table 29 below lists empirical papers that explore the impact of overconfidence on firm performance. The proxies for overconfidence are derived from: how the CEO is covered in the press (**Pr**), the options-trading behaviour of the CEO (**Op**), the stock-trading behaviour of the CEO (**St**), relative compensation of the CEO (**Co**), management budgets or forecasts (**Fc**), the CEO's tone in tweets, reports, calls (**To**), or some other measure (**Ot**). Firm performance is measured in multiple ways, which are broadly grouped into stock returns, price-to-book, accounting returns, risk-based measures, and other measures.

Study	Journal	OE	OL	OP	CEO / Group	Pr	Op	St	Co	Fc	To	Ot	Dependent variables
Stock returns													
(Bharati et al., 2016)	Journal of Contemporary Accounting and Economics	x			CEO		x						Stock return performance / abnormal returns
(Billett & Qian, 2008)	Management Science	x			CEO							x	3yr buy and hold excess return
(Hayward & Hambrick, 1997)	Administrative Science Quarterly	x			CEO and Group	x			x			x	Cumulative abnormal returns
(H. A. Kim et al., 2019)	Asia-Pacific Journal of Accounting and Economics	x			CEO	x	x						RNOA (return on net operating assets); also use ROE, ROI, ROA, and also <u>stock returns</u>
(Malmendier & Tate, 2008)	Journal of Financial Economics	x			CEO	x		x					Merger frequency, merger value creation using <u>cumulative abnormal returns</u>
(S.-S. Chen et al., 2014)	Financial Management	x	x		CEO		x						1, 3, and 5 year BHAR (buy-and-hold abnormal returns)

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Study	Journal	OE	OL	OP	CEO / Group	Pr	Op	St	Co	Fc	To	Ot	Dependent variables
Price-to-book													
(Hirshleifer et al., 2012)	Journal of Finance	x			CEO	x	x						Tobin's Q
(Li & Liu, 2012)	Advances in Information Sciences and Services Sciences	x			Group					x			Tobin's Q
(Mundi & Kaur, 2019)	Vision	x			CEO and Group	x	x			x			ROA and <u>Tobin's Q</u>
Accounting returns													
(Hilary et al., 2016)	Journal of Accounting and Economics	x		x	CEO and Group	x	x			x			ROA
(H. A. Kim et al., 2019)	Asia-Pacific Journal of Accounting and Economics	x			CEO	x	x						RNOA (return on net operating assets); also use ROE, ROI, ROA, and also stock returns
(Mundi & Kaur, 2019)	Vision	x			CEO and Group	x	x			x			<u>ROA</u> and Tobin's Q
(Park et al., 2018)	Journal of Business Ethics	x			CEO	x					x	x	ROA in excess of the industry median ROA
Risk													
(P.-H. Ho et al., 2016)	Journal of Financial Economics	x			CEO		x						Bank risk metrics
(Invernizzi et al., 2017)	International Small Business Journal: Researching Entrepreneurship	x			Group					x			Risk of venture fail
(J. B. Kim et al., 2016)	Contemporary Accounting Research	x			CEO and Group		x					x	Stock price crash risk
(J. E. Lee, 2016)	Journal of Applied Business Research		x		CEO and Group							x	Internal control weakness
(Leng et al., 2018)	SSRN	x			CEO			x					Bankruptcy risk
Other													

Study	Journal	OE	OL	OP	CEO / Group	Pr	Op	St	Co	Fc	To	Ot	Dependent variables
(Banerjee et al., 2018)	Journal of Banking and Finance	x			CEO	x	x						Stock repurchases
(Galasso & Simcoe, 2011)	Management Science	x			CEO		x						Innovation measures
(Hribar & Yang, 2016)	Contemporary Accounting Research	x		x	CEO	x	x						Likelihood of issuing a forecast, amount of optimism in management forecasts, precision of the forecast
(Hwang, Hyoseok et al., 2020)	SSRN		x		CEO		x						Deal completion, all cash offer
(M. C. Kim et al., 2017)	Journal of the Academy of Marketing Science	x			CEO	x							Spend on R&D, spend on advertising
(Lai et al., 2017)	International Business Review	x	x	x	CEO	x	x						Full vs partial ownership
(Malmendier & Tate, 2005a)	Journal of Finance	x			CEO		x						Sensitivity of investment to cash flow
(Malmendier & Tate, 2015)	Journal of Economic Perspectives	x			CEO		x						Corporate investment
(Malmendier et al., 2011)	Journal of Finance	x			CEO	x	x						Debt vs equity funding
(Phua et al., 2018)	Journal of Financial Economics	x			CEO	x	x						Supplier commitment, employee commitment
(Schrand & Zechman, 2012)	Journal of Accounting and Economics	x			CEO and Group	x						x	Accounting and Auditing Enforcement Releases
(M. Simon & Houghton, 2003)	Academy of Management Journal			x	CEO or 2IC							x	NPD success factors
(Tang et al., 2015)	Journal of Management	x			CEO							x	Market performance of new products (innovation)
(Zhao & Ziebart, 2017)	Accounting and Finance Research	x			Group					x			Cost of borrowing

Table 29: Empirical studies of the impact of overconfidence, of various types, on firm performance.

7.3 Proxies for overconfidence bias

Study	OC type ¹⁶²			Overconfidence proxy used								
	OE	OL	OP	Stock trading	Options trading	Press coverage	Market predictions	Firm performance / awards	CEO relative compensation	CEO tone in tweets, reports, calls	Investment and capital decisions	Management budget / forecast
(Banerjee et al., 2018)	x				x	x						
(Barros & da Silveira, 2007)	x		x	x								
(Bharati et al., 2016)	x				x							
(G. Chen et al., 2015)			x			x		x	x			
(Engelen et al., 2015)	x				x							
(Galasso & Simcoe, 2011)	x				x							
(Hayward & Fitza, 2017)			x									x
(Hayward & Hambrick, 1997)	x					x		x	x			
(Hilary et al., 2016)	x		x									x
(Hirshleifer et al., 2012)	x				x	x						
(P.-H. Ho et al., 2016)	x					x						
(Hribar & Yang, 2016)	x		x		x	x						
(Hwang et al., 2020)		x			x							
(Invernizzi et al., 2017)	x											x
(J. B. Kim et al., 2016)	x				x						x	
(H. A. Kim et al., 2019)	x				x							

162. OC type = type of overconfidence. Many papers listed in this table do not declare whether they are analysing overestimation, overprecision, or overplacement. We deduced the type of overconfidence being studied from the definition of overconfidence, e.g. hubris and optimism are considered to be overestimation, “better than average” is considered to be overplacement, and miscalibration is considered to be overprecision.

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Study	OC type ¹⁶²			Overconfidence proxy used								
	OE	OL	OP	Stock trading	Options trading	Press coverage	Market predictions	Firm performance / awards	CEO relative compensation	CEO tone in tweets, reports, calls	Investment and capital decisions	Management budget / forecast
(M. C. Kim et al., 2017)	x					x						
(Lai et al., 2017)	x	x	x		x	x						
(J. E. Lee, 2016)		x									x	
(J. M. Lee et al., 2017)	x				x					x		x
(Leng et al., 2018)	x			x								
(Li & Liu, 2012)	x											x
(Malmendier & Tate, 2005a)	x	x			x							
(Malmendier & Tate, 2008)	x			x		x						
(Malmendier & Tate, 2015)	x				x							
(Malmendier et al., 2011)	x				x							
(Merkle, 2017)	x	x	x				x					
(Mundi & Kaur, 2019)	x					x	x					x
(Park et al., 2018)	x					x		x		x		
(Phua et al., 2018)	x				x	x						
(S.-S. Chen et al., 2014)	x	x			x							
(Schrand & Zechman, 2012)	x				x						x	
(M. Simon & Houghton, 2003) ¹⁶³			x									
(Zhao & Ziebart, 2017)	x											x

163. Proxy is extreme certainty, measured subjectively.

Table 30: Overconfidence bias proxies used in empirical studies

7.4 Data preparation

7.4.1 Extracting data

Data was extracted from Bloomberg¹⁶⁴ and FactSet terminals. The fields that were extracted and their extract formulae are displayed in Table 31 below. The “Source” column uses a single letter to denote the source of the field, as follows: user-developed (U), Bloomberg (B), and FactSet (F). The “Type” column uses an indicator to refer to the type of field, as follows: unique identifier (UID), control variables (C), dependent variables (D), and working variables (W), from which other variables are derived.

Field	Source	Type	Description	Extraction formula	Source Definition
uid	U	UID	Firm unique identifier		
year	B	C	Firm year		
ticker	B	UID	Firm ticker		
id_sedol1	B	UID	Stock Exchange Daily Official List	=BQL(A2,"ID_SEDOL1")	Stock Exchange Daily Official List number (SEDOL). Numbers issued prior to March 8, 2004 consist of 7 digits. SEDOLs issued after this date consist of 7 alphanumeric characters, where the first character is always a letter. This SEDOL is associated with the country listed in the SEDOL1 ISO Country (ID208, SEDOL1_COUNTRY_ISO). This does not include any Sedol FMQs with the exception of funds. For funds, if the SEDOL1 is not available, this field will return an FMQ SEDOL if SEDOL Fund Manager Quote 1 (ID213, ID_SEDOL_FMQ1) is populated.
sp500	B	C	Membership of S&P500	=IF(VLOOKUP(B2,_sp500,1,FALSE)="#N/A",0,1)	
fy_end_string	B	W	Financial year end string	=BDP(A2,"eqy_fiscal_yr_end")	Returns the month/year of the last annual financial results announcement date. Companies can choose to report their annual financial results for a 12-month or 52/53 week period not ending on 12/31. For a period ending between the 1st and 15th days of the month, this field will return the prior calendar month.

