De-biasing bold forecasts using the 'outside view': The case of analysts' sales growth forecasts

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Abstract:
This paper examines how two complementary cognitive processes defined by Kahneman and Lovallo (1993) – the inside and outside view – relate to the generation and the properties of sell-side analyst forecasts. By studying the occurrence and properties of analysts' sales growth forecasts that are bold from a *statistical* mean-reversion perspective, I conclude that: 1) bold forecasts are associated with characteristics that highlight forecast setting specificity, consistent with analysts over-relying on setting-specific information (i.e., an inside view); and 2) relative to non-bold forecasts, bold forecasts exhibit stronger bias. Further, the degree of mean-reversion in the forecast setting appears associated with the frequency of bold forecasts and exacerbates their bias, consistent with analysts insufficiently *de-biasing* their forecasts using relevant 'outside view' information. This archival-empirical evidence complements experimental findings by Sedor (2002) on analysts' unintentional cognitive bias and illustrates the role of the analysts' cognitive process for their analysis (Bradshaw 2011).

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1. Introduction

Sell-side analysts play a crucial role in financial markets as producers of forecasts of firm-specific financial variables. However, despite a vast academic literature on the properties of these analyst forecasts, the process of how analysts produce and transform *information* into forecasts remains to a large extent a 'black box' (Bradshaw 2011; Brown, Call, Clement, and Sharp 2015). Indeed, while a large body of prior literature shows that analysts do not use information efficiently, it does not connect these findings to insights on the process of the analysts' 'analysis' (Bradshaw 2011). In this paper, I provide evidence on this connection by asking the question how two complementary *cognitive processes* – the inside and the outside view – adopted by sell-side analysts in the forecasting process relate to the generation and the properties of their forecasts.

The inside and outside view describe two cognitive processes introduced to the psychology literature by Kahneman and Lovallo [henceforth KL] (1993). The two views draw on different sources of information and apply different rules to the use of information for forecasting (KL, p. 25). In their standard text, Hastie and Dawes (2010, p. 157) describe the inside view as a process of *intuitive* decision making where the forecaster relies on consideration of a limited, systematically skewed subset of possible events, often guided by scenario construction (Hastie and Dawes 2010, p. 159). By contrast, the outside view is a rational forecasting process, whereby 'taking an outside view' means classifying a current decision problem in a class of similar problems and then applying the rules of probabilistic thinking to assess the likelihood of outcomes (Hastie and Dawes, 2010). While both cognitive processes complement each other, certain features of the forecast setting, such as its perceived uniqueness or personal involvement by the forecaster, promote a spontaneous adoption of the inside view and preclude forecasters from adopting a ‘statistical’ outside view. Importantly, KL conclude that a reliance on the inside view leads to what they call *bold* forecasts, i.e., forecasts that seemingly misjudge the distribution of future possible outcomes.[1] KL argue that bold forecasts are (too) extreme given the statistical evidence on the forecasted measure and exhibit predictable (optimistic) *bias*.[2] In the presence of this bias, KL consider the outside view a technique of reference-class forecasting aimed at *de-biasing* forecasts constructed using the inside-view: ‘when both methods are applied with equal intelligence and skill, the outside view is much more likely to yield a realistic estimate’ (KL, p.25).

In this paper, I study the role of the inside/outside view in the setting of sell-side analysts. I build on the experimental work by Sedor (2002), who shows that, just like managers, sell-side analysts are prone to producing unintentionally biased optimistic forecasts consistent with an (over-)reliance on inside view thinking. In her experiments, the analysts’ inside view thinking is prompted by the structure of the information presented to them: analysts make more optimistic forecasts of earnings when provided with information about management’s future plans in the form of scenarios rather than framed as lists. Importantly, Sedor’s experiments also show that the bias becomes stronger when analysts are confronted with an accounting loss that highlights the ‘uniqueness’ or specificity of the forecast setting and reduces the analysts’ focus on statistical time-series information when forecasting (Sedor 2002, p. 736).

While Sedor’s work highlights how a stylized *experimental* setting can promote inside view thinking by analysts, my starting point is that analysts will use the inside and outside view in

[1] The statistical definition of bold forecasts in KL and in this paper differs from the definition of bold forecasts in previous analyst literature, namely forecasts that stand out from consensus (e.g., Hong, Kubik, and Solomon 2000; Clement and Tse 2005; Evgeniou, Fang, Hogarth, and Karelaia 2013). See Section 5.1.

[2] KL point out that this bias ‘enable[s] cautious decision makers to take large risks’ (KL, p. 24). While KL do not define the concept of *risk* in their paper, the notion of risk they describe in their paper is broader than just *financial* risk. To illustrate, KL describe the role of the inside view in a setting that pertains to the design of a course curriculum for high schools in Israel. In that context, the notion of risk captures the likelihood that the outcomes will differ from expectations.

a complementary way to generate their forecasts in their professional setting as well. KL's characterization of the forecasting process suggests that analysts will start their analysis with a focus on setting-specific information (e.g., recent firm performance, the firm's presence in different markets, strategic growth plans presented by the firm's management, etc.).[3] To paraphrase KL, analysts will naturally 'bring to bear all they know' about the firm and its specific setting, emphasizing its unique aspects (KL, p. 26). However, analysts likely also have an array of reference-class information available (e.g., historical patterns of profitability of firms, growth differentials across industries, etc.). This broader distributional information can help them recalibrate initial estimates if they defy the odds of the relevant statistical patterns. To generate high quality, well-calibrated forecasts, analysts therefore need to balance their reliance on inside and outside view thinking. The analysis in KL and Sedor (2002) suggests that forecast setting *specificity* will affect the level of analysts' focus on statistical information in the forecasting process. Therefore, the extent to which analysts adopt both complementary views in their analysis and its effect on forecast properties are the empirical issues central to this paper.[4]

Different from Sedor and KL, my empirical setting uses archival data, similar to recent work on decision heuristics by Hirshleifer, Levi, Lourie and Teoh (2018), who highlight the importance of complementing experimental studies with archival data-based evidence. Specifically, I examine the empirical issues in a setting of sell-side analyst forecasts of sales growth for three main reasons. First, sales growth is a key metric in fundamental analysis (e.g., Curtis,

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[3] Kahneman and Tversky (1979) emphasize the role of intuition in all forecast settings, and following KL the psychology literature describes the inside view as a process of intuitive decision making (e.g., Hastie and Dawes, 2010).

[4] In a similar vein, Hirshleifer, Hsu and Li (2013) similarly refer to KL and the role of the inside vs. outside view in their study on *investors'* assessment of the innovative efficiency of firms. They describe how investors focus strongly on specific information about R&D efforts such as clinical trials, while they underappreciate statistical information about the historical performance of similar projects. While investors are firm-*outsiders* without a strong personal attachment to the R&D projects of firms, they tend to become overoptimistic about the prospects for success of these projects when they neglect unfavorable non-salient statistical information.

Lundholm, and McVay 2014). Further, recent work by Bradshaw, Lee, and Peterson (2016) concludes that market participants all behave as if sales (growth) forecasts are important. Analysts therefore will likely spend considerable effort and time forecasting this variable, creating a setting in which both cognitive processes potentially play a role. Second, Bradshaw et al. (2016) also find that revenue forecasts show much smaller associations with proxies for strategic analyst incentives than earnings forecasts. Therefore, a focus on sales growth forecasts better controls for these alternative influences on analyst behavior that have been shown to be important in other settings. Third, sales growth is characterized by a well-defined and well-known 'outside view' pattern, namely strong mean-reversion (Nissim and Penman 2001; Fairfield, Ramnath, and Yohn 2009). This final feature offers a twofold advantage: 1) it allows defining a statistically *bold* sales growth forecast as a forecast that 'ignores' the strong mean-reversion pattern in the distributional context of relevance; 2) analysts can easily retrieve the relevant statistical outside view information, allowing a direct test of their de-biasing efforts.

Exploiting the features of the empirical setting, I first examine if the occurrence of bold sales growth forecasts is associated with characteristics that highlight forecast setting specificity. Second, I examine if bold forecasts, when they occur, exhibit predictable deficiencies consistent with insufficient de-biasing by the analyst. I carry out my analyses in a sample of individual sell-side analyst sales growth forecasts over the period 2000-2015. To start, I define bold forecasts in reference to two relevant 'outside view' distributions: the time-series distribution of the firm's past sales growth realizations and the contemporaneous cross-sectional distribution of sales growth realizations of the firm's industry peers. In the spirit of KL, I use a statistical criterion to define bold forecasts: a forecast is bold if it falls in the outer *quartiles* of the mentioned reference distributions. I further classify bold forecasts into categories using two criteria. The first criterion is the reference distribution used to define the bold forecast (i.e., firm time-series vs. peer-group cross-sectional perspective); the second criterion considers the direction of the forecast (i.e., optimistic or pessimistic forecasts).[5] Descriptive analyses show that the distinct types of bold forecasts occur with different frequencies in the sample. Perhaps surprisingly, bold *pessimistic* time-series relative forecasts occur with the highest frequency, followed by both types of bold cross-sectional forecasts and bold optimistic time-series relative forecast. Forecasts that are bold from *both* a time-series and cross-sectional perspective occur with the lowest frequencies.

My first analysis shows a strong association between variables, such as momentum, turnover, revenue forecasting difficulty, intangibles, firm complexity or size, that highlight the specificity of the setting and the presence of bold forecasts (in the KL sense). Further, the direction of association varies with the type of bold forecast (pessimistic versus optimistic). Broadly speaking, the documented associations lend support to the conclusion in the behavioral literature that a sense of *perceived uniqueness* promotes reliance on an inside view and/or insufficient de-biasing (KL, Kahneman, Slovic, and Tversky, 1982). The results further highlight that the presence of management guidance on sales (growth) relates to the frequency of the time-series bold forecasts, suggesting that management guidance acts as an important input to the analysts' forecasting process, potentially affecting their de-biasing efforts.

Next, I address the question whether bold forecasts exhibit predictable deficiencies. While the discussion in KL emphasizes *bias* only, I follow the analyst literature and focus on two forecast properties, namely bias (signed forecast error) and inaccuracy (unsigned forecast errors) (Kothari, So, and Verdi 2016). Consistent with KL's analysis, the results show that bold forecasts are biased.

[5] While KL discuss mainly optimistic forecasting, they also highlight how overreliance on the inside view could also lead to unwarranted pessimism. They discuss unwarranted pessimism in the context of predictions made by parents of rebellious teenagers (KL, p. 27). See the discussion in Section 2.

They are too extreme relative to realized future sales growth: pessimistic (optimistic) bold forecasts exhibit a negative (positive) bias, ceteris paribus. Bold forecasts are also relatively *less* accurate, with one exception: bold time-series pessimistic forecasts are more accurate than other forecasts, all else equal. Further analysis finds that the presence of management guidance affects this result: in the presence of management guidance, bold pessimistic time-series forecasts exhibit no bias and are more accurate than other forecasts. This is consistent with Hutton, Lee, and Shu (2012), who show that management's information advantage over analysts resides at the *firm* level.

These base-line results are consistent with a role for the inside and outside view in the forecasting process of analysts. However, the archival setting of my analysis precludes me from reading the 'mindset' of analysts as they generate bold forecasts. Indeed, in addition to being guided by management forecasts, bold forecasts could be the result of strong *conviction* on the part of the analyst, rather than an underappreciation of the odds of the outcomes. In the latter case the analyst does not realize that the forecasts are statistically bold, while in the former case, the analyst does understand the low odds (i.e., *boldness*) of the outcomes but decides not to *de-bias* them. To distinguish between both possibilities, I examine the role of mean-reversion in the forecast setting. First, I assess how mean-reversion of sales growth relates to the occurrence of bold forecasts and find partial evidence that, e*x ante*, strong mean-reversion exhibits a *negative* association with the occurrence of bold forecasts. This is consistent with analysts considering the strength of mean-reversion when forecasting. Next, I find that *ex post* the extent of mean-reversion in the forecast setting exacerbates the bias of the majority of bold forecasts. This finding is consistent with analysts using the mean-reversion information insufficiently to de-bias bold forecasts. Therefore, while ex ante bold forecasts, at least partially, reflect analyst conviction, ex post their properties reflect insufficient reliance on the outside view to de-bias them.

In additional analyses, I relate my findings to the literature on analyst herding that has documented the properties of individual analyst forecasts that ‘stand out’ relative to consensus (e.g., Hong, Kubik, and Solomon 2000; Clement and Tse 2005; Evgeniou, Fang, Hogarth, and Karelaia 2013). In these analyses, I distinguish between forecast settings where the *median* consensus forecast is either statistically bold (i.e., analysts ‘herd to be bold’) or not. Given this distinction, the findings show that when median consensus is *not* bold, the properties of statistically bold *individual* analyst forecasts that ‘stand out’ from consensus are worse than the corresponding properties of the non-bold consensus forecasts. This last finding contrasts with Clement and Tse (2005) who show that forecasts that ‘stand out’ from consensus are of better quality. The evidence here suggests that the properties of bold individual analyst forecasts that ‘stand out’ relative to *both* the statistical and the consensus benchmark reflect insufficient de-biasing by the analyst.

My study contributes to the analyst literature in two ways. First, I contribute to the literature on analysts’ inefficient use of information by providing evidence on the role of the analysts’ cognitive process for forecasting. The findings complement recent work by Bradshaw et al. (2016), highlighting the importance of understanding the analyst’s cognitive process in the context of biased forecasts. Second, to my knowledge, my study is the first to extend direct evidence from experimental work on the role of the inside and outside view for sell-side analyst forecasting to an archival-empirical setting. Sedor (2002) first highlighted the role of the inside view and forecast setting specificity for the properties of analysts’ forecasts. Building on this work, Kadous, Krische and Sedor (2006) provide experimental evidence on the effectiveness of different approaches to de-bias scenario-induced analyst optimism. My findings in an archival setting are consistent with this experimental evidence on the analysts’ reliance on inside-view thinking, the role of specificity in the forecast setting, and the effectiveness of de-biasing efforts.

One important caveat of my research design is that my analyses cannot observe the cognitive process of the analysts. However, the design of the research setting allows concluding that the findings are consistent with the role of the cognitive processes studied. Specifically, my focus on sales growth forecasts offers the distinct advantage that, while important to analysts and investors, these are less affected by strategic analyst incentives (Bradshaw et al., 2016). Importantly, they also obey a well-known and easily retrievable statistical process, namely mean-reversion, that represents the relevant outside view process. This latter feature allows both an easy identification of statistically bold forecasts that appear consistent with the mechanism of the inside view, and an evaluation of de-biasing efforts by analysts in tests that control for time-invariant (unobserved) analyst and industry or firm characteristics.

Taken together, by showing how the inside and the outside view affect the generation and the properties of sell-side analysts' forecasts, I expand a literature that has already provided several explanations for analyst forecast deficiencies, including forecast complexity, analyst skills or experience and most prominently the analysts' response to strategic incentives (e.g., Bradshaw 2011; Kothari et al. 2016; Ramnath, Rock, and Shane 2008).

