Don’t Get to the Point. Overprecision in Management Capital Expenditure Forecasts

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Keywords: Management guidance; capital expenditure; forecast accuracy; precision bias.

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ABSTRACT

Motivated by precision bias theory, which suggests that the value of information decreases as it becomes overly precise, we examine whether capital expenditure forecast precision is associated with forecast accuracy, forecast revision rate, and future operating performance. We find that firms issuing point format forecasts issue less accurate forecasts, but that forecast precision is positively associated with accuracy among firms issuing range format forecasts. Similarly, forecast revision rate is increasing in forecast precision for range issuers, but is significantly lower for point issuers. Finally, we find that firms issuing range format forecasts have superior future operating performance compared to firms issuing point estimates. Our findings support the consensus view that increasingly precise information is associated with positive outcomes, but only within the sample of range forecast issuers. We argue that point estimates are likely an outcome of overprecision, hindering managerial learning and impeding forecast accuracy and future performance.

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1. INTRODUCTIOIN

We investigate capital expenditure (capex) forecast format type (i.e., point format versus range interval estimates) and forecast precision (i.e., relative forecast width) for evidence of overprecision bias. Specifically, we examine how precision and point formats relate to forecast accuracy, forecast revision rate, and future operating performance.[1] Prior research finds that accounting quality is increasing in information precision (Verrecchia 1990, 2001). Accordingly, existing studies generally argue that point estimates signal higher forecasting quality compared to range format forecasts because of the inherent precision of the issued forecast (Hughes and Pae 2004; Leuz and Wysocki 2016; Chen, Martin, Roychowdhury, Wang, and Billett 2018). However,

[1] We examine precision as the exactness of the interval estimate (range width) of a predicted outcome. Therefore, a point estimate represents maximal precision. This differs from accuracy, which is the proximity of the communicated prediction to the actual outcome and therefore measured ex post (Yaniv and Foster 1995; Hayward and Fitza 2017).

range estimates are a natural outcome for firms that utilize advanced risk-based forecasting, which increases the accuracy of forecasts (Ittner and Michels 2017). Moreover, precision bias theory warns against overprecision, which can contribute to a non-linear relationship between the exactness of a forecast and its associated benefits (Posen, Leiblein, and Chen 2018).[2] Accordingly, we examine the potential presence of precision bias in capex forecasts.

While precision is a desired characteristic in forecasts, overprecision can be detrimental (Moore and Healy 2008; Ren and Croson 2013; Posen et al. 2018; Kang and Kim 2021). Overprecision may hinder the acquisition and integration of new knowledge by discouraging the re-evaluation of established beliefs (Yaniv and Foster 1995). That said, imprecise forecasts may offer limited insight if they provide excessively broad targets without narrowing towards the most likely outcomes. Moreover, hitting relatively broad targets provides little information about forecasting ability (Yaniv and Foster 1995). Consequently, firms might be inclined to contract the forecast interval to signal expertise (Hayward and Fitza 2017). However, firms can reduce the forecast width by implementing risk-based forecasting (Ittner and Michels 2017), suggesting that narrow forecasts could be an outcome of either superior forecasting techniques or overprecision. We examine capital expenditure forecasts and seek to contribute to the literature by providing evidence that overly precise forecasts are less informative and are associated with negative performance outcomes. While the costs of imprecision are well documented, this research contributes to the forecasting literature by providing evidence of overprecision in capex forecasts.

While the processes which produce disclosed forecasts are opaque, the chosen forecast format can reveal insights about the firm's methodologies. Firms which utilize sophisticated planning tools are expected to set more refined investment targets and select projects that

[2] Precision bias theory has little to say regarding the point in the distribution when overprecision appears (Moore and Healy 2008).

contribute to superior future performance (COSO 2017). Such firms are also likely to acquire and integrate new information by updating their existing beliefs (Moore and Healy 2008). Moreover, advanced risk-based tools play a crucial role in facilitating managers' learning and adaptation towards their objectives (Ittner and Michels 2017; Jayaraman and Wu 2019; Blankespoor, deHaan, and Marinovic 2020; Bae, Biddle, and Park 2022). However, the desire to appear informative and authoritative may lead to overprecision (Kang and Kim 2021), which can be counteracted by risk-based forecasting tools and ongoing learning (Moore and Healy 2008; Guttman and Meng 2021). Overall, this suggests that increased precision is associated with better outcomes, unless or until overprecision is introduced, at which point a directional prediction may reverse.

Using capital expenditure forecasts issued by firms over the period 2003-2021, we find robust evidence that forecast accuracy is increasing in forecast precision for firms issuing range forecasts, but then decreases significantly when the range converges to a point, suggesting a non-linear, kinked association. Specifically, we find that while predicted accuracy increases with greater precision, it drops by 42 percent once the format becomes a point. We compare the distance from the midpoint of the range estimate to the distance from the point estimate to allow for a comparable assessment of accuracy. These results are consistent with the presence of overprecision in firms issuing point estimate forecasts.

As overprecision may impede managers' ability to learn and adjust their capital project portfolio planning (Posen et al. 2018), we next examine whether forecast format and precision are associated with forecast revision rate. These revisions are key indicators of managerial learning and adaptability; such adjustments suggest that firms are less prone to overprecision (Fischhoff, Slovic, and Lichtenstein 1977; Moore and Healy 2008; Posen and Levinthal 2011; Posen et al.

2018). Here we find evidence that revisions increase with rising precision within range forecast issuers, but then drop significantly when forecast precision converges to a point.

Finally, we examine the association between forecast format/precision and future performance. Prior research in entrepreneurship illustrates that precision can yield both positive and negative effects: while it encourages thorough opportunity evaluations and increases the likelihood of initiating a new venture (Robinson and Marino 2015; Kraft, Günther, Kammerlander, and Lampe 2022), it can also hamper performance and reduce the likelihood of firm survival (Gudmundsson and Lechner 2013). This dichotomy is relevant in our research setting. Overprecision could inhibit managers from seeking additional information (Guttman and Meng 2021), leading to inflexible strategic management, and ultimately diminishing performance (Kraft et al. 2022; Cassar and Gibson 2007). If point forecasts indicate overprecision relative to range forecasts, then firms issuing range forecasts should exhibit better future performance. Consistent with this interpretation, we find a negative association between the issuance of point formats and future operating cash flow.[3] Further, we observe a nonlinear association, i.e., firm performance is increasing in precision for range forecasters but decreases once potential overprecision is introduced: it drops by 64 percent when forecast formats converge to a point. Moreover, we find that only 4.9 (6.0) percent of the total effect of point (range precision) on operating cash flow is mediated through forecast accuracy, and that generally all range forecasters (not just narrow range forecasters) achieve superior future operating outcomes versus point forecasters. This suggests that capex forecast accuracy is not a dominant mechanism through which forecast format affects future operating performance.

[3] Since firms operating in uncertain environments are likely to issue range forecasts (Asay, Hribar, and Quinto 2023; Hughes and Pae 2004) and experience higher operating cash flow, we also measure performance by assessing whether a firm's operating cash flow exceeds its weighted average cost of capital.

Our research contributes to the accounting and management literatures by highlighting the conceivability of precision bias among managers issuing capex forecasts in point format. The drawbacks associated with precision bias, particularly concerning interval forecast estimates, have been relatively underexplored in accounting research. Thus, our findings challenge the prevailing notion that informativeness strictly increases with forecast precision (Hirst, Koonce, and Venkataraman 2008). Our results are consistent with existing theory when examining the approximately 50 percent of firms which issue range forecasts. Within this subset, we find that forecast accuracy, revision rate, and future performance are all increasing in forecast precision. However, a notable pattern emerges: once forecasts narrow down to a single point estimate, indicating maximum precision and aligning with overprecision, we observe significant decreases in accuracy, revision rate, and future performance. This paradoxical scenario echoes the findings of Ittner and Michels (2017), suggesting a nuanced view of precision: while analytics initially lead to broader range estimates (decreasing precision), risk-based forecasting techniques eventually refine these ranges (increasing precision) without succumbing to overprecision. Hence, decision makers in accounting can be receptive to learning and leverage risk-based forecasting processes to enhance precision while mitigating precision bias (Ittner and Michels 2017).

Moreover, our study sheds light on the dynamics of demand for forecast data (Baginski, Conrad, and Hassell 1993; Hribar and Yang 2016; Rupar 2017). Managers often grapple with balancing informativeness and accuracy, leading them to signal their expertise through excessively narrowed forecasts, thereby succumbing to overprecision (Hayward and Fitza 2017; Kang and Kim 2021). These observations carry significant implications for accounting disclosures. By advocating for risk-based forecasting devoid of biases, managers, investors, and lenders can make informed decisions, bolster risk management efforts, and achieve superior outcomes.

2. THEORY AND HYPOTHESIS DEVELOPMENT

Precision bias theory

Accounting theory suggests that an increase in the manager's information precision increases the likelihood of disclosure (Verrecchia 1990). Consequently, the demand for disclosure significantly influences managers' efforts to enhance information precision. This nuanced relationship enhances our comprehension of factors influencing forecast precision, including firm size, analyst following, proprietary costs, legal liability exposure, and forecast horizon length (Hirst et al. 2008). Firms' forecasts are also influenced by managerial overconfidence (e.g., Hribar and Yang 2016), which can manifest as overestimation of means, known as optimism bias, or underestimation of variance, referred to as precision bias (Moore and Healy 2008). Since forecast format (i.e., point versus various interval estimates within range forecasts) captures the precision of managers' beliefs regarding the future (King, Pownall, and Waymire 1990), we examine managers' forecasts through the lens of precision bias.

When issuing forecasts, managers tradeoff accuracy and informativeness (Kang and Kim 2021; Yaniv and Foster 1995), and although precision mechanically decreases forecast accuracy, it enhances informativeness, which managers may prioritize to signal expertise (Hayward and Fitza 2017; Kang and Kim 2021). Nevertheless, the pursuit of precision may inadvertently lead to precision bias, resulting in forecasts that are overly precise. In this case, highly precise estimates may not only be less accurate, but also less informative (Asay, Hribar, and Quinto 2023) because they distort the second moment of the forecast distribution or fail to provide any sense of the second moment, as is the case with point forecasts (Hribar, Huseman, and Melessa 2023; Dichev, Huang, Lee, and Zhao 2023).

Precision bias, often seen as overprecision, arises from excessive confidence in one's expertise and prior beliefs (Moore and Healy 2008; Posen et al. 2018). Overprecision can manifest in estimates with excessive decimal places, known as numeracy bias, or overly narrowed estimates resulting in a point estimate, termed interval estimate aversion (Dong, Liu, Lobo, and Ni 2022; McKenzie, Liersch, and Yaniv 2008). Moreover, overprecision can also lead to resistance to new information and expectation revisions because of overreliance on prior beliefs (Posen et al. 2018). This excessive certainty in one's knowledge is documented as the most pervasive type of overconfidence (Moore and Healy 2008; Moore 2022).