164. We used a Bloomberg LP terminal, accessed with UCT Libraries' subscription.

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Field	Source	Type	Description	Extraction formula	Source Definition
fy_month	B	C	Numeric month of financial year end		
bics_1	B	W	Bloomberg Industry classification level 1	=BDP(\$A2,"bics_level_1_sector_name")	Returns the Bloomberg Industry Classification System (BICS) level 1 name.
bics_2	B	W	Bloomberg Industry classification level 2	=BDP(\$A2,"bics_level_2_industry_group_name")	Returns the Bloomberg Industry Classification System (BICS) level 2 name.
industry_concentration	B	C	Industry concentration		Ratio of revenue of the revenue of the top 4 revenue earners over the top 20 revenue earners in a FactSet Sector.
revenue	B	C	Revenue	=BQL(\$B2,"SALES_REV_TURN(FPT=BA,FPR="&YEAR(d\$1)&")")/1e6	INDUSTRIALS Amount of sales generated by a company after the deduction of sales returns, allowances, discounts, and sales based taxes. Includes revenues from financial subsidiaries in industrial companies if the consolidation includes those subsidiaries throughout the report. Includes subsidies from federal or local government in certain industries (i.e. transportation or utilities). Excludes turnover from joint ventures and/or associates. Excludes inter-company revenue. Excludes revenues from discontinued operations. Figure is reported in millions; the Scaling Format Override (DY339, SCALING_FORMAT) can be used to change the display units for the field. Users can set their preference to return 'GAAP' (Generally Accepted Accounting Principles) or 'ADJUSTED' data through Fundamental Analysis Defaults. The field FA Adjusted Financials Override (DT094, FA_ADJUSTED) can be used to return Adjusted (excluding abnormal items) data ('Y') or GAAP data ('N').
capital_exp	B	C	Total capital expenditure	=-BQL(\$B2,"capital_expend(FPT=BA,FPR="&YEAR(D\$1)&")")/1e6	Amount the company spent on purchases of tangible fixed assets. May include intangible assets when not disclosed separately. The value is always negative. Figure is reported in millions; the Scaling Format Override (DY339, SCALING_FORMAT) can be used to change the display units for the field. INDUSTRIALS, BANKS, FINANCIALS, INSURANCE, UTILITIES, & MUNICIPAL REVENUE Returns Capital Expenditure CF017, CF_CAP_EXPEND_PRPTY_ADD for companies reported indirect cash flow statement method and CF052, CF_CAP_EXPEND_INC_FIX_ASSET for companies reported source and uses cash flow statement.
assets	B	C	Total assets	=BQL(\$B2,"bs_tot_asset(FPT=A,FPR="&YEAR(D\$1)&")")/1e6	INDUSTRIALS Total Assets: The total of all short and long-term assets as reported on the Balance Sheet. UTILITIES Total Assets: This account will generally equal Total Assets in the annual report, except when Utility plant is net of

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Field	Source	Type	Description	Extraction formula	Source Definition
					deferred income taxes. Deferred income taxes is presented on the credit or liability side of the balance sheet. This item is balancing both the debit (assets) and credit (liabilities and shareholders' equity) sides.
mrk_cap	B	C	Market Capitalisation	=@BQL(B2,"cur_mkt_cap(start=2001-01-01, end=2020-01-01, per=Y)/1e9")	Total current market value of all of a company's outstanding shares stated in the pricing currency. Capitalization is a measure of corporate size. For the fiscal period end market value, use Historical Market Cap (RR250, HISTORICAL_MARKET_CAP), returned in the fundamental currency. For historical current market cap, currency override (DS215, EQY_FUND_CRNCY) can be used to change currency displayed. For current market cap value with currency adjusted, please refer to Currency Adj Market Cap (RR910, CRNCY_ADJ_MKT_CAP).
buybacks	B	C	Share buybacks	=@BQL(\$B2,"cf_decr_cap_stock(fa_period_type=A, fa_period_reference=range(2009, 2020), fa_period_year_end=C)/1e6")	Repurchase (Buyback) of common stock, common stock warrants, or other common stock equivalents. Includes redemption of preferred share capital. Index: Figure reported is per-share. Equities, Corporates, Preferreds: Figure is reported in millions; the Scaling Format Override (DY339, SCALING_FORMAT) can be used to change the display units for the field. Available for all formats.
roa	B	D	Return on assets	=BQL(\$B2,"RETURN_ON_ASSET(FPT=BA,FPR="&YEAR(D\$1)&")")	Indicator of how profitable a company is relative to its total assets, in percentage. Return on assets gives an idea as to how efficient management is at using its assets to generate earnings. INDUSTRIALS, BANKS, FINANCIALS, UTILITIES, & REITS Calculated as: (Trailing 12M Net Income / Average Total Assets) * 100, where: Trailing 12M Net Income is RR813, TRAIL_12M_NET_INC Average Total Assets is the average of the beginning balance and ending balance of BS035, BS_TOT_ASSET
tsr	B	D	Total returns to shareholders	=@BQL(\$B3,"avg(rolling(total_return(calc_interval='1y'),iterationdates=range("&@BQL.Date(D\$2-10)&","&@BQL.Date(D\$2+10)&"))))")	The definition of TOTAL RETURN is as per its use on the {TRA} page in the Terminal: the cumulative percent change in an equity position taking into account price change (capital gains) and assuming fully reinvested dividends (reinvested on the ex-date).
roic	B	D	Return on invested capital	=@BQL(\$B3,"RETURN_ON_INV_CAPITAL(FPT=BA,FPR="&YEAR(D\$1)&")")	Indicates how effectively a company uses the sources of capital (equity and debt) invested in its operations. Average Invested Capital is the average of the beginning and ending balance of Total Invested Capital (RX215, TOTAL_INVESTED_CAPITAL). It is computed as: 100 x (T12M Net operating profit after tax / Average invested capital), where: T12M Net operating profit after tax is RX216, TRAIL_12M_NET_OP_PROF_AFTER_TAX Invested Capital is RX215, TOTAL_INVESTED_CAPITAL Average of Invested Capital is calculated based on the average of invested capital for current period and invested capital

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Field	Source	Type	Description	Extraction formula	Source Definition
					<p>for the same period a year ago. ROIC will not compute if:</p> <ol style="list-style-type: none"> 1. The year-over-year average of invested capital is negative. 2. Effective Tax Rate (RR037, EFF_TAX_RATE) or Trailing 12 Months Effective Tax Rate (RR712, TRAIL_12M_EFF_TAX_RT) is not available. <p>The calculation of this field includes only the basic adjustments listed under RX214, NET_OPER_PROFIT_AFTER_TAX and RX215, TOTAL_INVESTED_CAPITAL and therefore may not show the same value as WACC Return on Invested Capital (VMO13, WACC_RETURN_ON_INV_CAPITAL).</p>
dividends	B	C	Dividend payout	=BQL(\$B4,"DVD_PAYOUT_RATIO(FPT=BA,FPR="&YEAR(X\$2)&")")	<p>Fraction of net income a firm pays to its shareholders in dividends, in percentage. Calculated as: Total Common Dividends*100 / Income Before Extraordinary Items Less Minority and Preferred Dvd, where: Total Cash Common Dividend is IS052, IS_TOT_CASH_COM_DVD Income Before Extraordinary Items Less Minority and Preferred Dvd is RR092, INC_BEF_XO_LESS_MIN_INT_PREF_DVD</p>
sales_g	B	C	Sales growth	""=@BQL(\$B2,"SALES_GROWTH(FPT=BA,FPR="&YEAR(D\$1)&")")	<p>A percentage increase or decrease of sales revenue by comparing current period with same period prior year. Calculated as: (Revenue from Current Period - Revenue from Same Period Prior Year) * 100 / Revenue from Same Period Prior Year, where: Revenue is IS010, SALES_REV_TURN Revenue Growth is not computed if Revenue changes signs from prior year to current period. Please reference Revenue Growth Adjusted Year over Year (F1139, REVENUE_GROWTH_ADJUSTED_YOY) for the adjusted value that excludes the impact of abnormal items.</p>
tq	B	D	Tobin's Q	=@BQL(\$B2,"TOBIN_Q_RATIO(FPT=BA,FPR="&YEAR(D\$1)&")")	<p>Ratio of the market value of a firm to the replacement cost of the firm's assets. The Q ratio is useful for the valuation of a company. It is based in the hypothesis that in the long run the market value of a company should roughly equal the cost of replacing the company's assets. The ratio is computed as follows: (Market Cap + Total Liabilities + Preferred Equity + Minority Interest) / Total Assets, where: Market Cap is RR250, HISTORICAL_MARKET_CAP for historical periods and RR902, CUR_MKT_CAP for daily ratio Total Liabilities is RR005, BS_TOT_LIAB2 Preferred Equity is BS061, BS_PFD_EQTY_&_HYBRID_CPTL Minority Interest is BS062, MINORITY_NONCONTROLLING_INTEREST Total Assets is BS035, BS_TOT_ASSET</p>
shares	B	C	Number of share outstanding	=BQL(\$B2,"BS_SH_OUT(FPT=BA,FPR="&YEAR(Z\$1)&")/1m")	<p>All the shares of a corporation that have been authorized, issued, purchased, and held by investors as of period end date. Net of treasury shares which are shares held by the corporation itself if the number is disclosed. Excludes shares to be issued. For a company with multiple shares, all classes of shares both listed and unlisted with common stock characteristic are converted to common stock equivalents of Fundamental Ticker (DX895, EQY_FUND_TICKER). Please refer to Multiple Share Information (DY667, MULTIPLE_SHARE_INFO) for current multiple share information.</p>

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Field	Source	Type	Description	Extraction formula	Source Definition
op_margi n	B	C	Annual operating margin	=BQL(\$B2,"OPER_MARGIN(FPT=BA,FPR="&YEAR(D\$1)&")")	Ratio used to measure a company's pricing strategy and operating efficiency, in percentage. INDUSTRIALS, INSURANCE, UTILITIES, & MUNICIPAL REVENUE Calculated as: Operating Income (Losses) / Total Revenue * 100, where: Operating Income is IS033, IS_OPER_INC Total Revenue is IS010, SALES_REV_TURN
debt_equ ity	B	C	Debt to equity ratio	=BQL(\$B2,"TOT_DEBT_TO_TOT_EQY(FPT=BA,FPR="&YEAR(D\$1)&")")	INDUSTRIALS, BANKS, FINANCIALS, INSURANCE, UTILITIES & REITS Total debt divided by total shareholders' equity. Calculated as: Short and Long Term Debt / Shareholders' Equity * 100 Where: Short and Long Term Debt is RR251, SHORT_AND_LONG_TERM_DEBT Shareholders' Equity is RR007, TOTAL_EQUITY
rnd_exp	B	C	R&D expenditure	=BQL(\$B2,"rd_expend_to_net_sales(FPT=BA,FPR="&YEAR(D\$1)&")")	INDUSTRIALS Research and development (R&D) expenditures as a percentage of revenue (net sales). Calculated as: (R&D Expense / Revenue) * 100, where: R&D Expense is IS072, IS_RD_EXPEND Revenue is IS010, SALES_REV_TURN
employee s	B	C	Number of employees	=BQL(\$B2,"NUM_OF_EMPLOYEES(FPT=A,FPR="&YEAR(Z\$1)&")")	Number of people employed by the company, based on the number of full time equivalents. If unavailable, then the number of full time employees is used, excluding part time employees.
guidl	F	W	Low Guidance	=FDS(\$B3,"avail(MAX(FE_GUIDANCE(EPS,LOW,ANN_ROLL,"&D\$1&","&C3&"+1m,"&C3&"-3m,RANGE,")),MAX(FE_GUIDANCE(EPS,LOW,ANN_ROLL,"&D\$1&","&C3&"+1m,"&C3&"+2m,RANGE,")),MAX(FE_GUIDANCE(EPS,LOW,ANN_ROLL,"&D\$1&","&C3&"+2m,"&C3&"+3m,RANGE,"))))")	FE_GUIDANCE returns guidance data from the FactSet Estimates database. Guidance: companies provide guidance as an indication or estimate of their future earnings. FactSet Estimates allows you to view high, low, and mean guidance estimates for all companies. FactSet Estimates collects data into the Low / High Guidance Fields for each asset per fiscal period per item. If there is a record that only has either the Low or High field populated, a flag is triggered, and the Quality Team performs an additional check on the data. There are 4 scenarios that the team uses when populating the Low / High fields: <ul style="list-style-type: none"> • A firm reports a Range, thus the Low and High are populated respectively. Example "Sales will be between 8 to 10 million". • A firm reports a single value "COGS will be 5 Million". Estimates Team then populates both the Low and High value with "5 Million". • A firm reports a "greater than" or "less than" phrase in the report - "COGS will be less than \$10 Million", thus the High is set to 10 Million and the Low is set to Null (creating no record in the SDF database) • A firm reports a single Metric as a percentage - "COGS will be 5% higher this year than last year". The Estimates team then takes the percentage value and multiplies it times the numerical value from last year to determine the numerical value for this current period. If there was both a Low & High listed for the prior period, the 5% is applied
guidh	F	W	High Guidance	=FDS(\$B3,"avail(MAX(FE_GUIDANCE(EPS,LOW,ANN_ROLL,"&D\$1&","&C3&"+1m,"&C3&"-3m,RANGE,")),MAX(FE_GUI	