2. Prior Literature and Predictions

2.1 Forecasting and the Inside/Outside View

After its introduction by KL, the psychology literature adopted the distinction between the inside and outside view as part of the body of established knowledge in the context of judgment and decision making (e.g., Hastie and Dawes 2010). In addition, following the publication of KL, a vast body of academic work in economics, finance and accounting has referenced KL in the context of forecast settings that are distinct from the one in the original paper.[6] These papers often refer to the *potential* role or presence of the inside view in support of their predictions on forecast outcome properties. However, they typically do not explicitly test or document how the cognitive processes affect forecast outcomes in their empirical settings, partly because it is challenging to identify the outside view statistical process of relevance in the forecast setting.[7] My choice of empirical setting, as I describe in the next sections, helps overcome this empirical challenge to allow a more direct study of the inside and outside view in the setting of sell-side analyst forecasting.

2.2 Sell-Side Analysts and the Inside/Outside View

Immediately relevant to this study are papers in the analyst literature that reference KL's work, either to illustrate analysts' reliance on the specifics of the forecast setting or to show their underappreciation of statistical information. As discussed, the experimental work by Sedor (2002) and Kadous et al. (2006) documents the analysts' reliance on inside-view thinking, the role of specificity in the forecast setting, and the effectiveness of de-biasing efforts. In a similar vein, Michaely and Womack (1999) complement this experimental work with their archival-empirical study of analysts in the IPO process.[8] They observe that underwriter analysts are excessively bullish in their recommendations and propose as one explanation for their results that affiliated

[6] Papers that explicitly reference the inside/outside view include a focus on decisions and forecasts by investors (e.g., Bailey, Kumar, and Ng 2011; Hirshleifer et al. 2013), managers (Ahmed and Duellman 2013; Ittner and Michels 2017; Kato et al. 2009), entrepreneurs (e.g., Cassar 2010), venture capitalists (e.g., Benson and Ziedonis 2010), project managers (e.g., Flyvberg 2006), mutual fund managers (e.g., Willis 2001), employees (e.g., Spalt 2013), among others. In addition to referring explicitly to the distinction between the inside and outside view, several papers also refer to the cognitive biases of narrow framing or overconfidence that KL and others connect to the inside/outside view distinction (e.g., Camerer and Lovallo 1999).

[7] One exception in the entrepreneurship literature is Cassar (2010) who examines the rationality of the expectations of nascent entrepreneurs. He predicts and finds in a field study that those individuals who adopt an inside view to forecasting using plans and financial projections, will exhibit greater ex ante bias in their expectations and thus forecast more overly optimistic venture sales.

[8] In their study of IPO book-building activity, Degeorge, Derrien, and Womack (2007) reiterate Michaely and Womack's findings and discuss the role of KL's inside view in this context.

analysts, presumably since they have a stronger personal connection to the IPO, are more likely to adopt an inside view to formulate forecasts and recommendations while unaffiliated analysts will take an outside view.

The analyst literature also provides ample and comprehensive evidence on the analysts' underappreciation of 'statistical' or known information for forecasts. In his review, Bradshaw (2011) discusses and lists findings from papers, written since the early nineties, consistent with analysts being 'inefficient' with respect to known information. In recent work related to my study, Lundholm and Rogo (2016) show that analyst earnings forecasts are too volatile relative to the volatility of the underlying earnings variable. Like Michaely and Womack (1999), they suggest as one explanation for their findings the analysts' reliance on an inside view, which they describe as the analysts overweighting the specific details of the forecast at hand and underweighting baseline priors derived from previous forecasting exercises. In descriptive analyses, Lundholm and Rogo (2016) also present evidence of an association between certain analyst, broker and firm characteristics and excessively volatile earnings forecasts. They relate their findings to analysts' strategic behavior to differentiate themselves from each other, but they do not explore how they relate to the cognitive processes that analysts adopt in their analysis.

In sum, prior analyst literature shows that analyst forecasts are 'inefficient' in terms of their reliance on information. However, apart from the experimental work mentioned, the previous literature does not connect these findings to insights on the cognitive processes that guide the analysts' 'analysis' (the black box of analyst research) (Bradshaw 2011).[9] I describe next how and why the empirical setting in my study allows providing evidence on this connection.

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[9] The analyst literature has also provided archival-empirical evidence on related behavioral biases in analyst forecasts such as anchoring (e.g., Cen, Hilary and Wei, 2013). The psychology literature discusses how the inside/outside view are related to but distinct from the anchoring bias. It regards both views to be *processes* through which forecasters

2.3 Analyst Sales Growth Forecasts and Mean-Reversion

My study focuses on sell-side analyst forecasts of sales growth for several reasons. First, sales growth is a key metrics in fundamental analysis: any effort to value a firm based on fundamentals likely starts with a forecast of sales and sales growth (Curtis et al. 2014). Sales growth is also a crucial input to market participants' investment decisions as a prime indicator of firm growth: fundamental valuations connect sales growth to changes in profitability (via margins) and required investing (via asset turnovers) to sustain a growth trajectory for the firm (e.g., Fairfield et al. 2009). In support of these views, Bradshaw et al. (2016) conclude that managers, analysts and investors all behave as if sales (growth) forecasts are important, as witnessed by the increasing frequency of sales growth forecasts in recent years. This perceived importance of sales (growth) forecasts to market participants implies that analysts will likely devote considerable effort and time to forecasting sales (growth) and describing patterns of sales (growth) in their written research. Importantly, this level of effort implies that both cognitive processes will likely play a role in the analysis that generates the forecasts.

Second, sales growth is known to follow a strong pattern of mean-reversion (e.g., Fairfield et al. 2009; Nissim and Penman, 2001). This explicit *statistical* feature creates a forecast setting with an 'outside' view pattern that is well-known to financial markets and analysts. Further, the sales forecasting process in practice is typically guided by and discussed in terms of sales growth. The forecasting process is therefore strongly linked to the very metric that exhibits the reference-

establish anchors or baseline predictions. In other words, anchoring can occur as a function of an inside or outside view to forecasting. In this respect, Lovallo and Kahneman (2003) discuss the inside view as a process that leads to establishing optimistic anchors. In later work, Kahneman (2011) makes the point that, by drawing in distributional information on the forecast-attribute of relevance, the outside view amounts to reference-class forecasting to establish the correct baseline prediction, which he argues should be the anchor for further adjustments in forecasting (p. 248).

class characteristic of mean-reversion, implying that forecasters can easily retrieve this information for their analysis.[10]

Of course, sales growth is not the only firm performance attribute of relevance to the markets that exhibits mean-reversion. Freeman, Ohlson, and Penman (1982) and Fama and French (2000) show robust mean-reversion in firm profitability (return-on-assets or return-on-equity). However, several considerations suggest that my focus on sales growth allows me to better capture the cognitive process of analysts as they carry out their forecasting analysis. First, in practice, analysts do not always explicitly forecast profitability metrics. Rather, they forecast the components of the profitability metric separately. Second, the patterns of mean-reversion manifest themselves empirically much stronger for growth metrics than for profitability metrics (Fairfield et al., 2009; Nissim and Penman, 2001). Third, Fairfield et al. (2009) show different mean-reverting behavior of sales growth vis-à-vis profitability metrics: the former converges to an industry average whereas the latter converge to an economy-wide average. Since analyst coverage is typically organized by industry, I expect that if analysts want to incorporate an outside view in their analysis, they could do so more easily with sales growth.[11] Finally, the evidence in Bradshaw et al. (2016) show that revenue forecasts show much smaller associations with proxies for strategic analyst incentives than earnings forecasts. Therefore, a focus on sales growth forecasts better controls for these alternative influences on analyst behavior.

[10] My empirical analyses use machine-readable sales forecasts by sell-side analysts to construct sales *growth* forecasts. This is consistent with observed practice: analysts report pro-forma sales figures in their notes as they construct future pro-forma financial statements, but the *forecasting* of the pro-forma sales numbers is based on *growth* estimates. The discussion in the notes often centers around compound annual growth rates (CAGRs) of sales. See also the discussion in Curtis et al. (2014).

[11] Fairfield et al. (2009, p. 168) examine properties of Value Line forecasts of sales growth and conclude that the properties of these forecasts are consistent with analysts using industry information to forecast sales. Empirically, it is also the case that the patterns of mean-reversion manifest themselves much stronger for growth metrics than for profitability metrics (Fairfield et al., 2009; Nissim and Penman, 2001).

To summarize, the forecast metric of interest in this paper, sales growth, receives considerable analyst attention *and* follows a strong reference-class distribution that is known and in principle easily retrievable by the forecaster. Jointly, these qualities suggest that the empirical setting in this paper offers the opportunity to provide empirical evidence on the role of the inside and outside view in the analysts' 'analysis'.

2.4 Bold Forecasts and Predictions

After defining bold sales growth forecasts using a statistical criterion (see Section 3), my first analysis examines if features that highlight forecast setting specificity are associated with the occurrence of the bold forecasts. This first analysis follows from both KL's and Sedor's (2002) evidence on how the perceived uniqueness of the forecast setting affects the extent to which forecasters adopt an inside view and underappreciate the (low) odds of the bold outcomes they forecast. In a second analysis, I compare the properties of bold forecasts to those of non-bold forecasts. I predict that if bold forecasts exist because the analyst has underappreciated the statistical evidence on sales growth and thus has not sufficiently *de-biased* his/her forecasts, then bold forecasts will exhibit predictably worse bias than non-bold forecasts. As mentioned, the predictions from the KL framework only pertain to *bias*. However, since the analyst literature also focuses extensively on (in)accuracy of analyst forecasts, I complement the discussion on bias with descriptive evidence on the inaccuracy of bold forecasts without formulating specific predictions.

Next, I assess how the extent of mean-reversion affects the occurrence and the properties of bold forecasts as it could appear tautological that bold forecasts in the tails of the distribution also exhibit worse bias (and higher inaccuracy). The objective of this analysis is to gauge if an underappreciation of the odds of the outcomes, i.e., insufficient *de-biasing*, is the mechanism behind the bold forecasts. Analysts could generate bold sales growth forecasts for two reasons.

First, analysts could insufficiently use the outside view to de-bias their bold forecasts. This will happen if they do not *perceive* their forecasts to be bold since they have relied on an inside view to formulate them. I expect that in the absence of de-biasing efforts these bold forecasts will exhibit worse bias. Alternatively, analysts could formulate bold forecasts to express strong *conviction* (Lundholm and Rego 2016). In this case, analysts *do* understand the low odds of the outcomes but decide to go against the odds and *not* de-bias the forecasts. The properties of these bold forecasts will be a function of the calibration of the analyst forecast model, and this is an empirical issue.

The presence of strong mean-reversion in the forecast setting helps distinguish between both possibilities. Ex ante, if analysts consider the statistical 'outside view' when forecasting I expect a *negative* association between the extent of mean-reversion and the occurrence of bold forecasts. Ex post, if bold forecasts follow from an underappreciation of the odds as a function of mean-reversion in the setting, then I expect mean-reversion to *exacerbate* the bias in the bold forecasts. If the bold forecasts follow instead from analyst conviction (that considers the 'outside view'), then I expect no association between mean-reversion and bias in bold forecasts.

3. Research Design and Empirical Setting

3.1 Sample and Data

I collect my data from the I/B/E/S detail history file, the Compustat annual file, CRSP, the Chicago Board Options Exchange website, and the I/B/E/S guidance file. My main variable of interest is the annual sales forecast obtained per analyst/firm from the I/B/E/S detail history file. To obtain my sample I impose a number of data requirements. First, I restrict the sample to include *one-year* ahead forecasts only to ensure I obtain sufficient observations that satisfy my other data criteria (see below). Second, in each forecast period I select annual sales forecast made within 30 days after the prior-year earnings announcement. This ensures that the forecaster has had time to incorporate the prior-year information into his or her forecast, but also that the forecast horizon is still sufficiently long to present a forecasting challenge.[12] Third, I require that each firm-year forecast is represented by at least 5 observations in the sample, allowing the construction of 'consensus' forecasts for each firm-year forecast. Fourth, I require that each included firm-year observation can be matched with a historical Global Industry Classification Standard (GICS) industry code. I adopt this industry classification to be consistent with Fairfield et al. (2009).[13] I obtain historical GICS codes going back to 2000 and therefore I restrict the sample study period between 2000 and 2015 and also exclude observations from GICS 2-digit Sector 40 from the sample (Financials). Fifth, I use the Compustat annual file to calculate 'outside view' reference distribution statistics for each firm-year observation in the sample. I create time-series reference statistics for each firm-year observation based on 10 years of historical annual sales numbers *prior* to the forecast, requiring that at least 5 observations are available to compute the time-series reference statistics.[14] I compute cross-sectional reference statistics for each firm-year observation based on the contemporaneous annual sales information in the 6-digit GICS industry to which the firm-year belongs. I require that at least 20 observations are available to compute the cross-sectional reference statistics. Finally, I require data is available to compute the cross-sectional and control variables of interest for all observations (see below). These strict data-requirements tilt the sample towards large and mature firms that also enjoy an important analyst following. Therefore, while my predictions and analyses pertain to the population of firms at large, my evidence is based

[12] Bradshaw et al. (2016) discuss how forecast difficulty varies across the fiscal year.
[13] Research also shows that firms' growth measures have higher correlations with industry averages based on GICS than based on other classifications (Bhojraj, Lee, and Oler 2003). I base my 'outside view' reference statistics on the GICS classification to mimic the outside view that practitioners would consider.
[14] For example, to evaluate an annual forecast issued at the beginning of fiscal 2014, I compute the cross-sectional reference statistics based on GICS 6-digit annual observations in 2013. To compute the time-series statistics for the earlier years in the sample, I assume that the historical GICS classification remains stable between 1990 and 1999.

on a sample of a subset of firms. After imposing these data-restrictions, my remaining sample consists of 112,281 firm-year observations (1,994 firms, 6,303 analysts).

3.2 Characteristics of Sales Forecasts

My focus is on the one-year ahead sales growth forecasts (*SGFY1*) for each firm- analyst pair measured as (firm and analyst subscripts omitted):

$$SGFY1_{t+1} = \frac{Sales\ Forecast_{t+1}}{Sales_t} - 1$$

Here, $Sales\ Forecast_{t+1}$ is the estimate of one-year ahead sales forecasted at time t. Based on this forecast, I define forecast bias as follows:

$$Bias_t = \frac{Sales\ Forecast_{t+1}}{Sales_t} - \frac{Sales_{t+1}}{Sales_t} = SGFY1_{t+1} - SG_{t+1}$$

The second term in equation (2) is realized sales growth or SG_{t+1}. Finally, I define forecast inaccuracy as the absolute value of forecast bias, or:

$$Inaccuracy_t = Abs(Bias_t)$$

Table 1 reports descriptive statistics for these variables. Panel A shows that in the full sample, the average (median) realized sales growth (*SG*) is 9.8% (7.5%), with a standard deviation of 21.7%. These numbers are very comparable to the corresponding metrics reported by Fairfield et al. (2009) in their Table 2. Panel A further shows that one-year ahead sales growth forecasts closely track realizations: the average (median) one-year ahead consensus forecast (*SGFY1*) is 9.8% (7.7%) with a standard deviation of 17.2%. As a result, average (median) forecast (*BIAS*) is 0.0% (0.3%). However, the *BIAS* distribution shows a wide dispersion with a standard deviation of 13.4%. Finally, average (median) forecast inaccuracy (*INACCURACY*) is 8.7% (4.8%) with a standard deviation of 11.7%. In sum, panel A shows that revenue forecasts are generally quite accurate, consistent with the findings and discussion in Bradshaw et al. (2016). However, while the distribution of one-year ahead sales growth forecasts captures the central tendency of future realized sales growth well, the distribution exhibits sufficient variation to warrant a closer look at the features of the forecast setting associated with forecast bias and inaccuracy.