Forecasting processes can either amplify or alleviate precision bias. Advanced forecasting tools, such as probabilistic modeling, can mitigate precision bias by prompting managers to consider ranges of possibilities instead of fixating on a single point estimate (Ittner and Michels 2017). Planning analytics methodologies, such as modeling multiple scenarios and integrating distributions of outcomes, prompt managers to contemplate a spectrum of possibilities, circumventing extremely precise point estimates (Ittner and Michels 2017; Hollmann 2016). If advanced forecasting tools like probabilistic modeling are employed to generate range forecasts, then one would expect discernible benefits. Internal analysts often transform an initial point estimate into ranges of outcomes to assess potential risks, using various methodologies like scenario analysis and Bayesian probabilistic forecasting. Our study delves into this theory by examining forecast accuracy, revisions, and future operating performance.

Although point estimates in prior research are assumed to capture the precision of managers' beliefs about the future (King et al. 1990; Baginski et al. 1993; Hughes and Pae 2004), we argue that narrower ranges convey greater probabilistic confidence in future outcomes. In contrast, point forecasts could result from overprecision, potentially arising from deterministic modeling techniques and/or an illusion of control (Ben-David, Graham, and Harvey 2013; Kang and Kim 2021). We contend that advanced forecasting analytics should produce range formats, with more in-depth analyses subsequently refining these ranges (Ittner and Michels 2017).

There is considerable tension in our proposition linking point estimate forecasts to overprecision. Hughes and Pae (2004) link point formats to increased managerial certainty about future outcomes. Bae et al. (2022)'s findings suggest that managers issuing point estimates may be more confident, because they are less receptive to analyst feedback. Similarly, Hilary et al. (2016) utilize precise (narrower) formats as a proxy for overconfidence and tie such overconfidence to greater managerial effort. Cheng, Luo, and Yue (2013) find that forecast precision is associated with higher abnormal stock returns. Hayward and Fitza (2017) find that managers use forecast precision for impression management. Ittner and Michels (2017) document through their joint survey/archival study that the integration of risk and probability distributions expands forecasted range width, but risk-based tools generally increase precision. A recurring theme in this research is that precision remains a sought-after objective in many accounting scenarios. However, the potential presence of overprecision has received little attention.

Capital expenditure forecasts

We test for potential overprecision in management forecasts by focusing on capex forecasts for three broad reasons. First, trade associations and US Chamber of Commerce recommend that firms communicate their long-term business strategies (US Chamber of Commerce 2007). While capex forecasts provide insights into long-term plans, sales and earnings forecasts typically cover the current period (Ittner and Michels 2017). Moreover, capex forecasts are among the most commonly disclosed types of annual guidance (Call, Hribar, Skinner, and Volant 2022) and their disclosure is deemed a rational outcome (Lu and Wu Tucker 2012). Firms that issue capex forecasts are likely to possess valuable private information (Verrecchia 1990, 2001). Within a firm's portfolio of capital projects, the "cost of ignorance" or "value of information" signifies the difference between expected cash flows from safer projects and riskier ones (Guttman and Meng 2021). Managers can mitigate their cost of ignorance by acquiring additional information about high-risk projects. Thus, capex forecasts may offer insights into the elements involved in value generation (Lu and Tucker 2012). Consequently, firms openly communicating their project investment plans are presumed to possess superior information.

Second, incentives to meet or beat earnings or sales forecasts can significantly influence the forecasting process, disclosure decisions, and accounting choices (e.g., Bamber and Cheon 1998; Dutta and Gigler 2002; Houston, Lev, and Tucker 2010). Managerial motivations behind actual and forecasted earnings and sales often reveal noticeable asymmetric tendencies (Kasznik 1999). Exceeding (or falling short of) earnings or sales forecasts is typically construed as positive (negative) news, prompting managers to set real internal targets for EPS or sales above the midpoint of a disclosed range (Call et al. 2022; Ciconte, Kirk, and Tucker 2014). However, neither overspending nor underspending against a capex forecast inherently constitutes positive or negative news and is context dependent. For example, discontinuing projects which no longer are estimated to drive future operating returns (underspending) versus escalating commitment to such projects (overspending) or implementing newly identified profitable projects (overspending) (Décaire, Gilje, and Taillard 2020; Brüggen and Luft 2016). Thus, studying firms issuing capex guidance provides a setting relatively devoid of incentives to report figures above the forecast.

Third, while most earnings (89 percent) and sales (79 percent) forecasts are issued as ranges (Jensen and Plumlee 2020), capex forecasts are balanced, with 48 percent of firms issuing range format forecasts from 2003 through 2021. This provides more power to investigate associations between information precision and forecast outcomes. Therefore, the capex forecast setting provides a better context to test for the presence of overprecision. Moreover, based on email responses from investor relations responses, there is anecdotal evidence that the processes for income statement forecasts (EPS and sales) differ within firms from the processes driving capex forecasts.[4] This could be a reason for the variance in the format across different types of forecasts.

These arguments align with Ittner and Michels (2017)'s survey/archival evidence that risk-based forecasting and planning methodologies have different impacts on EPS, sales, and capex forecast processes. While sales and capex forecast errors are mildly correlated with each other, they find no significant association between capex and EPS forecast errors. Ittner and Michels (2017) also observe that errors are larger for capex than EPS and sales forecasts.

Forecast format, precision, and accuracy

Incorporating advanced planning tools, ranging from scenario analysis to probability distributions, enhances a firm's ability to secure their objectives (COSO 2017). Phadnis, Caplice, Sheffi, and Singh (2015) emphasize that expert decision-makers modify portfolio plans based on scenario analysis. Probabilistic planning, risk driver assessment, and quantitative analyses are linked with superior operating performance (Ittner and Michels 2017). Application of risk-based forecasting processes and advanced analytics is likely to result in a range of possible outcomes. Further, advanced analytics can handle complex information inputs and allow managers to evaluate multiple future states (Brüggen, Grabner, and Sedatole 2021). However, range forecasts may merely reflect aggregated expected outcomes within an arbitrary level of variability. It is also

[4] One investor relations response stated "Our capital expenditures projection for a given fiscal year is based on our Business Plan for that year. Capital spending for the majority of projects in the Business Plan is based on pre-committed contracts (i.e., aircraft) which, due to the high capital intensity nature of our business and inherently longer lead times, are generally entered into well before the Business Plan for any year is finalized. This allows us the ability to forecast capital expenditures with higher level of precision than other financial metrics, such as EPS."

worth noting that although advanced analytics may shift forecasts away from an initial simplistic estimate, they may not be enough to prevent a reversion to overprecision. Finally, continuous process refinement will generate increasingly precise ranges as learning unfolds (Ittner and Michels 2017).

Recognizing 1) the significance of precision and assuming that firms are less likely to issue range forecasts of any interval when overprecision exists and 2) that range format forecasts are an expected outcome of superior planning processes and learning-focused analytics, we expect firms producing more precise range forecasts to reduce forecast errors. As firms consider multiple scenarios in their capital portfolio, they transition from a simple point to a broad interval window of future outcomes. Subsequent analyses and risk-mitigation activities lead to the contraction of these predicted intervals. However, managers need to avoid anchoring on an initial single aggregation of projects and reversion to a simplistic estimate in the final stages of the planning process. In summary, narrow forecasts may accurately represent precise information from proactive risk assessments, as opposed to points (Ittner and Michels 2017). We anticipate a stronger association between target achievement and range (reasonably precise) forecasts than with point (overprecise) forecasts, and within range forecasts, narrower interval estimates will be more significantly associated with accuracy. Formally, we hypothesize:

H1a: Point format forecasts are less accurate than range format forecasts.

H1b: Forecast accuracy is increasing in forecast precision for range format forecasts.

Forecast format, precision, and revisions

Our second research considers the intersection of forecast format, precision, and the rate of forecast revisions. Managers displaying precision bias tend to resist adjusting their priors when presented with new information (Mannes and Moore 2013). Such managers may also underinvest in acquiring new information related to their capital portfolio. Precision bias, stemming from an inaccurate perception of uncertainty, leads to delayed learning and adjustments in expectations (Posen and Levinthal 2011; Posen et al. 2018). Consequently, we propose that capex point forecast issuers, linked to rather exact estimates, are more susceptible to precision bias.

Overprecision, characterized by anchoring beliefs on prior information and reluctance to embrace new pertinent data, can inhibit information-seeking as projects progress (Guttman and Meng 2021). It also hampers subsequent adjustments (Kraft et al. 2022; Cassar and Gibson 2007). If overprecision leads to a slower modification of beliefs in response to new information, then managers exhibiting this trait might issue fewer forecast revisions (Ren and Croson 2013). If point forecast issuers are predisposed to overprecision, they may generally lag in their response to new information. Additionally, managerial planning approaches that don't rely on risk-based forecasting can exacerbate overprecision (Flyvbjerg 2006; Farshchian and Heravi 2018; Posen et al. 2018).

While the arguments above may hold on average, several factors may obscure the association between forecast format/precision and forecast revision rates. First, firms with superior forecasting processes might produce estimates that remain relevant for longer periods, necessitating less frequent revisions. The absence of forecast revisions may signify adequacy rather than overprecision. Second, if the learning processes underpinning forecasting are effective, a firm could develop immense confidence in its forecasts, thereby reducing the need for frequent revisions and convergence on point estimates. Nonetheless, proactive approaches to business dynamics, marked by swift integration of changes into expectations (Posen et al. 2018), and enhanced forecasting processes, would incorporate the latest data from all pertinent sources. Consequently, if point formats are an outcome of overprecision, firms disclosing such estimates would revise their forecasts less frequently and might refrain from providing updated estimates to capital market participants. This line of reasoning leads us to our second hypothesis:

H2a: Firms issuing point format forecasts will revise their estimates less frequently.

H2b: Forecast revisions are increasing in forecast precision for range format forecasts.

Forecast format, precision, and performance

Our third hypothesis delves into the association between forecast format/precision and future performance. Prior research sheds light on agency conflicts arising from risk-averse managers' reluctance to select all positive-NPV projects from their investment options (Holmstrom and Ricart i Costa 1986; Jensen 1986). Our study expands this perspective to investigate whether precision bias may be linked to firm performance.

