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Endogenous Overconfidence in
Managerial Forecasts

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Abstract

We examine whether attribution bias that leads managers who have experienced short-term forecasting success to become overconfident in their ability to forecast future earnings. Importantly, this form of overconfidence is endogenous and dynamic. We also examine the effect of this cognitive bias on the managerial credibility. Consistent with the existence of dynamic overconfidence, managers who have predicted earnings accurately in the previous four quarters are less accurate in their subsequent earnings predictions. These managers also display greater divergence from the analyst consensus and are more precise. Lastly, investors and analysts react less strongly to forecasts issued by overconfident managers.

1. Introduction

Managerial forecasts play an important economic role in financial markets. Hirst, Koonce, and Venkataraman (2008, p. 2) note that "they represent one of the key voluntary disclosure mechanisms by which managers establish or alter market earnings expectations, preempt litigation concerns, and influence their reputation for transparent and accurate reporting." We examine whether recent success in making accurate forecasts leads managers to become overconfident in their ability to predict future earnings and whether market participants are aware of the effect of such overconfidence. The behavioral economics literature indicates that overconfidence affects managerial decisions in various economic settings. For example, acquisitions, cash flow sensitivity, and personal equity sales have been shown to be influenced by managerial overconfidence (Malmendier and Tate, 2005, 2008; Jin and Kothari, 2008; Ben-David, Graham, and Harvey, 2007). However, previous research has typically treated overconfidence as a cross-sectional exogenous variable. In contrast, we examine the possibility that this overconfidence is rooted in managers' past performance, and investigate the idea of dynamic overconfidence. We further depart from the literature by focusing on time-series properties rather than cross-sectional variations and by examining the short-term dynamics of the managerial forecasts issued by *a given manager*. We examine two types of effects that past managerial performance may have. The first is the effect of a manager's past earnings forecast accuracy on his or her current accuracy, and the second is the effect of past accuracy on managerial credibility in the financial markets, that is, the extent to which investors and analysts rely on the current management earnings forecast.

Self-attribution theory suggests that individuals too strongly attribute events that confirm the validity of their actions to their own ability, but attribute events that disconfirm their actions

to external noise (Hastorf et al., 1970). In the context of this study, the self-attribution principle suggests that managers who have successfully forecasted earnings in the past attribute too much of their success to their superior ability and too little of it to chance. The resulting overconfidence in their forecasting abilities results in suboptimal behavior, whereby managers place too great a weight on their own private information and too little on public signals, such as market prices and financial analyst forecasts. This framework is consistent with previous studies showing that overconfident individuals place too much weight on their own private information (see Kraemer et al., 2006 for an experimental study and Barber and Odean, 2001 for a large-sample test). We thus hypothesize that these managers are likely to overemphasize their private signals and, as a consequence, be less accurate in their next forecast than would have been the case in the absence of such cognitive bias. This reduces the likelihood that their next forecast will be superior to analyst forecasts.

Our framework also predicts how market participants such as investors and financial analysts are likely to react to forecasts issued by overconfident managers. It might be expected that these participants would place great weight on forecasts issued by managers who have usually been accurate in the past, as such accuracy may be evidence of superior managerial skill or stronger incentives to forecast earnings accurately. However, our framework predicts that the forecasts issued after a short series of accurate predictions by a given manager will be of lower quality than those issued by *the same manager* in the absence of such a series. If market participants recognize this phenomenon, then they should react less strongly to these forecasts than to those that are issued by managers who are not overconfident (after controlling for managerial skill and environment).

Our empirical results are consistent with our hypotheses. We first show that managers who forecasted earnings accurately in the previous four quarters are less accurate in their subsequent earnings predictions. We also find that these managers deviate further from the consensus analyst forecast and are more precise. Our results thus indicate that after making a short series of accurate predictions, managers are more likely to simultaneously downplay public signals (relative to their private beliefs) and become less accurate than their skill and the environment would predict. These results are both statistically and economically significant. Lastly, we find that investors and financial analysts appear to recognize the effects of such overconfidence on forecast characteristics and, accordingly, react less strongly to these forecasts.

This study contributes to the literature in at least two ways. First, it investigates whether dynamic overconfidence affects the decision-making process of individuals in an important economic setting, that of managerial earnings forecasts. We examine the short-term dynamics of managerial forecasts by considering the influence of past success on current forecasts. Our focus on such dynamics diverges from that of most previous empirical research, which primarily considers static bias and treats overconfidence as an exogenous cross-sectional managerial property.[1] For example, Barber and Odean (2001) employ gender as a partitioning variable between more or less overconfident investors, whereas we consider this attribute to be endogenous. We demonstrate that the overconfidence phenomenon emerges from a manager's

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[1] One exception is Hilary and Menzly (2006) who examine a similar issue using analyst forecasts. However, Clarke and Subramanian (2006) challenge their interpretation and suggest that their results can be explained by nonlinearities in the analyst objective function caused by promotion concerns rather than by overconfidence. Our results are consistent with those of Hilary and Menzly (2006). We provide an out-of-sample test of their findings employing an economically important alternative setting. Managerial forecasts influence financial markets in a significant way (as explained, for example, by Hirst, Koonce, and Venkataraman, 2008) and are largely unaffected by the promotion-related issues discussed in Clarke and Subramanian (2006). In addition, we extend the work of

4

behavior and thus should not be treated as a characteristic that is purely exogenously attributed by the researcher. Consequently, our approach yields clear time-series predictions, rather than cross-sectional predictions, about the behavior of management forecasts. Second, our results have a counterintuitive implication for financial market practitioners. If two managers are believed to possess identical skills, but only one has made a recent series of high-quality predictions, then, counterintuitively, investors and analysts may be inclined to rely more on the subsequent forecasts of the historically less accurate manager. We demonstrate that this is indeed the case. Investors and analysts react less strongly to overconfident forecasts. To the best of our knowledge, the reaction of market participants to overconfident forecasts has never before been considered in the literature.

The remainder of the paper is organized as follows. In the next section, we discuss the theoretical foundation of our analysis and develop our research hypotheses. In Section 3, we describe the sample and the empirical design. We present the estimation results for managerial behavior in Sections 4 and 5, and those for the users of management forecasts in Sections 6. In Section 7, we consider alternative explanations and present evidence to discount them. Finally, we conclude the paper in Section 8.

2. Hypothesis development

In this section, we present our theoretical motivation for investigating the short-term dynamics of managerial forecasts. We first describe the underlying theoretical foundation, which is based on the two main principles of self-attribution and "static" overconfidence, and then describe their interaction in a unified framework.

Hilary and Menzly (2006) by considering market participants' reaction to potentially overconfident forecasts, a test

2.1. Theoretical foundation

The basic premise of this study is that individuals do not always update their beliefs in a Bayesian fashion. Instead, they suffer from various types of bias that may lead them to an inaccurate perception of their own skills. We examine some of these types of bias and specifically consider on the two psychological principles of self-serving attribution and "static" overconfidence.