Table 1, Panel B shows the averages of the main variables of interest across sample years. The panel shows that 2001, 2008-2009, 2012 and 2015 exhibited severe drops in sales growth. By contrast, 2003 and 2010 marked strong recoveries relative to the previous year. Further, the panel shows that while sales growth forecasts *SGFY1* generally reflected subsequent realized sales growth *SG* well over the sample period, both *BIAS* and *INACCURACY* exhibit large variation across sample years. Analysts seemingly were taken by surprise in a number of years, resulting in large positive or negative *BIAS* and relatively large *INACCURACY* outcomes (e.g., 2000-2002, 2008, and 2015).

Finally, Table 1, Panel C shows that the averages of the main variables across GICS 2-digit sectors vary considerably pointing to different levels of forecast difficulty across sectors. The results in panels B and C of Table 1 suggest that both sample year and GICS sector have a strong influence on average forecast bias and inaccuracy.[15]

3.3 Bold Sales Growth Forecasts

Table 2 presents evidence on the frequency of bold forecasts in the sample. To distinguish between different types of bold forecasts, I define indicator variables as follows: 1) *TSLO* (*TSHI*) equals one if the sales growth forecast falls in the first (fourth) quartile of the time-series reference distribution, and zero otherwise; 2) *XSLO* (*XSHI*) equals one if the sales growth forecast falls in the first (fourth) quartile of the cross-sectional reference distribution, and zero otherwise; 3) *BOTHLO* (*BOTHHI*) equals one if the sales growth forecast falls in the first (fourth) quartile of both the time-series and cross-sectional reference distributions, and zero otherwise.

[15] The samples used in the main analyses include 60 6-digit GICS industries.

Panel A of Table 2 shows that *TSLO* and *TSHI* identify 37.8% and 10.1%, respectively, of forecasts as being bold relative to the time-series reference distributions in the full sample. Similarly, *XSLO* and *XSHI* identify 14.0% and 16.8%, respectively, of forecasts as bold relative to the cross-sectional reference distributions of forecasts. Finally, *BOTHLO* and *BOTHHI* identify 10.1% and 5.5%, respectively, of forecasts as bold relative to both reference distributions of forecasts. Forecasts are therefore more often bold and *low* relative to the time-series reference distributions, while they are more often bold and *high* relative to the cross-sectional reference distributions. Further, the time-series and cross-sectional reference distributions affect the frequency of bold optimistic and pessimistic forecasts differently.

Panel B shows a large variation in the frequency of bold forecasts across the sample period. One striking pattern relates to the frequency of low (i.e., pessimistic) forecasts in two specific sample years: 2001 and 2009. *TSLO* jumps to its highest values (70.6% and 72.3%, respectively) in these years, while *XSLO* reaches its highest value in 2009, namely 37.7%. In the same years, *TSHI* drops to its lowest values of 5.5% and 4.0%; the effect is less pronounced on *XSHI* though. The effects in 2001 and 2009 are similarly reflected in the patterns of *BOTHLO* and *BOTHHI*. The sample year of 2001 follows the peak of the markets in 2000 and comprises the events of September 11, 2001 while the forecasts in 2009 follow the financial crisis in the 4th quarter of 2008, respectively. In a similar vein, the pattern of results for 2010 suggests that analysts reversed their views on the outlook for sales growth and *TSHI*, *XSHI* and *BOTHHI* all show a marked increase relative to the previous year.

Panel C of Table 2 shows both a wide variation in the pattern of bold forecast variables across GICS sectors and a divergence between the time-series and cross-sectional indicator variables. Some sectors exhibit pronounced patterns of pessimistic forecasts (e.g., Energy (10)), while others tend to exhibit higher frequencies of optimistic forecasts (e.g., Materials (15)).

In sum, the patterns in Table 2 lead to two main observations. First, the time-series and cross-sectional reference distributions ('outside views') appear to identify distinct sets of bold forecasts. Second, the patterns show a large variation across sample years and GICS sectors. Overall, the sample exhibits a larger frequency of pessimistic forecasts relative to optimistic forecasts, perhaps highlighting the role of macro-economic shocks during the sample period.

3.4 Descriptive Statistics on Bold Forecast Properties

Table 3 shows descriptive statistics for bold forecasts and their bias and inaccuracy properties. Panel A.1 shows that *XSLO* identifies more negative pessimistic forecasts than *TSLO*: the respective means (medians) are -9.7% (-6.3%) and 1.1% (3.1%). Conversely, Panel A.2 shows that *TSHI* forecasts are on average slightly higher than their *XSHI* counterparts: means (medians) are 32.1% (24.4%) vs. 29.2% (22.5%) respectively. *BOTHLO* and *BOTHHI* identify the most extreme forecasts.

Panel B shows that the average bias (*BIAS*) for pessimistic bold forecasts in Panel B.1 is negative, although median bias is slightly positive. Panel B.2 shows that optimistic bold forecasts from a cross-sectional perspective (*XSHI*) exhibit average negative bias (i.e., they are on average too low) while *TSHI* and *BOTHHI* exhibit average *positive* bias, suggesting they are too high. The evidence in Panel B therefore does not unambiguously support the prediction that bold forecasts will exhibit strong directional forecast bias. The results in Panel C show that, except for *TSLO* forecasts, inaccuracy is worse in all subsamples of bold forecasts when compared to the total sample (i.e., average and median *INACCURACY* are higher than in the total sample).

In sum, the descriptive evidence in Table 3 points to differences in *BIAS* and *INACCURACY* for bold forecasts that, relative to the full sample, are largely consistent with the predictions. As these univariate analyses in Table 3 do not control for the large variation in bold forecasts across sample years and GICS sectors or potential cross-sectional forecast setting characteristics associated with bold forecasts, the next section addresses these issues.

4. Main Analyses

This section presents the main empirical results. First, I examine if specificity characteristics of forecast settings are associated with the occurrence of bold forecasts in a multivariate context. Next, I examine whether bold forecasts exhibit predictable forecast bias and inaccuracy differences relative to other forecasts. Third, I study the relation between mean-reversion in the forecast setting and both the occurrence of bold forecasts and their properties.

4.1 Forecast Setting Specificity and Bold Forecasts: Descriptive Evidence

The behavioral literature concludes that characteristics, such as complexity or uncertainty, lead to a perceived uniqueness of the setting that promotes the adoption of inside view thinking. In this first analysis, I identify variables to capture specificity characteristics and explore their association with the occurrence of bold forecasts. In the spirit of KL and Sedor (2002), I focus on characteristics that promote a view of the forecast setting as potentially non-generic or specific and steer the analyst's focus away from generic and known statistical patterns, in this case mean-reversion of sales growth. First, I include two proxies for market *attention* to the stock immediately preceding the forecasts. A first variable measures the 90-day stock return prior to the announcement date of the sales growth forecasts (*MOM90*). Next, I include *TURNOVER90*, the natural log of the 90-day share turnover prior to the measurement date of the consensus sales growth forecasts. While both variables measure the level of market attention to the stock, *MOM90* also captures the direction of this attention. I also include *VIX90*, the natural log of the 90-day average VIX prior to the announcement date of the sales growth forecasts, to captures the broad level market *uncertainty* immediately preceding the forecasts.[16] In recent work Loh and Stulz (2017) find that a higher level of market uncertainty contributes to the analysts putting more effort into their forecasting activities, thus potentially accentuating the specificity of the forecast setting.

Next, I include variables that measure forecasting complexity or *difficulty*. Increased forecasting difficulty could prompt analysts to gather and focus on more setting- and or firm-specific information as they generate their forecasts. I adopt a first proxy for revenue forecasting difficulty from Bradshaw et al. (2016) who measure predictability of revenues using firm-specific AR (1) regressions of revenues on lagged revenues over the prior six years. As per Bradshaw et al. (2016) I define revenue difficulty or *REVDIFF* as $1\text{-}R^2$ from these regressions. A second variable measures the presence of intangibles assets in the asset structure. Following Barth, Kasznik, and McNichols (2001), the literature interprets the presence of intangible assets as a proxy for the difficulty of the forecast setting: high intangible assets describe a setting with important firm-specific information that analysts can uncover. Therefore, high intangible asset intensity contributes to the specificity of the forecast setting for a given firm. I measure intangible asset intensity, or *INTAN*, as intangible assets scaled by total assets.

Third, I include an additional cross-sectional measure of the firm's operational *complexity*. Following, among others, Li (2008) and Muslu, Radhakrishnan, Subramanyan, and Lim (2015) I define metrics of operational complexity based on the number of reported segments and I include

[16] VIX stands for the daily volatility index calculated on the Standard & Poor's 100 options. This index is calculated by the Chicago Board Options Exchange (CBOE) and I obtain historical values for VIX from CBOE's website. Prior research has used VIX to gauge the level of macro-uncertainty in the US stockmarket (see Bloom (2009), among others).

the natural log of the number of business segments reported on Compustat, or *LNSEGMENT*.[17] Muslu et al. (2015) relate operational complexity to information asymmetry about the firm's prospects. *A priori* operating complexity, measured through the number of segments, could influence the difficulty of revenue forecasting and/or reliance on an 'inside view' of the firm in two ways. On the one hand, the complexity of the organization could make forecasting aggregate revenues for the firm more difficult. For example, the presence of intersegment dependencies could promote a perception of 'uniqueness' of the firm and thus a reliance on the 'inside view'. On the other hand, a large number of segments could help forecasting aggregate revenues if the segments represent 'pure-play' components of the firm that operate independently. This setting would encourage the use of reference class statistics for forecasting.

Fourth, I include the size of the firm as a proxy for the richness of the information setting: *SIZE* equals the natural log of actual sales of the firm, in line with the forecast attribute of interest. Again, *a priori*, the direction between *SIZE* and potential reliance on the 'inside view' is not clear. Forecasting revenues for larger firms in a richer information setting could emphasize the unique aspects of the firm's revenue pattern. By contrast, larger firms could also be perceived by analysts as obeying more stable distributions of fundamentals and this could enhance a focus on reference-class information (e.g., base rates).

In addition to the above variables aimed at capturing forecast setting specificity, I include a number of control variables in the specification. The next three variables capture additional features of the forecast setting with a potential influence on the analysts' forecasting behavior. A first variable relates to analyst incentives: *LOSSEPS* is an indicator variable that takes the value of 1 if the median consensus EPS forecast is negative, and 0 otherwise. I include *LOSSEPS* following

[17] I also define a variable capturing the number of geographical segments but similar to the results in Muslu et al. (2015) I find that this variable does not load in the equation.

Bradshaw et al. (2016) who argue that analysts will face a stronger incentive to issue optimistic revenue forecasts when they forecast a loss for the firm. Second, the analyst literature documents evidence consistent with anchoring by analysts (e.g., Cen, Hilary and Wei, 2013), leading me to include the most recent realization of sales growth (*PASTSG*), in the specifications.[18] While anchoring could be associated with bold forecasts, the psychology literature views anchoring and the inside/outside view as related but distinct, i.e., the inside/outside view are processes that help forecasters establish anchors (e.g., Lovallo and Kahneman, 2003). Finally, I control for the presence of management guidance on sales using *GUIDANCE*, an indicator variable that takes the value of one if management provided guidance on future sales during the last fiscal year, and zero otherwise. As mentioned, Sedor (2002) and Kadous et al. (2006) discusses how the presence and format of management forecasts affects how analysts map setting-specific information into their forecasts. Relatedly, Hutton et al. (2012) discuss how management appears to have a distinct firm-specific information advantage over analysts when it comes to forecasting. The presence of management guidance on sales therefore could relate to the frequency of bold forecasts if it prompts analysts to reduce debiasing efforts.

The final three variables control for additional forecast characteristics. *HORIZON* is the natural log of the number of days between the announcement date of the forecast and the fiscal year-end date of the next fiscal year (i.e., the forecast horizon). *CV_EST* is the coefficient of variation of all estimates that relate to the same firm-year as the individual forecast of interest (i.e., the standard deviation of the estimates scaled by their mean – winsorized at the 1^{st} and 99^{th} percentile). *NUM_EST* is the natural log of the number of estimates that relate to the same firm-year as the individual forecast of interest.

[18] The sample forecasts are issued shortly after the release of the previous year's realized sales growth, and so I control for this potential anchor in the specification.

Table 4 shows descriptive statistics for the cross-sectional variables of interest. The descriptive statistics on the sentiment variables shows that *MOM90* on average is positive (1.043) and *TURNOVER90* (raw value) is 12.962 on average (10.194 median). The average level of *VIX90* (raw value) during the sample period is 21, but the distribution shows that particular forecasts occurred when market uncertainty was considerable higher (p99=59). Average (median) *REVDIFF* of 0.352 (0.231) are comparable although slightly lower than corresponding numbers in Bradshaw et al. (2016). The table shows considerable variation in *REVDIFF* across the sample though. Similarly, the other variables measuring forecast difficulty exhibit large variation across observations (*INTAN* and *LNSEGM*). The distribution of *SIZE* (lagged sales) suggests the sample includes a wide range of firms on this dimension with average sales of $10.003bn and with a standard deviation of $24.667bn.

The table further shows that analysts forecast an earnings loss (*LOSSEPS*) for 7.6% of observations. *PASTSG* exhibits characteristics similar to those reported for *SG* in Table 1, albeit with a mean (12.5%) and median (9.1%) slightly above the values for *SG*. Firm management provided sales (growth) guidance (*GUIDANCE*) for 58.0% of the observations. In terms of additional forecast characteristics, the table shows that the average *HORIZON* in days is 322 days; the average (median) coefficient of variation of individual estimates is 0.177 (0.154); and the average number of estimates related to each observation is 14, with a p1-value of 5 (by design) and a p99-value of 41.