Building on the work of Guttman and Meng (2021), which posits that the effectiveness of project selection influences a company's future operating returns, we analyze whether firms issuing capex point estimate forecasts have lower future operating performance compared to those issuing range format forecasts. Guttman and Meng (2021) posit that suboptimal information acquisition and processing during later stages of portfolio decision-making can result in lower expected cash flows. This decline is attributed to the heightened costs of remaining uninformed about the crucial aspects of the chosen projects. Therefore, if firms issuing point forecasts neglect meticulous data acquisition and thorough analysis, they may encounter diminished future operating performance. Such firms may lack the flexibility to explore various scenarios and develop contingency plans, leaving them vulnerable to uncertainties.

Further, drawing from the insights provided by Kraft et al. (2022), we argue that overprecision hampers future firm performance by impeding managers' ability to promptly identify and address risks. Managers susceptible to overprecision might miss valuable opportunities and struggle to respond effectively to changing circumstances, which could further hamper their firms' adaptability and performance. Overall, precision bias can lead to missed opportunities, inadequate risk management, and difficulties in navigating uncertainties, ultimately lowering the firm's performance. Consequently, we present our third hypothesis:

H3a: Firms issuing point format forecasts will have lower future operating performance.

H3b: Firm operating performance is increasing in forecast precision for range format forecasts.

3. DATA

Table 1 provides an overview of our sample composition. We combine data from the Compustat and Institutional Brokers Estimate System (I/B/E/S) databases from 2003 to 2021. Excluding firms in the utilities and finance sectors, we are left with 18,817 firm-year observations with capex forecasts. To minimize potential errors from the I/B/E/S Guidance database relevant to our research questions, we filter out firms that issued forecasts in multiple formats during the fiscal year and observations where the variance between actual and forecasted values exceeds 100 percent (Choi, Hann, Subasi, and Zheng 2020).[5] Consequently, our final sample consists of 14,410 firm-year observations featuring constant-format capex forecasts, 48.3 (51.7) percent of which are in range (point) format. We compute our forecast variables from I/B/E/S Guidance data. *Forecast* is an indicator variable equal to one if an annual capex forecast was disclosed within the 12 months prior to the fiscal year-end, and zero otherwise.[6] We use the final forecast issued for our study.

Research in accounting and management often adopts one of two approaches to capture precision: 1) differentiating point and range forecasts using indicator or categorical variables (Bamber and Cheon 1998; Rupar 2017; Bae et al. 2022), or 2) multiplying continuous forecast range width variable by –1 as a measure of forecast precision, with point forecasts equal to zero

[5] Results are robust to including these observations. We also note that in untabulated tests, firms which narrow their range forecast issue more accurate forecasts; to a lesser extent, so do firms which narrow their forecast to a point estimate.
[6] Consistent with prior research (i.e., Hilary and Hsu 2011; Hilary et al. 2016; Bae et al. 2022), our sample includes only range and point format forecasts. See Table 1 for the format classification criteria.

(Cheng et al. 2013; Hayward and Fitza 2017; Hilary, Hsu, Segal, and Wang 2016; Ittner and Michels 2017). In our study, to provide evidence of overprecision in capex forecasts, we code *Point* (*Range)* as an indicator variable equal to one if the firm consistently issued a point (range) format forecast, and zero otherwise[7]. *Precision* is equal to one if the format was a point, otherwise one minus the range width, where range width is calculated as the difference between the high and low estimate divided by the midpoint; we mean-center *Precision* in all estimations. Various measures of forecast precision have been used in the accounting literature. Leuz and Wysocki (2016) recognize the measurement of precision through forecast format. Hilary et al. (2016) interpret earnings forecast range width as a negative proxy for overconfidence. According to this measure, precise estimates are more likely to be issued by overconfident managers. As overprecision is a form of overconfidence (Kraft et al. 2022) and a cognitive bias (Moore and Healy 2008; Posen et al. 2018), we argue that the narrowest format, points, represents the aspect of overconfidence characterized by overprecision.

Count is the number of capex forecasts issued within the 12 months prior to the fiscal year-end. *Revisions* is the number of capex forecast revisions issued within the 12 months prior to the fiscal year-end. Our operating performance variables are operating cash flow and whether the firm's cash flows surpass its required rate of return. *OCF* is cash flow from operations less extraordinary items, scaled by total assets. *WACC* is an indicator variable equal to one if the firm's cash flows from operations exceed its weighted average cost of capital, and zero otherwise.

We estimate forecast accuracy in two ways. First, *Hit Target* is an indicator variable equal to one if the firm's actual capital expenditures were within ±15 percent of the disclosed forecast,

[7] See Table 1 for an explanation of the format identification process using I/B/E/S codification. For example, some single-estimate forecasts were open-ended; these are typically classified as "Other" format in the forecast guidance literature; we naturally exclude these from "Range" but also exclude such forecasts from the "Point" grouping since they lack precision.

and zero otherwise. Following the literature, the capex forecast estimate is defined as the midpoint of the range for range forecasts and simply the disclosed estimate for point forecasts (Hilary and Hsu 2011; Hilary et al. 2016; Schabus 2022). Second, *Accuracy*, is the absolute value of the difference between actual capex and the disclosed forecast (using the midpoint for ranges), divided by the disclosed forecast and then multiplied by negative one.[8]

Our analyses include an extensive set of control variables drawn from the prior literature and from our deductions regarding potential confounds. We include an indicator variable equal to one for overconfidence (*Overconfidence*) if management was overconfident following Schrand and Zechman (2012) to control for overconfidence aside from overprecision (Schrand and Zechman 2012; Hribar and Yang 2016). We include analyst following (*Analyst Coverage*), given that investors/analysts seek forward-looking disclosures (Lang and Lundholm 1996; Hirst et al. 2008). We include capex uncertainty (*Capex Uncertainty*) since firms with general instability with selecting and executing their capital project portfolio may be less likely to issue capex forecasts or achieve accuracy with those forecasts. We control for financial leverage (*Leverage*), since firms may disclose capex plans to satisfy debt covenants (Ali, Fan, and Li 2020); firm size (*Size*), as larger firms tend to disclose more externally (Lang and Lundholm 1996; Bae et al. 2022); earnings volatility (*Earnings Volatility*), as more volatile firms are less likely to disclose business plans (Waymire 1985); litigation risk (*Litigious*), since firms in more litigious industries may need to communicate frequently and accurately with capital markets to avoid lawsuits (Rogers and

[8] Point forecast issuers hit their target (variance equals zero) only 0.3 percent of the time (21 of 7,454 firm-years), whereas range forecast issuers hit their target (actual capex falls within the forecasted interval) over 30 percent of the time (2,118 of 6,956 firm years). Consequently, we employ both the general ±15 percent deviation from the point/midpoint window and the difference from the point/midpoint to foster a degree of comparability.

Stocken 2005; Ittner and Michels 2017); and changes in earnings (*Change in Earnings*), as capex redirects focus towards multi-period profits instead of current year (Hribar and Yang 2016). [9]

We include the firm's market-to-book ratio (*Market-to-book*), as it often indicates expected firm growth and subsequent investment (Bamber and Cheon 1998; Hribar and Yang 2016), as well as controls for debt and equity financing raised (*Financing*) and M&A activity (*Acquisition*) (Frankel, McNichols, and Wilson 1995; Hribar and Yang 2016). We account for internal control deficiencies (*Weakness*) as they are linked with less accurate forecasts (Feng, Li, and McVay 2009). We control for return on assets (*RoA*) and *Loss* as performance trends influence disclosure decisions (Miller 2002); and discretionary accruals (*Accruals*) as earnings management can affect disclosure decisions. We limit the influence of outliers by winsorizing all continuous variables at the first and ninety-ninth percentiles. We also include year and industry fixed effects to account for temporal trends and industry-specific effects on disclosure choices (Lin, Mao, and Wang 2017).

Table 2, Panel A presents descriptive statistics. As noted earlier, just over half of our sample forecasts are point format (52 percent). Approximately 63 percent of observations fall within +/- 15 percent of the targets. The average capex guidance firm issues 2.752 forecasts per year, with 0.673 revisions. In Table 2, Panel B, we present a correlation matrix of our capex forecast variables. We observe that although most of these variables of interest are correlated with each other, variance inflation factor (VIF) outputs suggest that multicollinearity is generally not a concern for our research design.[10]

4. RESULTS

4.1 Determinants of capex forecast issuance and forecast format

[9] Our findings are robust to including institutional ownership variables, but these are only available through 2019. Our results are also robust to various approaches for calculating *Capex Uncertainty*.
[10] Correlations between control variables are not tabulated for brevity, but appear consistent with prior studies.

Our analysis begins with an examination of the economic factors associated with the decision to disclose capex forecasts, as well as the format and width of these forecasts. We estimate the following model using logistic regression (logit) and ordinary least squares (OLS), regressing the issuance/format of forecast guidance on a set of firm attributes drawn from the literature.

$$Forecast\ (Point, Precision)_{i,t} = \beta_0 + \beta_1 Overconfidence_{i,t} + \beta_2 Capex\ Uncertainty_{i,t} + \beta_3 Analyst\ Coverage_{i,t} + \beta_4 Leverage_{i,t} + \beta_5 Size_{i,t} + \beta_6 Earnings\ Volatility_{i,t} + \beta_7 Litigious_{i,t} + \beta_8 Change\ in\ Earnings_{i,t} + \beta_9 Market\ to\ Book_{i,t} + \beta_{10} Financing_{i,t} + \beta_{11} Acquisition_{i,t} + \beta_{12} Overconfidence_{i,t} + \beta_{13} Weakness_{i,t} + \beta_{14} RoA_{i,t} + \beta_{15} Loss_{i,t} + \beta_{16} Accruals_{i,t} + \beta_{17} Inverse\ Mills_{i,t} + IndustryFE + YearFE + \varepsilon_{i,t} \quad (1)$$

We present results from estimates of equation (1) in Table 3. Regarding the decision to issue a capex forecast (Column (1)), we find that analyst following, leverage, RoA, and accruals are positively associated with guidance issuance. Capex uncertainty, firm size, earnings volatility, litigation risk, change in earnings, market-to-book ratio and internal control weaknesses are negatively associated with guidance issuance. The results largely align with the existing literature.

Results from analysis of forecast format (*Point*) are presented in column (2). Firm size, leverage, issuance of external financing, and negative earnings are positively associated with issuing a point format forecast, while M&A activity is negatively associated. Results from analysis of forecast precision are presented in column (3). Leverage, firm size, and external financing are positively associated with forecast precision, while capex uncertainty, earnings volatility and M&A activity are negatively associated. In both of our second stage models we note that the inverse mills ratio is not statistically significant, we find that far fewer variables are associated with forecast format or precision than are associated with forecast issuance, and in general the models explain far less variation in the forecast properties. While the choice of forecast format and precision obviously follow from the decision to issue a forecast, it appears that the factors that explain significant variance in the decision to issue a forecast are largely unrelated to the properties of the forecast that we examine.

