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ABSTRACT

Human inference and estimation is subject to systematic biases. In particular, there is a long literature showing that overconfidence due to cognitive biases can lead to sub-optimal decisions. We depart from this research by showing empirically that a) over-optimism is a related but different bias, b) it can emerge dynamically in a rational framework rather than because of cognitive biases, and importantly, c) it can improve firm's welfare, more specifically, firms' profitability and market value.

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1. Introduction

One of the best-established stylized facts in the behavioral literature is that individuals are over-optimistic about future outcomes (e.g., Weinstein (1980), Dunning, Heath, and Suls (2004)). Over-optimism is related to overconfidence but is distinct. To use the terminology of Hackbarth (2008), optimistic managers overestimate the growth rate of earnings while overconfident managers underestimate the riskiness of earnings.[1] In other words, over-optimism creates an upward bias in the *mean* of the distribution while overconfidence creates an upward bias in its *precision*. Importantly, prior analytical work also suggests the possibility that over-optimism can increase firm performance (e.g., Van den Steen (2004)), but little empirical work exists on this topic.

We investigate whether past performance leads to managerial over-optimism and whether this optimism encourages managers to exert a greater effort. We first note that individuals are over-optimistic in general, and particularly so regarding the effect of their own actions (we call this phenomenon "static over-optimism"). In addition, managers may suffer from a biased attribution of causality after a series of good performance that leads them to under-estimate the role of random noise and over-attribute successes to their own actions (we call this phenomenon "dynamic overconfidence"). The combination of these two phenomena leads to an increase in over-optimism after a series of successes (we call this phenomenon "dynamic over-optimism"): optimistically-biased managerial actions receive an increasingly disproportionate weight in the

[1] Heaton (2002) defines managers as "optimistic" when they systematically overestimate the probability of good firm performance and underestimate that of bad performance.

overall estimation of the project success. Thus, our first hypothesis posits that the degree of managerial over-optimism should increase after a series of successes. Importantly, we then consider the effect of this estimation bias on managerial effort and in turn on a firm's welfare. Perhaps paradoxically, this miscalibration in managerial prediction may encourage managers to exert a greater effort. Our second hypothesis conjectures that firm performance should increase following a series of successes, even if the increase remains below the level expected by an over-optimistic manager. Since our predictions are largely about forecast dynamics rather than static biases, our tests focus on *time-series* properties for *a given manager* rather than on cross-sectional ones.[2]

We note that our hypotheses can be motivated in an economic framework in which individuals are Bayesian and fully rational. For example, Van den Steen (2004) proposes a model in which rational agents are endowed with different priors. In the most basic setting of this framework, a manager can choose from a menu of actions. For each action, the manager's prior over the likelihood of success equals the true probability plus a random error. The manager optimally chooses the action for which her prior is highest, which is also the action whose probability of success the manager is most likely to over-estimate. This generates the "static" over-optimism we discuss above. This framework also allows for a rational (i.e., Bayesian) but biased attribution of performance that yields a form of dynamic overconfidence. Combined with "static" over-optimism, this

[2] The fact that static optimism and dynamic overconfidence are intertwined provides the foundation for our analysis. Section IV of Van den Steen (2004) elaborates on the theoretical links between these two biases in our framework. The links are empirically important in our setting because, as we note in Section 2.2, "static" over-optimism is difficult to test in a cross-sectional setting. The dynamic form of over-optimism allows us to use fixed effect specifications.

phenomenon generates the "dynamic over-optimism" that is the core of our first hypothesis. Our second hypothesis relies on the idea that over-optimism can elicit higher effort from management. This emerges naturally in an economic framework if effort and probability of success are complements (e.g., the payoff is increasing in effort when the action is successful). As discussed below, we provide empirical results based on comparative statics that are consistent with this overall framework.[3]

Our empirical findings support the presence of dynamic over-optimism. First, we show that managers who experienced more frequent successes in the past four quarters subsequently issue more optimistic forecasts. Similarly, textual analysis indicates that earnings press releases display an increasingly optimistic tone as managers experience more short-term successes. Importantly, these results hold in specifications with manager fixed effects. By showing that over-optimism has an endogenous and dynamic component, our results suggest that, at least to some extent, managers are made (not born) over-optimistic. Our results are robust to a number of alternative definitions of past successes.