4.2 Forecast Setting Specificity and Bold Forecasts

To document the association between forecast setting specificity and bold forecasts, I estimate the following regression (time, firm, analyst-subscripts omitted)[19]:

[19] I estimate relation (1) using OLS to avoid the so-called incidental parameter problem (e.g., Lancaster 2000). Results based on logit estimation of relation (1) are qualitatively similar to the results reported.

$$Bold\ Forecast\ Variable = \alpha_0 + \alpha_1\ YEAR + \alpha_2\ GICS + \alpha_3\ ANALYST + \beta_1\ MOM90$$
$$+ \beta_2\ TURNOVER90 + \beta_3\ VIX90 + \beta_4\ REVDIFF + \beta_5\ INTAN + \beta_6\ LNSEGM + \beta_7\ SIZE$$
$$+ \beta_8\ LOSSEPS + \beta_9\ PASTSG + + \beta_{10}\ GUIDANCE + \beta_{11}\ TIMING + \beta_{12}\ CV\_EST + \beta_{13}\ NUM\_EST + \mathcal{E}\ (1)$$

Bold Forecast Variable stands for each of the earlier defined bold forecast variables, i.e., *TSLO*, *XSLO*, *BOTHLO*, *TSHI*, *XSHI* or *BOTHHI*. *YEAR*, *GICS*, and *ANALYST* are indicator variables to capture sample year, industry, analyst-fixed effects. I include the latter two types of fixed effects to control for time-invariant industry and analyst characteristics to isolate better the role of *specificity* characteristics at the time of the bold forecasts. All other variables are listed in Appendix A. I also double-cluster the coefficient standard errors by firm and by year.

The results in Table 5 lead to several observations. First, the coefficients on the *attention* variables *MOM90* and *TURNOVER90* are significant across the majority of specifications. When significant, the coefficients on *TURNOVER90* are positive consistent with attention being associated with bold forecasts; the coefficients on *MOM90* switch sign across pessimistic and optimistic bold forecast specifications, consistent with this variable also reflecting the direction of the attention: positive stock price momentum is associated with a lower (higher) frequency of pessimistic (optimistic) bold forecasts. The coefficients on *VIX90* are mostly not significant suggesting that macro-uncertainty does not relate to the occurrence of bold forecasts.

The coefficients on the *difficulty* variables *REVDIFF* and *INTAN* are also significant in most specifications. The signs of the coeffocient on *REVDIFF* switch across the type and direction of bold forecasts but overall *REVDIFF* appears to exhibit a stronger relation with time-series bold forecasts, consistent with its measurement being firm-specific. Further, in most cases, the coefficient on *INTAN* is positive, consistent with a higher presence of *INTAN* indicating a stronger specificity in the forecast setting. The coefficients on *LNSEGM* load more strongly in the time-series bold forecast specifications then the cross-sectional specifications. Across specifications, higher firm *complexity* is associated with more optimistic forecasting. Finally, the coefficients on *SIZE* are significant in all specification and also switch sign across pessimistic and optimistic bold forecast specifications: *SIZE* is associated with more (fewer) pessimistic (optimistic) forecasts.

Focusing on the controls, both *LOSSEPS* and *PASTSG* obtain significant coefficients across most of the specifications. When significant, the coefficients on *LOSSEPS* are positive, regardless of the type of bold forecasts. While this variable controls for analysts' incentives to produce optimistic revenue forecasts, following Bradshaw et al. (2016), this result is also consistent with Sedor's (2002) finding that losses emphasize the specificity of the forecast setting and promote inside view thinking and the presence of bold forecasts. The coefficients on *PASTSG* exhibit two patterns consistent with analyst anchoring. First, the coefficients switch sign between specifications with the sign of the coefficients being negative (positive) for pessimistic (optimistic) bold forecasts specifications. Second, *PASTSG* appears more strongly associated with time-series than cross-sectional bold forecasts. Finally, *GUIDANCE* relates to time-series related forecasts only and exhibits a changing sign across specifications: the negative (positive) sign in relation to *TSHI* (*TSLO*) suggests that management guidance is associated with *lower* forecast outcomes.

The 'technical' characteristics of the forecasts (*HORIZON*, *CV_EST*, and *NUM_EST*) are not consistently related to the bold forecast frequencies across equations. Finally, the results for *BOTHLO* and *BOTHHI* typically reflect the average characteristics of the results for the separate time-series and cross-sectional bold forecasts. Taken together, the results in Table 5 therefore suggest that an association exists between (most) specificity variables and the frequency of bold forecasts, with the nature of the relation varying across variables and specifications.[20]

[20] In untabulated analysis, I re-estimate eq. (1) with *firm* fixed effects included instead of industry effects. The results remain qualitatively similar with one notable change: the coefficient on *GUIDANCE* is no longer significant in the *TSLO* specification.

4.3 Ex Post Properties of Bold Forecasts

The previous section shows an association between many specificity characteristics and the presence of bold forecasts. If this association exists because analysts have insufficiently *de-biased* their (initial) forecasts, then I predict that bold forecasts will exhibit worse properties than non-bold forecasts. I examine this prediction formally by estimating the following regression models (firm-, time-, and analyst-subscripts omitted):

$$BIAS \text{ or } INACCURACY = \alpha_0 + \text{FIXED EFFECTS} + \boldsymbol{\beta_1\, TSLO + \beta_2\, XSLO} + CONTROLS + \mathcal{E} \qquad (2a)$$
$$BIAS \text{ or } INACCURACY = \alpha_0 + \text{FIXED EFFECTS} + \boldsymbol{\beta_1\, BOTHLO} + CONTROLS + \mathcal{E} \qquad (2b)$$

$$BIAS \text{ or } INACCURACY = \alpha_0 + \text{FIXED EFFECTS} + \boldsymbol{\beta_1\, TSHI + \beta_2\, XSHI} + CONTROLS + \mathcal{E} \qquad (3a)$$
$$BIAS \text{ or } INACCURACY = \alpha_0 + \text{FIXED EFFECTS} + \boldsymbol{\beta_1\, BOTHHI} + CONTROLS + \mathcal{E} \qquad (3b)$$

I include the specificity and other variables discussed earlier (listed in Appendix A) as controls in each equation, as they have been associated with bias and inaccuracy in the literature, and I include year-, firm-, and analyst fixed-effects. I include the latter to control for time-invariant firm and analyst characteristics that could affect forecast properties. Also, by including the setting characteristics from eq. (1) in the models, the coefficients on the bold forecast variables capture the *incremental* effects of the cognitive processes that have generated them, rather than reflect the effects these setting characteristics have on the forecast properties.

Table 6, Panel A shows the results for *BIAS*. As a reference point, column (1) in the panel shows the results for a base model that includes only the setting variables and fixed effects. Several of the cross-sectional setting variables are associated with *BIAS*, but not all in the same direction. Recent stock-specific momentum *MOM90* is negatively associated with *BIAS* (i.e., forecasts are too low), whereas *TURNOVER90* and *VIX90* are positively associated: market attention to the stock and high market uncertainty map into forecasts that are too high. Forecast difficulty (*REVDIFF*) and firm size (*SIZE*) also map into higher bias. The coefficients on all control variables stay qualitatively similar across most other specifications in the panel.

Focusing on the pessimistic bold forecasts, columns (2) and (3) show negative and statistically significant coefficients on the bold forecast variables. By contrast, the coefficients on the bold forecast variables in specifications (4) and (5) are all positive and statistically significant. In other words, the evidence suggests that bold pessimistic (optimistic) forecasts are too low (high), as predicted. The evidence on the relation between *BIAS* and the presence of bold forecasts here is stronger than the initial descriptive evidence presented in Table 3. The findings also speak to the discussion in KL that *both* pessimistic and optimistic bold forecasts exhibit *BIAS* (see fn. 5).

While I formulate no prediction on the accuracy of bold forecasts, Panel B presents the descriptive results on *INACCURACY*. The base line model in column (1) shows that several cross-sectional variables are associated with inaccuracy. *MOM90, TURNOVER90, LOSSEPS,* and *HORIZON* all obtain positive coefficients consistent with higher inaccuracy. By contrast, *VIX90, REVDIFF, INTAN,* and *SIZE* map into lower inaccuracy via negative coefficients. Focusing on the bold forecast variables, the results across specifications (2) through (5) generally point to relatively *worse* inaccuracy for bold forecasts (positive coefficients). One exception is the *negative* coefficient on *TSLO* in specification (2), suggesting that *TSLO* forecasts are more accurate than other forecasts, all else equal. While surprising, this finding is consistent with the earlier descriptive evidence in Table 3, Panel C.

I explore this result further in untabulated analyses. I estimate eq. (2a) in subsamples based on whether management provided guidance or not. I focus on *GUIDANCE* since Table 5 shows a significant positive association between *GUIDANCE* and *TSLO*. The estimations highlight the role of management guidance in relation to *TSLO* forecasts. In the *BIAS* specification, the coefficient on *TSLO* attenuates substantially and becomes insignificant when management provides guidance. By contrast, the coefficient is more negative and highly significant in the absence of guidance (-

0.028, t=-6.03). The *INACCURACY* specification shows a coefficient on *TSLO* that is (more) negative and highly significant (-0.009, t=-3.26) in the subsample of firms with guidance and insignificant for firms without guidance. In other words, *TSLO* forecasts issued in the presence of management guidance are *less* biased and *more* accurate than other forecasts.[21]

Taken together, the results in Table 6 are consistent with the prediction that bold forecasts exhibit stronger bias. They further show that bold forecasts generally exhibit larger inaccuracy relative to other forecasts.

4.4 The Role of Mean-Reversion in the Forecast Setting

From a cognitive standpoint, bold forecasts could result from either the analysts' underappreciation of the odds of the outcomes or their strong *conviction*. To distinguish between both possibilities I explore next the role of mean-reversion in the forecast setting. In the tests that follow, I rely on a measure of the extent of mean-reversion of sales growth that I define and discuss in Appendix B.

4.4.1 Mean-Reversion and Bold Forecasts

To examine if the extent of mean-reversion is associated with the occurrence of bold forecasts, I augment equation (1) to include a variable capturing the historical degree of mean-reversion of sales growth in the 6-digit GICS industry to which the observation belongs (*HIMR*):

$$\textit{Bold Forecast Variable} = \alpha_0 + \alpha_1\, \textit{YEAR} + \alpha_2\, \textit{GICS} + \alpha_2\, \textit{ANALYST} + \boldsymbol{\beta_1}\, \textbf{\textit{HIMR}} + \textit{Controls} + \mathcal{E} \qquad (4)$$

As before, *Bold Forecast Variable* stands for each of the earlier defined bold forecast variables, i.e., *TSLO*, *XSLO*, *BOTHLO*, *TSHI*, *XSHI* or *BOTHHI*. *HIMR* is an indicator variable that captures the degree of one-year mean-reversion in sales growth. *HIMR* takes the value of 1 if

[21] I similarly examine the properties of *TSHI* forecasts in the two guidance-based subsamples. The findings show that the coefficients on *TSHI* attentuate in the guidance subsample and strengthen in the non-guidance subsample; however, the result showing higher *BIAS* and higher *INACCURACY* remains present.

the firm-year observation belongs to a GICS industry in the top 30% of the annual GICS industry mean-reversion distribution (thus exhibiting strong 1-year horizon mean-reversion in the year preceding the observation), and zero otherwise. Appendix B discusses the calculation of the GICS-industry mean-reversion measure and presents descriptive statistics. All other variables are listed in Appendix A. The standard errors are double-clustered by firm and by year.[22]

Table 7 shows descriptive statistics on the frequency of bold forecasts as a function of *HIMR* in Panel A and the results of estimating equation (4) across the different specifications in Panel B. Panel A shows that in most cases the frequency of bold forecasts is *lower* in the *HIMR* subsample. The exception is *XSHI* and also *BOTHHI.* Panel B provides evidence corroborating this pattern. While the coefficients in the *TSLO* and *BOTHHI* specifications are not significant in this multivariate setting, the negative and significant coefficients in the *XSLO*, *BOTHLO*, and *TSHI* specifications suggest that a high degree of recent historic mean-reversion is associated with a *lower* occurrence of these bold forecasts. In Panel B, the coefficient in the *XSHI* specification is *positive* and significant, consistent with the frequency result in Panel A. It seems therefore that the association between mean-reversion and the occurrence of *XSHI* differs from the other variables.[23]

Taken together, the results in Table 7 provide partial evidence that the degree of mean-reversion is associated with the occurrence of bold forecasts. The negative and significant coefficients are consistent with analysts acknowledging mean-reversion in the forecast setting. By extension, the result also implies that bold forecasts could reflect analyst conviction, consistent

[22] The sample size in these analyses drops by 1,311 observations that do not satisfy the data-requirements for the mean-reversion metrics.

[23] The result for *XSHI* could point to a mechanical effect where stronger cross-sectional mean-reversion is naturally associated with a higher frequency of optimistic bold forecast. However, the same effect would likely play a role for the occurrence of *XSLO.* When I re-estimate this regression using a stricter definition of bold forecasts based on the *deciles* of the reference distributions, the significant coefficient on *HIMR* becomes insignificant, while the other results do not change.

with the conjecture in Lundholm and Rogo (2016) that analysts forecast bold outcomes to differentiate themselves from the other analysts.

4.4.2 Mean-Reversion and the Ex Post Properties of Bold Forecasts

To examine how the degree of mean-reversion affects the properties of bold forecasts, I expand regressions (2a) through (3b) to include the earlier defined *HIMR* and interactions between the bold forecast variables with this metric of mean-reversion:

$$BIAS\ or\ INACCURACY = \alpha_0 + FIXED\ EFFECTS + \boldsymbol{\beta_1\, TSLO + \beta_2\, TSLO{*}HIMR + \beta_3\, XSLO} \\ \boldsymbol{+ \beta_4\, XSLO{*}HIMR + \beta_5\, HIMR} + CONTROLS + \mathcal{E} \tag{5a}$$

$$BIAS\ or\ INACCURACY = \alpha_0 + FIXED\ EFFECTS + \boldsymbol{\beta_1\, BOTHLO} + \boldsymbol{\beta_2\, BOTHLO{*}HIMR} \\ \boldsymbol{+ \beta_3\, HIMR} + CONTROLS + \mathcal{E} \tag{5b}$$

$$BIAS\ or\ INACCURACY = \alpha_0 + FIXED\ EFFECTS + \boldsymbol{\beta_1\, TSHI + \beta_2\, TSHI{*}HIMR + \beta_3\, XSHI} \\ \boldsymbol{+ \beta_4\, XSHI{*}HIMR + \beta_5\, HIMR} + CONTROLS + \mathcal{E} \tag{6a}$$

$$BIAS\ or\ INACCURACY = \alpha_0 + FIXED\ EFFECTS + \boldsymbol{\beta_1\, BOTHHI} + \boldsymbol{\beta_2\, BOTHHI{*}HIMR} \\ \boldsymbol{+ \beta_3\, HIMR} + CONTROLS + \mathcal{E} \tag{6b}$$

All variables are as defined before and listed in Appendix A. If strong mean-reversion affects the degree of *BIAS* and *INACCURACY* of bold forecasts, I expect the coefficients on the interactive variables to be significant. The specifications also include year-, firm-, and analyst-fixed effects as before and standard errors are double-clustered by firm and by year.

Table 8 presents the results of this analysis and is organized in the same way as Table 6. Focusing on *BIAS* in Panel A, column (1) shows a base model that does not include the bold forecast variables and finds that the coefficient on *HIMR* is not statistically significant in the presence of the other controls and fixed effects. Therefore, stronger mean-reversion by itself does not relate to the magnitude of *BIAS* in any particular direction. The specifications in columns (2) through (5) however show that strong mean-reversion exacerbates *BIAS* in *all* bold forecasts, except *TSLO* and *XSHI* forecasts. Untabulated analyses again show that management guidance relates to the specific case of *TSLO*: *TSLO* forecasts in the absence of guidance exhibit a negative coefficient on *TSLO*HIMR* (-0.018, t-stat -1.92) whereas this is not the case for *TSLO* forecast issued when management provided guidance (-0.005, t-stat -0.83). The result for *XSHI* underlines the different association between this variable and the extent of mean-reversion shown in Table 7.