2.1.1. Self-serving attribution

Past research indicates that individuals employ different causal explanations to account for their successes and failures (e.g., Fitch, 1970; Weiner and Kukla, 1970; Kukla, 1972). In a review article, Kunda (1990, p. 480) notes that "there is considerable evidence that people are more likely to arrive at the conclusions that they want to arrive at, but their ability to do so is constrained by their ability to construct seemingly reasonable justifications for these conclusions." According to the theory of self-attribution, individuals too strongly attribute events that confirm the validity of their own actions to their ability, but attribute events that disconfirm their actions to external noise (Hastorf et al., 1970). For example, Johnson et al. (1964) and Beckman (1970) find that teachers tend to claim responsibility for improved student performance, but attribute poor student performance to external causes, such as a lack of student motivation or situational factors. Miller (1976) suggests that the tendency toward self-attribution is stronger when the task is "ego-involving" (i.e., important) for the individual. Consistent with this view, Hirshleifer (2001, p. 1549) notes that "people tend to interpret ambiguous evidence in a fashion consistent with their own beliefs. They give careful scrutiny to inconsistent facts and

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that was not considered in their study.

6

explain them as due to luck or faulty data gathering." Similarly, Hales (2007) reports experimental evidence indicating that investors are motivated to agree intuitively with information which suggests that they might make money on their investments, but to disagree with information which suggests that they may lose money. He concludes that the literature suggests that "the amount of scrutiny given to information is not constant but rather depends on whether the information is seen in a favorable light or not, given the decision maker's preferences. When people are presented with information that is counter to their directional preferences, they are motivated to interpret it skeptically. In contrast, people unthinkingly accept news that they prefer to hear." (Hales, 2007, p. 613).

2.1.2. Overconfidence

"Static" overconfidence has been shown to be a common type of cognitive bias. For example, the prior literature suggests that individuals often overstate their own capacity and rate their attributes as better than average. Consistent with this idea, Peterson (2007, p. 110) reports that "depending on the study, between 65 and 80% [of people] believe they are above-average drivers." Overconfidence in decision-making has been identified among financial experts, such as investment bankers (Stael von Holstein, 1972), entrepreneurs (Cooper, Woo, and Dunkelberg, 1988), executives (Russo and Schoemaker, 1992), and managers (Dittrich, Alexis, Guth, and Maciejovsky, 2005).

In addition to the "better than average" effect, the literature suggests the existence of two other forms of overconfidence. The first involves either extreme beliefs relative to an objective standard (e.g., estimating that an event occurs with 90% probability when, in fact, it takes place less often) or confidence intervals that are too tight (e.g., setting 90% confidence intervals which

mean that "surprises" occur more than 10% of the time). In the context of this study, this "miscalibration effect" implies that overconfident individuals may issue forecasts that are narrower than those issued by unbiased individuals. Klayman et al. (1999, p. 216) note that "many studies have reported that the confidence people have in their judgments exceeds their accuracy and that overconfidence increases with the difficulty of the task."[2]

A second form of overconfidence, the "weighting effect," involves the relative use of private versus public information. In our study setting, overconfident individuals believe that their private information is more accurate than it actually is, and hence accord it too much weight (Kraemer et al., 2006). The existence of this form of overconfidence is consistent with the extant experimental literature. Hung and Plott (2001), for example, report that the subjects in their experimental setting placed excessive weight on free private information, and Huck and Oechssler (2000) report that the heuristic "follow your (private) signal" explains observed behavior better than Bayes' law. Kraemer et al. (2006) examine a setting in which individuals incur a cost in acquiring private information and (p. 424) conclude that "about one half of the individuals act rationally, whereas the other participants overestimate the private signal value." Bloomfield et al. (2000) report experimental evidence which suggests that people are overconfident in their ability to interpret data (relative to the ability of a disciplined trading strategy) and underperform as a result. Some studies, including those carried out by Harvey et al. (2000) and Yaniv (2004), similarly show that individuals do not optimally weight advice. For example, Yaniv (2004) reports that people place greater weight on their own opinion than on that of an adviser, even though taking the latter's advice improves accuracy. Yaniv (2004) also finds that more knowledgeable individuals are more likely to discount advice.

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[2] Klayman et al. (1999) discuss methodological issues with the initial research but show that, even after controlling

2.2. Hypothesis development

2.2.1. Performance relative to a manager's own expected performance

The combination of the two aforementioned types of cognitive bias yields a dynamic notion of overconfidence and a framework in which a manager becomes overconfident in his or her ability to predict future earnings after a series of good predictions. This framework is germane to the theoretical frameworks developed by Daniel et al. (1998), Gervais and Odean (2001), and Hilary and Menzly (2006) in different contexts. For example, Daniel et al. (1998) propose a theory of securities market under- and overreactions based on investors' confidence in the precision of their private information and biased self-attribution, which cause symmetric shifts in such confidence as a function of investment outcomes. The self-attribution principle predicts that managers who have successfully forecasted earnings in the past attribute too much of their success to superior skill and too little of it to luck.

Such overconfidence in one's personal abilities results in suboptimal behavior, whereby managers place too great a weight on their own private information and too little on public signals. Hence, the subsequent forecast of a manager who has made a series of successful predictions is more likely to deviate from an optimal forecast that an unbiased Bayesian would make. This lead to a forecast that is more inaccurate on average relative to what it would have been without overconfidence.[3] This notion is predicated on the previously documented observation that managers care about their forecast accuracy. For example, Zamora (2009)

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for these issues, overconfidence still appears to exist in an experimental setting.

[3] For example, suppose that analysts and the manager start with a common prior. The manager subsequently receives a private and informative signal and she revises her prior before issuing a forecast. If the manager is overconfident in the signal precision, the forecast will be more inaccurate and further away from the initial prior

shows that managers who are classified as superior forecasters gain greater performance-based bonus pay and offers some evidence indicating that these managers garner higher equity-based pay. She also finds that managers are more likely to advance in their careers and enjoy higher salaries (relative to their current salaries) and equity-based pay (relative to their current equity holdings) in the year after a successful forecast. Hence, we expect managers to care about forecast accuracy and, accordingly, posit the following.

H1: The management forecast accuracy of a given manager decreases after a series of accurate forecasts.