Second, and importantly, we show that the over-optimism we document can increase firm performance and that managers appear to exert greater effort to meet their own over-optimistic forecasts. Specifically, contemporaneous firm performance (as measured by return on assets) increases in the number of times the firm has met or exceeded managerial expectations over the last four quarters.

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[3] We note that our main hypotheses are also consistent with explanations based on cognitive biases. We distinguish between these two frameworks (rational and cognitive) by considering comparative statics in Section 4.1.

The quarterly market return also increases as the number of prior successes rises. In contrast, measures of accruals or real earnings management are not affected by the number of past forecast successes. These results suggest that the increase in firm performance is genuine, and that managers, being over-optimistic regarding the likelihood of meeting the expectations they set, may not feel the need to manage earnings to reach their forecasts. Firm performance over the subsequent four quarters is also positively affected, suggesting that the effect is persistent at least over one year.

Third, using comparative statics, we show that our empirical findings are consistent with the economic framework (such as the one proposed by Van den Steen (2004)), which predicts that over-optimism increases with the diffusion of priors and decreases with managerial experience. In contrast, we do not find support for the cognitive framework (e.g., Calderon (1993)), which predicts that people are more optimistically biased when the forecast environment is more uncertain or when a forecast's horizon is greater, and are less optimistically biased when prediction accuracy is likely to be challenged or when the consequences of inaccuracy are more severe. A key difference between these models is that the agent is Bayesian (but biased) in the economic framework but not in the cognitive one.

We contribute to the literature in several ways. First, we show that over-optimism can increase firm performance. Although prior analytical work suggests this possibility (e.g., Benabou, and Tirole (2002), Compte and Postlewaite (2004), Gervais, Heaton, and Odean (2007), Hackbarth (2008)), little empirical work exists on this topic. Second, we present evidence consistent with the comparative statics and ancillary predictions of the economic over-optimism framework. In fact, this framework provides a well-integrated motivation for our empirical tests and our study is able to shed light on most of the testable implications that have been identified by the prior literature. In contrast, we find weaker empirical support for the cognitive explanation. Lastly, we empirically distinguish between overconfidence and over-optimism. The importance of this distinction has been noted by the prior literature. For example, Moore and Healy (2008) explain (p. 503) that the "first problem with overconfidence research" is that the most popular research paradigm confounds the overestimation of one's actual ability, performance, level of control, or chance of success on the one hand and excessive certainty regarding the accuracy of one's belief on the other hand. There is now an established literature on overconfidence in managerial behavior (see Glaser and Weber (2010) for a review) but much less is known about over-optimism in this context.[4]

The remainder of the paper proceeds as follows. In Section 2, we discuss our hypotheses development and our empirical design. In Section 3, we present our main empirical results. In Section 4, we provide additional empirical results. Section 5 concludes.

[4] A small number of recent studies investigate the possibility that overconfidence is a dynamic phenomenon (e.g., Hilary and Menzly (2006), Hilary and Hsu (2011)). Our study differs from those studies in three important ways. First, we consider how the bias in forecast affects the managers' effort. We believe ours is one of the first empirical studies showing that biased (optimistic) expectations lead to an improvement in firm performance. Second, we show that past successes affect the <u>level</u> of the bias, while those studies focus on the precision of the forecast. In other words, we distinguish between over-optimism and overconfidence. Third, those studies rely on research in psychology to motivate their empirical analysis. We empirically explore a rational framework that does not rely on cognitive biases to motivate our hypotheses. To our knowledge, we provide the first archival study that is consistent with a rational explanation of over-optimism.