Next, Column (1) in Panel B shows that strong mean-reversion by itself also does not relate to forecast *INACCURACY* in the presence of controls and fixed effects. The results across columns (2) through (5) also do not show a clear pattern between the extent of mean-reversion and the inaccuracy of forecasts. The results exhibit significant positive coefficients on the interactions of mean-reversion with *TSHI* and *BOTHHI* only.[24] Panel B therefore finds only partial evidence on the effect of mean-reversion on *INACCURACY*.

The main take-away from Table 8 is that strong mean-reversion is related to an exacerbation of the *BIAS* of most bold forecasts, consistent with the predictions and the findings by KL in their setting. Analysts appear to ignore reference-class information and insufficiently de-bias their bold forecasts. This pattern again applies to both optimistic and pessimistic forecasts, illustrating how analysts underappreciate the low odds of these bold forecasts, regardless of their direction.[25]

5. Additional and Robustness Analyses

5.1 Herding and Bold Forecasts

[24] Management guidance in this case does not affect the *TSLO* result: mean-reversion does not affect the accuracy of *TSLO* forecasts in either of the management guidance subsamples.

[25] I carry out additional analyses using different variables to measure *HIMR* to verify the robustness of the results. First, I re-define *HIMR* using a measure of mean-reversion that considers a 3-year horizon rather than just the most recent year. The analyses using this longer-horizon metric of mean-reversion generally show weaker results than those reported in Table 8. In other words, the effects of mean-reversion relate to the properties of bold forecasts most prominently when mean-reversion is strong over the short 1-year horizon. This is not surprising for two reasons: 1) the main variable of interest, sales growth, focuses on the one-year horizon; 2) the largest portion of the mean-reversion of sales growth occurs in the first year (see Appendix B Figures 1-3). Second, I redefine *HIMR* using the *median* of the overall GICS-industry mean-reversion distribution in the full sample (as opposed to the annual GICS distribution of mean-reversion metrics). This definition classifies a larger portion of observations as *HIMR*. The original definition classifies 37% of firm-year observations as *HIMR* because not all GICS sectors and industries are equally represented in the sample. Naturally, the median definition classifies 50% as *HIMR*. Using this metric, I find results that, while qualitatively similar, are substantially weaker than those reported in Table 8.

The literature on analyst herding defines *bold* forecasts as forecasts that make the analyst 'stand out from the crowd', i.e., forecasts that are distinct from consensus (e.g., Hong et al., 2003; Clement and Tse 2005; Evgeniou et al., 2013). Since I adopt a definition of bold forecasts based on a statistical criterion related to a reference-class distribution, the two approaches to defining bold forecasts are not mutually exclusive. To understand their relation, I distinguish between settings where the median 'consensus' estimate of sales growth is statistically bold (i.e., analysts 'herd to be bold') or not.

Table 9 evaluate the properties of both types of statistically bold forecasts. In Panel A, *HERD* identifies individual analyst bold forecasts issued when the median forecast is also statistically bold while *NOHERD* identifies the other category. The results show that within each category of bold forecast the proportion of *NOHERD* forecasts varies, going from 9.3% for *TSLO* and 22.7% for *BOTHHI*. The panel further shows that within each category there is a higher proportion of management guidance when the median consensus forecast is bold (*HERD*) than when it is not. Management guidance therefore relates to 'herding' behavior but does not preclude the issuance of bold forecasts that 'stand out from the crowd'. Importantly, the panel shows that the properties of the bold forecasts differ substantially: *NOHERD* bold forecasts exhibit substantially stronger *BIAS* and higher *INACCURACY* than *HERD* bold forecasts. In other words, when group-think drives the bold forecasts, they are of higher quality than when the analysts issue bold forecasts that stand out.

Panel B examines the pattern of *BIAS* and *INACCURACY* findings in a multivariate context. The Panel shows the results of estimations of augmented version of eq. (2a) through (3b) that include indicator variables with suffix *_NOHERD* to identify bold forecasts issued by individual analysts at a time when median consensus forecasts are *not* statistically bold. With one exception, all results corroborate the earlier findings of Panel A: the coefficients on the *NOHERD* indicator variables point to increased *BIAS* and higher *INACCURACY* for these forecasts relative to the *HERD* category of bold forecasts.[26] Finally, to complement this evidence, in Panel C I focus on subsamples that only contain *NOHERD* forecasts to show that in these subsamples the *BIAS* and *INACCURACY* of individual *NOHERD* forecasts is always worse compared to median consensus forecasts.

Taken together, the findings in Table 9 show that when median consensus is *not* bold, the properties of statistically bold *individual* analyst forecasts that 'stand out' from median consensus are worse than the corresponding properties of the non-bold consensus forecasts. This pattern contrasts with the findings in Clement and Tse (2005) who show that forecasts that 'stand out' from consensus are of better quality. However, Clement and Tse (2005) focus on a different forecast metric, earnings per share, and do not consider a statistical reference-class benchmark to evaluate bold forecasts.[27] The evidence here extends their findings by showing that when analysts issue forecasts that are distant relative to *both* a statistical and a consensus benchmark, they exhibit worse properties than other forecasts, ceteris paribus.

5.2 Robustness Analysis Using Decile-Based Bold Forecasts

I re-estimate the main set of analyses adopting a stricter definition of bold forecasts based on the *deciles* of the reference distributions. These untabulated analyses broadly show, that while the base-line results remain similar or even become stronger, the mean-reversion results weaken. This pattern of results could reflect either a power issue or the fact that the stricter bold forecasts

[26] The one exception is the coefficient on *XSHI_NOHERD* that obtains a t-stat of 1.53 in Panel B.2.
[27] The forecast attribute (earnings per share) in Clement and Tse (2005) does not lend itself well to an inside vs. outside view categorization. Clearly, market participants will benchmark EPS forecasts against prior EPS realizations. However, there is no *unique* statistical process, like mean-reversion, that can guide forecasting of EPS in a time-series and cross-sectional context. Despite this fact, research has examined the relative performance of time-series random walk forecasts versus analyst forecasts of EPS and finds that the latter do not necessarily dominate (e.g., Bradshaw, Drake, Myers, and Myers 2012).

are the result of stronger conviction by the analysts, rather than an underappreciation of mean-reversion in the setting. *Ex post*, this stronger conviction does appear misguided as the base-line results overall point to stronger bias and higher inaccuracy of these forecasts.

6. Conclusion

Using a setting of sell-side analyst forecasts of sales growth, this paper shows how two complementary *cognitive processes* adopted by sell-side analysts – the inside and the outside view – relate to the generation and the properties of their forecasts. These cognitive processes describe how forecasters draw on different sources of information and apply different rules to the use of information for forecasting. The paper shows how characteristics of forecast setting specificity are associated with (statistically) bold forecasts, suggesting that they reflect an (over-)reliance by analysts on the specifics of the forecast setting (i.e., an inside view) or an underappreciation of statistical information pertinent to the forecast setting (i.e., insufficient de-biasing using an outside view). In support of this interpretation, the next set of findings shows that bold forecasts are predictably biased and that the extent of mean-reversion of sales growth, i.e., the relevant outside view, in most cases exacerbates this bias.

In sum, the paper draws the attention to the relative weight that analysts put on information sources as they carry out their analysis, even when this involves 'routine' forecasting. This observation resonates with recent findings that show how analysts approach their forecasting task differently in good versus bad times (e.g., Amiram, Landsman, Owen, and Stubben 2017; Bochkay and Joos 2018; Loh and Stulz 2017). A further exploration of the role of cognitive processes in forecasting can therefore offer a promising route for future research to complement earlier findings on analyst forecast behavior and analyst forecast properties. An understanding of the role of cognitive processes can also guide the implementation of forecasting approaches in practical settings. For example, the combination of the inside/outside view mechanism of forecasting can provide a needed feedback loop when the forecast attributes (e.g., fundamental risk – see Joos, Piotroski, and Srinivasan 2016), or forecast settings (e.g., valuing ‘unicorn’ *fintech* companies) call for a *thinking-in-scenarios* approach to forecasting. While thinking-in-scenarios is a powerful tool to tackle these difficult forecast challenges, it is particularly susceptible to over-reliance on the inside view (Sedor 2002); as a consequence, this is where the outside view can provide the necessary input ‘to avoid the snares of scenario thinking’ (e.g., Hastie and Dawes, 2010; KL 1993; Chapter 23 in Kahneman, 2011; Tetlock, 2005; Tetlock and Gardner, 2015).

Appendix A
Variable Definitions

Variable	Definition	Data Source
SG	One-year ahead sales growth, measured as ($Sales_{t+1}$ / $Sales_t$ – 1)	Compustat
SGFY1	One-year ahead median consensus sales growth, measured as (Median Sales $Forecast_{t+1}$/ $Sales_t$ – 1)	I/B/E/S
BIAS	Forecast bias, measured as *SGFY1 – SG*	I/B/E/S, Compustat
INACCURACY	Forecast inaccuracy, measured as the absolute value of *BIAS*	I/B/E/S, Compustat
TSLO	Indicator variable to denote a low bold forecast from a time-series perspective: equals one if *SGFY1* falls in the first quartile of the time-series distribution of the firm's past sales growth realizations, and zero otherwise.	I/B/E/S, Compustat
TSHI	Indicator variable to denote a high bold forecast from a time-series perspective: equals one if *SGFY1* falls in the fourth quartile of the time-series distribution of the firm's past sales growth realizations, and zero otherwise.	I/B/E/S, Compustat
XSLO	Indicator variable to denote a low bold forecast from a cross-sectional perspective: equals one if *SGFY1* falls in the first quartile of the 6-digit GICS cross-sectional distribution of contemporaneous sales growth realizations, and zero otherwise.	I/B/E/S, Compustat
XSHI	Indicator variable to denote a high bold forecast from a cross-sectional perspective: equals one if *SGFY1* falls in the fourth quartile of the 6-digit GICS cross-sectional distribution of contemporaneous sales growth realizations, and zero otherwise.	I/B/E/S, Compustat
BOTHLO	Indicator variable equaling one if *TSLO=1* and *XSLO=1*, zero otherwise	I/B/E/S, Compustat
BOTHHI	Indicator variable equaling one if *TSHI=1* and *XSHI=1*, zero otherwise	I/B/E/S, Compustat
IQR	Measure based on the annual ranking by 6-digit GICS code of sales growth observations in deciles. I compute median sales growth by decile in the year of decile formation and the years following. *IQR* is the interquartile range of decile medians of sales growth in the year of decile formation and the years thereafter	Compustat
IQRRAT'l'	Measure of mean-reversion derived from an annual ranking by 6-digit GICS code of sales growth observations in deciles. I compute the median sales growth by decile in the year of decile formation and the years following. *IQRRAT'l'* is the ratio of the interquartile range of decile medians of sales growth in year 'l' scaled by the interquartile range of decile medians in the year of decile formation	Compustat
HERD	Indicator variable equaling one if the individual analyst forecast is bold and the median consensus forecasts is also bold in a given forecast period, zero otherwise	I/B/E/S, Compustat
HIMR	Indicator variable equaling one if the firm belongs to a GICS industry in the top 30% of the annual GICS industry mean-reversion distribution, zero otherwise	Compustat
MOM90	90-day firm-specific stock return prior to the forecast measurement date	CRSP
NOHERD	Indicator variable equaling one if the individual analyst forecast is bold and the median consensus forecasts is not bold in a given forecast period, zero otherwise	I/B/E/S, Compustat
TURNOVER90	Natural log of the 90-day firm-specific share turnover prior to the forecast measurement date	CRSP
VIX90	Natural log of the 90-day average VIX index level prior to the forecast measurement date	CBOE
REVDIFF	$1- R^2$ where R^2 is the r-squared of firm-specific AR(1) regressions of revenues on lagged revenues over the prior six years (see Bradshaw et al.,2016)	Compustat
INTAN	Intangible Assets scaled by Total Assets	Compustat
LNSEGM	Natural log of the number of reported business segments	Compustat
SIZE	Natural log of the firm's sales as of the forecast measurement date	Compustat
LOSSEPS	Indicator variable that takes on the value of 1 if median consensus EPS forecast is negative, and zero otherwise	I/B/E/S
HORIZON	Natural log of the number of days between the forecast date and the fiscal year-end	I/B/E/S
CV_EST	Coefficient of variation of all estimates in a given annual forecast period	I/B/E/S
NUM_EST	Natural log of the number of estimates that make up the consensus sales forecast	I/B/E/S
GUIDANCE	Indicator variable equaling one if the firm provided guidance on sales forecasts in the previous fiscal year, and zero otherwise	I/B/E/S
PASTSG	Most recent sales growth realization	Compustat

Appendix B
Descriptive Evidence on Sales Growth Mean-Reversion in the Sample

The starting point and underlying assumption in this paper is that strong mean-reversion is the relevant statistical outside view process that describes sales growth. Previous research by Nissim and Penman (2001) documents the existence of this strong mean-reversion pattern in sales growth on an economy-level (Fig. 6 (a) on p. 145). In this Appendix, I replicate the analysis in Nissim and Penman (2001) and construct a similar fade-diagram to illustrate that strong mean-reversion pattern describes the statistical process of sales growth for my entire sample over the study period (Figure B.1). Fairfield et al. (2009) extend Nissim and Penman (2001) by showing strong patterns of mean-reversion in sales growth on an industry-level. Like Fairfield et al. (2009) I estimate a measure of mean-reversion of sales growth at a 6-digit GICS industry-level.