2.2.2. Performance relative to the performance of other managers

In our framework, a streak of forecasting successes increases the likelihood that the forecast that follows will have a greater (absolute) forecast error and hence reduces the likelihood that it will be superior to analyst forecasts. Thus, in our setting, overconfidence is not a fixed characteristic, but rather a recurring and dynamic phenomenon that varies in intensity over time. Superior past performance leads managers to become overconfident and, accordingly, to a greater likelihood of future inferior predictions, which then triggers a negative feedback mechanism. Inferior performance leads managers to revise downward their perception of their skill, which reduces their overconfidence. However, in this study's framework, overconfident managers do not necessarily underperform other managers or analysts unconditionally; rather, they underperform relative to their own performance (i.e., the one that would be expected if they

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than it would be had the manager been a fully unbiased Bayesian updater. The perceived confidence interval will also be smaller than it would be for an unbiased updater, which may lead to a more precise forecast.

did not suffer from cognitive bias).[4] If the effect of overconfidence is small relative to other characteristics such as endowed skill, then it is possible that overconfident managers will consistently outperform managers who do not suffer from such bias in predicting future earnings. Successful managers will remain "locked" into the cycle and consistently exhibit some degree of overconfidence. Thus, our framework does not predict (nor does it preclude) that managers who have experienced a series of successful predictions will make lower quality forecasts than those who have not experienced such success. Rather, it predicts that overconfident managers will issue lower quality forecasts than their skill and the environment would otherwise predict (that is, in the absence of overconfidence). In other words, our framework describes time-series behavior, rather than making cross-sectional predictions.[5]

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[4] Hutton and Stocken (2009) indicate that managers who issue forecasts repeatedly and accurately over several years are in a better position to alter market expectations. Our research question differs from theirs in that they ask whether, over an extended period, managers develop a reputation for forecasting skill, whereas we focus on short-term dynamics. This difference also means that our research setting differs from theirs in several respects. For example, they focus on yearly estimates, whereas we focus on quarterly forecasts. Their approach is more natural for investigating effects over many years; ours is more natural for a consideration of short-term dynamics. They also employ a pooled cross-sectional specification that estimates both the cross-sectional and time-series aspects of reputation, whereas we use a panel specification that controls for cross-sectional differences in intrinsic skills. Thus, the results of their study and ours are not inconsistent, and we do not preclude the possibility that managers may have different intrinsic forecasting skills and that investors may learn of their level of skill over several years. However, our results point to the possibility that this learning process is more complicated when managers are subject to cognitive bias.

[5] Another possible prediction may have been that the likelihood of issuing a forecast is affected by past managerial performance. However, the decision to issue a forecast seems to be largely irreversible. Untabulated results indicate that less than 20% of the forecasts in our sample are not followed by a forecast in the following quarter.

2.2.3. Reaction of market participants

We next consider the reaction of the users of management forecasts to the forecasts of overconfident managers. These users, particularly investors and financial analysts, may be expected to assign greater weight to forecasts that are issued by managers who are historically more accurate. That is, past performance should play a key role in helping them to ascertain a manager's skill and, accordingly, the weight that should be placed on his or her management forecasts relative to the other signals that investors and analysts receive. However, our framework predicts that the forecasts that are issued by a given manager after a series of good predictions will be of lower quality than those that are issued in the absence of such a series. If market participants recognize this phenomenon, then they will downplay and react less strongly to the forecasts of that manager (after controlling for managerial skill), which leads to our second set of hypotheses.

H2a: Investor reactions to the management forecasts issued by a given manager weaken after that manager has issued a series of accurate forecasts.

H2b: Financial analyst reactions to the management forecasts issued by a given manager weaken after that manager has issued a series of accurate forecasts.

Given that our framework essentially describes the dynamics of a short-term time series, it is not necessarily suitable for describing the decision to issue a forecast.

3. Data and empirical design

3.1. Data

We retrieve our management forecast data, which cover the 1994-2007 period, from the *FirstCall* database. To increase data consistency, we focus on quarterly predictions and exclude pre-announcements (i.e., forecasts made after the end of the fiscal period). We include only the last forecast made by a given manager before the end of the fiscal period because earlier predictions may be drawn from a different distribution of forecasts. Our sample includes only point and range forecasts and excludes qualitative forecasts that do not provide a numerical value of earnings per share. To obtain a meaningful measure of relative accuracy, we also require that there be at least two analysts who issued forecasts in the previous 90 days. We also require that the manager in question to have issued forecasts in at least four quarters over the previous two years and that the same CEO to have been managing the firm at the time that these forecasts were made. We obtain CEO information from the *ExecuComp* database, and drop firms for which we are unable to obtain such information. These sampling criteria generate 5,768 management forecasts that begin in the last quarter of 1996 and finish in the last quarter of 2007, approximately 85% of which are range forecasts. We match the forecast data with the corresponding records of *FirstCall* reported earnings.[6] The accounting and stock price data come from Compustat's quarterly data files, and the stock return data from the daily files of the Center for Research in Security Prices.

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[6] Both forecasts and realized earnings per share are split-adjusted on the same basis.

3.2. Definitions of the dependent variables

We first examine the effect of short-term past success on the current management forecast error. To measure this error, we define *ERR* as the absolute value of the difference between the management forecast and realized earnings. We adopt the value of the point forecasts and the midpoint of the range forecasts to determine a numeric value for each management forecast, and deflate *ERR* by the stock price two days before the issuance of the forecast.[7] Our hypotheses also generate predictions regarding the reactions of market participants to the forecasts issued by potentially overconfident managers. To test these predictions, we employ two measures of the change in expectations induced by managerial forecasts. For investors, we use *RET*, which is the ratio of the three-day size-adjusted stock return around the management forecast announcement to the change in investor expectations of earnings. We proxy this change with the difference between the management forecast and the consensus analyst forecast (which is also scaled by the price two days before the issuance of the management forecast).[8] We delete management forecasts made within −1 to +1 days of an earnings announcement, using the Compustat quarterly file to identify the earnings announcement dates. Although we lose approximately two-thirds of our management forecast observations through such deletion, doing so reduces the likelihood that the observed stock price reactions can be explained by earnings announcement news. This approach is consistent with that adopted in previous work (e.g., Atiase et al., 2005). For financial analysts, we employ *REV*, which is the ratio of an individual analyst forecast revision to the difference between the

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[7] Our conclusions remain unaffected when we deflate *ERR* by the stock price at the beginning of the quarter (untabulated results).

management forecast and the consensus forecast before the issuance of a new management forecast.[9] An individual analyst forecast revision is defined as the difference between an analyst forecast issued within 30 days of the management forecast date and one issued by the same analyst up to 90 days before that date.[10]

3.3. Methodology

In our framework, managers are postulated to become overconfident after a short run of good predictions, which is captured with the variable *STREAK*. To construct this variable, we first determine whether a given forecast is accurate by forming an indicator variable that takes a value of one if the management forecast error is less than the consensus forecast error, and zero otherwise. In our main specification, we employ the consensus forecast 90 days before the issuance of the management forecast, although our main results are also robust to the use of a shorter horizon (e.g., 60 days).[11] We define *STREAK* as the number of consecutive accurate predictions for a given firm in the last four quarters before the current prediction is made.[12] For

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[8] In essence, we scale the change in price by the apparent change in expectations. This approach is similar in spirit to the earnings response coefficients but, instead of calculating average values through regressions, we use the specific value around a forecast revision (and, of course, we employ the management forecast rather than earnings).

[9] We treat analysts who did not revise their forecasts within 30 days of a management forecast as missing observations, although setting *REV* to zero for these analysts does not change our conclusions (untabulated results).

[10] One concern is that the deflator may take extreme values as it approaches zero. To further ensure that our results are not driven by this issue, we re-estimate the regressions in which *RET* or *REV* is the dependent variable and drop observations for which either variable is in the bottom or top 5% of the distribution. The significance of these alternative results varies between less than 1% and less than 10% (untabulated).