4.2 Forecast accuracy

Our first hypothesis predicts that point forecasts will be less accurate than precise range forecasts and that the association between precision and accuracy is increasing within range forecasters. Visually, we present evidence in support of this hypothesis in Figure 1. Here, the precision of range format forecasts is presented with narrower ranges taking higher values and point estimates taking a value of 1. We observe a consistent increase in forecast accuracy as range width narrows. The association is linear within range forecasters, and then accuracy decreases significantly for point estimate forecasts. Formally, we test hypothesis 1 by estimating the following regression model:

$$Accuracy_{i,t} = \beta_0 + \beta_1 Point_{i,t} + \beta_2 Precision_{i,t} + \sum \beta_k Controls + IndustryFE + YearFE + \varepsilon_{i,t} \quad (2)$$

Accuracy is either *Hit Target* or *Accuracy*, as defined in Section 3. To estimate format precision, we adopt two approaches. First, we include *Point*, an indicator variable equal to 1 for point forecasts, and equal to 0 for range forecasts. Second, we include *Precision*, which is equal to one if the format was a point, otherwise one minus the range width, where range width is calculated as the difference between the high and low estimate divided by the midpoint. This approach allows us to isolate the association between *Point* and *Precision*, and simultaneously estimate the association between *Precision*, which only varies within *Range* format issuers, and *Precision*. We mean-center *Precision* to report average partial effects in each tabulation and include *Precision Squared*, the quadratic of *Precision*, to assess whether there is a non-linear association between forecast precision and accuracy within the *Range* forecasters (Haans, Pieters, and He 2016). A negative and significant coefficient on *Precision Squared* would suggest potential overprecision in relatively narrow range forecasts.

In addition to the variables included in equation (1), we include *Horizon*, the number of days prior to the fiscal year-end that the forecast was issued, since it may be pertinent to forecast behavior and target achievement in equation (2). The results are presented in Table 4. In Panel A, we present evidence that point forecasts are less accurate, as the coefficient on *Point* is negative and significant (columns 1 through 4). Computing the average marginal effect, we find that a point forecast is 9.2 percent less likely than a range forecast to hit the firm's target and 3.1 percent less accurate overall. Further, we find a significant positive association between *Precision* and accuracy and but an insignificant association between *Precision Squared* and accuracy for the range format issuers (Columns (2) and (4)). These results are consistent when accuracy is measured as either *Hit Target* or *Accuracy*.[11]

In untabulated tests, we estimate the average marginal effects of *Precision* from Column (2) and (4), which assess precision within the range forecasting group. We re-confirm a linear association. From these results, we observe that the association between *Precision* and *Accuracy* for the full sample is not a curved, inverted U, but has a rather steep kink, where the effects of precision are increasing until a sharper drop for point forecast issuers.

We define a firm as hitting its target if actual capex falls within +/- 15 percent of the midpoint of the forecast. This is done to provide a fair basis to compare accuracy with point format forecasts. However, it is possible that our results are unique to the range chosen to measure *Hit Target*. To address this possibility, we redefine *Hit Target* as falling within either +/- 5 percent, +/- 10 percent, or +/- 20 percent. The results are presented in Table 4, Panel B. *Point* remains

[11] These results are also robust to including forecast count and forecast revisions.

negative and significant in all cases. Interestingly, we find that while *Precision* is positive and significant with all target windows, but that *Precision Squared* is also positive and significant when the targets are +/- 5 percent or +/- 10 percent, suggesting that greater precision within range format forecasts is associated with increased likelihood of hitting narrower targets. *Precision Squared* lacks significance at the wider target window of +/- 20 percent.[12]

We observe that within range forecast issuers, our results tie to prior research: as precision increases within this group, there are increasing benefits observed with the attainment of the disclosed capex target. However, contrary to prior literature but consistent with precision bias theory, we report a clear drop in accuracy once formats become exactly precise, that is, a point. This new evidence reinforces that precision is a positive attribute for a large proportion of the sample, but convergence to maximal precision may be a negative signal. Together, these findings suggest that existing theories motivating prior work should allow for more nuance.

4.3 Forecast counts and revisions

Our second hypothesis focuses on learning and adaptation, as proxied using forecast updating via revision rates. We predict that firms issuing point forecasts will issue revisions less frequently than firms issuing range forecasts. We present visual evidence in Figure 2. Here, the number of forecast revisions is plotted against our continuous measure of forecast precision, ranging from 0.6 to 1, with point forecasts taking a value of 1. We find evidence that the forecast revision rate increases as intervals narrow throughout the distribution of range widths and that it drops significantly when forecasts converge to a point estimate. To formally test this hypothesis, we estimate the following Poisson regression model:

[12] To address one potential source of endogeneity, we re-estimate our results with an entropy balanced sample (Hainmueller 2017). All key results remain statistically significant at similar levels with little change in economic magnitudes. The results are not tabulated for brevity.

$$Revisions_{i,t} = \beta_0 + \beta_1 Point_{i,t} + \beta_2 Precision_{i,t} + \sum \beta_k Controls + IndustryFE + YearFE + \varepsilon_{i,t} \quad (3)$$

where *Revisions* is the number of forecast revisions made during the year. Once again, *Point*, mean-centered *Precision*, and *Precision Squared* are our measures of format precision.

We present the results in Table 5.[13] The results in Panel A suggest that point forecast issuers revise their forecasts less often throughout the year. The coefficient on *Point* is negative and significant in all cases. We find evidence that the association between precision and the number of forecasts issued is convex with a significant increase as range widths narrow, followed by a significant decrease for point estimate forecasts, as evidenced by the positive coefficient estimate on *Precision* (all estimates) and *Precision Squared* (Columns (2) and (4)). Calculating the inflection point from *Precision* and *Precision Squared*, we observe that the slope switches from negative to positive at 0.71, suggesting an exponential increase in revisions as precision increases within range forecast issuers. We emphasize the associations between *Point* and *Precision* are significant for *Revisions* when controlling for *Count*, which is mechanically associated with forecast revision issuance. This is consistent with relatively higher learning and adaptation during the year among firms issuing range forecasts, as firms are unlikely to modify their forecasts without acquiring new information during the interim forecasting process. However, this learning and adaptation seem to diminish drastically among firms issuing a point forecast, which we interpret as a proxy for overprecision. We expect that overprecision is negatively associated with revisions, learning, or adaptation during the year.

[13] The difference between the results in columns 1 and 2 compared to columns 3 and 4 is the inclusion of *Count* as a control variable. Firms often issue confirming forecasts during the year, so *Revisions* and *Count* capture different, but similar events, but the number of revisions is mechanically related to the number of total forecasts.

Although equation (2) controls for forecast *Horizon* before fiscal year end and a closer target is easier to achieve, it is still possible that the forecast revision rate explains part of the association between precision and accuracy. To better understand the path(s) through which forecast format and precision are associated with accuracy we utilize path analysis. The results are presented in Table 5, Panel B. We consider both direct and indirect effects through revisions to better interpret our results. We use revisions because 1) forecast changes suggest learning has occurred since the last forecast disclosure; and 2) new forecasts must be issued (*Count*) for there to be any forecast changes, and *Count* is the most significant predictor of forecast revisions. For firms issuing point forecasts, the decreased forecast accuracy involves a significant negative indirect effect through forecast revisions (*Revisions*). We also find that *Precision* has a positive significant indirect effect through *Revisions* as it impacts *Accuracy*. Taken together, these findings suggest a learning effect among range forecast issuers that facilitates achieving forecasted targets, especially as their precision increases, which would support the avoidance of overprecision.

Overall, our findings highlight a consistent difference across various metrics arising from the precision of a firm's forecast format. Capex point estimate issuers seem to exhibit symptoms related to overprecision bias (Moore and Healy 2008; Mannes and Moore 2013; Posen et al. 2018). Range forecasts are generally more accurate than point estimates conditional upon the range's precision, and these firms issue more total forecasts and make more frequent changes to their forecasts. We emphasize that within the sample of firms issuing range forecasts, the results get stronger as range width narrows, which is consistent with the possibility of such firms adopting risk-based forecasting techniques as documented in Ittner and Michels (2017). Importantly, the analysis controls for both capex uncertainty and earnings volatility, so the results are not simply a function of risk. Achieving accuracy is not random, and revised forecasts are unlikely to result from the same data inputs. We argue that this is evidence that range forecast issuers gather, learn from, and process more and better information on average than point forecast issuers.

However, since we cannot directly observe a firm's planning processes, it could also be that the disclosure of a range of varying widths or a point forecast may be influenced by factors unrelated to forecasting rigor. To gather anecdotal evidence on planning processes, we contacted the investor relations departments of 120 firms from our sample (58 range and 62 point issuers). Our aim was to inquire about their underlying planning processes, focusing on more recent reporting years. Our inquiries revolved around forecasting tools but received more insights from respondents regarding their internal planning processes. These emails were sent with the following query: "Hi Investor Relations Team, I noticed that your firm, ___, consistently used single point (range) estimates when issuing capex guidance between 2008 and 2018. Did you use sensitivity analyses or probabilistic analyses at the project portfolio level to determine your capex forecast targets? Best regards…".

Although we received responses from 31 firms, some investor relations staff could not discuss their internal processes due to regulatory restrictions and proprietary concerns. Ultimately, we obtained insights from 22 firms out of the initial 120 (10 range and 12 point). We report the feedback we received in Table 6. Interestingly, half of the range format sample mentioned some form of probabilistic analysis as part of their process, compared to one third of the point format sample. Additionally, 70 percent of the range sample provided unprompted explanations of their internal learning and updating process over the year, while none of the point sample mentioned such ongoing learning. Appendix B provides two response examples. Despite the limited sample size of respondents, this anecdotal evidence is consistent with our findings and the interpretation of the results presented in Table 5, providing supplemental evidence for Hypothesis 2.

4.4 Future operating performance

Our third hypothesis examines the association between forecast format/precision and future operating performance. Given that the principal aim of capital investment is to secure future operating returns (Jensen 1986), improved returns can partly stem from enhanced capital project selection, planning, and execution (Malmendier and Tate 2005; Bai, Hsu, and Krishnan 2014; Nezlobin, Reichelstein, and Wang 2015), encapsulated in the concept of investment capacity management (Song, van Houtum, and van Mieghem 2019). If firms that produce range forecasts have integrated more effective forecasting tools, augmented by enhanced learning and adaptation processes, and/or their management is less prone to overprecision bias generally, then we would anticipate these firms will have better future operating performance than point forecast issuers, conditional upon their utilizing their enhanced tools to refine expectations and implement risk mitigation measures. We provide visual evidence in support of hypothesis 3 in Figure 3 where we observe that operating cash flows increase with forecast precision along the entire distribution of range forecast issuers, and then significantly decrease as narrow ranges converge to point estimates. Formally, we test hypothesis 3 by estimating the following OLS and logistic regressions:

$$Performance_{i,t+1} = \beta_0 + \beta_1 Point_{i,t} + \beta_2 Precision_{i,t} + \sum \beta_k Controls + IndustryFE + YearFE + \varepsilon_{i,t} \quad (4)$$

Performance is measured as: *Operating Cash Flow* (*OCF*), defined as cash flow from operations less extraordinary items, then divided by assets, and *WACC*, which is an indicator variable equal to one if the firm’s operating cash flow returns exceeded their weighted average cost of capital, zero otherwise; this variable thus considers each firm’s risk profile. We include *Accuracy* in equation (4), which is otherwise identical to equation (2).[14] All other variables in the model are as defined in Appendix A.