I construct this measure in three steps. First, I rank firms *annually* on realized sales growth into ten deciles within each 6-digit GICS industry with sufficient observations (I require a minimum of 20 observations). Second, I track the *median* sales growth in each of these deciles for up to ten years after decile formation. Third, for each GICS industry-year combination that allows tracking the decile medians of sales growth, I define a non-parametric measure of mean-reversion based on the interquartile range of the medians of the sales growth distribution at T0 and T1-T10:

$$IQRRAT'l' = \frac{IQR\ Sales\ Growth\ T'l'}{IQR\ Sales\ Growth\ T0}$$

Here *l* refers to the year relative to decile formation. T0 indicates the year of decile information and T1 through T10 indicate post-formation years. For each horizon, the interpretation of *IQRRAT* is straightforward: stronger mean-reversion results in *lower IQRRAT* as the future distributions of decile medians of sales growth tighten.[28] I choose *IQRRAT* as my primary mean-reversion measure in subsequent analyses as it relates closely to my definition of bold forecasts.[29]

While my subsequent analyses use mean-reversion metrics measured at the GICS industry level, Figures B.2 and B.3 illustrate the pattern of the interquartile ranges of the sales growth distributions at T0 and T1-T10 and the pattern of *IQRRATs* over the corresponding horizons at the full sample level. Consistent with the pattern in Figure B.1, both Figures B.2 and B.3 show a strong mean-reversion of sales growth in the early years after decile formation (T1 and T2) that stabilizes from year T3 onwards. Table B.1 provides descriptive evidence on the mean-reversion of sales growth in the sample. Panel A shows the mean-reversion measures for the full sample that generate Figure B.2. For the sake of parsimony, Panel B illustrates how the strength of mean-reversion varies across the full sample at the GICS sector-level for T1, T3 and T5.[30] Importantly, the findings show that, while strong mean-reversion in sales growth exists in all sectors, the extent of mean-reversion across sectors varies (e.g., Energy (10), Health Care (35), and Information Technology (45) exhibit stronger mean-reversion relative to other sectors).[31] Taken together, the descriptive findings in Figures B.1-B.3 and Table B.7 provide evidence of strong mean-reversion of sales

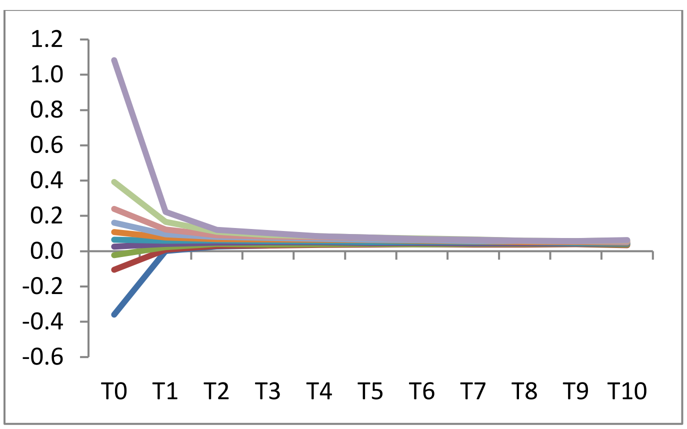
[28] For example, assume that in a given GICS industry in 2010 the interquartile range of decile medians of sales growth in the year of decile formation (T0, i.e., 2010) is 0.292 and that the *corresponding* interquartile range of decile medians of sales growth in the year post-formation (T1 i.e., 2011) is 0.148. In this case *IQRRAT1* = 0.148/0.292 = 0.507 and this metric measures the extent of mean-reversion in sales growth from 2010 to 2011 in the given GICS industry.
[29] In untabulated analysis, I complement *IQRRAT* with a parametric counterpart based on the standard deviations of the distributions of the decile medians distributions. This measure is similar to the metric introduced by Nissim and Penman (2001) to capture mean-reversion in their study (see Nissim and Penman, 2001, Table 3). Using this measure, I find qualitatively similar patterns of mean-reversion in the sample.
[30] I compute similar metrics across GICS sectors using the parametric counterpart of *IQRRAT*. The untabulated rank correlations between the patterns of mean-reversion based on both metrics are 0.84, 0.92, and 0.94 respectively for the T1, T3 and T5 patterns, suggesting that they capture mean-reversion across GICS sectors in a similar fashion.
[31] A discussion of the drivers of these different degrees of mean-reversion is beyond the scope of this paper. Previous research suggests that these are likely related to the degree of competition in the product markets in the different industry settings. See for example Fama and French (2000) and Healy, Serafeim, Srinivasan, and Yu (2014) for discussions on competition and mean-reversion of accounting measures of firm performance.

growth in the sample in support of the adoption of mean-reversion as the 'outside view' in this forecast setting.

Finally, I avoid a *look-ahead* bias in my subsequent analyses by ensuring that the relevant patterns of mean-reversion by 6-digit GICS industry are known to the analyst and the market at the time of the sales growth forecast.[32] For example, when the analyst estimates sales growth for fiscal 2010 at the beginning of 2010, the patterns of mean-reversion relevant to this forecast pertain to fiscal 2009 and earlier. For example, in this case, I measure the strength of the one-year mean-reversion (*IQRRAT1*) by contrasting the pattern of sales growth in 2009 relative to sales growth in 2008, i.e., the year of decile formation (T0) in this case is 2008 and one-year post-formation (T1) is 2009.

Figure B.1
Mean-reversion of sales-growth: Full sample fade diagram

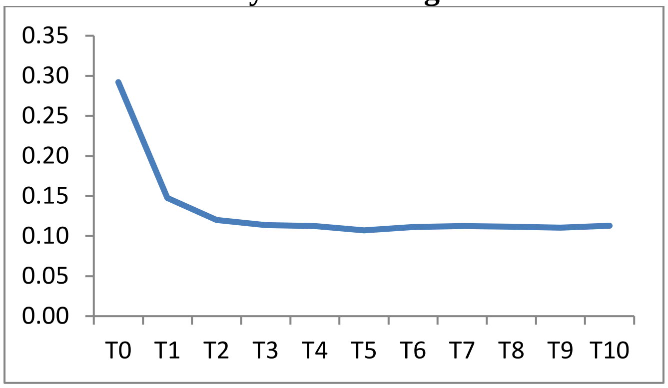
Figure B.1 below mimics Fig. 6(a) from Nissim and Penman (2001). I construct Figure B.1 in three steps. First, I rank firms annually on realized sales growth into ten deciles. Second, I track the *median* sales growth in each of these deciles for up to ten years after decile formation. Third, I take the average of these annual decile medians over the sample period. Figure B.1 graphs these means of annual medians. T0 denotes the year of decile formation and T1 through T10 indicate the post-formation years.



The figure is based on ranking sales growth observations annually into deciles and computing decile medians in the year of decile formation and the years thereafter. The figure graphs the means of the ten decile medians across the sample period relative to year of decile formation (T0).

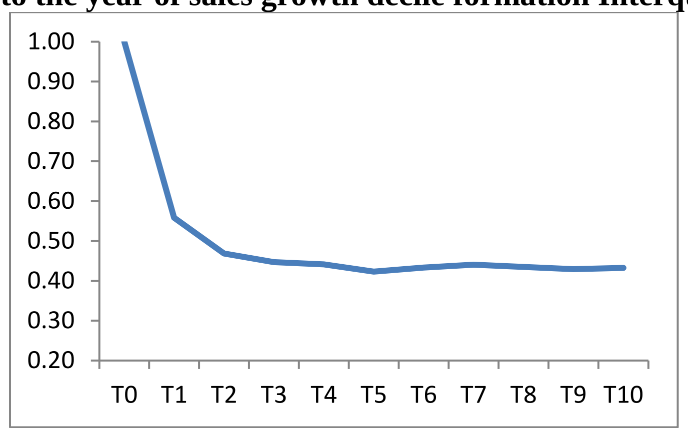
[32] As described, I require that the sales growth forecast occurs within 30 days after the prior-year earnings announcement. In this case, if the firm has a December year-end and it announced earnings for 2009 on January 21, 2010, I require that the analyst formulates his/her forecast of 2010 sales growth within 30 days after January 21, 2010.

Figure 2
Mean-reversion of sales growth:
Interquartile range (*IQR*) of sales growth decile medians
over time relative to the year of sales growth decile formation



The figure is based on ranking sales growth observations annually into deciles and computing decile medians in the year of decile formation and the years thereafter. The figure graphs the interquartile range of the decile medians across the sample period relative to year of decile formation (T0).

Figure 3
Mean-reversion of sales growth:
Interquartile range ratio (*IQRRAT*) of sales growth decile medians
over time relative to the year of sales growth decile formation Interquartile range ratio



The figure is based on ranking sales growth observations annually into deciles and computing decile medians in the year of decile formation and the years thereafter. The figure graphs *IQRRAT* or the ratio of the interquartile range of the decile medians in each year relative to the year of decile formation (T1-T10) scaled by the interquartile range of the decile medians in the year of decile formation (T0).

Table B.1
Mean-reversion patterns of sales growth: Descriptive statistics

This table presents descriptive evidence on the mean-reversion patterns of sales growth over the sample period studied (2000-2015). Panel A describes mean-reversion in the full sample. Panel B describes the extent of mean-reversion across GICS sectors. All variables are defined in Appendix A.

Panel A: Sales growth: Mean-reversion measures in the full sample

Variable	T0	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
IQR	0.292	0.148	0.120	0.114	0.113	0.107	0.111	0.112	0.112	0.110	0.113
IQRRAT	1.000	0.558	0.469	0.447	0.441	0.423	0.434	0.441	0.435	0.429	0.433

Panel B: Sales growth: Mean-reversion measures across GICS Sectors

		IQRRAT HORIZON		
GICS Sector	GICS Code	1	3	5
Energy	10	0.365	0.294	0.295
Materials	15	0.521	0.499	0.484
Industrials	20	0.582	0.474	0.457
Cons. Discretionary	25	0.638	0.459	0.432
Cons. Staples	30	0.571	0.516	0.502
Health Care	35	0.499	0.357	0.291
Inform. Techn.	45	0.473	0.323	0.316
Telecom. Svcs.	50	0.604	0.450	0.349
Utilities	55	0.648	0.657	0.713

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Table 1
Sales growth forecasts: Descriptive statistics

This table presents descriptive evidence on the main variables of interest over the sample period studied (2000-2015). *SG* equals one-year ahead sales growth, measured as ($Sales_{t+1}$ /$Sales_t$ – 1); *SGFY1* equals one-year ahead median consensus sales growth, measured as (Median Sales $Forecast_{t+1}$/$Sales_t$ – 1). In each forecast period I select individual sales forecasts, made within 30 days after the prior-year earnings announcement. *BIAS* is the forecast bias, measured as *SGFY1 – SG; INACCURACY* is the forecast inaccuracy, measured as the absolute value of *BIAS.*

Panel A: Full sample descriptives

Variable	Obs.	Mean	StDev.	p1	p10	p25	p50	p75	p90	p99
SG	112,281	0.098	0.217	-0.446	-0.110	-0.007	0.075	0.173	0.327	0.999
SGFY1	112,281	0.098	0.172	-0.390	-0.050	0.023	0.077	0.153	0.271	0.834
BIAS	112,281	0.000	0.134	-0.565	-0.123	-0.045	0.003	0.051	0.127	0.446
INACCURACY	112,281	0.087	0.117	0.001	0.008	0.020	0.048	0.105	0.201	0.708

Panel B: Descriptive statistics by year: No. observations and variable means

Year	Obs.	SG	SGFY1	BIAS	INACCURACY
2000	164	0.156	0.353	0.151	0.248
2001	385	-0.076	-0.021	0.053	0.142
2002	1,711	0.059	0.089	0.028	0.102
2003	3,611	0.154	0.114	-0.039	0.097
2004	5,553	0.195	0.165	-0.027	0.099
2005	6,152	0.161	0.133	-0.027	0.087
2006	6,752	0.154	0.149	-0.004	0.088
2007	7,316	0.145	0.132	-0.012	0.086
2008	7,419	0.079	0.111	0.033	0.106
2009	8,178	-0.016	-0.020	-0.007	0.093
2010	10,326	0.146	0.121	-0.025	0.086
2011	11,319	0.139	0.120	-0.019	0.087
2012	11,363	0.078	0.098	0.021	0.074
2013	11,465	0.082	0.087	0.006	0.072
2014	10,594	0.090	0.092	0.004	0.078
2015	9,973	-0.014	0.033	0.045	0.092

Panel C: Descriptive statistics by GICS sector: No. observations and variable means

GICS Sector	GICS Code	Obs.	SG	SGFY1	BIAS	INACCURACY
Energy	10	10,986	0.096	0.092	-0.005	0.153
Materials	15	6,245	0.068	0.088	0.020	0.103
Industrials	20	15,770	0.074	0.080	0.007	0.073
Cons Disc.	25	23,581	0.074	0.075	0.001	0.057
Cons Staples	30	4,476	0.062	0.069	0.007	0.053
Health Care	35	15,974	0.153	0.142	-0.010	0.093
Inform Tech.	45	31,871	0.116	0.115	-0.001	0.092
Telecomm Serv.	50	1,780	0.085	0.076	-0.006	0.056
Utilities	55	1,598	0.029	0.032	0.005	0.121

Table 2
Bold sales growth forecasts: Frequencies

This table presents descriptive evidence on the frequency of bold sales growth forecasts over the sample period studied (2000-2015). Panel A describes the frequency of the different types of bold forecasts in the full sample. Panel B describes the frequency of the different types of bold forecasts across sample years. Panel C describes the frequency of the different types of bold forecasts across GICS sectors. All variables are defined in Appendix A.

Panel A: Full sample bold forecast frequency

		Pessimistic			Optimistic		
	Obs.	TSLO	XSLO	BOTHLO	TSHI	XSHI	BOTHHI
Total Sample	112,281	0.378	0.140	0.101	0.101	0.168	0.055

Panel B: Bold forecast frequency by year

		Pessimistic			Optimistic		
Year	Obs.	TSLO	XSLO	BOTHLO	TSHI	XSHI	BOTHHI
2000	164	0.305	0.030	0.012	0.305	0.250	0.128
2001	385	0.706	0.210	0.182	0.055	0.070	0.021
2002	1,711	0.490	0.066	0.058	0.086	0.271	0.058
2003	3,611	0.430	0.022	0.020	0.093	0.231	0.048
2004	5,553	0.292	0.076	0.051	0.137	0.207	0.080
2005	6,152	0.325	0.167	0.095	0.098	0.124	0.043
2006	6,752	0.316	0.105	0.066	0.092	0.122	0.046
2007	7,316	0.346	0.154	0.094	0.083	0.093	0.036
2008	7,419	0.418	0.118	0.097	0.084	0.105	0.037
2009	8,178	0.723	0.377	0.356	0.040	0.111	0.023
2010	10,326	0.315	0.032	0.015	0.149	0.471	0.117
2011	11,319	0.240	0.145	0.051	0.138	0.128	0.052
2012	11,363	0.339	0.169	0.105	0.112	0.132	0.050
2013	11,465	0.385	0.086	0.065	0.083	0.168	0.056
2014	10,594	0.335	0.072	0.060	0.101	0.149	0.056
2015	9,973	0.463	0.260	0.214	0.085	0.110	0.050

Panel C: Bold forecast frequency by GICS sector

GICS Sector	GICS CODE	Obs	TSLO	Pessimistic XSLO	BOTHLO	TSHI	Optimistic XSHI	BOTHHI
Energy	10	10,986	0.398	0.312	0.258	0.099	0.159	0.051
Materials	15	6,245	0.294	0.176	0.110	0.150	0.208	0.097
Industrials	20	15,770	0.312	0.149	0.097	0.114	0.177	0.057
Cons Disc.	25	23,581	0.415	0.120	0.088	0.100	0.199	0.044
Cons Staples	30	4,476	0.357	0.132	0.100	0.106	0.134	0.057
Health Care	35	15,974	0.439	0.075	0.064	0.121	0.109	0.065
Inform Tech.	45	31,871	0.369	0.115	0.072	0.073	0.166	0.044
Telecomm Serv.	50	1,780	0.384	0.108	0.070	0.098	0.157	0.080
Utilities	55	1,598	0.271	0.257	0.175	0.156	0.278	0.131

Table 3
Bold forecasts and their forecast properties: Descriptive statistics

This table presents descriptive evidence on forecast bias and inaccuracy across sample partitions based on the distribution of bold forecasts over the sample period studied (2000-2015). Panel A presents descriptive statistics for the bold forecasts *SGFY1*. Panel B shows forecast bias (*BIAS*) across sample partitions and Panel C presents descriptive statistics for forecast inaccuracy (*INACCURACY*) across sample partitions. All variables are defined in Appendix A.