[11] If an analyst issues more than one forecast within this 90-day period, then we use only the most recent forecast to compute the consensus.

[12] We do not scale the variable by the number of prior forecasts because all of the observations in our main tests have exactly four prior forecasts. We choose four quarters as a compromise between reducing the period too much (which would not allow us to capture the forecast sequence) and extending it too much (which would represent the

example, if the indicator variable is equal to 1, 0, 0, and 1 (counting backward from quarters t-1 to t-4), then *STREAK* will be equal to 1. If it is equal to 1, 1, 0, and 1 (counting backward from quarters t-1 to t-4), then *STREAK* will be equal to 2. We then estimate the following regression to test H1.

$$ERR_{i,t} = \alpha_i + \beta\ STREAK_{i,t} + \gamma^k\ C^k_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where *ERR* and *STREAK* are our previously defined variables measured for firm i in period t; C^k represents a vector of the K control variables. *Hor* is the forecast horizon measured as the log of the number of days between the management forecast date and the end of the fiscal period. We include this variable to control for the amount of information available at the time of the forecast (e.g., Bamber and Cheon, 1998; Johnson, Kasznik, and Nelson, 2001). *Size* is the log of total assets at the beginning of the quarter. Although size is likely to be correlated with different variables, we include it to control for the manager's degree of sophistication. We control for growth opportunities (e.g., Bamber and Cheon, 1998) by including *B-to-M*, which is the book value divided by the market value of the firm's equity at the beginning of the quarter. *Loss* is an indicator variable that takes a value of one if the earnings are negative, and zero otherwise. *StdEarn* is the standard deviation of the quarterly return on assets over at least eight of the preceding twelve quarters. *RetVol* is the standard deviation of the stock return six months before the management forecast date. *B-to-M*, *Loss*, *StdEarn*, and *RetVol* control for difficulty in predicting earnings*. Cover* is the log of the number of analysts covering the firm in a quarter, and is included to control for the amount of public information available. Except for the count variables (e.g., *STREAK*) and the binary variables, all of the data are winsorized at the 1% level.

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long-run dynamics subsumed by the CEO fixed effects). We perform a robustness check on this assumption in

We employ a panel (fixed effect) technique to estimate the equations. The manager fixed-effect regression is particularly suitable for testing our hypothesis, which focuses on the short-term dynamics of manager's forecasts, as it eliminates cross-sectional variation in the means while leaving the time-series dynamics of these forecasts intact. The use of manager fixed effects also provides a natural control for omitted variables. For example, constant differences in managerial skill levels, prediction bias, the tendency to walk down analyst forecasts (so that managers can more easily beat them), or constant firm characteristics such as industry classification are all controlled. In our main specifications, we employ CEO fixed effects (we revisit this issue in Section 4.3).[13] The standard errors are calculated according to the procedure outlined in Cameron, Gelbach, and Miller (2006) and are groupwise heteroskedasticity-consistent (i.e., adjusted simultaneously for heteroskedasticity and the clustering of observations by CEO and year). Untabulated results indicate that our key results hold if we bootstrap the data instead.[14] If managers suffer from overconfidence in their forecasting skill after a series of good predictions, then we expect the coefficient on *STREAK*, β, to be positive when *ERR* is the dependent variable.

Our second set of hypotheses predicts that market participants will react less strongly to the forecasts issued by potentially overconfident managers. To investigate this possibility, we estimate the following two models.

Section 4.3.

[13] In our main specifications, we drop observations for which the CEO identification is missing. As a robustness test, we use all of the observations and adopt firm identification as a substitute for the missing CEO identification. The results (untabulated) are unaffected. Our results (untabulated) are also robust to the use of CEO-firm fixed effects instead of CEO fixed effects.

[14] We calculate the confidence interval using a bias corrected bootstrapping procedure that allows for clustering of observations by CEO and year.

$$RET_{i,t} = \alpha_i + \beta\, STREAK_{i,t} + \gamma^k\, C^k_{i,t} + \varepsilon_{i,t} \qquad\qquad (2)$$

$$REV_{i,t} = \alpha_i + \beta\, STREAK_{i,t} + \gamma^k\, C^k_{i,t} + \varepsilon_{i,t}, \qquad\qquad (3)$$

where *RET*, *REV*, *STREAK*, and *C* are as previously defined. We again include CEO fixed effects. H2a predicts that β will be negative in Equation (2), and H2b that it will be negative in Equation (3).

3.4. Descriptive statistics

We present general descriptive statistics in Table 1. Panel A provides unconditional descriptive statistics. We note that the mean and median are materially different for *ERR* (2.04 versus 0.97).[15] The average value of *STREAK* is 0.97, which suggests that, on average, managers' forecasts are more accurate than analysts' consensus forecasts approximately half of the time.[16] This estimate is consistent with the literature (e.g., Hutton and Stocken, 2009). The fact that managers experience difficulties in consistently outperforming analyst forecast accuracy is conducive to overconfidence resulting from successful managerial forecasts. Lastly, our control variables are reasonably symmetric. We present a correlation matrix in Table 2. Consistent with our hypothesis, *STREAK* is significantly and positively correlated with *ERR*. The degree of correlation among the different control variables is reasonably low, which suggests that multicollinearity is not an issue. We do not include *RET* and *REV* in our correlation table because these two variables are calculated using samples different from the one

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[15] We discuss the alternative measures of management forecast accuracy in Section 4.2. One of these alternative measures, the square root of *ERR* (*SqrERR*), is much more symmetric than the distribution of *ERR*.

[16] If the likelihood of being more accurate than the consensus forecast is 50%, then the expected value of *STREAK* is $\frac{1}{2} + \frac{1}{4} + \frac{1}{8} + \frac{1}{16}$, which is approximately equal to 0.94.

we use for equation (1) and the correlation table. The untabulated results reveal that the univariate correlation between *STREAK* and *RET* (*REV*) is -0.04 (0.01).

4. Empirical results on managerial overconfidence

4.1. CEO overconfidence

We report the results of our regression estimation for equation (1) in Table 3, using *ERR* as the dependent variable. They support for our overconfidence hypothesis (H1). The coefficient associated with *STREAK* is positive, which indicates that managers who have experienced a series of accurate predictions subsequently issue less accurate forecasts. This effect is statistically significant. The z-statistics (corrected for heteroskedasticity and the simultaneous clustering of observations by CEO and year) is 2.61. The effect is also economically significant. Increasing *STREAK* by one standard deviation increases *ERR* by 14% of its median value.[17] The R^2 is 45.04%, which is explained in part by the inclusion of CEO fixed effects.[18] Neither the addition of fiscal quarter indicator variables nor a change in the magnitude of special items in the reported earnings (scaled by total assets) affects our conclusions. The inclusion of yearly indicator variables materially increases the significance of the tests (in this case, the z-statistic equals 4.56). Dropping all of the control variables (except for CEO fixed effects) and re-estimating the regressions has no effect on our conclusions, which suggests that our results are not spuriously created by the inclusion of irrelevant control variables (the results of these different robustness checks are untabulated).