2. Hypothesis development and empirical design

2.1. Hypothesis development

Economics has traditionally assumed that people begin the decision-making process with subjective beliefs over the different possible states of the world and use a Bayesian approach to update these beliefs as they receive additional information. Under such a framework, individuals hold unbiased beliefs that typically converge toward the true parameter as more signals are received. However, this view has been challenged as numerous systematic biases have been identified. In particular, individuals have been shown to be over-optimistic and overconfident. These two biases are similar but distinct. Over-optimism involves an excessive belief that future events will be positive, while overconfidence involves placing too much weight on the accuracy of private information and an excessive belief in one's own skills. For example, Weinstein (1980) notes in his seminal study on over-optimism that people believe negative events are less likely to happen to them than to others whereas positive events are more likely to happen to them than to others.

The notion of static over-optimism can be explained both in an economic framework and in a cognitive one. On the economic side, Van den Steen (2004) proposes a model in which rational (Bayesian) individuals are endowed with a menu of actions that will lead to either a successful outcome or an unsuccessful outcome. The manager who selects actions has a prior with respect to the likelihood of whether a given action will be successful. If, for exogenous reasons, managers sometimes overestimate and sometimes underestimate the probability of an action's success (relative to other individuals such as analysts or relative to the true underlying probability) and select the action with the highest perceived probability of success, then they are more likely to select actions that overstate the probability of success the most. They will therefore be over-optimistic about the success of the actions they take. This mechanism is reminiscent of the winner's curse (i.e., the winner of auctions in which bidders have incomplete information is the bidder who has the most optimistic estimate of the asset's value). Under this framework, the random variation in priors together with systematic choice leads to systematic bias.[5] Moore and Healy (2008) provide an alternative model in which Bayesian individual can rationally overestimate their chance of success for difficult tasks while Benoit and Dubra (2011) show how a majority of Bayesian individuals may rationally believe they have greater skills than the majority of the population. On the cognitive side, research on dispositional optimism (e.g., Scheier and Carver (1985), Scheier, Carver, and Bridges (1994)) views optimism as generalized positive expectations about future events. Prior research in neuroscience demonstrates that specific brain regions subserve the imagining of future events (e.g., Addis, Wong, and Schacter (2007)), and that individuals can mentally distance themselves more easily from future negative events than past ones, allowing for an optimistic bias (Sharot et al. (2007)).[6]

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[5] In our setting, these actions are related to the management of the firm (e.g., increasing the level of inventory, starting an advertising campaign, and so forth) and we predict that managers subject to this over-optimism bias will expect higher earnings than justified. These actions are context specific and their precise nature is not the subject of our investigation.

[6] The cognitive literature proposes alternative explanations for over-optimism. For example, Weinstein (1980, 2003) suggests that unrealistic optimism is based on a need to defend self-

More than static over-optimism, our focus is on dynamic over-optimism. A recent empirical literature investigates the possibility that overconfidence (and managerial overconfidence in particular) is a dynamic phenomenon (e.g., Hilary and Hsu (2011)). Research on dynamic over-optimism is more limited although the dynamic aspect can be incorporated in both the economic and the cognitive frameworks. For example, Van den Steen's (2004) model leads to biased attribution of causality. In particular, the manager will rationally underestimate the role of exogenous factors in the case of success and overestimate their role in the case of failure. In the case of success, this biased attribution will lead the manager to gradually put more weight on the expected effect of her own actions (for which the prior distribution is optimistically biased) and less weight on the effect of random noise (for which the prior distribution may not be similarly biased). This change in weights will lead to a gradual increase in overall over-optimism even though the perceived probability of success for each individual action does not change over time. Rabin and Schrag (1999) and Gervais and Odean (2001) provide alternative theoretical economic rationalizations for the existence of dynamic overconfidence. From a cognitive point of view, a similar effect can be obtained through different channels.[7] Contrary to the economic framework, the cognitive framework suggests that individuals do not behave in a Bayesian fashion. Armor and Taylor (2002) conclude that this line of research

esteem against possible threats, while others (e.g., Dunning, Heath, and Suls (2004)) suggest that non-motivational factors such as egocentric neglect may play a role.