Field	Source	Type	Description	Extraction formula	Source Definition
				DANCE(EPS,LOW,ANN_ROLL,"&D\$1&","&C3&"+1m,"&C3&"+2m,RANGE,")),MAX(FE_GUIDANCE(EPS,LOW,ANN_ROLL,"&D\$1&","&C3&"+2m,"&C3&"+3m,RANGE,"))))"	to both values. If there was only a Low reported for the prior period, then the 5% will only be applied to that Low number, and the High will remain Null. Note: some gaps in the FactSet guidance data were filled with manually captured guidance data from the Bloomberg terminal.
eps	F	W	EPS Actual	=@FDS(\$B2,"FE_ACTUAL(AC TUAL,EPS,ANN_ROLL,"&C\$1&",""))"	Represents the fiscal period earnings per share (EPS) for the period and date(s) requested. It may return either diluted or basic EPS depending on how the company reports and may follow country-specific reporting patterns. This item is as-reported by the company except for Sweden where the Standard Tax Method is used when EPS is not reported. Where EPS is reported for Swedish companies, it may be after standard or actual tax. An estimate will be computed based on the respective country's generic definition, if the company does not report its EPS. Preference stock participating with common/ordinary shares in the profits of the company is included in the share base.

Table 31: Extracted variables from Bloomberg and FactSet.

7.4.2 Loading data

After the data has been extracted from the source terminals, the data is compiled into MS Excel workbooks of their respective categories: master data, dependent variables, control variables, ESG control variables, firm EPS and guidance, and industry concentration. The compilation process takes care to align variables to the correct firm with the use of a simple matching function, which indicates if the data are misaligned. After compilation, the various sheets are individually pasted into the Stata data editor to create a Stata data file for each workbook. Following the generation of the data files, the full dataset is merged in Stata. A graphical illustration of this process is provided in [Figure 22](#).

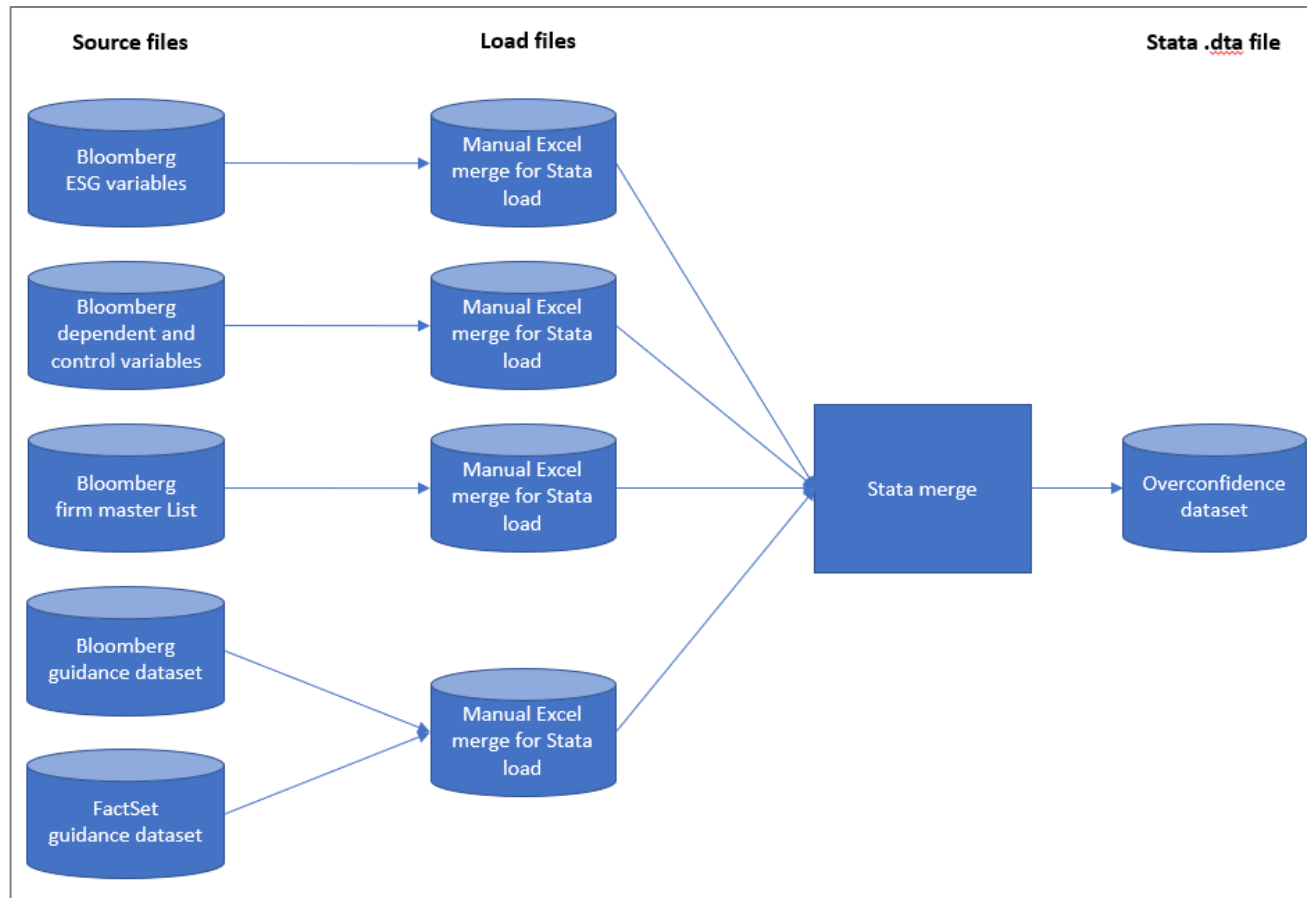


Figure 22: Flow from source data to load file to Stata .dta file

7.4.3 Variable generation, transformation, and outlier treatment

Once the data has been loaded into Stata, it is transformed to be ready for analysis. The transformation includes the generation of variables and the treatment of outliers.

7.4.3.1 Generation and transformation of variables

Our variables available for modelling are displayed in Table 32 below. The “Type” column uses an indicator to refer to the type of field, as follows: dependent variables (D), treatment variables (T), control variables (C), supplementary dependent variables (S), and working variables (W), from which other variables are derived. The column “Operation” explains, using Stata code, how the variables are generated. The source variables are listed in Table 31.

Once the variables have been generated, we inspected their distributions. To prevent treatment and control variables influencing each other, we desired the variables to be close to being normally distributed, with zero mean, and similar standard deviations. We found that most of our candidate control variables require transformation. We applied a natural log transform plus scaling and offsetting for some variables and we created binary variables in some other cases. Variables that have been log or binary transformed are renamed with upper case letters.

Variable name	Type	Description	Unit of measure	Stata operation
indmed_roa	W	Industry median ROA	%	egen indmed_roa = median(roa), by(BICS1)
adjROA	W	Industry industry-adjusted ROA	%	gen adjROA = roa - indmed_roa
adjROA_1	W	Industry industry-adjusted ROA offset	%	bys uid : gen adjROA_1 = adjROA[_n-1]
adjROA_2	W	Industry industry-adjusted ROA offset	%	bys uid : gen adjROA_2 = adjROA[_n-2]
adjROA_3	W	Industry industry-adjusted ROA offset	%	bys uid : gen adjROA_3 = adjROA[_n-3]
adjROA_4	W	Industry industry-adjusted ROA offset	%	bys uid : gen adjROA_4 = adjROA[_n-4]
adjROA_5	W	Industry industry-adjusted ROA offset	%	bys uid : gen adjROA_5 = adjROA[_n-5]
adjROA_c1	D	Industry industry-adjusted ROA cumulative	%	gen adjROA_c1 = adjROA_1
adjROA_c2	D	Industry industry-adjusted ROA cumulative	%	gen adjROA_c2 = adjROA_1 + adjROA_2
adjROA_c3	D	Industry industry-adjusted ROA cumulative	%	gen adjROA_c3 = adjROA_1 + adjROA_2 + adjROA_3
adjROA_c4	D	Industry industry-adjusted ROA cumulative	%	gen adjROA_c4 = adjROA_1 + adjROA_2 + adjROA_3 + adjROA_4
adjROA_c5	D	Industry industry-adjusted ROA cumulative	%	gen adjROA_c5 = adjROA_1 + adjROA_2 + adjROA_3 + adjROA_4 + adjROA_5
oe	T	Overestimation	%	* EPS Guidance gen guidl_chk = 1 if guidl != . gen guidh_chk = 1 if guidh != . gen rangeguidance = 1 if guidl_chk == 1 & guidh_chk == 1 & guidl != guidh & eps != . * Range gen range = guidh - guidl if rangeguidance == 1