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[17] To obtain the estimate, we multiply the value of the coefficient (0.86, from Table 3) by the standard deviation of *STREAK* (1.29, from Table 1) and divide the product by the median value of *DEV* (0.97, from Table 1).

4.2. Alternative specifications

We next consider the robustness of our results to alternative definitions of our treatment and dependent variables. First, we consider five alternative measures of past performance (*STREAK*, *FREQ*, *MACC*, *WFREQ*, and *WMACC*) as our treatment variable. *STREAK* is as previously defined. *FREQ* is the number of accurate management forecasts in the previous four quarters (as opposed to the number of accurate forecasts in a row). *MACC* is the mean difference between consensus analyst forecast error and management forecast error in the last four quarters. This variable thus takes into account the magnitude by which a manager's forecasts beat, or fall short of, consensus analyst forecasts. Both *FREQ* and *MACC* assign the same weight to forecast accuracy in each of the previous four quarters, but it could be argued that more weight should be given to more recent quarters. To address this possibility, we form *WFREQ* and *WMACC*, which are similar to *FREQ* and *MACC* but assign a different weight to each quarter. The weight assigned to the most recent quarter is 4 over 10, and those to the second, third, and fourth most recent quarters are 3 over 10, 2 over 10, and 1 over 10 (10 being equal to 4 + 3 + 2 + 1), respectively.

We also consider four alternative measures of current accuracy (*ERR*, *SqrERR*, *ERRD*, and *RelERR*) as the dependent variables. *ERR* is as previously defined. The descriptive statistics in Table 1 indicate the presence of skewness in the distribution of *ERR*. To ensure that such skewness does not affect our conclusions, we also calculate *SqrERR*, the square root of *ERR*.[19] *ERRD* is a measure of relative forecast error. It is an indicator variable that is equal to one if the management forecast is less accurate than the consensus analyst forecast, and zero otherwise.

[18] Untabulated results indicate that our conclusions hold in pooled specifications from which fixed effects are omitted.

[19] We do not use a log transformation because *ERR* can be equal to zero or close to zero.

RelERR is the ratio of the management forecast error divided by the consensus analyst forecast error.

We then regress the four aforementioned dependent variables on the five treatment variables and the control variables (for 20 specifications in total). When the dependent variable is continuous, we use a model similar to model (1). When it is binary, we employ a logit specification that includes CEO fixed effects and correct the standard errors for the double clustering of observations by CEO and year. We tabulate the coefficients associated with the different treatment variables and the corresponding z-statistics in Table 4 (the coefficients and z-statistics for the control variables are not tabulated to conserve space). The coefficient associated with the treatment variable is significantly positive in all 20 specifications (the z-statistics range from 2.10 and 7.44). In particular, we obtain similar results if we measure the dependent variable and the treatment variables both on an absolute basis or both on a relative basis. We thus conclude that our results are robust to alternative definitions of the dependent and treatment variables.

4.3. Additional robustness checks

Before considering other properties of management forecasts in the next section, we consider two additional untabulated robustness checks. First, our specifications thus far include CEO fixed effects. This approach implicitly assumes that CEOs play a significant role in the issuance of forecasts and that forecasts are important to them, an assumption that is consistent with anecdotal evidence. For example, after General Electric (GE) missed an earnings forecast, Jack Welch (the chairman and CEO of GE from 1981 to 2001) stated in an April 16, 2008 interview on CNBC that "*Jeff* [Immelt, GE's current CEO; emphasis added] has a credibility

issue." Such an assumption is also consistent with academic research. For example, Lee, Matsunaga, and Park (2010) report the probability of CEO turnover to be significantly higher when the magnitude of management forecast error is greater. Untabulated F-tests also indicate that CEO fixed effects are jointly significant in all of our specifications (the p-value is less than 0.01 in all cases). However, it could be argued that the CFO also plays an important role in the issuance of earnings forecasts. To investigate this possibility, we re-estimate equation (1) using CFO fixed effects in place of CEO fixed effects, but the results are qualitatively similar.[20]

Second, our framework posits that overconfidence is a short-term phenomenon that varies in intensity. However, its exact length is an empirical question. *STREAK* is formed on the basis of four lagged predictions (i.e., from quarters t-4 to t-1). If we employ too short a period to estimate *STREAK*, then we run the risk of the large amount of random noise in the variable creating a severe estimation problem. We also risk missing the effect of overconfidence if it takes longer to build up. At the same time, however, if we expand our estimation period too much, then we may inadvertently capture intrinsic managerial skill in predicting earnings, a characteristic that is absorbed by CEO fixed effects, in which case *STREAK* may also appear to be insignificant. The choice of period length thus represents a trade-off between obtaining greater variation in the *STREAK* variables and diluting their effect. Given that we have no strong theory to guide us in this choice, we re-compute *STREAK* using different lagged-period lengths

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[20] We focus on CEO specifications because information about a firm's CEO is usually reported in *ExecuComp*, whereas information about its CFO is sometimes missing (our sample size drops from 5,768 to 4,709 observations when we adopt CFO specifications instead). In addition, *ExecuComp* provides the exact date on which a manager becomes CEO, but only gives the appointment year for the CFO, which introduces noise to the data. Finally, we examine the data visually and note that, in many cases, CEO and CFO tenure overlap, which renders it difficult to distinguish between the CEO's and CFO's effects on forecasting behavior empirically.

(from three to six quarters).[21] The untabulated results indicate that all of the coefficients associated with *STREAK* are significantly positive. The untabulated z-statistics are 2.27 when we use three quarters,[22] 2.56 when we use five, and 2.13 when we use six. We thus conclude that our results are reasonably robust to our initial choice of estimation period.

5. Additional forecast properties

Having established that prior performance affects managerial forecast accuracy, we consider other aspects of the management forecast. Our framework predicts that managers are likely to overemphasize their private signals and, as a consequence, to be less accurate in their subsequent forecast than would have been the case in the absence of such cognitive bias. We now test two additional implications of this framework.

First, our framework predicts that managers should downplay common public signals. If this is the case, then we would expect the forecasts issued by overconfident managers to be further away from the consensus forecast. To measure this distance, we define *DEV* as the absolute distance between the management and consensus analyst forecasts (deflated by the stock price two days before the issuance of the management forecast). We interpret *DEV* as a proxy for the extent to which the manager overweighs his or her private information. The (untabulated) correlation between *ERR* and *DEV* is significantly positive (0.54), which suggests that managers' forecasts that deviate from the consensus forecast are less accurate. We then estimate a model similar to model (1), but with *DEV* as the dependent variable. The results are

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[21] Carlson and Shu (2007) suggest that the occurrence of at least three events in a row is necessary for individuals to form the subjective belief that a streak has emerged.

reported in Column (1) of Table 5, and are consistent with our expectation. The coefficient associated with *STREAK* is significantly positive (the z-statistic equals 2.03). In itself, this correlation between *STREAK* and *DEV* is consistent with CEOs either rationally basing their forecasts on a private but informative signal or suffering from the effect of dynamic overconfidence. However, the combination of the positive correlations between *STREAK* and both *ERR* and *DEV* suggests that dynamic overconfidence is more likely to explain these correlations.