The results are presented in Panel A of Table 7 and suggest that firms issuing point format forecasts have lower OCF and are less likely to exceed their WACC compared to firms issuing range format forecasts (columns (1) through (4)). As observed in Figure 3, there is a linear increase in performance as precision increases among range forecast issuers, as evidenced by the positive and significant coefficient on *Precision*. Further, we find that this is generally a linear association between forecast precision and future operating performance within range forecast issuers since the coefficient on *Precision Squared* in columns (2) and (4) lacks statistical significance. When estimating average marginal effects from these columns' estimations, we confirm that the effects of *Precision* are essentially linear within the sample of range forecast issuers.[15]

To discern whether the performance results are driven directly by the elements behind format or primarily emerge from accuracy, we use path analysis to examine both direct and mediated effects. This analysis could help determine if the presumed learning advantages enjoyed by managers free from precision bias drive improved performance directly or whether they primarily arise from hitting intermittent targets (Kraft et al. 2022). Reported in Table 7, Panel B, the indirect effects from *Point* to future *OCF* are small but significant. The total effects are also significant at the 0.01 level, with the majority (95.1 percent) driven by the direct effects from *Point* to future *OCF*. Likewise, the indirect effects from *Precision* through *Accuracy* onto future *OCF* are positive and significant at the 0.01 threshold, with the majority of the total effect from *Precision*

[14] Our results for these estimations are robust to including *Count* and *Revisions* as well.
[15] Forecast type and width may also be a function of firm risk (Gebhardt, Lee, and Swaminathan 2001; Baginski and Wahlen 2003). Consequently, firms with higher risk may issue range forecasts and have higher performance. Therefore, we also examine the association between forecast format precision with residual income (whether the firm exceeds its weighted average cost of capital), which accounts for firm risk. The results are similar.

arising from its direct effect on *OCF* (94.0 percent). These analyses support H3a and H3b, suggesting that narrow firms issuing (relatively narrow) range forecasts perform better than firms issuing point estimate forecasts. This is consistent with overprecision in point estimates (Ittner and Michels 2017; Posen et al. 2018).

5. ADDITIONAL ANALYSES

To reduce concerns that our results for *Precision* are driven by its measurement, we re-estimate our tests using a percentile rank variable for precision. Here, *Precision* is an index variable from 0.01 to 1, with forecast range narrowness increasing from 0.01 to 0.99 and point formats equal to 1. Our results are robust to this alternate calculation; they reinforce that the effects of *Precision* are primarily linear within range format issuers, but kink negative at point estimates[16].

Next, we perform impact threshold of a confounding variable assessments (ITCV) to directly assess the potential impact of confounding variables (Frank 2000; Larcker and Rusticus 2010). ITCV quantifies the extent to which an omitted variable must be correlated with both dependent and independent variables in a regression to negate the statistical significance of the independent variable's coefficient, given the included controls. In Table 9, we report impact thresholds for *Point* and *Precision* in Column (1) from the estimations reported for outcome variables *Accuracy* and *OCF* in Tables 4 and 7, respectively. For *Point*, the calculated impact thresholds are −0.031 and -0.033 for *Accuracy* and *OCF*, respectively. For *Precision*, the calculated impact thresholds are 0.028 and 0.025 for *Accuracy* and *OCF*, respectively. Following Ittner and Michels (2017), we consider the partial correlations of the included controls, and report

[16] We find similar results measuring *Precision* as a decile-ranked variable. Percentile rankings help address the more numerous observations of raw precision at the narrower end of the spectrum. The rank variables (deciles and 99 percentiles) suggest that the effects of precision diminish at the narrowest ranges but maintain robust support that the effects of precision are significantly linear within range issuers, followed by a downward kink for point format issuers.

the impact of the nearest control variable in Column (2). For the impact thresholds and *Accuracy*, *Horizon* has the strongest partial impact for both *Point* and *Precision*, which suggests that excluding *Horizon* would have been tantamount to omitting a relevant confounding variable. For the outcome variable *OCF*, *Accuracy* has the closest impact on *Point* and *Change in Earnings* has the nearest impact on Precision. No other variable's partial impacts approach the impact thresholds of *Point* or *Precision*, and for our models to have likely suffered from an omitted variable bias, such an excluded variable would have needed to have a similar impact as *Horizon* with respect to *Accuracy*. Summarily, to invalidate the significance of *Point* and *Precision*, an omitted variable, would need to exhibit stronger correlations with *Accuracy*/*OCF* and *Point*/*Precision* than any existing control variables. Such a scenario is unlikely, which provides more confidence that our research design is free from such an endogeneity issue.

6. CONCLUSION

Motivated by precision bias theory, we investigate the association between capital expenditure forecast type (point versus range format) and forecast precision with accuracy, revision rate, and future operating performance. We find that range format forecasts are more accurate than point format forecasts, but that accuracy is increasing in precision among range format issuers. We find similar results when examining forecast revision rates and future operating performance. Our results suggest an intriguing paradox: extreme precision in forecasts can lead to decreases in both accuracy and informativeness. This suggests that managers can be susceptible to precision bias when forecasting capital expenditures and become overprecise in their estimates.

This study makes several significant contributions to the literature. First, and contrary to consensus beliefs, our study provides empirical evidence demonstrating the presence of precision bias at firms which employ point forecasts, while providing support for existing theory arguing the value of precision (within range format forecasts). That point format forecasts are less accurate is consistent with the presence of overprecision. That firms issuing point format forecasts issue fewer revisions is also consistent with precision bias and suggests a lower rate of learning during the period. Finally, that firms issuing point format forecasts have lower future operating performance suggests negative consequences to precision bias and supports that these firms have a lower rate of learning and adaptation during the year. These findings reconcile prior research by underscoring that although information precision can be enhanced through rigorous analytics and learning, precision bias can afflict managers who strive to be excessively precise with their forecast estimates. Such overprecision can adversely impact firm results, affecting both short-term target achievement and subsequent performance. Future studies might extend this inquiry to the realm of earnings and sales forecasts, potentially offering a more holistic view on the presence and consequences of overprecision.

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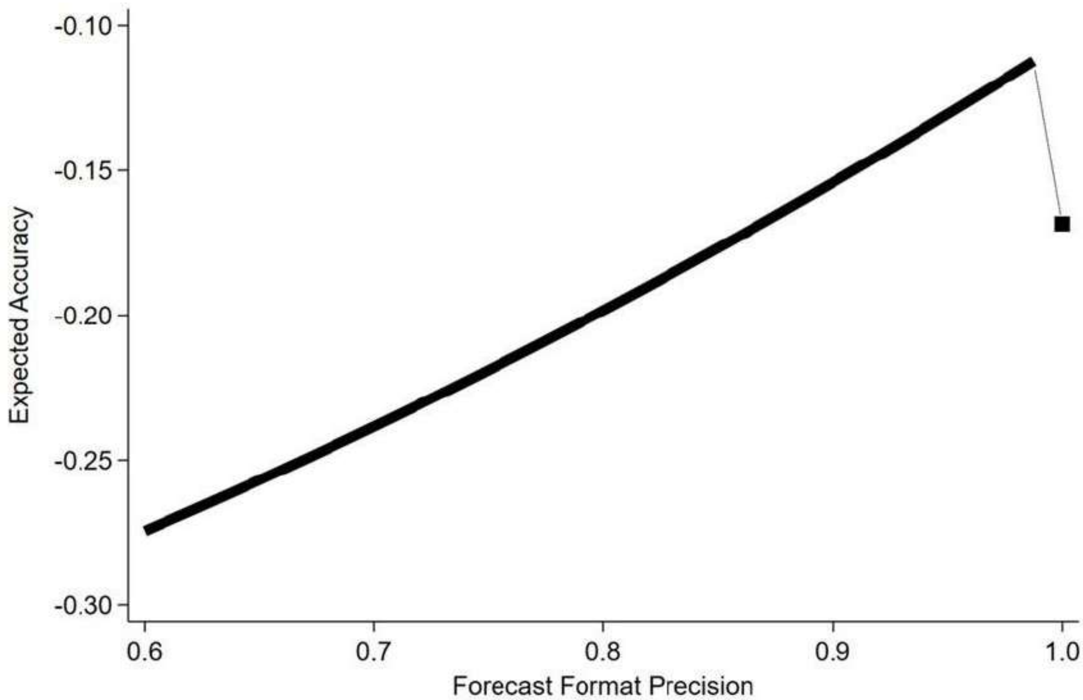
FIGURE 1

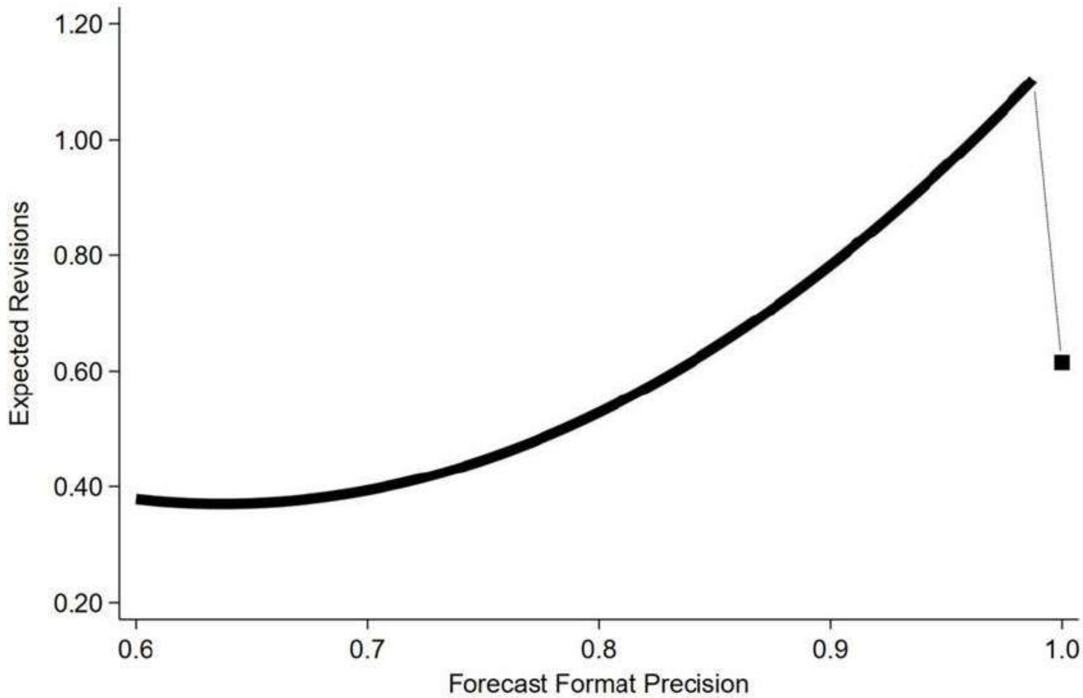
Forecast Format Precision and Forecast Accuracy.