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Variable name	Type	Description	Unit of measure	Stata operation
				<pre> * Midpoint gen midpnt = (guidh + guidl)/2 * Deviation gen a_devl = guidl - eps if guidl > eps & rangeguidance == 1 gen a_devh = guidh - eps if guidh < eps & rangeguidance == 1 gen a_devc = 0 if (guidl <= eps guidh >= eps) & rangeguidance == 1 egen a_cal_dev = rowtotal(a_devl a_devh a_devc) if a_devl != . a_devh != . a_devc != . * Overestimation gen a_mid_dev = (a_cal_dev/abs(midpnt))*100 if rangeguidance == 1 bys uid : gen a_mid_dev1 = a_mid_dev[_n+1] gen oe = (fymonth/12)*(a_mid_dev) + ((12-fymonth)/12)*(a_mid_dev1) replace oe = (a_mid_dev) if fymonth >= 6 & oe == . </pre>
op	T	Overprecision	%	<pre> * Overprecision gen cal_op = (-1*(range/abs(midpnt)))*100 if rangeguidance == 1 & oe != 0 bys uid : gen cal_op1 = cal_op[_n+1] gen op = (fymonth/12)*(cal_op) + ((12-fymonth)/12)*(cal_op1) replace op = (cal_op) if fymonth >= 6 & op == . </pre>
BB	C	Log of buybacks percentage	Ln(%)	<pre> gen bb = -1*buybacks/mrk_cap gen BB = ln(bb + 1) </pre>
DE	C	Log of debt-to-equity	Ln(%)	<pre> rename debt_equity de gen DE = ln(de + 1) </pre>
EE	C	Log of employees	Ln(count)	<pre> rename employees ee gen EE = ln(ee) </pre>
LEV	C	Log of leverage ratio	Ln(%)	<pre> rename assets asset rename liabilities liab gen LEV = ln(liab/asset*100) </pre>
II	C	Investment intensity	%	<pre> rename assets asset ii = (capital_exp/assets)+(((rnd_exp*revenue)/100)/assets) </pre>
RD	C	Log of research and development spend	Ln(%)	<pre> rename rnd_exp rd gen RD = ln(rd + 1) </pre>
DIV	C	Log of dividends	Ln(%)	<pre> rename dividend div gen DIV = ln(div + 1) </pre>

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Variable name	Type	Description	Unit of measure	Stata operation
tq	C	Tobin's Q	%	N/A
concn	C	Industry concentration	%	rename industry_concentration concn
opm	C	Operating margin	%	rename op_margin opm
soecat	T	Overestimation categorical		egen neg_1 = pctl(a_neg), p(25) egen neg_2 = pctl(a_neg), p(50) egen neg_3 = pctl(a_neg), p(75) egen pos_1 = pctl(a_pos), p(50) gen neg_s1 = 0 if a_neg <= neg_1 & a_neg != . gen neg_s2 = 1 if a_neg > neg_1 & a_neg <= neg_2 gen neg_s3 = 2 if a_neg > neg_2 & a_neg <= neg_3 gen neg_s4 = 3 if a_neg > neg_3 & a_neg != . gen cal_s1 = 4 if a_cal == 1 & a_cal != . gen pos_s1 = 5 if a_pos <= pos_1 & a_pos != . gen pos_s2 = 6 if a_pos > pos_1 & a_pos != . egen soecat = rowtotal(neg_s1 neg_s2 neg_s3 neg_s4 cal_s1 pos_s1 pos_s2) if neg_s1 != . neg_s2 != . neg_s3 != . neg_s4 != . cal_s1 != . pos_s1 != . pos_s2 != .
sopcat	T	Overprecision categorical		* Need to rerun the do file without the exclusion (oe != 0) in the definition of cal_op gen sopc = op if op != . egen sopc_1 = pctl(sopc), p(15) egen sopc_2 = pctl(sopc), p(29) egen sopc_3 = pctl(sopc), p(43) egen sopc_4 = pctl(sopc), p(57) egen sopc_5 = pctl(sopc), p(71) egen sopc_6 = pctl(sopc), p(85) gen sopc_q1 = 0 if sopc <= sopc_1 & sopc != . gen sopc_q2 = 1 if sopc > sopc_1 & sopc <= sopc_2 & sopc != . gen sopc_q3 = 2 if sopc > sopc_2 & sopc <= sopc_3 & sopc != . gen sopc_q4 = 3 if sopc > sopc_3 & sopc <= sopc_4 & sopc != . gen sopc_q5 = 4 if sopc > sopc_4 & sopc <= sopc_5 & sopc != . gen sopc_q6 = 5 if sopc > sopc_5 & sopc <= sopc_6 & sopc != . gen sopc_q7 = 6 if sopc > sopc_6 & sopc != . egen sopcat = rowtotal(sopc_q1 sopc_q2 sopc_q3 sopc_q4 sopc_q5 sopc_q6 sopc_q7) if sopc != .
y_*	C	Year dummies		gen y_9 = 1 if year == 2009 gen y_10 = 1 if year == 2010

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Variable name	Type	Description	Unit of measure	Stata operation
				<pre> gen y_11 = 1 if year == 2011 gen y_12 = 1 if year == 2012 gen y_13 = 1 if year == 2013 gen y_14 = 1 if year == 2014 gen y_15 = 1 if year == 2015 gen y_16 = 1 if year == 2016 gen y_17 = 1 if year == 2017 gen y_18 = 1 if year == 2018 gen y_19 = 1 if year == 2019 gen y_20 = 1 if year == 2020 recode y_9-y_20 (.=0) </pre>
oexop	T	Overestimation overprecision interaction term		<pre> gen oexop = oe*op </pre>
adjrev_g1	S	Industry-adjusted revenue growth	%	<pre> rename revenue rev bys uid : gen rev_1 = rev[_n-1] gen rev_g1 = ((rev/rev_1)-1)*100 forvalues y = 2009/2019 { egen indmed_rev_g1_`y' = median(rev_g1) if year == `y', by(BICS1) } egen indmed_rev_g1 = rowtotal(indmed_rev_g1_2009 indmed_rev_g1_2010 indmed_rev_g1_2011 indmed_rev_g1_2012 indmed_rev_g1_2013 indmed_rev_g1_2014 indmed_rev_g1_2015 indmed_rev_g1_2016 indmed_rev_g1_2017 indmed_rev_g1_2018 indmed_rev_g1_2019) gen adjrev_g1 = rev_g1 - indmed_rev_g1 </pre>
adja_g1	S	Industry-adjusted asset growth	%	<pre> rename assets asset Same as above for rev, but "asset" in place of "rev" </pre>
adjrd	S	Industry-adjusted research and development spend	%	<pre> rename rnd_exp rd Same as above for rev, but "rd" in place of "rev" </pre>
adjii	S	Industry-adjusted investment intensity	%	<pre> gen ii = ((capital_exp/assets)+(((rnd_exp*revenue)/100)/assets))*100 Same as above for rev, but "asset" in place of "rev" </pre>
adjde	S	Industry-adjusted debt-to-equity	%	<pre> rename debt_equity de Same as above for rev, but "asset" in place of "rev" </pre>
adjlev	S	Industry-adjusted leverage	%	<pre> gen lev = liabilities/assets*100 Same as above for rev, but "asset" in place of "rev" </pre>

Variable name	Type	Description	Unit of measure	Stata operation
adjopm	S	Industry-adjusted operating margin	%	rename op_margin opm Same as above for rev, but “asset” in place of “rev”

Table 32: Variables available for modelling.

7.4.3.2 Calendarisation

The variables in our dataset conform to different reporting periods – some, like market capitalization are reported aligned to the calendar year, while others like Return on Assets are aligned to a firm’s financial year, illustrated in Figure 23. To allow for meaningful comparison, we have aligned all of our data to the calendar year. This calendarization process was completed automatically during extraction by the data terminals for all our financial year-aligned data, with the exception of guidance data.

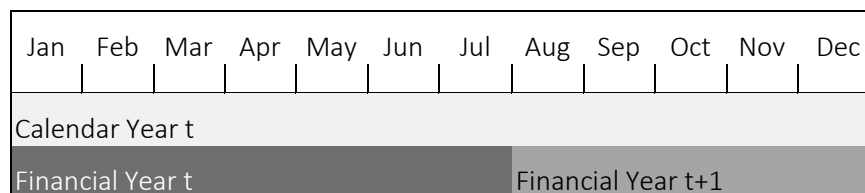


Figure 23: Calendar year and financial year.

For our guidance data, we undertook a manual transformation within Stata to align this data to the calendar year. First, we defined our proxy variables for overestimation and overconfidence using the guidance data aligned to the firm’s financial year. We then applied a weighted average of our proxies across financial years to achieve a calendarized variable according to the following equation, which shows an example for calendarizing overestimation (oe) for the year 2014.

$$oe_{CY2014} = \frac{FY_{end}}{12} (oe_{FY2014}) + \frac{12 - FY_{end}}{12} (oe_{FY2015})$$

Where FY_{end} is the numeric of the financial year end month of the firm.

7.4.3.3 Sample selection

We reduced our data set by removing financial services firms because many of our variables of interest, like ROA, are not comparable between industrial firms and financial services firms.

7.4.3.4 Outlier treatment

We treated outliers using winsorisation. Dependent on the variable characteristics, we winsorised using Stata’s user-defined winsor2 function (Yujun, n.d.) at the 1st and 99th percentiles, at the 1st percentile, at the 99th percentile, or not at all, as displayed in Table 33. In this table we also indicate which variables were log transformed, binary transformed, and/or scaled to have roughly span 100 units and be mean centred on zero.

	Winsorised at p1	Winsorised at p99	Scaled	Binary transformed	Log transformed
Dependent variables					
adjROA_c1	x	x			
adjROA_c2	x	x			
adjROA_c3	x	x			
adjROA_c4	x	x			
adjROA_c5	x	x			
Treatment variables					
oe	x	x			
op	x				
oexop	x	x			
Control variables					
BB				x	x
EE			x		x
LEV		x	x		x
RD		x		x	x
tq		x	x		
Supplementary analysis variables					
adjrev_g1		x			
adja_g1		x			
adjrd		x			
adjii		x			
adjde		x			
adjlev		x			
adjopm	x	x			

Table 33: Variable winsorisation and transformation approach.

7.5 Model development and results

7.5.1 Bivariate analysis

This section contains the detailed results of the bivariate analysis from a number of perspectives, namely a consolidated view of treatment and controls on each lagged dependent variable (Table 34), detailed view of the treatment variables (Table 35), and a detailed view of the control variables (Table 36).

The table below shows the bivariate analysis of each of the model variables on adjROA under its five lagged conditions.