Second, we consider the effect of past performance on the precision of the current forecast (i.e., the size of the forecast range). If managers become overconfident in their skill, then they may issue more precise forecasts than they otherwise would have. To test this conjecture, we form *RAND*, an indicator variable that is equal to one if the management forecast range is smaller than the analyst forecast range, and zero otherwise. We estimate a logit regression with CEO fixed effects and our usual control variables. The results reported in column (2) of Table 5 indicate that *STREAK* is significantly positive (the z-statistic is 2.36). Alternatively, we define *RANGE* as the absolute value of the difference between the upper and lower bounds of the forecast (scaled by the dispersion of analyst forecasts to reflect uncertainty in the economic situation over time). We regress this variable on *STREAK* and our usual control variables. The untabulated results indicate that the coefficient associated with *STREAK* is negative and significant at the 10% level. Again, the correlation between *STREAK* and *RAND* is consistent with CEOs either rationally basing their forecasts on a more precise private information or suffering from the effect of dynamic overconfidence. However, the combination

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[22] We define *STREAK* using the previous three quarters within one year instead of two years (we use two years when we define *STREAK* over the previous four, five or six quarters). The z-statistic becomes 1.92 if we consider the last three quarters of the previous two years instead of the last three quarters of the prior year.

of the positive correlations between *STREAK* and both *ERR* and *RAND* suggests again that dynamic overconfidence is more likely to explain these correlations. However, the correlation between *STREAK* and *RAND* supports the first form of such overconfidence presented in Section 2.1 (the "miscalibration effect") rather than the second (the "weighting effect"), which we document in the error and *DEV* regressions.

6. Empirical results on the behavior of market participants

Our results thus far suggest that managers who have experienced recent success become overconfident in their forecasting ability. One implication of this finding is that rational users of management forecasts should discount forecasts that have been issued by managers who have recently been successful (holding managerial skill constant). To investigate whether they do so, we regress *RET* and *REV* on *STREAK*, our usual control variables, and CEO fixed effects. The results of investor reaction, which are consistent with the prediction of H2a, are reported in column (1) of Table 6. *STREAK* is negative with a z-statistic of -2.49 (with the double clustering by CEO and year of the standard errors). The economic magnitude is such that increasing *STREAK* by one standard deviation reduces the sensitivity of the three-day return to the forecast revision (*RET*) by approximately 40% of the median sensitivity. We also consider the reaction of financial analysts, and report the results from the estimation of model (3) with the clustering (by CEO, analyst, and year) of the standard errors in column (2) of Table 6. Consistent with H2b, *STREAK* is significantly negative, with a z-statistic of -2.75. The economic magnitude is such that increasing *STREAK* by one standard deviation reduces the sensitivity of the analyst reaction to the management forecast revision (*REV*) by more than 50% of the median sensitivity. This finding suggests that both investors and analysts recognize that the forecasts issued by

25

overconfident managers are less accurate and, as a consequence, react less strongly to these forecasts than to those issued by managers who have not had a recent run of successful predictions. An untabulated F-test indicates that CEO fixed effects are jointly significant in models (2) and (3) (the p-value is less than 0.01), which suggests that CEOs' intrinsic characteristics, such as managerial skill, are also important in establishing credibility among investors and analysts.

7. Alternative explanations

Before concluding the study, we consider alternative explanations for some of our results and present empirical evidence to reject them.

7.1. Mean reversion

It could be argued that what we are capturing in Table 3 is a mechanical relationship between past forecast error and contemporaneous forecast error if the error process is mean-reverting. However, we note that *STREAK* is based on the relative forecast error, whereas *ERR* is based on the absolute error, which reduces the potential for a mechanical relationship based on mean reversion. In addition, although this phenomenon could potentially explain the relation between *STREAK* and *ERR*, it is more difficult to explain that between *STREAK* and *DEV* or that between *STREAK* and forecast precision in this way. Nevertheless, we conduct an additional test to further rule out this alternative explanation. Psychological research suggests that individuals place too much weight on their successes and too little on their failures, but that the phenomenon is asymmetric. For example, Fiske and Taylor (1991) state that self-enhancing attributions of success are more common than self-protective attributions of failure, which implies that underconfidence should be less significant than overconfidence. To test whether this is the case,

we compute *InvSTREAK* as the number of consecutive quarters in which the management forecast is less accurate than the consensus analyst forecast within the past four quarters. *InvSTREAK* is statistically insignificant (the z-statistic equals 0.15) when *ERR* is the dependent variable. These findings are consistent with those in the psychology literature, but not with the mean-reversion hypothesis.

7.2. Accrual manipulation

It is also conceivable that managers are not prone to overconfidence and that there is no variation in their forecasting skill, but rather that they wish to manipulate earnings through accruals to meet their forecast targets in certain quarters. By manipulating their accruals, managers would achieve seemingly superior forecasts in the initial quarters. As accruals must revert at some point in time, they may add noise to subsequent forecasts and create surprises in subsequent periods, thus explaining the pattern in forecast error that we find. However, if this explanation were valid, then it would suggest that managers do not understand the time-series properties of accruals and are surprised by their reversals. In addition, it is not immediately obvious why such manipulation would affect the divergence from consensus forecasts or forecast precision in the way that we have documented. Nevertheless, to further ensure that our results are not driven by this alternative explanation, we include the amount of total contemporaneous accruals, both signed and unsigned, as additional control variables in our regression. *STREAK* remains essentially unchanged in both cases. As another alternative, we also follow Barton and Simko (2002) and control for net operating assets, but our results (untabulated) are unaffected. We also regress total accruals, both signed and unsigned, on *STREAK*, controlling for our usual independent variables and CEO fixed effects. The untabulated results indicate that *STREAK* is

insignificant (the p-values equal 0.75 and 0.95, respectively), which suggests that any effect of accruals is orthogonal to the effect of *STREAK*. Hence, the results do not support this alternative explanation.

7.3. Over-optimism versus overconfidence

A third possibility is that managers become overly optimistic, rather than overly confident, following a series of forecasting successes. If this is the case, then managers may expect earnings to be higher than they actually are, which would create a larger forecast error and, to the extent that analysts do not suffer from the same bias, greater deviation from the consensus analyst forecast. The two explanations are not mutually exclusive. If this conjecture is correct, then we would expect managers to issue optimistic forecasts after a series of accurate predictions. To investigate this possibility, we perform a number of additional tests. First, we include *GoodNews* as an additional control variable. *GoodNews* is an indicator variable that takes a value of one if the management forecast exceeds the consensus analyst forecast, and zero otherwise. Our results are unaffected. Second, we estimate logit regressions that consider the likelihood of issuing a forecast that is *ex post* above the realized earnings or one that is greater than the current consensus (i.e., *GoodNews* equals 1). *STREAK* is insignificant in the first specification and negative in the second. Third, we split the sample based on (a) whether realized earnings are above or below the forecasted earnings and (b) whether the forecast is above or below the consensus forecast, and then estimate equation (1) for each subsample. The untabulated results indicate that the coefficients associated with *STREAK* are not significantly different between the samples of optimistic and pessimistic forecasts (the p-value is 0.53 for the former (a) and 0.50 for the latter (b)). These results fail to support the idea that managers become overly optimistic after a series of good predictions.