This figure plots predicted associations between *Precision* and *Accuracy*, as presented in Table 4, Panel A, Column 4. The x-axis, *Precision*, is equal to one if the format was a point, otherwise one minus the range width, where range width is calculated as the difference between the high and low estimate divided by the midpoint. Smaller x-axis values represent wider forecasted range windows, with lower precision to the left. The y-axis, *Accuracy*, is the absolute value of the expected actual capital expenditure minus forecasted capital expenditure target (using midpoint for ranges), divided by the target and multiplied by negative one, at that level of precision.

FIGURE 2

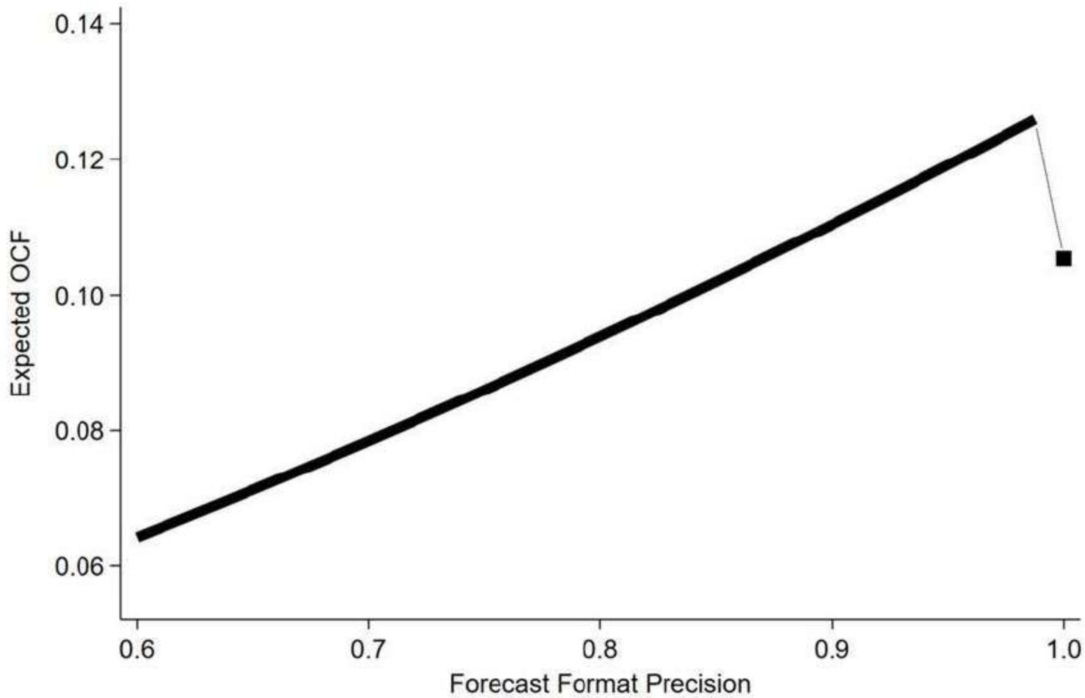
Forecast Format Precision and Forecast Revisions



This figure plots predicted associations between *Precision* and *Revisions*, as presented in Table 5, Panel A, Column 4. The x-axis, *Precision*, is equal to one if the format was a point, otherwise one minus the range width, where range width is calculated as the difference between the high and low estimate divided by the midpoint. Smaller x-axis values represent wider forecasted range windows, with lower precision to the left. The y-axis, *Revisions*, is the expected count of forecast revisions issued in the 12 months prior to fiscal year end at that level of precision.

FIGURE 3

Forecast Format Precision and Future Operating Cash Flows



This figure plots predicted associations between *Precision* and *OCF*, as presented in Table 7, Panel A, Column 2. The x-axis, *Precision*, is equal to one if the format was a point, otherwise one minus the range width, where range width is calculated as the difference between the high and low estimate divided by the midpoint. Smaller x-axis values represent wider forecasted range windows, with lower precision to the left. The y-axis, *OCF*, is expected cash flow from operations less extraordinary items divided by assets (at time t+1) at that level of precision.

TABLE 1
Sample Selection

Description of Selection Criteria	**Observations Lost**	**Observations Remaining**
Observations in Compustat excluding Utilities & Financials, 2003-2021		132,373
Less: missing inputs for variable calculations	29,383	102,990
Less: no I/B/E/S annual capex forecast	66,993	18,817
Less: not constant capex forecast format (range or point)	4,829	14,410
Final sample		14,410
Range capex forecast format (48.3% of the sample)		6,956
Point capex forecast format (51.7% of the sample)		7,454

Table 1 provides sample selection criteria obtained from the Compustat and I/B/E/S databases. The sample is reduced for observations missing data for variable calculations, missing matched I/B/E/S capex forecast data, "Other" format of forecasts, and lack of constant format over the period leading to the fiscal year end. There were 96,859 capital expenditure forecasts recorded in I/B/E/S prior to merging with Compustat and prior to filtering to the final forecast, and this quantity includes multiple capex forecasts for the same firm-year. To classify each I/B/E/S forecast as a "Range", "Point", or "Other" format, we applied the following criteria. "Range" forecast formats were identified in I/B/E/S as coded "01 Between (&)" (40,775 observations), "06 High end of" (38 observations), or "08 Low end of" (44 observations) and required that the upper and lower ends of the interval estimate were not missing and different from one another. "Point" forecast formats were identified as coded "02 About" (53,460 observations) or "14 Comfortable with" (7 observations), or as a range which had the upper and lower estimates identical to one another (25 observations). "Other" forecasts also contained only a single estimate but were open-ended, coded in I/B/E/S as "03 More than" (561 observations), "04 at least" (62 observations), "10 less than" (1,068 observations), "11 may exceed" (38 observations), "12 slightly more than" (125 observations), "13 slightly less than" (95 observations), "15 significantly less than" (5 observations), "16 significantly more than" (4 observations), "17 not to exceed" (267 observations), or "18 N/A" (285 observations). We exclude these "Other" formats from the "Point" classification since they are open-ended and thus imprecise rather than plausibly overprecise. After merging each firm-year's final forecast into Compustat and filtering on firms which were retained a constant format over the 12 months prior to fiscal year end, we report 6,956 Range observations and 7,454 Point observations.

TABLE 2, PANEL A
Descriptive Statistics

Variable	Mean	Std. Dev.	P25	Median	P75
Point	0.517	0.500	0.000	1.000	1.000
Precision	0.937	0.088	0.895	1.000	1.000
Hit Target	0.626	0.484	0.000	1.000	1.000
Accuracy	-0.168	0.183	-0.221	-0.104	-0.044
Count	2.752	1.591	1.000	3.000	4.000
Revisions	0.673	0.867	0.000	0.000	1.000
OCF	0.106	0.080	0.061	0.100	0.147
WACC	0.865	0.342	1.000	1.000	1.000
Horizon	0.374	0.281	0.164	0.191	0.650
Overconfidence	0.522	0.500	0.000	1.000	1.000
Capex Uncertainty	0.457	0.338	0.237	0.370	0.569
Analyst Coverage	2.392	0.720	1.946	2.485	2.944
Leverage	0.282	0.220	0.111	0.260	0.407
Size	7.569	1.663	6.449	7.545	8.711
Earnings Volatility	0.058	0.073	0.017	0.032	0.068
Litigious	0.295	0.456	0.000	0.000	1.000
Change in Earnings	-2.308	38.567	-1.217	0.222	2.118
Market-to-Book	3.199	5.844	1.325	2.247	3.849
Financing	0.998	0.040	1.000	1.000	1.000
Acquisition	0.486	0.500	0.000	0.000	1.000
Weakness	0.040	0.197	0.000	0.000	0.000
RoA	0.037	0.103	0.007	0.047	0.087
Loss	0.220	0.414	0.000	0.000	0.000
Accruals	0.691	1.946	0.036	0.104	0.358
Inverse Mills	0.871	0.466	0.517	0.782	1.139

Table 2, Panel A presents descriptive statistics for all 14,410 observations used to test our hypotheses. Variables are defined in Appendix A.

TABLE 2, PANEL B
Correlation Matrix

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
(1) Point		0.933*	0.027*	-0.021*	-0.075*	-0.003
(2) Precision	0.741*		-0.023*	0.025*	-0.015	0.057*
(3) Horizon	0.011	-0.092*		-0.634*	-0.467*	-0.247*
(4) Count	-0.005	0.080*	-0.657*		0.622*	0.257*
(5) Revisions	-0.069*	0.046*	-0.475*	0.570*		0.165*
(6) Accuracy	-0.004	0.090*	-0.269*	0.236*	0.158*	

Table 2, Panel B presents Pearson (below) and Spearman (above) correlation coefficients for all capital expenditure forecast variables used in our study. *Point* is an indicator variable equal to one if the firm consistently issued a point forecast format for all capex guidance disclosures in the 12 months prior to fiscal year end, zero otherwise. *Precision* is equal to one if the format was a point, otherwise one minus the range width, where range width is the difference between the high and low estimate divided by the midpoint (mean-centered in all estimations). *Horizon* is the number of days prior to the fiscal year end that the forecast was issued. *Count* is the count of forecasts issued in the 12 months prior to the fiscal year end. *Revisions* is the count of forecast revisions issued in the 12 months prior to fiscal year end. *Accuracy* is the absolute value of the actual capital expenditure minus forecasted capital expenditure target (using midpoint for ranges), divided by the target and multiplied by negative one. * denotes significance at the $p<0.05$ level.