Panel A: Bold forecasts *SGFY1* across bold forecast sample partitions

Variable	Obs.	Mean	StDev.	p1	p10	p25	p50	p75	p90	p99
Panel A.1: Pessimism										
TSLO	42,423	0.011	0.140	-0.399	-0.172	-0.044	0.031	0.089	0.158	0.313
XSLO	15,758	-0.097	0.140	-0.399	-0.332	-0.177	-0.063	0.002	0.049	0.163
BOTHLO	11,311	-0.140	0.133	-0.399	-0.379	-0.232	-0.104	-0.037	0.007	0.070
Panel A.2: Optimism										
TSHI	11,333	0.321	0.248	0.034	0.080	0.129	0.244	0.435	0.761	0.904
XSHI	18,875	0.292	0.226	-0.021	0.076	0.134	0.225	0.378	0.634	0.904
BOTHHI	6,148	0.443	0.261	0.077	0.145	0.231	0.379	0.623	0.904	0.904
Total Sample	112,281	0.098	0.217	-0.446	-0.110	-0.007	0.075	0.173	0.327	0.999

Panel B: Forecast bias (*BIAS)* across bold forecast sample partitions

Variable	Obs.	Mean	StDev.	p1	p10	p25	p50	p75	p90	p99
Panel B.1: Pessimism										
TSLO	42,423	-0.005	0.127	-0.552	-0.124	-0.044	0.002	0.046	0.116	0.332
XSLO	15,758	-0.006	0.158	-0.578	-0.179	-0.052	0.011	0.070	0.150	0.367
BOTHLO	11,311	-0.014	0.170	-0.578	-0.220	-0.061	0.009	0.073	0.155	0.358
Panel B.2: Optimism										
TSHI	11,333	0.014	0.180	-0.578	-0.152	-0.055	0.008	0.074	0.204	0.495
XSHI	18,875	-0.002	0.179	-0.578	-0.179	-0.071	-0.002	0.067	0.181	0.495
BOTHHI	6,148	0.027	0.218	-0.578	-0.205	-0.064	0.019	0.110	0.317	0.495
Total Sample	112,281	0.000	0.134	-0.565	-0.123	-0.045	0.003	0.051	0.127	0.446

Panel C: Forecast inaccuracy (*INACCURACY*) across bold forecast sample partitions

Variable	Obs.	Mean	StDev.	p1	p10	p25	p50	p75	p90	p99
Panel C.1: Pessimism										
TSLO	42,423	0.081	0.108	0.001	0.007	0.019	0.045	0.098	0.189	0.594
XSLO	15,758	0.107	0.131	0.001	0.010	0.026	0.063	0.135	0.257	0.750
BOTHLO	11,311	0.117	0.141	0.001	0.010	0.026	0.069	0.148	0.285	0.750
Panel C.2: Optimism										
TSHI	11,333	0.127	0.170	0.001	0.010	0.026	0.064	0.144	0.321	0.750
XSHI	18,875	0.126	0.160	0.001	0.010	0.029	0.069	0.149	0.310	0.750
BOTHHI	6,148	0.168	0.202	0.001	0.013	0.035	0.088	0.206	0.482	0.750
Total Sample	112,281	0.087	0.117	0.001	0.008	0.020	0.048	0.105	0.201	0.708

Table 4
Cross-sectional variables: Descriptive statistics

This table presents descriptive evidence on the cross-sectional variables of relevance over the sample period studied (2000-2015). All variables are defined in Appendix A.

Variable	Obs.	Mean	StDev	p1	p10	p25	p50	p75	p90	p99
MOM90	112,281	1.043	0.188	0.538	0.816	0.939	1.049	1.148	1.257	1.583
TURNOVER90	112,281	2.326	0.672	0.545	1.485	1.885	2.322	2.777	3.186	3.922
TURNOVER90 (X)	112,281	12.962	10.585	1.725	4.415	6.587	10.194	16.076	24.194	50.486
VIX90	112,281	2.960	0.392	2.401	2.548	2.651	2.852	3.131	3.399	4.079
VIX90(X)	112,281	21	11	11	13	14	17	23	30	59
REVDIFF	112,281	0.352	0.325	0.004	0.023	0.070	0.231	0.619	0.904	0.999
INTAN	112,281	0.205	0.194	0.000	0.000	0.035	0.154	0.332	0.500	0.747
LNSEGM	112,281	0.814	0.753	0.000	0.000	0.000	1.099	1.386	1.792	2.197
SEGM(#)	112,281	3	2	1	1	1	3	4	6	9
SIZE	112,281	7.944	1.611	4.051	5.895	6.838	7.920	9.041	10.051	11.616
SIZE($)	112,281	10,003	24,667	57	363	933	2,752	8,442	23,171	110,875
LOSSEPS	112,281	0.076	0.266	0.000	0.000	0.000	0.000	0.000	0.000	1.000
PASTSG	112,281	0.125	0.229	-0.417	-0.083	0.012	0.091	0.198	0.365	1.082
GUIDANCE	112,281	0.580	0.494	0.000	0.000	0.000	1.000	1.000	1.000	1.000
HORIZON	112,281	5.772	0.072	5.624	5.707	5.740	5.781	5.814	5.832	5.858
HORIZON (X)	112,281	322	18	277	301	311	324	335	341	350
CV_EST	112,281	0.177	1.375	-6.981	-0.451	0.060	0.154	0.353	0.841	6.455
NUM_EST	112,281	2.498	0.547	1.609	1.792	2.079	2.485	2.890	3.258	3.714
NUM_EST (X)	112,281	14	8	5	6	8	12	18	26	41

Table 5
Forecast setting specificity and bold forecasts

This table presents the results of different specifications of the following regression:

$$Bold\ Forecast\ Variable = \alpha_0 + \alpha_1\ YEAR + \alpha_2\ GICS + \alpha_3\ ANALYST + \beta_1\ MOM90 + \beta_2\ TURNOVER90 + \beta_3\ VIX90 + \beta_4\ REVDIFF + \beta_5\ INTAN + \beta_6\ LNSEGM + \beta_7\ SIZE + \beta_8\ LOSSEPS + \beta_9\ PASTSG + + \beta_{10}\ GUIDANCE + \beta_{11}\ TIMING + \beta_{12}\ CV\_EST + \beta_{13}\ NUM\_EST + \mathcal{E} \quad (1)$$

The table shows six specifications, each focusing on a specific bold forecast variable. All variables are defined in Appendix A. T-statistics (in parentheses) are calculated using standard errors double-clustered at the firm and year level. The indicators ***, **, and * indicate that the estimated coefficient is significantly different from zero at the one, five or ten percent level (two-tailed test), respectively. N=112,281.

	Pessimism						Optimism					
	TSLO		XSLO		BOTHLO		TSHI		XSHI		BOTHHI	
MOM90	-0.219	***	-0.206	***	-0.204	***	0.131	***	0.173	***	0.076	***
	(-4.17)		*(-4.13)*		*(-4.19)*		*(5.28)*		*(3.95)*		*(3.80)*	
TURNOVER90	0.041	***	0.046	***	0.036	***	0.007		0.044	***	0.016	***
	(4.24)		*(4.09)*		*(3.91)*		*(1.52)*		*(8.11)*		*(4.60)*	
VIX90	0.057		0.148		0.134		-0.013		-0.178	*	-0.021	
	(0.61)		*(1.46)*		*(1.39)*		*(-0.57)*		*(-1.74)*		*(-0.99)*	
REVDIFF	-0.390	***	0.082	***	-0.002		0.094	***	-0.050	**	0.038	***
	(-22.78)		*(3.75)*		*(-0.14)*		*(6.85)*		*(-2.33)*		*(5.28)*	
INTAN	0.060	**	-0.042	*	-0.017		0.040	**	0.072	***	0.059	***
	(2.06)		*(-1.79)*		*(-0.93)*		*(2.06)*		*(2.93)*		*(4.62)*	
LNSEGM	-0.033	***	0.009		0.005		0.019	***	0.010	**	0.012	***
	(-4.41)		*(1.42)*		*(1.24)*		*(4.15)*		*(2.01)*		*(4.38)*	
SIZE	0.035	***	0.027	***	0.021	***	-0.018	***	-0.052	***	-0.018	***
	(4.94)		*(5.34)*		*(3.71)*		*(-4.07)*		*(-11.70)*		*(-5.84)*	
LOSSEPS	-0.001		0.032	*	0.030	**	0.053	***	0.095	***	0.072	***
	(-0.11)		*(1.69)*		*(2.04)*		*(3.62)*		*(5.33)*		*(5.31)*	
PASTSG	-0.101	**	-0.012		-0.049	*	0.058	***	0.151	**	0.046	***
	(-2.42)		*(-0.24)*		*(-1.74)*		*(3.26)*		*(2.21)*		*(2.93)*	
GUIDANCE	0.024	**	0.000		-0.004		-0.017	**	-0.004		-0.006	
	(2.26)		*(0.01)*		*(-0.50)*		*(-2.40)*		*(-0.43)*		*(-1.16)*	
HORIZON	-0.183	***	-0.127		-0.154	*	-0.031		0.018		-0.047	
	(-2.77)		*(-1.32)*		*(-1.79)*		*(-1.20)*		*(0.54)*		*(-1.51)*	
CV_EST	-0.018	***	-0.020	***	-0.019	***	0.002	*	0.002		0.001	
	(-5.42)		*(-5.22)*		*(-6.29)*		*(1.75)*		*(1.48)*		*(1.28)*	
NUM_EST	0.020		-0.050	***	-0.041	***	-0.004		0.046	***	0.001	
	(1.51)		*(-4.08)*		*(-3.36)*		*(-0.49)*		*(6.63)*		*(0.24)*	
Year, GICS, Analyst Fixed Effects	Included		Included		Included		Included		Included		Included	
Adj. R-Squared	0.250		0.253		0.250		0.131		0.247		0.135	

Table 6
Ex post properties of bold forecasts

This table presents the results of different specifications of the following regressions:

$$BIAS\ or\ INACCURACY = \alpha_0 + \alpha_1\ YEAR + \alpha_2\ FIRM + \alpha_3\ ANALYST + \boldsymbol{\beta_1\ TSLO + \beta_2\ XSLO} + CONTROLS + \mathcal{E} \quad (2a)$$

$$BIAS\ or\ INACCURACY = \alpha_0 + \alpha_1\ YEAR + \alpha_2\ FIRM + \alpha_3\ ANALYST + \boldsymbol{\beta_1\ BOTHLO} + CONTROLS + \mathcal{E} \quad (2b)$$

$$BIAS\ or\ INACCURACY = \alpha_0 + \alpha_1\ YEAR + \alpha_2\ FIRM + \alpha_3\ ANALYST + \boldsymbol{\beta_1\ TSHI + \beta_2\ XSHI} + CONTROLS + \mathcal{E} \quad (3a)$$

$$BIAS\ or\ INACCURACY = \alpha_0 + \alpha_1\ YEAR + \alpha_2\ FIRM + \alpha_3\ ANALYST + \boldsymbol{\beta_1\ BOTHHI} + CONTROLS + \mathcal{E} \quad (3b)$$

The table shows the results for *BIAS* in Panel A and *INACCURACY* in Panel B. All variables are defined in Appendix A. T-statistics (in parentheses) are calculated using standard errors double-clustered at the firm and year level. The indicators ***, **, and * indicate that the estimated coefficient is significantly different from zero at the one, five or ten percent level (two-tailed test), respectively. N=112,281.

Panel A: Bias

	Base		Pessimism							Optimism	
	Model		Separate		Joint			Separate		Joint	
	(1)		(2)		(3)			(4)		(5)	
TSLO			-0.011	***			TSHI	0.017	***		
			(-4.16)					*(4.27)*			
XSLO			-0.025	***			XSHI	0.019	***		
			(-4.67)					*(3.42)*			
BOTHLO					-0.041	***	BOTHHI			0.043	***
					(-6.02)					*(4.30)*	
MOM90	-0.052	***	-0.060	***	-0.061	***	MOM90	-0.057	***	-0.055	***
	(-5.38)		*(-5.51)*		*(-5.77)*			*(-5.65)*		*(-5.60)*	
TURNOVER90	0.015	**	0.017	***	0.017	***	TURNOVER90	0.014	**	0.014	**
	(2.56)		*(2.96)*		*(2.93)*			*(2.22)*		*(2.26)*	
VIX90	0.032	**	0.035	*	0.036	*	VIX90	0.035	**	0.032	**
	(1.97)		*(1.88)*		*(1.92)*			*(2.08)*		*(1.97)*	
REVDIFF	0.015	*	0.014		0.009		REVDIFF	0.017	*	0.016	**
	(1.83)		*(1.61)*		*(0.35)*			*(1.92)*		*(1.97)*	
INTAN	0.015		0.007		0.004		INTAN	0.004		0.007	
	(0.61)		*(0.29)*		*(0.97)*			*(0.14)*		*(0.29)*	
LNSEGM	0.004		0.004		0.112	***	LNSEGM	0.003		0.003	
	(1.04)		*(0.95)*		*(9.14)*			*(0.82)*		*(0.84)*	
SIZE	0.107	***	0.114	***	-0.007		SIZE	0.114	***	0.113	***
	(9.27)		*(9.25)*		*(-0.68)*			*(9.88)*		*(9.57)*	
LOSSEPS	-0.008		-0.007		0.009		LOSSEPS	-0.010		-0.010	
	(-0.77)		*(-0.73)*		*(0.53)*			*(-0.94)*		*(-0.98)*	
GUIDANCE	0.003		0.010		0.009		GUIDANCE	0.009		0.010	
	(0.66)		*(0.64)*		*(0.63)*			*(0.62)*		*(0.66)*	
PASTSG	0.011		0.003		0.000		PASTSG	0.003		0.003	
	(0.75)		*(0.73)*		*(0.00)*			*(0.71)*		*(0.72)*	
HORIZON	0.016		0.011		-0.002	*	HORIZON	0.017		0.017	
	(0.92)		*(0.62)*		*(-1.83)*			*(0.96)*		*(0.97)*	
CV_EST	-0.001		-0.002		0.003		CV_EST	-0.001		-0.001	
	(-1.02)		*(-1.64)*		*(0.53)*			*(-1.08)*		*(-1.08)*	
NUM_EST	0.004		0.004		0.003		NUM_EST	0.004		0.004	
	(0.82)		*(0.67)*		*(0.70)*			*(0.70)*		*(0.78)*	
Year, Firm, Analyst Fixed Effects	Included		Included		Included		Year, Firm, Analyst Fixed Effects	Included		Included	
Adj. R-Squared	0.370		0.374		0.375		Adj. R-Squared	0.373		0.374	