7.4. Reputation building

A fourth possibility is that managers do not become overconfident after a series of successful forecasts, but instead build up their reputation and then "cash in" by manipulating expectations and issuing biased and inaccurate forecasts once their reputation has been established. The results in Table 6 indicate that, if this were indeed their strategy, then it would be an unsuccessful one, as market participants discount forecasts that have been issued after a series of good predictions. It is not immediately obvious why managers would choose to pursue an unsuccessful strategy. In addition, if managers were trying to manipulate market participants, then it would be expected that they would, on average, inflate expected earnings. However, as indicated by the results discussed in the foregoing paragraph, this is not the case. *STREAK*'s effect on forecast error is no different for positive or negative error. Again, we find no support for this alternative explanation.

7.5. Convex utility function

Finally, yet another possible explanation for our results is that the pay-off function for managers is convex in the number of good forecasts. That is, if managers achieve several superior forecasts in a row, they receive a particularly large pay-off. This issue has been discussed in the context of analyst overconfidence. For example, Clarke and Subramanian (2006) propose a learning model to examine the relationship between analyst forecasting behavior and performance, in which a competitive market for banking services leads to such convexity in the pay-off. However, this setting does not appear to be relevant to our context; it is not immediately clear *ex ante* what would cause convexity in the manager's pay-off function in our setting. In untabulated empirical results, we consider the two key predictions yielded by the Clarke and Subramanian (2006) framework (i.e., a U-shaped relationship between past forecast

performance and boldness and a positive relation between boldness and experience). We do not find any support for either of them in our setting.

8. Conclusion

Motivated by two major behavioral principles, we investigate the short-term dynamics of manager's forecasts and examine whether managers become overconfident in their ability to predict future earnings after a series of good predictions. In contrast to other studies (e.g., Hribar and Yang, 2010), we treat overconfidence as endogenous, with an intensity that varies with the length of success. Overconfidence in this setting implies that managers weight their own estimates too heavily and rely too little on public signals. If this is the case, then the subsequent forecasts of these managers would be more likely to display a greater prediction error. To test this hypothesis, we regress forecast error on the number of accurate predictions in the previous four quarters, and find that forecast error in the current period is positively correlated with past success. The effect is both statistically and economically significant. In addition, these overconfident managers display greater divergence from the analyst consensus and are more precise. Finally, we find that market participants downplay the forecasts issued by overconfident managers. More specifically, after controlling for manager fixed effects, we find that both investors and financial analysts place less weight on the forecasts issued by managers who have recently made a series of accurate predictions.

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Table 1
Descriptive statistics

Variable	N	Mean	Median	Std. Dev.
ERR	5,768	2.04	0.97	3.27
RET	1,269	21.65	14.53	88.98
REV	25,204	0.94	1.00	1.42
STREAK	5,768	0.97	0.00	1.29
Hor	5,768	3.77	4.14	0.79
Size	5,768	7.72	7.64	1.44
B-to-M	5,768	0.40	0.36	0.23
StdEarn	5,768	0.02	0.01	0.02
RetVol	5,768	0.02	0.02	0.01
Cover	5,768	1.88	1.95	0.65
Loss	5,768	0.04	0.00	0.20

ERR is the absolute value of the difference between forecasted and realized earnings, deflated by the stock price two days before the issuance of the management forecast. *RET* is the ratio of the three-day size-adjusted stock return around the management forecast announcement to the difference between the management forecast and the consensus analyst forecast (scaled by the price two days before the issuance of the management forecast), based on a subsample that excludes management forecasts made within −1 to +1 days of an earnings announcement. *REV* is the ratio of an individual analyst forecast revision to the difference between the management forecast and the consensus analyst forecast. An individual analyst forecast revision is defined as the difference between an analyst forecast issued up to 30 days after the management forecast date and a forecast issued by the same analyst up to 90 days before the management forecast date. *STREAK* is the number of consecutive quarters in which the management forecast is more accurate than the consensus analyst forecast within the last four quarters. *Hor* is the forecast horizon measured as the log of the number of days between the management forecast date and the end of the forecast period. *Size* is the log of total assets at the beginning of the quarter. *B-to-M* is the book value divided by the market value of the firm's equity at the beginning of the quarter. *StdEarn* is the standard deviation of the quarterly return on assets over at least eight of the preceding twelve quarters. *RetVol* is the standard deviation of the stock return six months before the management forecast date. *Cover* is the log of the number of analysts covering the firm in a quarter. *Loss* is an indicator variable that takes a value of one if the earnings are negative, and zero otherwise. The means, medians, and standard deviations are computed for the entire sample, which begins in the last quarter of 1996 and finishes in the last quarter of 2007. *ERR* is multiplied by 1,000 for better readability.

Table 2
Correlation table

	ERR	STREAK	Hor	Size	B-to-M	StdEarn	RetVol	Cover
STREAK	**0.07**							
Hor	**0.07**	-0.04						
Size	**-0.07**	**-0.09**	**-0.05**					
B-to-M	**0.27**	**0.12**	-0.03	-0.04				
StdEarn	**0.15**	0.03	0.02	**-0.22**	0.02			
RetVol	**0.16**	**0.09**	0.02	**-0.36**	**0.23**	**0.47**		
Cover	**-0.05**	0.00	**-0.16**	**0.29**	**-0.15**	**0.08**	**0.04**	
Loss	**0.33**	**0.09**	-0.02	**-0.08**	**0.22**	**0.28**	**0.29**	0.00

The correlations in bold are significant at the 5% level or less.

ERR is the absolute value of the difference between forecasted and realized earnings, deflated by the stock price two days before the issuance of the management forecast. *STREAK* is the number of consecutive quarters in which the management forecast is more accurate than the consensus analyst forecast within the last four quarters. *Hor* is the forecast horizon measured as the log of the number of days between the management forecast date and the end of the forecast period. *Size* is the log of total assets at the beginning of the quarter. *B-to-M* is the book value divided by the market value of the firm's equity at the beginning of the quarter. *StdEarn* is the standard deviation of the quarterly return on assets over at least eight of the preceding twelve quarters. *RetVol* is the standard deviation of the stock return six months before the management forecast date. *Cover* is the log of the number of analysts covering the firm in a quarter. *Loss* is an indicator variable that takes a value of one if the earnings are negative, and zero otherwise.