TABLE 3
Determinants of Capital Expenditure Forecast Guidance, Forecast Format, and Forecast Precision

Variable	Forecast (1)	Point (2)	Precision (3)
Overconfidence	0.067*	-0.003	0.002
	(1.90)	(-0.06)	(1.09)
Capex Uncertainty	-0.376***	-0.102	-0.008**
	(-8.82)	(-1.02)	(-2.04)
Analyst Coverage	1.474***	0.093	-0.002
	(48.27)	(0.37)	(-0.22)
Leverage	0.516***	0.421**	0.023***
	(9.09)	(2.33)	(3.33)
Size	-0.088***	0.199***	0.009***
	(-5.46)	(6.00)	(7.50)
Earnings Volatility	-1.045***	-0.108	-0.032
	(-5.38)	(-0.25)	(-1.64)
Litigious	-0.733***	-0.121	0.003
	(-7.23)	(-0.67)	(0.49)
Change in Earnings	-0.001***	-0.000	-0.000
	(-6.57)	(-0.61)	(-1.53)
Market-to-Book	-0.010***	-0.005	0.000
	(-4.41)	(-1.19)	(0.40)
Financing	-0.701	1.034**	0.030*
	(-1.49)	(2.33)	(1.79)
Acquisition	0.054	-0.146**	-0.004**
	(1.31)	(-2.49)	(-2.13)
Weakness	-0.257***	-0.129	0.002
	(-4.22)	(-1.19)	(0.39)
RoA	1.308***	0.132	-0.012
	(10.02)	(0.31)	(-0.71)
Loss	-0.130***	0.202***	-0.001
	(-3.03)	(2.68)	(-0.33)
Accruals	0.022***	-0.007	0.001
	(5.34)	(-0.71)	(1.45)
Inverse Mills		0.373	-0.015
		(0.87)	(-0.90)
Constant	-5.488***	-3.030*	0.858***
	(-8.05)	(-1.93)	(28.02)
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	102,990	14,410	14,410
Pseudo (Adjusted) R^2	0.40	0.05	(0.10)

***, **, * Denote two-tailed statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3 presents the results of logistic and OLS regressions of capex forecast guidance issuance, format, and precision on their determinants (equation 1). The sample period is from 2003 through 2021. In Column (1), *Forecast* is an indicator variable equal to one if management disclosed a capex forecast within 12 months of the fiscal year end, zero otherwise. In Column (2), *Point* is an indicator variable equal to one if firm management always issued a point as its forecast format, zero otherwise. In Column (3), *Precision* is equal to one if the format was a point, otherwise one minus the range width, where range width is calculated as the difference between the high and low estimate divided by the midpoint. All continuous variables are winsorized at the 1st and 99th percentiles. Robust z- and t-statistics are in parentheses (standard errors clustered at the firm level). Variables are defined in Appendix A.

TABLE 4, PANEL A
Capital Expenditure Forecast Format, Precision, and Accuracy

Variable	**Hit Target (1)**	**Hit Target (2)**	**Accuracy (3)**	**Accuracy (4)**
Point	-0.456***	-0.540***	-0.030***	-0.031***
	(-6.82)	(-5.31)	(-5.58)	(-4.18)
Precision	2.518***	3.340***	0.168***	0.179***
	(7.07)	(3.96)	(5.30)	(2.80)
Precision^2		3.267		0.044
		(1.10)		(0.18)
Horizon	-1.922***	-1.921***	-0.158***	-0.158***
	(-25.73)	(-25.71)	(-23.80)	(-23.81)
Overconfidence	-0.052	-0.052	-0.008**	-0.008**
	(-1.06)	(-1.07)	(-2.01)	(-2.01)
Capex Uncertainty	-0.537***	-0.535***	-0.047***	-0.047***
	(-6.63)	(-6.61)	(-6.13)	(-6.11)
Analyst Coverage	0.103	0.098	-0.010	-0.010
	(0.51)	(0.48)	(-0.56)	(-0.56)
Leverage	-0.080	-0.079	-0.013	-0.013
	(-0.58)	(-0.57)	(-0.96)	(-0.96)
Size	0.128***	0.128***	0.010***	0.010***
	(4.87)	(4.87)	(4.28)	(4.28)
Earnings Volatility	-0.409	-0.404	-0.026	-0.026
	(-1.14)	(-1.13)	(-0.75)	(-0.74)
Litigious	-0.026	-0.024	-0.005	-0.005
	(-0.16)	(-0.14)	(-0.28)	(-0.27)
Change in Earnings	-0.000	-0.000	-0.000	-0.000
	(-0.53)	(-0.52)	(-0.73)	(-0.73)
Market-to-Book	0.006	0.006	0.000	0.000
	(1.57)	(1.58)	(1.34)	(1.34)
Financing	0.409	0.406	0.059	0.059
	(0.68)	(0.68)	(0.98)	(0.98)
Acquisition	-0.062	-0.061	-0.005	-0.005
	(-1.22)	(-1.22)	(-1.13)	(-1.13)
Weakness	-0.267**	-0.264**	-0.030***	-0.030***
	(-2.57)	(-2.54)	(-3.14)	(-3.13)
RoA	0.167	0.165	0.054	0.054
	(0.47)	(0.46)	(1.62)	(1.62)
Loss	-0.044	-0.046	-0.001	-0.001
	(-0.63)	(-0.65)	(-0.18)	(-0.19)
Accruals	0.015	0.015	0.001	0.001
	(1.38)	(1.37)	(1.64)	(1.64)
Inverse Mills	-0.078	-0.086	-0.038	-0.039
	(-0.22)	(-0.24)	(-1.18)	(-1.18)
Constant	0.333	0.391	-0.138*	-0.138*
	(0.27)	(0.31)	(-1.82)	(-1.81)
Industry Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Observations	14,410	14,410	14,410	14,410
Pseudo (Adjusted) R^2	0.11	0.11	(0.14)	(0.14)

***, **, * Denote two-tailed statistical significance at the 1, 5, and 10 percent levels, respectively.
Table 4, Panel A presents the results of logistic and OLS regression estimates of equation (2), testing the association between forecast accuracy and forecast format and precision. The sample period is from 2003 through 2021. *Point* is an indicator variable equal to one if the firm issued only point format forecasts, zero otherwise. *Precision* is equal

to one if the format was a point, otherwise one minus the range width, where range width is calculated as the difference between the high and low estimate divided by the midpoint; it is mean-centered in these estimations. *Hit Target* is an indicator variable equal to one if the firm's actual capital expenditure was within ±15 percent of the forecasted target, zero otherwise. *Accuracy* is actual capex minus forecasted capex target divided by the target (midpoint if it was a range), multiplied by negative one. All continuous variables are winsorized at the 1st and 99th percentiles. Robust z- and t-statistics are in parentheses (standard errors clustered at the firm level). Variables are defined in Appendix A.

TABLE 4, PANEL B
Capital Expenditure Forecast Format, Precision, and Forecast Accuracy

Variable	Hit ±5% (1)	Hit ±5% (2)	Hit ±10% (3)	Hit ±10% (4)	Hit ±20% (5)	Hit ±20% (6)
Point	-0.434***	-0.619***	-0.442***	-0.590***	-0.454***	-0.458***
	(-6.62)	(-6.61)	(-6.99)	(-6.33)	(-6.17)	(-4.15)
Precision	2.892***	4.828***	2.852***	4.351***	2.547***	2.582***
	(6.77)	(5.79)	(7.72)	(5.48)	(6.65)	(0.45)
Precision^2		8.933***		6.374**		0.132
		(2.73)		(2.12)		(0.04)
Constant	-1.720	-1.600	-0.812	-0.711	0.582	0.584
	(-1.55)	(-1.44)	(-0.76)	(-0.67)	(0.41)	(0.41)
Controls	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	14,410	14,410	14,410	14,410	14,410	14,410
Pseudo R^2	0.07	0.07	0.09	0.09	0.12	0.12

***, **, * Denote two-tailed statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4, Panel B presents the results of logistic regression estimates of equation (2), testing the association between forecast accuracy and forecast format and precision. The sample period is from 2003 through 2021. *Point* is an indicator variable equal to one if the firm issued only point format forecasts, zero otherwise. *Precision* is equal to one if the format was a point, otherwise one minus the range width, where range width is calculated as the difference between the high and low estimate divided by the midpoint; it is mean-centered in these estimations. *Hit Target* is an indicator variable equal to one if the firm's actual capital expenditure was within ±5, 10, or 20 percent of the forecasted target as labeled, zero otherwise. All continuous variables are winsorized at the 1st and 99th percentiles. Robust z-statistics are in parentheses (standard errors clustered at the firm level). Variables are defined in Appendix A.

TABLE 5, PANEL A
Capital Expenditure Forecast Format, Precision, and Forecast Revisions

Variable	Revisions (1)	Revisions (2)	Revisions (3)	Revisions (4)
Point	-0.592***	-0.683***	-0.474***	-0.586***
	(-14.11)	(-12.59)	(-12.12)	(-11.25)
Precision	3.085***	4.060***	2.222***	3.424***
	(11.08)	(8.68)	(8.82)	(7.87)
Precision^2		4.710**		5.630***
		(2.53)		(3.30)
Count			0.393***	0.393***
			(43.83)	(43.82)
Constant	-2.903**	-2.828**	-2.477**	-2.406**
	(-2.38)	(-2.32)	(-2.07)	(-2.01)
Controls	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Observations	14,410	14,410	14,410	14,410
Pseudo R^2	0.05	0.05	0.17	0.17

***, **, * Denote two-tailed statistical significance at the 1, 5, and 10 percent levels, respectively.
Table 5, Panel A presents the results of Poisson regression estimates of equation (3), testing the association between forecast revisions and forecast format and precision. The sample period is from 2003 through 2021. *Revisions* is a count variable for the number of forecast changes. *Count* is a count variable for the number of forecasts issued. *Point* is an indicator variable equal to one if the firm issued only point format forecasts, zero otherwise. *Precision* is equal to one if the format was a point, otherwise one minus the range width, where range width is calculated as the difference between the high and low estimate divided by the midpoint; it is mean-centered in these estimations. All continuous variables are winsorized at the 1st and 99th percentiles. Robust z-statistics are in parentheses (standard errors clustered at the firm level). Variables are defined in Appendix A.

TABLE 5, PANEL B
Mediation: Direct, Indirect, and Total Effects of Precision and Point on Accuracy

Variable Name and Interaction		Revisions (1)	Accuracy (2)
Precision	$\gamma_1 =$	1.221***	
		(10.67)	
Precision * Revisions	$\gamma_1 * \delta_1 =$		0.0047*
			(1.84)
Direct Effect of Precision	$\delta_2 =$		0.1645***
			(5.22)
Total Effects of Precision			0.1692***
			(5.37)
Point	$\gamma_2 =$	-0.2845***	
		(-12.10)	
Point * Revisions	$\gamma_2 * \delta_3 =$		-0.0011*
			(-1.86)
Direct Effect of Point	$\delta_4 =$		-0.0284***
			(-5.34)
Total Effects of Point			-0.0295***
			(-5.57)

***, **, * Denote two-tailed statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 5, Panel B presents the results of mediation analysis related to equation (3). The sample period is from 2003 through 2021. *Revisions* is a count variable for the number of forecast changes. *Accuracy* is actual capex minus forecasted capex target divided by the target (midpoint if it was a range), multiplied by negative one. *Point* is an indicator variable equal to one if the firm issued only point format forecasts, zero otherwise. *Precision* is equal to one if the format was a point, otherwise one minus the range width, where range width is calculated as the difference between the high and low estimate divided by the midpoint; it is mean-centered in these estimations. All continuous variables are winsorized at the 1st and 99th percentiles. Robust z-statistics are in parentheses (standard errors clustered at the firm level). Variables are defined in Appendix A.