VARIABLES	adjROA_c1	adjROA_c2	adjROA_c3	adjROA_c4	adjROA_c5
L(n).oe	-0.0758*** (0.00942)	-0.139*** (0.0172)	-0.180*** (0.0254)	-0.191*** (0.0319)	-0.186*** (0.0364)
L(n).op	0.205*** (0.0321)	0.202*** (0.0554)	0.133* (0.0791)	0.0827 (0.0823)	-0.0454 (0.0874)
L(n).BB	1.175*** (0.437)	1.243 (0.812)	0.872 (1.085)	-0.418 (1.279)	-1.405 (1.488)
L(n).EE	-0.384*** (0.0787)	-0.829*** (0.155)	-1.259*** (0.225)	-1.596*** (0.298)	-1.798*** (0.405)
L(n).LEV	-0.396*** (0.0483)	-0.417*** (0.0907)	-0.460*** (0.146)	-0.490*** (0.178)	-0.574** (0.231)
L(n).RD	-1.511 (1.581)	-3.823 (3.769)	-6.009 (6.423)	-6.678 (8.512)	-8.710 (8.965)
L(n).tq	0.185*** (0.0175)	0.377*** (0.0344)	0.498*** (0.0504)	0.519*** (0.0682)	0.430*** (0.0907)

Table 34: Bivariate analysis of treatment and control variables with respect to each lagged version of the dependent variable.

Notes regarding the table:

- ***, **, * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.
- Robust standard errors are shown in parentheses below coefficients.
- Pink cells reflect negative values and green cells reflect positive values.

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- In many of the analyses displayed, regressors are lagged. Lagged regressors are depicted by the actual lag number, such as “L3.” for a 3-year lag, or using “L(n).” where the “(n)” matches the dependent variable in the column, for example a column with “adjROA_c3” will imply that “L(n).” of the regressor equates to “L3.”.

The table below shows the bivariate analysis of the treatment variables on adjROA under its five lagged conditions.

VARIABLES	adjROA_c1	adjROA_c2	adjROA_c3	adjROA_c4	adjROA_c5	adjROA_c1	adjROA_c2	adjROA_c3	adjROA_c4	adjROA_c5
L.oe	-0.0758*** (0.00942)									
L2.oe		-0.139*** (0.0172)								
L3.oe			-0.180*** (0.0254)							
L4.oe				-0.191*** (0.0319)						
L5.oe					-0.186*** (0.0364)					
L.op						0.205*** (0.0321)				
L2.op							0.202*** (0.0554)			
L3.op								0.133* (0.0791)		
L4.op									0.0827 (0.0823)	
L5.op										-0.0454 (0.0874)
Constant	1.203*** (0.0105)	2.274*** (0.0208)	3.357*** (0.0283)	4.473*** (0.0383)	5.685*** (0.0512)	2.785*** (0.235)	4.066*** (0.388)	4.768*** (0.515)	5.299*** (0.479)	5.746*** (0.465)
Observations	3,060	2,762	2,424	2,080	1,743	3,060	2,762	2,424	2,080	1,743
R-squared	0.079	0.110	0.115	0.102	0.082	0.057	0.027	0.010	0.002	0.000
No. of uid	580	555	522	493	458	580	555	522	493	458

Table 35: Bivariate analysis of the treatment variables on adjROA under its five lagged conditions.

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The table below shows the bivariate analysis of the control variables on adjROA under its 1-year, 3-year, 5-year lagged conditions.

VARIABLES	adjROA_c1	adjROA_c3	adjROA_c5	adjROA_c1	adjROA_c3	adjROA_c5	adjROA_c1	adjROA_c3	adjROA_c5	adjROA_c1	adjROA_c3	adjROA_c5	adjROA_c1	adjROA_c3	adjROA_c5
L.BB	1.175*** (0.437)														
L3.BB		0.872 (1.085)													
L5.BB			-1.405 (1.488)												
L.EE				-0.384*** (0.0787)											
L3.EE					-1.259*** (0.225)										
L5.EE						-1.798*** (0.405)									
L.LEV							-0.396*** (0.0483)								
L3.LEV								-0.460*** (0.146)							
L5.LEV									-0.574** (0.231)						
L.RD										-1.511 (1.581)					
L3.RD											-6.009 (6.423)				
L5.RD												-8.710 (8.965)			
L.tq													0.185*** (0.0175)		
L3.tq														0.498*** (0.0504)	
L5.tq															0.430*** (0.0907)
Constant	0.348	2.864***	7.050***	3.217***	9.898***	14.95***	1.883***	4.120***	6.432***	2.205**	7.180*	11.18**	0.886***	2.710***	5.434***
Observations	3.06	2.424	1.743	3.06	2.424	1.743	3.06	2.424	1.743	3.06	2.424	1.743	3.06	2.424	1.743
R-squared	0.005	0.001	0.001	0.021	0.053	0.059	0.083	0.026	0.023	0.001	0.004	0.005	0.104	0.165	0.067
No. of uid	580	522	458	580	522	458	580	522	458	580	522	458	580	522	458

Table 36: Bivariate analysis of the control variables on adjROA under its 1-year, 3-year, 5-year lagged conditions

7.5.2 Multivariate analysis

The table below shows the full model results of the impact of (a) the baseline model with no treatment variables, (b) overestimation only, (c) overprecision only, and (d) overestimation and overprecision, on adjROA under its five lagged conditions. The cells with black borders indicate where there is a difference to the bivariate analysis.

VARIABLES	(a) Baseline model with no treatment variables					(b) Overestimation only				
	adjROA_c1	adjROA_c2	adjROA_c3	adjROA_c4	adjROA_c5	adjROA_c1	adjROA_c2	adjROA_c3	adjROA_c4	adjROA_c5
L(n).EE	0.0373 (0.0703)	-0.169 (0.157)	-0.551** (0.277)	-0.945** (0.440)	-1.396** (0.578)	-0.129* (0.0684)	-0.381*** (0.128)	-0.604*** (0.184)	-0.922*** (0.242)	-1.132*** (0.338)
L(n).LEV	-0.426*** (0.0420)	-0.399*** (0.0677)	-0.193** (0.0848)	-0.0243 (0.114)	0.0121 (0.154)	-0.365*** (0.0429)	-0.271*** (0.0718)	-0.201* (0.105)	-0.131 (0.128)	-0.205 (0.179)
L(n).RD	-1.642 (1.194)	-1.828 (2.192)	-3.184 (2.998)	-4.841 (3.698)	-7.904* (4.061)	-1.083 (0.980)	-3.532 (2.216)	-5.480 (4.198)	-6.518 (6.208)	-9.464 (6.880)
L(n).BB	1.183*** (0.249)	1.690*** (0.435)	1.653*** (0.568)	1.173* (0.692)	0.461 (0.764)	1.200*** (0.382)	1.742** (0.685)	1.923** (0.902)	1.523 (1.128)	1.031 (1.362)
L(n).tq	0.218*** (0.0139)	0.500*** (0.0285)	0.680*** (0.0474)	0.722*** (0.0643)	0.657*** (0.0755)	0.169*** (0.0203)	0.368*** (0.0386)	0.491*** (0.0569)	0.514*** (0.0742)	0.454*** (0.0969)
L(n).oe						-0.0596*** (0.00837)	-0.101*** (0.0167)	-0.128*** (0.0251)	-0.142*** (0.0322)	-0.145*** (0.0375)
L(n).op										
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Constant	-0.112 (0.683)	-1.362 (1.279)	-1.372 (1.743)	1.492 (2.197)	6.003** (2.364)	2.141** (0.868)	3.410** (1.598)	4.635* (2.774)	8.805** (4.036)	14.82*** (4.688)
Observations	9,838	8,896	7,840	6,801	5,757	3,060	2,762	2,424	2,080	1,743
R-squared	0.163	0.189	0.186	0.161	0.128	0.253	0.302	0.311	0.273	0.213
Number of uid	1,423	1,396	1,333	1,277	1,225	580	555	522	493	458

VARIABLES	(c) Overprecision only					(d) Overestimation and Overprecision				
	adjROA_c1	adjROA_c2	adjROA_c3	adjROA_c4	adjROA_c5	adjROA_c1	adjROA_c2	adjROA_c3	adjROA_c4	adjROA_c5
L(n).EE	-0.190** (0.0774)	-0.487*** (0.157)	-0.766*** (0.235)	-1.078*** (0.331)	-1.396*** (0.461)	-0.155** (0.0714)	-0.419*** (0.143)	-0.663*** (0.215)	-1.002*** (0.297)	-1.279*** (0.417)
L(n).LEV	-0.321*** (0.0412)	-0.257*** (0.0744)	-0.168 (0.108)	-0.120 (0.142)	-0.212 (0.206)	-0.315*** (0.0414)	-0.239*** (0.0712)	-0.151 (0.0993)	-0.0913 (0.133)	-0.185 (0.191)
L(n).RD	-0.108 (1.023)	-3.070 (2.903)	-6.445 (5.456)	-5.515 (6.348)	-7.068 (6.197)	-0.00345 (0.837)	-2.819 (2.432)	-5.970 (4.771)	-5.265 (5.915)	-7.012 (6.095)
L(n).BB	1.272*** (0.438)	2.134** (0.860)	2.769** (1.140)	1.928 (1.399)	1.472 (1.709)	1.303*** (0.393)	2.111*** (0.754)	2.641*** (1.016)	2.001 (1.317)	1.846 (1.691)
L(n).tq	0.184*** (0.0204)	0.398*** (0.0401)	0.554*** (0.0608)	0.576*** (0.0809)	0.526*** (0.108)	0.154*** (0.0200)	0.338*** (0.0383)	0.478*** (0.0586)	0.496*** (0.0794)	0.455*** (0.107)
L(n).oe						-0.0638*** (0.00787)	-0.112*** (0.0161)	-0.136*** (0.0267)	-0.151*** (0.0348)	-0.152*** (0.0407)
L(n).op	0.163*** (0.0275)	0.152*** (0.0449)	0.0913 (0.0589)	0.0957 (0.0723)	0.0134 (0.0871)	0.191*** (0.0249)	0.210*** (0.0435)	0.175*** (0.0595)	0.216*** (0.0720)	0.172* (0.0914)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Constant	2.983*** (0.995)	4.724** (2.191)	5.324 (3.765)	8.922** (4.510)	14.41*** (4.968)	3.069*** (0.876)	4.562** (1.899)	5.387 (3.354)	9.403** (4.219)	14.73*** (4.769)
Observations	2,443	2,218	1,935	1,654	1,392	2,443	2,218	1,935	1,654	1,392
R-squared	0.261	0.276	0.288	0.235	0.176	0.321	0.350	0.355	0.300	0.231
Number of uid	557	536	505	474	437	557	536	505	474	437

Table 37: Multivariate analysis results showing the impact of (a) the baseline model (no treatment variables), (b) overestimation only, (c) overprecision only, and (d) overestimation and overprecision, on adjROA under its five lagged conditions.