Panel B: Inaccuracy

	Base Model	Pessimism			Optimism	
		Separate	Joint		Separate	Joint
	(1)	(2)	(3)		(4)	(5)
TSLO		-0.005 **		TSHI	0.017 ***	
		(-1.97)			*(4.78)*	
XSLO		0.007 *		XSHI	0.016 ***	
		(1.80)			*(3.21)*	
BOTHLO			0.009 *	BOTHHI		0.042 ***
			(1.92)			*(7.06)*
MOM90	0.013 **	0.013 **	0.015 **	MOM90	0.010	0.011 *
	(2.11)	*(2.12)*	*(2.33)*		*(1.55)*	*(1.78)*
TURNOVER90	0.010 ***	0.010 ***	0.009 ***	TURNOVER90	0.009 ***	0.009 ***
	(3.03)	*(2.99)*	*(2.90)*		*(2.64)*	*(2.66)*
VIX90	-0.014 *	-0.015 **	-0.015 **	VIX90	-0.011	-0.013 *
	(-1.92)	*(-1.99)*	*(-1.98)*		*(-1.46)*	*(-1.74)*
REVDIFF	-0.026 ***	-0.027 ***	-0.026 ***	REVDIFF	-0.025 ***	-0.025 ***
	(-3.34)	*(-3.58)*	*(-3.32)*		*(-3.25)*	*(-3.32)*
INTAN	-0.042 **	-0.041 **	-0.041 *	INTAN	-0.053 ***	-0.050 **
	(-2.02)	*(-1.98)*	*(-1.96)*		*(-2.59)*	*(-2.48)*
LNSEGM	0.001	0.001	0.001	LNSEGM	0.000	0.000
	(0.28)	*(0.25)*	*(0.28)*		*(0.11)*	*(0.10)*
SIZE	-0.054 ***	-0.053 ***	-0.055 ***	SIZE	-0.047 ***	-0.048 ***
	(-7.31)	*(-7.08)*	*(-7.60)*		*(-6.13)*	*(-6.44)*
LOSSEPS	0.011	0.012	0.011	LOSSEPS	0.010	0.009
	(1.53)	*(1.54)*	*(1.50)*		*(1.37)*	*(1.30)*
PASTSG	-0.003	-0.004	-0.002	PASTSG	-0.005	-0.004
	(-0.28)	*(-0.39)*	*(-0.23)*		*(-0.50)*	*(-0.44)*
GUIDANCE	0.002	0.002	0.002	GUIDANCE	0.002	0.002
	(0.53)	*(0.55)*	*(0.52)*		*(0.65)*	*(0.69)*
HORIZON	0.057 ***	0.057 ***	0.058 ***	HORIZON	0.058 ***	0.058 ***
	(5.42)	*(5.36)*	*(5.45)*		*(5.30)*	*(5.36)*
CV_EST	0.000	0.000	0.000	CV_EST	0.000	0.000
	(0.45)	*(0.56)*	*(0.83)*		*(0.35)*	*(0.37)*
NUM_EST	0.007 *	0.008 *	0.008 *	NUM_EST	0.007	0.007
	(1.69)	*(1.82)*	*(1.79)*		*(1.56)*	*(1.60)*
Year, Firm, Analyst Fixed Effects	Included	Included	Included	Year, Firm, Analyst Fixed Effects	Included	Included
Adj. R-Squared	0.441	0.442	0.442	Adj. R-Squared	0.445	0.446

Table 7
Mean-reversion and bold forecasts

Panel A of this table presents descriptive statistics on the frequency of bold forecasts as a function of mean-reversion, measured using the *HIMR* variable defined in Appendix A. Panel B of this table presents the results of different specifications of the following regression:

$$\textit{Bold Forecast Variable} = \alpha_0 + \alpha_1\, YEAR + \alpha_2\, GICS + \alpha_3\, ANALYST + \beta_1\, HIMR + Controls + \varepsilon \qquad (4)$$

The panel shows six specifications, each focusing on a specific bold forecast variable. All variables are defined in Appendix A. T-statistics (in parentheses) are calculated using standard errors double-clustered at the firm and year level. The indicators ***, **, and * indicate that the estimated coefficient is significantly different from zero at the one, five or ten percent level (two-tailed test), respectively. N=110,970.

Panel A: Frequency of bold forecast as a function of mean-reversion: Descriptive statistics

		Pessimism						Optimism					
	Obs.	TSLO		XSLO		BOTHLO		TSHI		XSHI		BOTHHI	
Low MR	69,459	0.391		0.155		0.109		0.104		0.159		0.052	
High MR	41,511	0.358		0.116		0.086		0.096		0.182		0.058	
Diff High-Low		-0.032	***	-0.039	***	-0.024	***	-0.008	***	0.023	***	0.006	***
t-stat		*-10.73*		*-18.10*		*-12.62*		*-4.14*		*9.86*		*4.33*	

Panel B: Mean-reversion and bold forecasts: Regression test

	Pessimism					Optimism					
	TSLO	XSLO		BOTHLO		TSHI		XSHI		BOTHHI	
HIMR	0.015	-0.051	***	-0.031	***	-0.024	**	0.039	***	-0.003	
	(1.04)	*(-3.02)*		*(-2.72)*		*(-2.39)*		*(3.11)*		*(-0.45)*	
Controls	Included	Included		Included		Included		Included		Included	
Year, GICS, Analyst Fixed Effects	Included	Included		Included		Included		Included		Included	
Adj. R-Squared	0.251	0.257		0.252		0.131		0.248		0.134	

Table 8

Mean-reversion and the ex *post* properties of bold forecasts

This table presents the results of different specifications of the following regressions:

BIAS or INACCURACY = α_0 + *FIXED EFFECTS* + β_1 ***TSLO* + **β_2 ***TSLO*HIMR* +**
β_3 ***XSLO* + **β_4 ***XSLO*HIMR*** + β_5 ***HIMR*** + *CONTROLS* + $\mathcal{E}$ (5a)

BIAS or INACCURACY = α_0 + *FIXED EFFECTS* + β_1 ***BOTHLO*** + β_3 ***BOTHLO*HIMR***+
β_4 ***HIMR*** + *CONTROLS* + $\mathcal{E}$ (5b)

BIAS or INACCURACY = α_0 + *FIXED EFFECTS* + β_1 ***TSHI* + **β_2 ***TSHI*HIMR* +**
β_3 ***XSHI* + **β_4 ***XSHI*HIMR*** + β_5 ***HIMR*** + *CONTROLS* + $\mathcal{E}$ (6a)

BIAS or INACCURACY = α_0 + *FIXED EFFECTS* + β_1 ***BOTHHI*** + β_3 ***BOTHHI*HIMR*** +
β_4 ***HIMR*** + *CONTROLS* + $\mathcal{E}$ (6b)

The table shows the results for *BIAS* in Panel A and *INACCURACY* in Panel B. All variables are defined in Appendix A. T-statistics (in parentheses) are calculated using standard errors double-clustered at the firm and year level. The indicators ***, **, and * indicate that the estimated coefficient is significantly different from zero at the one, five or ten percent level (two-tailed test), respectively. N=110,970.

Panel A: Bias

	Base Model	Pessimism Separate	Pessimism Joint		Optimism Separate	Optimism Joint
	(1)	(2)	(3)		(4)	(5)
TSLO		-0.008 ***		TSHI	0.010 *	
		(-2.73)			*(1.91)*	
TSLO*HIMR		-0.008		TSHI*HIMR	0.023 **	
		(-1.49)			*(2.36)*	
XSLO		-0.016 **		XSHI	0.012	
		(-2.32)			*(1.37)*	
XSLO*HIMR		-0.025 *		XSHI*HIMR	0.015	
		(-1.92)			*(1.45)*	
BOTHLO			-0.032 ***	BOTHHI		0.028 *
			(-4.52)			*(1.76)*
BOTHLO * HIMR			-0.028 *	BOTHHI * HIMR		0.037 *
			(-1.86)			*(1.75)*
HIMR	-0.001	0.005	0.001	HIMR	-0.005	-0.002
	(-0.13)	*(0.98)*	*(0.26)*		*(-1.38)*	*(-0.62)*
Controls	Included	Included	Included	Controls	Included	Included
Year, Firm, Analyst Fixed Effects	Included	Included	Included	Year, Firm, Analyst Fixed Effects	Included	Included
Adj. R-Squared	0.370	0.375	0.376	Adj. R-Squared	0.375	0.375

Panel B: Inaccuracy

	Base Model	Pessimism Separate		Pessimism Joint			Optimism Separate		Optimism Joint	
	(1)	(2)		(3)			(4)		(5)	
TSLO		-0.005	**			TSHI	0.007	*		
		(-1.99)					*(1.79)*			
TSLO*HIMR		-0.002				TSHI*HIMR	0.030	***		
		(-0.46)					*(4.20)*			
XSLO		0.003				XSHI	0.014	***		
		(0.93)					*(3.45)*			
XSLO*HIMR		0.011				XSHI*HIMR	0.002			
		(1.46)					*(0.32)*			
BOTHLO				0.005		BOTHHI			0.024	***
				(1.10)					*(4.73)*	
BOTHLO * HIMR				0.013		BOTHHI * HIMR			0.045	***
				(1.35)					(3.37)	
HIMR	-0.002	-0.002		-0.003		HIMR	-0.005	*	-0.004	
	(-0.66)	*(-0.62)*		*(-0.92)*			*(-1.86)*		*(-1.43)*	
Controls	Included	Included		Included		Controls	Included		Included	
Year, Firm, Analyst Fixed Effects	Included	Included		Included		Year, Firm, Analyst Fixed Effects	Included		Included	
Adj. R-Squared	0.442	0.443		0.443		Adj. R-Squared	0.447		0.449	

Table 9
Bold forecasts and herding

This table presents evidence on the properties of bold forecasts depending on whether they arise when median forecasts are statistically bold (*HERD*) as well or whether this is not the case (*NOHERD*). All statistics pertain to the sample period studied (2000-2015). Panel A presents descriptive statistics on the two types of bold forecasts. The indicators ***, **, and * indicate that the difference between average *BIAS* and *INACCURACY* across *HERD* and *NOHERD* subsamples is significantly different from zero at the one, five or ten percent level (two-tailed test), respectively. Panel B shows the results of multivariate regressions that evaluate the *BIAS* and *INACCURACY* of *HERD* and *NOHERD* forecasts. T-statistics (in parentheses) are calculated using standard errors double-clustered at the firm and year level. The indicators ***, **, and * indicate that the estimated coefficient is significantly different from zero at the one, five or ten percent level (two-tailed test), respectively. Panel C compares the bias and accuracy of bold individual analyst forecast to the bias and accuracy of the median consensus forecasts (*MEDIAN*) in the subsample of *NOHERD* bold forecasts. The indicators ***, **, and * indicate that the differences are significantly different from zero at the one, five or ten percent level (two-tailed test), respectively. All variables are defined in Appendix A. N=112,281.

Panel A: Descriptive Statistics *HERD vs. NOHERD* bold forecasts

		Obs	Prop%	GUIDANCE	BIAS		INACCURACY	
TSLO	HERD	38,484	90.7%	61.1%	0.002		0.076	
	NOHERD	3,939	9.3%	43.7%	-0.071		0.124	
	Difference				0.073	***	-0.047	***
XSLO	HERD	13,206	83.8%	49.7%	0.013		0.096	
	NOHERD	2,552	16.2%	37.9%	-0.106		0.164	
	Difference				0.119	***	-0.068	***
BOTHLO	HERD	9,051	80.0%	47.7%	0.011		0.102	
	NOHERD	2,260	20.0%	36.6%	-0.113		0.178	
	Difference				0.124	***	-0.076	***
TSHI	HERD	9,130	80.6%	53.8%	0.000		0.118	
	NOHERD	2,203	19.4%	37.0%	0.072		0.164	
	Difference				-0.072	***	-0.047	***
XSHI	HERD	16,540	87.6%	55.6%	-0.014		0.123	
	NOHERD	2,335	12.4%	44.4%	0.081		0.144	
	Difference				-0.095	***	-0.021	***
BOTHHI	HERD	4,755	77.3%	54.3%	0.005		0.154	
	NOHERD	1,393	22.7%	36.0%	0.102		0.218	
	Difference				-0.098	***	-0.064	***

Panel B.1: Bias

	Pessimism					Optimism			
	Separate		Joint			Separate		Joint	
TSLO	-0.003				TSHI	0.003			
	(-1.08)					*(0.64)*			
TSLO_NOHERD	-0.053	***			TSHI_NOHERD	0.062	***		
	(-9.43)					*(5.46)*			
XSLO	-0.009	*			XSHI	0.008			
	(-1.90)					*(1.43)*			
XSLO_NOHERD	-0.081	***			XSHI_NOHERD	0.068	***		
	(-7.99)					*(8.31)*			
BOTHLO			-0.018	***	BOTHHI			0.019	*
			(-3.64)					*(1.78)*	
BOTHLO_NOHERD			-0.097	***	BOTHHI_NOHERD			0.102	***
			(-7.82)					*(6.37)*	
Controls	Included		Included		Controls	Included		Included	
Year, Firm, Analyst Fixed Effects	Included		Included		Year, Firm, Analyst Fixed Effects	Included		Included	
Adj. R-Squared	0.386		0.382		Adj. R-Squared	0.381		0.378	

Panel B.2: Inaccuracy

	Pessimism					Optimism			
	Separate		Joint			Separate		Joint	
TSLO	-0.009	***			TSHI	0.010	**		
	(-3.38)					*(2.37)*			
TSLO_NOHERD	0.025	***			TSHI_NOHERD	0.031	***		
	(4.67)					*(3.48)*			
XSLO	-0.001				XSHI	0.014	**		
	(-0.36)					*(2.44)*			
XSLO_NOHERD	0.043	***			XSHI_NOHERD	0.014			
	(3.85)					*(1.53)*			
BOTHLO			-0.004		BOTHHI			0.031	***
			(-0.78)					*(5.42)*	
BOTHLO_NOHERD			0.055	***	BOTHHI_NOHERD			0.102	***
			(3.65)					*(3.63)*	
Controls	Included		Included		Controls	Included		Included	
Year, Firm, Analyst Fixed Effects	Included		Included		Year, Firm, Analyst Fixed Effects	Included		Included	
Adj. R-Squared	0.445		0.444		Adj. R-Squared	0.446		0.447	

Panel C: Bold 'stand out' forecasts vs. median consensus forecasts: Bias and Accuracy

		BIAS				*INACCURACY*			
	Obs.	NOHERD	MEDIAN	*Differ-ence*		NOHERD	MEDIAN	*Differ-ence*	
TSLO	3,939	-0.071	0.006	0.077	***	0.124	0.086	-0.037	***
XSLO	2,552	-0.106	0.011	0.117	***	0.164	0.107	-0.058	***
BOTHLO	2,260	-0.113	0.016	0.129	***	0.178	0.112	-0.066	***
TSHI	2,203	0.072	-0.060	-0.132	***	0.164	0.142	-0.023	***
XSHI	2,335	0.081	-0.016	-0.097	***	0.144	0.115	-0.030	***
BOTHHI	1,393	0.102	-0.085	-0.188	***	0.218	0.187	-0.031	***