Table 3
CEO overconfidence

	Dependent Variable
	ERR
STREAK	**0.86**
	(2.61)
HOR	3.16
	(5.92)
SIZE	-3.28
	(-1.07)
B-to-M	50.47
	(5.22)
Loss	13.67
	(4.88)
StdEarn	69.04
	(0.82)
RetVol	-259.17
	(-3.36)
Cover	0.07
	(0.12)
Number of observations	5,768
R-square	45.04

ERR is the absolute value of the difference between forecast and realized earnings, deflated by the stock price two days before the issuance of the management forecast. *STREAK* is the number of consecutive quarters in which the management forecast is more accurate than the consensus analyst forecast within the last four quarters. *Hor* is the forecast horizon measured as the log of the number of days between the management forecast date and the end of the forecast period. *Size* is the log of total assets at the beginning of the quarter. *B-to-M* is the book value divided by the market value of the firm's equity at the beginning of the quarter. *Loss* is an indicator variable that takes a value of one if the earnings are negative, and zero otherwise. *StdEarn* is the standard deviation of the quarterly return on assets over at least eight of the preceding twelve quarters. *RetVol* is the standard deviation of the stock return six months before the management forecast date. *Cover* is the log of the number of analysts covering the firm in a quarter. CEO fixed effects are included. For readability, all of the coefficients are multiplied by 1,000. The z-statistics, which are reported in parentheses, are calculated using double clustering by CEO and year to control for heteroskedasticity-consistent standard errors.

Table 4
Alternative specifications

	Dependent Variable			
	ERR	*SqrERR*	*ERRD*	*RelERR*
STREAK	0.86	9.42	0.17	0.04
	(2.61)	(3.94)	(5.81)	(2.10)
FREQ	0.89	12.38	0.33	0.08
	(2.34)	(4.16)	(7.44)	(3.88)
MACC	0.12	1.05	69.06	60.72
	(2.48)	(3.09)	(2.73)	(2.24)
WFREQ	3.55	45.89	1.05	0.25
	(2.49)	(4.21)	(7.04)	(3.01)
WMACC	0.13	1.10	64.46	56.38
	(3.33)	(4.09)	(2.64)	(2.10)
Number of observations	5,768	5,768	5,348	5,198

ERR is the absolute value of the difference between forecast and realized earnings, deflated by the stock price two days before the issuance of the management forecast. *SqrERR* is the square root of *ERR*. *ERRD* is an indicator variable that equals one if the management forecast is less accurate than the consensus analyst forecast, and zero otherwise. *RelERR* is the ratio of the management forecast error divided by the consensus analyst forecast error. *STREAK* is the number of consecutive quarters in which the management forecast is more accurate than the consensus analyst forecast within the last four quarters. *FREQ* is the number of accurate forecasts, whether consecutive or not, within the last four periods. *MACC* is the mean difference between the consensus analyst forecast error and the management forecast error in the last four quarters. *WFREQ* and *WMACC* are similar to *FREQ* and *MACC* but assign a different weight to each quarter. The weight given to the most recent quarter is 4 over 10, and those to the second, third, and fourth most recent quarters are 3 over 10, 2 over 10, and 1 over 10, respectively (10 being equal to 4 + 3 + 2 + 1). CEO fixed effects are included. For readability, all of the coefficients except *MACC* and *WMACC* in the first two columns are multiplied by 1,000. The z-statistics, which are reported in parentheses, are calculated using double clustering by CEO and year to control for heteroskedasticity-consistent standard errors.

Table 5
Additional forecast properties

	Dependent Variable	
	DEV	*RAND*
STREAK	**0.74**	**0.08**
	(2.03)	**(2.36)**
HOR	-1.55	0.47
	(-2.76)	(7.09)
SIZE	0.88	0.60
	(0.34)	(2.64)
B-to-M	42.97	-0.06
	(2.58)	(-0.09)
Loss	14.64	0.36
	(7.59)	(2.06)
StdEarn	74.79	0.82
	(0.79)	(0.18)
RetVol	177.71	0.39
	(1.47)	(0.05)
Cover	-1.59	1.31
	(-1.80)	(13.42)
Number of observations	5,768	4,825
R-square	39.27	21.89

DEV is the absolute value of the difference between the management forecast and the consensus analyst forecast (defined as the median of the analyst predictions up to 90 days before the management forecast date), deflated by the stock price two days before the issuance of the management forecast. *RAND* is an indicator variable that is equal to one if the management forecast range is smaller than the analyst forecast range, and zero otherwise. *STREAK* is the number of consecutive quarters in which the management forecast is more accurate than the consensus analyst forecast within the last four quarters. *Hor* is the forecast horizon measured as the log of the number of days between the management forecast date and the end of the forecast period. *Size* is the log of total assets at the beginning of the quarter. *B-to-M* is the book value divided by the market value of the firm's equity at the beginning of the quarter. *Loss* is an indicator variable that takes a value of one if the earnings are negative, and zero otherwise. *StdEarn* is the standard deviation of the quarterly return on assets over at least eight of the preceding twelve quarters. *RetVol* is the standard deviation of the stock return six months before the management forecast date. *Cover* is the log of the number of analysts covering the firm in a quarter. CEO fixed effects are included. For readability, all of the coefficients in the first column are multiplied by 1,000. The z-statistics, which are reported in parentheses, are calculated using double clustering by CEO and year to control for heteroskedasticity-consistent standard errors.

Table 6

Reactions to forecasts issued by overconfident managers

	Dependent Variable	
	RET	*REV*
STREAK	**-4.31**	**-4.06**
	(-2.49)	**(-2.75)**
HOR	-10.72	-1.78
	(-4.15)	(-0.95)
SIZE	-6.19	2.89
	(-0.47)	(0.33)
B-to-M	-2.93	-20.38
	(-0.05)	(-0.71)
Loss	21.40	19.53
	(1.73)	(3.03)
StdEarn	917.77	4.75
	(1.95)	(0.04)
RetVol	-924.15	346.45
	(-2.82)	(1.50)
Cover	-39.40	5.58
	(-4.82)	(1.97)
Number of observations	1,269	25,204
R-square	37.47	8.76

RET is the ratio of the three-day size-adjusted stock return around the management forecast announcement to the difference between the management forecast and the consensus analyst forecast (scaled by the price two days before the issuance of the management forecast). *REV* is the ratio of an individual analyst forecast revision to the difference between the management forecast and the consensus forecast before the issuance of the new management forecast. *STREAK* is the number of consecutive quarters in which the management forecast is more accurate than the consensus analyst forecast within the last four quarters. *Hor* is the forecast horizon measured as the log of the number of days between the management forecast date and the end of the forecast period. *Size* is the log of total assets at the beginning of the quarter. *B-to-M* is the book value divided by the market value of the firm's equity at the beginning of the quarter. *Loss* is an indicator variable that takes a value of one if the earnings are negative, and zero otherwise. *StdEarn* is the standard deviation of the quarterly return on assets over at least eight of the preceding twelve quarters. *RetVol* is the standard deviation of the stock return six months before the management forecast date. *Cover* is the log of the number of analysts covering the firm in a quarter. CEO fixed effects are included. For readability, all of the coefficients in the last column are multiplied by 100. The z-statistics, which are reported in parentheses, are calculated using double clustering by CEO and year in the first column and clustering by CEO, analyst, and year in the last column to control for heteroskedasticity-consistent standard errors.

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