Notes regarding the table:

- ***, **, * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.
- Robust standard errors are shown in parentheses below coefficients.
- Pink cells reflect negative values and green cells reflect positive values.
- In many of the analyses displayed, regressors are lagged. Lagged regressors are depicted by the actual lag number, such as “L3.” for a 3-year lag, or using “L(n).” where the “(n)” matches the dependent variable in the column, for example a column with “adjROA_c3” will imply that “L(n).” of the regressor equates to “L3.”.

7.5.2.1 Robustness tests

We tested the sensitivity of our model to the data sample. We compared four alternative outlier treatments (Table 39) and inspected each for coefficient sign consistency with respect to our baseline model (Table 38), which was winsorised at p1/p99 as defined in Table 33.

Baseline: Winsorised at p1/p99 and scaled			
VARIABLES	adjROA_c1	adjROA_c3	adjROA_c5
L(n).oe	-0.0638*** (0.00787)	-0.136*** (0.0267)	-0.152*** (0.0407)
L(n).op	0.191*** (0.0249)	0.175*** (0.0595)	0.172* (0.0914)
L(n).EE	-0.155** (0.0714)	-0.663*** (0.215)	-1.279*** (0.417)
L(n).LEV	-0.315*** (0.0414)	-0.151 (0.0993)	-0.185 (0.191)
L(n).RD	-0.00345 (0.837)	-5.970 (4.771)	-7.012 (6.095)
L(n).BB	1.303*** (0.393)	2.641*** (1.016)	1.846 (1.691)
L(n).tq	0.154*** (0.0200)	0.478*** (0.0586)	0.455*** (0.107)
Year fixed effects	Y	Y	Y
Constant	3.069*** (0.876)	5.387 (3.354)	14.73*** (4.769)
Observations	2,443	1,935	1,392
R-squared	0.321	0.355	0.231
Number of uid	557	505	437

Table 38: Baseline multivariate model.

Robustness to outlier treatment

VARIABLES	Cleaned at p1/p99 and scaled			Scaled but not cleaned			No scaling or cleaning			Winsorised at p5/p95 and scaled		
	adjROA_c1	adjROA_c3	adjROA_c5	adjROA_c1	adjROA_c3	adjROA_c5	adjROA_c1	adjROA_c3	adjROA_c5	adjROA_c1	adjROA_c3	adjROA_c5
L(n).oe	-0.0117** (0.00504)	-0.0279* (0.0144)	-0.0197 (0.0170)	-0.0641*** (0.00847)	-0.133*** (0.0209)	-0.108*** (0.0305)	-0.0117** (0.00504)	-0.0279* (0.0144)	-0.0197 (0.0170)	-0.0736*** (0.00958)	-0.181*** (0.0310)	-0.204*** (0.0491)
L(n).op	0.0530*** (0.0160)	0.0571** (0.0266)	0.0157 (0.0327)	0.224*** (0.0426)	0.290*** (0.0861)	0.158 (0.146)	0.0530*** (0.0160)	0.0571** (0.0266)	0.0157 (0.0327)	0.259*** (0.0353)	0.323*** (0.0971)	0.264* (0.136)
L(n).EE	-0.186** (0.0828)	-0.689*** (0.238)	-1.302*** (0.442)	-0.126* (0.0704)	-0.577*** (0.219)	-1.057*** (0.398)	-1.273** (0.565)	-4.707*** (1.622)	-8.890*** (3.017)	-0.136** (0.0666)	-0.558*** (0.187)	-1.167*** (0.363)
L(n).LEV	-0.353*** (0.0438)	-0.214* (0.114)	-0.225 (0.212)	-0.306*** (0.0387)	-0.185* (0.102)	-0.187 (0.190)	-6.610*** (0.818)	-4.007* (2.126)	-4.210 (3.969)	-0.254*** (0.0314)	-0.0861 (0.0825)	-0.0507 (0.157)
L(n).RD	-0.373 (1.229)	-6.556 (5.540)	-7.189 (6.335)	0.307 (0.791)	-5.699 (4.475)	-6.673 (6.047)	-0.373 (1.229)	-6.556 (5.540)	-7.189 (6.335)	0.490 (0.633)	-5.564 (4.577)	-6.129 (5.802)
L(n).BB	1.590*** (0.476)	3.210*** (1.135)	1.853 (1.712)	1.262*** (0.369)	2.266** (1.019)	1.150 (1.697)	1.590*** (0.476)	3.210*** (1.135)	1.853 (1.712)	0.893*** (0.324)	1.999** (0.876)	0.802 (1.549)
L(n).tq	2.318*** (0.370)	7.745*** (1.117)	6.838*** (2.162)	0.142*** (0.0183)	0.474*** (0.0529)	0.548*** (0.114)	1.867*** (0.298)	6.237*** (0.900)	5.506*** (1.741)	0.0920*** (0.0102)	0.309*** (0.0292)	0.338*** (0.0572)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Constant	2.605** (1.045)	4.849 (3.750)	14.17*** (4.978)	2.912*** (0.945)	5.826* (3.322)	13.25*** (4.787)	35.18*** (6.357)	47.18*** (16.91)	94.52*** (32.14)	2.951*** (0.784)	5.351* (3.199)	13.98*** (4.374)
Observations	2,443	1,935	1,392	2,338	1,862	1,346	2,443	1,935	1,392	2,443	1,935	1,392
R-squared	0.235	0.315	0.184	0.287	0.332	0.216	0.235	0.315	0.184	0.302	0.352	0.254
Number of uid	557	505	437	540	491	429	557	505	437	557	505	437

Table 39: Sensitivity of our multivariate model to alternative outlier treatment.

Notes regarding the table:

- ***, **, * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.
- Robust standard errors are shown in parentheses below coefficients.
- Pink cells reflect negative values and green cells reflect positive values.
- In many of the analyses displayed, regressors are lagged. Lagged regressors are depicted by the actual lag number, such as “L3.” for a 3-year lag, or using “L(n).” where the “(n)” matches the dependent variable in the column, for example a column with “adjROA_c3” will imply that “L(n).” of the regressor equates to “L3.”.

We tested the sensitivity of our data sample by year (Table 40) and by industry (Table 41). In these analyses, we focused on the third lag of the dependent variable, namely adjROA_c3.

Robustness to year								
Year =	2012	2013	2014	2015	2016	2017	2018	2019
VARIABLES	adjROA_c3	adjROA_c3	adjROA_c3	adjROA_c3	adjROA_c3	adjROA_c3	adjROA_c3	adjROA_c3
L3.oe	-0.134*** (0.0397)	-0.186*** (0.0479)	-0.220*** (0.0606)	-0.236*** (0.0582)	-0.177*** (0.0423)	-0.118** (0.0545)	-0.158** (0.0680)	-0.181*** (0.0523)
L3.op	0.246* (0.142)	0.360*** (0.104)	0.210 (0.182)	0.264* (0.140)	0.419*** (0.135)	0.104 (0.125)	0.144 (0.116)	0.323*** (0.112)
L3.EE	0.109 (0.0916)	-0.0413 (0.0844)	0.00452 (0.0761)	0.117 (0.0804)	0.160** (0.0730)	0.291* (0.172)	0.220 (0.165)	0.342* (0.189)
L3.LEV	-0.129 (0.144)	-0.143 (0.147)	-0.212 (0.141)	-0.130 (0.101)	-0.193* (0.101)	-0.182 (0.114)	-0.144 (0.118)	-0.248* (0.147)
L3.BB	2.210 (1.780)	4.569** (1.908)	6.324** (2.647)	4.332** (2.169)	3.851** (1.910)	1.513 (2.258)	4.152 (3.367)	3.060 (2.888)
L3.tq	0.893*** (0.0763)	0.682*** (0.101)	0.732*** (0.104)	0.815*** (0.0706)	0.570*** (0.0617)	0.674*** (0.0698)	0.709*** (0.0673)	0.695*** (0.0686)
Constant	8.395*** (2.068)	4.326** (1.833)	0.853 (2.975)	1.918 (2.594)	1.399 (1.930)	-0.928 (2.859)	-0.680 (3.579)	-1.811 (3.870)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	219	225	224	233	262	266	250	228
R-squared	0.556	0.564	0.610	0.682	0.568	0.507	0.439	0.526

Table 40: Sensitivity of our multivariate model to individual years.

Notes regarding the table:

- ***, **, * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.
- Robust standard errors are shown in parentheses below coefficients.
- Pink cells reflect negative values and green cells reflect positive values.

Robustness to industry

BICS1 =	1	2	3	4	6	7	8	9	11
VARIABLES	adjROA_c3	adjROA_c3	adjROA_c3	adjROA_c3	adjROA_c3	adjROA_c3	adjROA_c3	adjROA_c3	adjROA_c3
L3.oe	0.0770 (0.0571)	-0.271*** (0.0568)	-0.108* (0.0563)	0.0454 (0.0698)	-0.123*** (0.0401)	-0.111*** (0.0293)	-0.115** (0.0524)	-0.0359* (0.0216)	1.383 (0)
L3.op	-0.122 (0.0798)	0.351*** (0.133)	0.182 (0.195)	0.278 (0.558)	0.136 (0.0981)	0.159 (0.109)	0.243*** (0.0734)	-0.106 (0.120)	6.890 (0)
L3.EE	-2.174* (1.010)	-0.749 (0.595)	0.897 (0.724)	0.571 (0.621)	-0.781* (0.433)	-0.395 (0.305)	-1.074 (1.124)	-0.489 (0.371)	-1.093 (0)
L3.LEV	0.197 (0.361)	-0.389 (0.301)	-0.484* (0.243)	0.286 (0.537)	-0.101 (0.186)	-0.0836 (0.228)	0.0272 (0.206)	-0.0188 (0.118)	3.194 (0)
L3.RD	0 (0)	-21.94*** (5.342)	13.51*** (4.635)	0 (0)	-1.925 (4.993)	-0.911 (1.824)	-4.347** (1.616)	-17.21 (11.70)	0 (0)
L3.BB	8.442 (4.730)	3.777 (3.276)	0.495 (3.977)	-9.817 (8.617)	-0.636 (2.385)	3.856*** (1.004)	-0.643 (1.350)	1.635 (1.601)	26.73 (0)
L3.tq	0.661*** (0.199)	0.593*** (0.109)	0.299*** (0.106)	0.205 (0.386)	0.352*** (0.103)	0.675*** (0.113)	0.599*** (0.158)	0.476*** (0.0829)	10.97 (0)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Constant	-8.275** (3.125)	7.151 (5.210)	-15.77* (8.923)	-7.739 (21.26)	5.224 (4.096)	-0.182 (3.895)	11.64 (6.935)	15.50 (9.328)	103.0 (0)
Observations	38	339	181	43	459	459	125	277	14
R-squared	0.724	0.573	0.400	0.666	0.320	0.393	0.496	0.509	1.000
Number of uid	12	90	48	14	112	104	36	86	3

Table 41: Sensitivity of our multivariate model to individual industries.