TABLE 6
Summary of Responses from Firms' Investor Relations Departments

	Range Forecast Issuers	Point Forecast Issuers
Investor Relations Departments Emailed	58	62
Response Received	10	12
Response Rate	17%	19%
Use probabilistic analysis	5	4
Probabilistic analysis rate	50%	33%
Internal learning and updating	7	0
Learning and updating rate	70%	0%

Table 6 summarizes the responses from Investor Relations departments which we identified as being either consistently range forecast issuers or point forecast issuers in the recent past. The email/data request submission from us had the following language: "Hi Investor Relations Team, I noticed that your firm, ___, consistently used single point (range) estimates when issuing capex guidance between 2008 and 2018. Did you use sensitivity analyses or probabilistic analyses at the project portfolio level to determine your capex forecast targets? Best regards, , PhD". See the Appendix B for sample responses as well.

TABLE 7, PANEL A
Capital Expenditure Forecast Precision and Performance Outcomes

Variable	OCF (1)	OCF (2)	WACC (3)	WACC (4)
Point	-0.013***	-0.013***	-0.545***	-0.745***
	(-5.67)	(-4.24)	(-4.69)	(-3.99)
Precision	0.061***	0.064**	1.846***	3.716**
	(4.70)	(2.53)	(3.36)	(2.55)
Precision^2		0.012		6.589
		(0.13)		(1.40)
Accuracy	0.024***	0.024***	0.913***	0.915***
	(5.72)	(5.72)	(4.79)	(4.80)
Constant	0.048	0.048	-2.146	-1.988
	(1.51)	(1.51)	(-1.09)	(-1.00)
Controls	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Observations	13,060	13,060	11,774	11,774
Adjusted (Pseudo) R^2	0.37	0.37	-0.27	-0.27

***, **, * Denote two-tailed statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 7, Panel A presents the results of OLS and logistic regression estimates of equation (4), testing the association between future operating performance and forecast format and precision. The sample period is from 2003 through 2021. *OCF* is cash flow from operations less extraordinary items divided by assets. *WACC* is an indicator equal to one if the firm's operating cash flows exceeded its WACC, zero otherwise. *Point* is an indicator variable equal to one if the firm issued only point format forecasts, zero otherwise. *Precision* is equal to one if the format was a point, otherwise one minus the range width, where range width is calculated as the difference between the high and low estimate divided by the midpoint; it is mean-centered in these estimations. *Accuracy* is actual capex minus forecasted capex target divided by the target (midpoint if it was a range), multiplied by negative one. All continuous variables are winsorized at the 1st and 99th percentiles. Robust t- and z-statistics are in parentheses (standard errors clustered at the firm level). Variables are defined in Appendix A.

TABLE 7, PANEL B
Mediation: Direct, Indirect, and Total Effects of Precision and Point on OCF

Variable Name and Interaction		**Accuracy** (1)	**OCF_{t+1}** (2)
Precision	γ_1 =	0.0447***	
		(4.81)	
Precision * Accuracy	$\gamma_1 * \delta_1$ =		0.0011***
			(3.67)
Direct Effect of Precision	$\delta 2_2$ =		0.0172***
			(4.84)
Total Effects of Precision			0.0182***
			(5.16)
Point	γ_2 =	-0.0306***	
		(-5.26)	
Point * Accuracy	$\gamma_2 * \delta_3$ =		-0.0007***
			(-3.86)
Direct Effect of Point	δ_4 =		-0.0135***
			(-5.80)
Total Effects of Point			-0.0142***
			(-6.14)

***, **, * Denote two-tailed statistical significance at the 1, 5, and 10 percent levels, respectively.
Table 7, Panel B presents the results of mediation analysis related to equation (4). The sample period is from 2003 through 2021. *Point* is an indicator variable equal to one if the firm issued only point format forecasts, zero otherwise. *Precision* is equal to one if the format was a point, otherwise one minus the range width, where range width is calculated as the difference between the high and low estimate divided by the midpoint. *Accuracy* is actual capex minus forecasted capex target divided by the target (midpoint if it was a range), multiplied by negative one. *OCF* is cash flow from operations less extraordinary items divided by assets. All continuous variables are winsorized at the 1st and 99th percentiles. Robust z-statistics are in parentheses (standard errors clustered at the firm level). Variables are defined in Appendix A.

TABLE 8
Impact of Unobservable Confounding Variables
Capital Expenditure Forecast Precision, Accuracy, and OCF

Variable	**ITCV (1)**	**Impact (2)**
Point in relation to Accuracy. Nearest variable: Horizon	-0.031	-0.030
Point in relation to OCF. Nearest variable: Accuracy	-0.033	-0.003
Precision in relation to Accuracy. Nearest variable: Horizon	0.028	0.035
Precision in relation to OCF. Nearest variable: Change in earnings	0.025	0.003

Table 8 presents the effect of *Precision* (*Point*) on *Accuracy* and *OCF* as presented in Table 4, Column (3), and Table 7, Column (2), respectively, with an assessment of the impact of unobservable confounding variables based on Frank (2000). We report the variables which have the greatest impact on *Point* and *Precision* out of all variables included in our estimations. All other variables' impacts are far below the impact threshold reported in column (1) for each variable of interest and dependent variable combination. The sample period is from 2003 through 2021. *Accuracy* is actual capex minus forecasted capex target divided by the target (midpoint if it was a range), multiplied by negative one. *OCF* is cash flow from operations less extraordinary items divided by assets. *Point* is an indicator variable equal to one if the firm issued only point format forecasts, zero otherwise. *Precision* is equal to one if the format was a point, otherwise one minus the range width, where range width is calculated as the difference between the high and low estimate divided by the midpoint; it is mean centered in these estimations. All continuous variables are winsorized at the 1st and 99th percentiles. Robust t-statistics are in parentheses (standard errors clustered at the firm level). Variables are defined in Appendix A.

APPENDIX A
Variable Definitions

Variable	Definition
Data Source: I/B/E/S	
Forecast	An indicator variable equal to one if the firm issued an annual capex forecast in the 12 months prior to fiscal year end, zero otherwise.
Point (Range)	An indicator variable equal to one if the firm consistently issued a point (range) forecast format for all capex guidance disclosures in the 12 months prior to fiscal year end, zero otherwise.
Precision	Equal to one if the format was a point, otherwise one minus the range width, where range width is the difference between the high and low estimate divided by the midpoint. Mean-centered in all estimations.
Hit Target	An indicator variable equal to one if the firm's actual capital expenditure was within ±15 percent of the forecasted target (using midpoint for ranges), zero otherwise.
Accuracy	The absolute value of actual capital expenditure minus forecasted capital expenditure target (using midpoint for ranges), divided by the target and multiplied by negative one.
Count	The count of forecasts issued in the 12 months prior to the fiscal year end.
Revisions	The count of forecast revisions issued in the 12 months prior to fiscal year end.
Horizon	The number of days prior to the fiscal year end that the forecast was issued.
Analyst Coverage	The natural logarithm of one plus the number of analysts following the firm.
Data Source: Compustat	
OCF	Operating cash flow less extraordinary items divided by assets.
WACC	An indicator variable equal to one if the firm's operating cash flow exceeds its weighted average cost of capital.
Overconfidence	An indicator variable equal to one if firm management was overconfident following Schrand and Zechman (2012) four factor model, zero otherwise.
Capex Uncertainty	The standard deviation of the annual change in the natural logarithm of capital expenditure over the prior 5 years.
Leverage	The firm's financial leverage measured as all debt divided by total assets.
Size	The natural logarithm of market value of equity.
Earnings Volatility	The standard deviation of the firm's earnings scaled by assets over the prior 5 years.
Litigious	An indicator variable equal to one if the firm's industry had greater litigation risk, zero otherwise.
Change in Earnings	The difference in income before extraordinary items scaled by year end price.
Market-to-Book	The ratio of the firm's market value of equity to its book value.
Financing	An indicator variable equal to one if the firm raised external financing in that year, zero otherwise.
Acquisition	An indicator variable equal to one if the firm reported M&A activity, zero otherwise.
RoA	Return on assets as earnings before extraordinary items divided by assets.
Loss	An indicator variable equal to one if the firm reported negative earnings before extraordinary items, zero otherwise.
Accruals	Discretionary accruals calculated using the modified Jones model.
Data Source: Audit Analytics	
Weakness	An indicator variable equal to one if the firm had a SOX 404 control weakness, zero otherwise.

APPENDIX B

Investor Relations Responses

From a range forecaster:

Hello ___,

Thanks for your inquiry and more importantly, thanks for what you do. As a CPA myself, I have great respect for you and others who teach accounting to those who will come up the ranks behind me.

The short answer to your question is that we take more of a probable/flexible/adaptive approach to our guidance ranges. While there are many different scenarios that can play out over the course of a year, in general, we get fairly close. Being a very capital-intensive marine company, we have a fixed timeline as to when our shipyards will fall (vessels are on a maintenance schedule regulated by the Coast Guard). There's always a chance a shipyard or new vessel build project will be delayed due to unforeseen circumstances (labor issues, weather events, supply chain, etc.), but generally these things don't fluctuate a lot over the course of a year.

The areas that are a little harder to predict, or that can be accelerated/deferred depending on business conditions, generally are small for us and don't have a major impact on the total. These items would include facility upgrades, new vehicles, computer equipment, etc.

We do use sensitivity analysis for other areas like financial models for M&A, flexing discount rates for example.

I hope this helps to answer your question. If I can be of further assistance, please let me know.

Best regards,

______, Vice President, Investor Relations

From a point forecaster:

____,

Our capital expenditures projection for a given fiscal year is based on our Business Plan for that year. Capital spend for the majority of projects in the Business Plan is based on pre-committed contracts (e.g., aircraft) which, due to the high capital intensity nature of our business and inherently longer lead times, are generally entered into well before the Business Plan for any year is finalized. This allows us the ability to forecast capital expenditures with higher level of precision than other financial metrics, such as EPS.

Best regards,

____

____ Investor Relations