In the table above, the BICS1 industries are as follows: 1 = Communications, 2 = Consumer Discretionary, 3 = Consumer Staples, 4 = Energy, 6 = Health Care, 7 = Industrials, 8 = Materials, 9 = Technology, 11 = Utilities.

We tested the sensitivity of our data sample to S&P 500 membership by segmenting our sample into firms that, at any time in our period of interest from 2003 to 2019, were members of the S&P 500 and those what were not (Table 42).

VARIABLES	Not SP500 adjROA_c1	SP500 adjROA_c1	All adjROA_c1	Not SP500 adjROA_c3	SP500 adjROA_c3	All adjROA_c3	Not SP500 adjROA_c5	SP500 adjROA_c5	All adjROA_c5
L(n).oe	-0.0690*** (0.00917)	-0.0498*** (0.0139)	-0.0638*** (0.00787)	-0.146*** (0.0347)	-0.111*** (0.0297)	-0.136*** (0.0267)	-0.164*** (0.0558)	-0.152*** (0.0407)	-0.140*** (0.0375)
L(n).op	0.176*** (0.0253)	0.230*** (0.0682)	0.191*** (0.0249)	0.150** (0.0649)	0.260** (0.122)	0.175*** (0.0595)	0.218* (0.114)	0.172* (0.0914)	0.177* (0.104)
L(n).EE	-0.217** (0.0996)	-0.107 (0.101)	-0.155** (0.0714)	-0.929*** (0.335)	-0.478* (0.285)	-0.663*** (0.215)	-2.122*** (0.795)	-1.279*** (0.417)	-0.634* (0.380)
L(n).LEV	-0.346*** (0.0572)	-0.229*** (0.0554)	-0.315*** (0.0414)	-0.136 (0.129)	-0.0566 (0.153)	-0.151 (0.0993)	-0.160 (0.245)	-0.185 (0.191)	-0.0766 (0.331)
L(n).RD	0.193 (1.042)	0.00162 (1.513)	-0.00345 (0.837)	-2.018 (3.299)	-11.94 (9.619)	-5.970 (4.771)	-4.829 (6.645)	-7.012 (6.095)	-9.816 (9.561)
L(n).BB	1.987*** (0.547)	0.739 (0.568)	1.303*** (0.393)	3.339** (1.482)	2.154 (1.351)	2.641*** (1.016)	3.654 (2.700)	1.846 (1.691)	-0.269 (1.616)
L(n).tq	0.180*** (0.0265)	0.131*** (0.0246)	0.154*** (0.0200)	0.529*** (0.0672)	0.429*** (0.0841)	0.478*** (0.0586)	0.407*** (0.155)	0.455*** (0.107)	0.510*** (0.136)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Constant	0.380 (0.964)	4.571*** (1.740)	3.069*** (0.876)	-3.771* (2.279)	13.58* (7.757)	5.387 (3.354)	-0.570 (4.664)	14.73*** (4.769)	22.04** (8.749)
Observations	1,143	1,300	2,443	894	1,041	1,935	634	1,392	758
R-squared	0.416	0.215	0.321	0.403	0.319	0.355	0.275	0.231	0.228
Number of uid	298	259	557	261	244	505	212	437	225

Table 42: Sensitivity of our multivariate model to S&P 500 membership.

We tested the sensitivity of our data sample to the inclusion (or not) of Tobin's Q as a control variable (Table 43).

VARIABLES	adjROA_c1	adjROA_c1	adjROA_c2	adjROA_c2	adjROA_c3	adjROA_c3	adjROA_c4	adjROA_c4	adjROA_c5	adjROA_c5
L.oe	-0.0767*** (0.00761)	-0.0638*** (0.00787)	-0.144*** (0.0156)	-0.112*** (0.0161)	-0.180*** (0.0256)	-0.136*** (0.0267)	-0.192*** (0.0341)	-0.151*** (0.0348)	-0.183*** (0.0406)	-0.152*** (0.0407)
L.op	0.217*** (0.0278)	0.191*** (0.0249)	0.270*** (0.0494)	0.210*** (0.0435)	0.249*** (0.0681)	0.175*** (0.0595)	0.280*** (0.0804)	0.216*** (0.0720)	0.210** (0.0989)	0.172* (0.0914)
L.EE	-0.229*** (0.0772)	-0.155** (0.0714)	-0.586*** (0.153)	-0.419*** (0.143)	-0.972*** (0.236)	-0.663*** (0.215)	-1.303*** (0.329)	-1.002*** (0.297)	-1.393*** (0.445)	-1.279*** (0.417)
L.LEV	-0.345*** (0.0479)	-0.315*** (0.0414)	-0.282*** (0.0847)	-0.239*** (0.0712)	-0.197* (0.117)	-0.151 (0.0993)	-0.163 (0.153)	-0.0913 (0.133)	-0.292 (0.209)	-0.185 (0.191)
L.RD	-0.239 (1.022)	-0.00345 (0.837)	-3.150 (2.920)	-2.819 (2.432)	-7.029 (5.564)	-5.970 (4.771)	-6.716 (6.701)	-5.265 (5.915)	-7.543 (6.561)	-7.012 (6.095)
L.BB	1.214*** (0.407)	1.303*** (0.393)	1.911** (0.770)	2.111*** (0.754)	2.047* (1.066)	2.641*** (1.016)	1.114 (1.355)	2.001 (1.317)	1.161 (1.686)	1.846 (1.691)
L.tq		0.154*** (0.0200)		0.338*** (0.0383)		0.478*** (0.0586)		0.496*** (0.0794)		0.455*** (0.107)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Constant	5.077*** (0.962)	3.069*** (0.876)	8.441*** (2.235)	4.562** (1.899)	11.32*** (3.868)	5.387 (3.354)	15.05*** (4.765)	9.403** (4.219)	17.32*** (5.039)	14.73*** (4.769)
Observations	2,457	2,443	2,232	2,218	1,949	1,935	1,666	1,654	1,402	1,392
R-squared	0.256	0.321	0.227	0.350	0.218	0.355	0.198	0.300	0.167	0.231
No. of uid	563	557	542	536	513	505	482	474	444	437

Table 43: Sensitivity to inclusion of Tobin's Q as a control variable.

We tested the sensitivity of our data sample to an alternative operationalisation of the dependent variable (Table 44).

VARIABLES	adjROA_c1	zROA_c1	adjROA_c2	zROA_c2	adjROA_c3	zROA_c3	adjROA_c4	zROA_c4	adjROA_c5	zROA_c5
L(n).oe	-0.0638***	-0.0131***	-0.112***	-0.0205***	-0.136***	-0.0251***	-0.151***	-0.0296***	-0.152***	-0.0300***
	(0.00787)	(0.00157)	(0.0161)	(0.00297)	(0.0267)	(0.00477)	(0.0348)	(0.00611)	(0.0407)	(0.00718)
L(n).op	0.191***	0.0394***	0.210***	0.0465***	0.175***	0.0318***	0.216***	0.0415***	0.172*	0.0229
	(0.0249)	(0.00478)	(0.0435)	(0.00903)	(0.0595)	(0.0113)	(0.0720)	(0.0147)	(0.0914)	(0.0207)
L(n).EE	-0.155**	-0.0340**	-0.419***	-0.0727**	-0.663***	-0.125***	-1.002***	-0.183***	-1.279***	-0.244***
	(0.0714)	(0.0151)	(0.143)	(0.0314)	(0.215)	(0.0430)	(0.297)	(0.0580)	(0.417)	(0.0793)
L(n).LEV	-0.315***	-0.0628***	-0.239***	-0.0423***	-0.151	-0.0287	-0.0913	-0.0296	-0.185	-0.0349
	(0.0414)	(0.00958)	(0.0712)	(0.0163)	(0.0993)	(0.0227)	(0.133)	(0.0295)	(0.191)	(0.0406)
L(n).RD	-0.00345	-0.0379	-2.819	-0.517	-5.970	-1.141	-5.265	-1.018	-7.012	-1.407
	(0.837)	(0.150)	(2.432)	(0.377)	(4.771)	(0.776)	(5.915)	(0.953)	(6.095)	(1.050)
L(n).BB	1.303***	0.275***	2.111***	0.357**	2.641***	0.544***	2.001	0.490*	1.846	0.424
	(0.393)	(0.0805)	(0.754)	(0.153)	(1.016)	(0.198)	(1.317)	(0.258)	(1.691)	(0.331)
L(n).tq	0.154***	0.0316***	0.338***	0.0756***	0.478***	0.101***	0.496***	0.104***	0.455***	0.0915***
	(0.0200)	(0.00482)	(0.0383)	(0.00965)	(0.0586)	(0.0137)	(0.0794)	(0.0180)	(0.107)	(0.0239)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Constant	3.069***	0.632***	4.562**	0.775**	5.387	0.943	9.403**	1.666**	14.73***	2.771***
	(0.876)	(0.174)	(1.899)	(0.339)	(3.354)	(0.578)	(4.219)	(0.735)	(4.769)	(0.877)
Observations	2,443	2,443	2,218	2,218	1,935	1,935	1,654	1,654	1,392	1,392
R-squared	0.321	0.316	0.350	0.35	0.355	0.358	0.300	0.311	0.231	0.212
Number of uid	557	557	536	536	505	505	474	474	437	437

Table 44: Sensitivity to alternative operationalisation of the dependent variable.

7.5.2.2 Hausman test

Once we had a “working” model we determined whether it is better suited to fixed-effects or random-effects. This determination was both theoretical and analytical. The theoretical consideration is discussed in section 3.7, while the analytical determination was by using the Hausman test. We ran our midpoint dependent variable adjROA_c3 model using fixed effects (fe) without robust (robust), then we ran it using random effects (re), also without robust, and then ran Stata’s Hausman test. The Hausman test has a null hypothesis which, if accepted, would indicate that random-effects should be selected. Our result was a Hausman test statistic X^2 of 103 with a p-value of 0.0000, which was statistically significant, thus the null hypothesis was convincingly rejected and hence we found analytical support for using fixed-effects.

7.5.3 Supplementary analysis

This Appendix provides the results of the supplementary analyses referred to in section 4.4.

7.5.3.1 Effect of firm past performance on overestimation and overprecision

VARIABLES	oe	oe	op	op
L.adjROA_c1	0.183 (0.135)		0.184*** (0.0501)	
L2.adjROA_c2		0.0983 (0.110)		0.0331 (0.0624)
Year fixed effects	Y	Y	Y	Y
Constant	1.557* (0.815)	1.230 (0.819)	-6.998*** (0.344)	-7.131*** (0.360)
Observations	4,164	3,140	3,107	2,327
R-squared	0.012	0.009	0.028	0.007
Number of uid	745	669	707	636

Table 45: Effect of firm past performance on overestimation and overprecision.

7.5.3.2 Effect of past overestimation and overprecision on current overestimation and overprecision

VARIABLES	oe	oe	op	op
L.oe	0.0561 (0.0459)	-0.0338 (0.0598)	-0.113*** (0.0148)	-0.0828*** (0.0187)
L2.oe		-0.0921* (0.0475)		-0.00259 (0.0124)
L.op	0.605*** (0.116)	0.469** (0.207)	0.389*** (0.0576)	0.304*** (0.0907)
L2.op		0.170 (0.153)		-0.0580 (0.0694)
Year fixed effects	Y	Y	Y	Y
Constant	5.465*** (1.323)	4.351** (1.893)	-4.472*** (0.333)	-5.190*** (0.603)
Observations	3,055	1,953	2,457	1,595
R-squared	0.086	0.067	0.244	0.181
Number of uid	667	526	620	454

Table 46: Effect of past overestimation and overprecision on current overestimation and overprecision

7.5.3.3 Effect of overestimation and overprecision on mediating variables that are related to adjROA

Category	Mediating variables	Calculated as ...
Growth	adjrev_g1	$adjrev_{g1,t} = rev_{g1,t} - \text{industry median}(rev_{g1,t})$, where $rev_{g1,t} = \left(\frac{rev_t}{rev_{t-1}} - 1 \right)$ And <i>rev</i> is the firm's revenue
	adja_g1	$adja_{g1,t} = asset_{g1,t} - \text{industry median}(asset_{g1,t})$, where $asset_{g1,t} = \left(\frac{asset_t}{asset_{t-1}} - 1 \right)$ And <i>asset</i> is the firm's total balance sheet assets
Investments	adjrd	$adjrd_t = rd_t - \text{industry median}(rd_t)$, where <i>rd</i> is R&D spend as a percentage of revenue
	adjii	$adjii_t = ii_t - \text{industry median}(ii_t)$, where <i>ii</i> is the investment intensity, calculated as R&D spend plus capital expenditure as a percentage of assets
Capital structure	adjde	$adjde_t = de_t - \text{industry median}(de_t)$, where <i>de</i> is the debt-to-equity ratio
	adjlev	$adjlev_t = lev_t - \text{industry median}(lev_t)$, where <i>lev</i> is the leverage ratio, calculated as liabilities divided by assets
Operating margin	adjopm	$adjopm_t = opm_t - \text{industry median}(opm_t)$, where <i>opm</i> is the operating profit margin

Table 47: Mediating variables that are related to firm performance.

We executed bivariate regression analyses (Table 48) of each of the mediating variables against our measure of firm performance, industry-adjusted ROA, where both variables were in the same time period.

VARIABLES	adjROA_c1	adjROA_c1	adjROA_c1	adjROA_c1	adjROA_c1	adjROA_c1	adjROA_c1
adjrev_g1	-0.0233*** (0.00673)						
adja_g1		0.0335*** (0.00387)					
adjrd			-0.450*** (0.0488)				
adjii				0.125 (5.139)			
adjde					-0.00619*** (0.000861)		
adjlev						-15.02*** (1.296)	
adjopm							0.113*** (0.00987)
Constant	-0.320*** (0.0169)	-0.595*** (0.0205)	0.300*** (0.0773)	-0.412*** (0.0801)	0.0338 (0.0413)	-0.202*** (0.0183)	-0.303*** (0.0120)
Observations	15,383	14,767	13,625	13,614	14,105	14,763	15,548
R-squared	0.004	0.015	0.037	0.000	0.012	0.055	0.050
Number of uid	1,884	1,830	1,744	1,743	1,797	1,830	1,895

Table 48: Bivariate analysis of adjROA_c1 on adjrev_g1, adja_g1, adjrd, adjii, adjde, adjlev, adjopm.

We executed multivariate regression analyses of each of the mediating variables against overestimation and overprecision as continuous (Table 49) and as categorical (Table 50) variables.

VARIABLES	adjrev_g1	adja_g1	adjrd	adjii	adjde	adjlev	adjopm
L.oe	-0.0518** (0.0223)	-0.0590** (0.0283)	0.00169 (0.00280)	1.91e-05 (3.16e-05)	0.00175 (0.00278)	1.93e-05 (3.14e-05)	-0.0424*** (0.0132)
L.op	0.141** (0.0691)	0.0647 (0.0801)	-0.0323 (0.0254)	-0.000240 (0.000201)	-0.0337 (0.0270)	-0.000231 (0.000208)	0.0739 (0.0501)
L.EE	-1.672*** (0.327)	-2.938*** (0.523)	0.0680 (0.0429)	0.000430 (0.000460)	0.0802* (0.0482)	0.000478 (0.000501)	-0.370 (0.240)
L.LEV	0.0646 (0.160)	-0.660*** (0.248)	0.0232 (0.0248)	2.56e-05 (0.000268)			0.0511 (0.107)
L.RD	-2.188 (4.063)	4.121 (6.843)			0.607*** (0.183)	0.00559 (0.00372)	-1.286 (1.130)
L.BB	-0.736 (1.229)	0.965 (1.979)	0.272* (0.141)	0.00385** (0.00185)	0.249* (0.128)	0.00383** (0.00182)	1.142 (0.774)
L.tq	0.237*** (0.0505)	0.667*** (0.107)	-0.00372 (0.00673)	0.000531*** (0.000133)	-0.00417 (0.00651)	0.000533*** (0.000133)	0.187*** (0.0282)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y
Constant	14.67*** (3.580)	21.07*** (6.034)	-0.507 (0.494)	-0.00669 (0.00503)	46.19** (20.43)	0.00751 (0.0153)	2.341 (2.078)
Observations	2,252	2,194	2,147	2,147	2,125	2,194	2,264
R-squared	0.086	0.123	0.042	0.045	0.071	0.261	0.077
Number of uid	545	525	521	521	513	525	549

Table 49: Multivariate analysis of mediating variables against the treatment variables (oe and op) in their continuous form.

VARIABLES	adjrev_g1	adja_g1	adjrd	adjii	adjde	adjlev	adjopm
0bL.soecat	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
1L.soecat	-1.047 (1.287)	-0.530 (2.175)	-0.0394 (0.294)	-0.00184 (0.00280)	-8.059 (8.788)	0.00352 (0.00968)	-0.466 (0.707)
2L.soecat	-2.857** (1.172)	-2.401 (2.112)	0.147 (0.179)	0.00191 (0.00230)	-7.302 (13.23)	0.00746 (0.00944)	-1.181** (0.594)
3L.soecat	-3.906*** (1.194)	-2.333 (2.346)	0.0318 (0.160)	0.00106 (0.00215)	6.065 (9.645)	0.00768 (0.00875)	-1.130** (0.541)

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4L.soecat	-3.460*** (1.239)	-2.864 (2.085)	0.00420 (0.164)	0.000764 (0.00205)	3.630 (10.90)	0.0101 (0.00793)	-1.003* (0.553)
5L.soecat	-3.894*** (1.260)	-0.605 (2.432)	0.165 (0.170)	0.00182 (0.00231)	26.60** (11.31)	0.0278*** (0.00920)	-2.316*** (0.684)
6L.soecat	-2.305 (1.444)	-4.796** (2.040)	0.189 (0.172)	-0.00147 (0.00221)	19.44* (10.84)	0.0352*** (0.00907)	-3.177*** (0.706)
0bL.sopcat	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
1L.sopcat	-1.370 (1.456)	-0.795 (1.976)	-0.105 (0.117)	-0.00105 (0.00205)	3.927 (12.43)	-0.0235** (0.00968)	0.852 (0.887)
2L.sopcat	-0.00811 (1.640)	-0.519 (2.119)	-0.145 (0.104)	-9.96e-05 (0.00244)	13.99 (18.07)	-0.0163 (0.0120)	0.939 (1.172)
3L.sopcat	0.647 (1.553)	-2.548 (2.136)	-0.126 (0.126)	-0.000245 (0.00252)	-3.792 (15.48)	-0.0351*** (0.0134)	2.255** (1.004)
4L.sopcat	1.011 (1.722)	0.895 (2.525)	-0.00516 (0.130)	0.00219 (0.00254)	12.49 (17.34)	-0.0295** (0.0133)	2.163** (1.094)
5L.sopcat	3.347* (1.949)	0.889 (2.767)	0.00205 (0.129)	0.000291 (0.00279)	2.296 (16.77)	-0.0402*** (0.0149)	3.822** (1.491)
6L.sopcat	3.754* (2.225)	-0.913 (3.017)	0.0884 (0.204)	0.00165 (0.00346)	3.309 (17.58)	-0.0380** (0.0165)	3.399** (1.361)
L.EE	-1.622*** (0.274)	-2.853*** (0.465)	0.0422 (0.0340)	0.000326 (0.000391)	0.266 (1.738)	0.00296 (0.00189)	-0.344* (0.192)
L.LEV	0.0583 (0.139)	-0.597*** (0.218)	0.0244 (0.0259)	-3.08e-05 (0.000259)			0.0849 (0.107)
L.RD	-0.648 (3.662)	8.547 (6.922)			44.47*** (16.22)	0.0551** (0.0234)	-1.475 (1.076)
L.BB	-1.493 (1.085)	-0.446 (1.622)	0.198* (0.105)	0.00307** (0.00150)	-5.391 (8.487)	-0.0175** (0.00727)	1.181* (0.611)
L.tq	0.217*** (0.0475)	0.688*** (0.103)	-0.00490 (0.00636)	0.000486*** (0.000123)	1.702** (0.752)	0.000897* (0.000521)	0.173*** (0.0260)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y
Constant	14.14*** (3.351)	19.81*** (5.634)	0.0613 (0.318)	-0.00163 (0.00455)	39.75** (18.76)	0.0269 (0.0235)	1.133 (2.023)
Observations	2,805	2,727	2,704	2,704	2,644	2,727	2,820
R-squared	0.081	0.117	0.024	0.042	0.046	0.052	0.083
Number of uid	567	543	539	539	533	543	571

Table 50: Multivariate analysis of mediating variables against the categorical treatment variables: soecat and sopcat.