[7] Klaaren, Hodges, and Wilson (1994) shows that people with positive expectations put a favorable spin on the outcome they observe. Einhorn and Hogarth (1978) suggest that individuals have a tendency to look for confirming evidence (rather than for disconfirming evidence), while Lord, Ross, and Lepper (1979) suggest that individuals place too much trust in confirming evidence. Cooper and Artz (1995) show that entrepreneurs' level of satisfaction after three years of ownership is positively correlated with their initial expectations of success.

suggests that individuals who are highly optimistic going into a situation may be more likely to view their outcome favorably, which may further exacerbate their initial optimism. Based on this discussion, our first hypothesis is that individuals become dynamically over-optimistic following a series of successes.

We then turn our attention to the effect of over-optimism on the firm's welfare. Economic theory suggests that managers should work harder if effort complements the likelihood of success (e.g., Van den Steen (2004)).[8] For example, suppose the strictly positive payoff is increasing in effort in the case of success and is zero in the case of failure. Further assume that the cost of effort is increasing and strictly convex. The amount of effort is increasing in the perceived probability of success: the greater the expected probability, the greater the effort. To the extent that this effort increases firm performance, we expect an increase in firm performance after a series of successes, even if the increase is not sufficient to reach the level predicted in the forecast. Again, note that this prediction is also consistent with the cognitive framework. The induction of positive expectation can lead to a significant improvement in performance (e.g., Campbell and Fairey (1985), Peake and Cervone (1989), Sherman, Skov, Hervitz, and Stock (1981)). This appears to be true even for predictions that, at the time they are made, can be considered overly optimistic (Sherman (1980), Armor and Taylor (2002)). In the finance literature, Puri and Robinson (2007) show that individuals displaying greater dispositional optimism work harder. Based on this discussion, our second

[8] The complementarity of effort is an assumption. If effort were a substitute, our second hypothesis may run in the opposite direction.

hypothesis is that the firm's performance should gradually improve as managers become more optimistic.

2.2. Empirical design

To test these predictions, we focus on managerial forecasts of firm quarterly earnings. In doing so we obtain a measure of managerial expectations about future firm performance that we can benchmark against both common expectations at the time of issuance (as proxied by analyst forecasts) and subsequent realizations.

We decompose the public forecast F into two components, namely, the best estimate of the realization privately observed by the manager and a strategic negative bias that allows the manager to meet or beat her own forecast more easily.

$$F(X)_{i,t} = E(X)_{i,t} + b_{i,} \qquad (1)$$

where X is the realized earnings for firm-manager pair i in period t, F is the manager's public forecast of X, E(X) is the manager's private expectation of X, and b is the manager's strategic bias. Following Hilary and Hsu (2013), we assume that the strategic bias is constant (and typically negative) for each firm-forecaster pair. We further assume that the manager's private expectation is a combination of personal and public expectations regarding the results of the action, a, chosen by the manager. The combination of the two takes the form

$$E(X)_{i,t} = \alpha_{i,t}\, E_m(a)_i + (1-\alpha_{i,t})\, E_p(a)_{i,} \qquad (2)$$

where $E_m(a)$ represents the manager's personal expectation (formed independently of the public signal), $E_p(a)$ represents the public expectation, and α represents the weight that the manager places on her personal expectation. We next assume that the public expectation of the action taken by the manager is well calibrated (i.e., $E_p(a)$ is equal to the average realization of a, â). As discussed before, we expect the manager to be over-optimistic with respect to the effect of her actions (i.e., the manager's personal expectation of a, $E_m(a)$, is greater than â). For convenience, we also initially assume that this degree of static over-optimism, β_i (i.e., $E_m(a)_i - \hat{a}_i$), remains constant over time for a given firm-manager (we revisit this issue in Section 4.1). The overall bias in the management forecast released by the manager, $B_{i,t}$, is equal to $\alpha_{i,t}\,\beta_i + b_i$. It is thus impossible to know the average sign of the overall bias without knowing the precise value of the three parameters. This makes cross-sectional predictions difficult. However, as previously discussed, we expect that positive outcomes will make the manager more overconfident with respect to the effect of her actions. In other words, α is increasing with past successes and the overall bias is relatively more positive (or less negative) after a series of successes. This expectation yields time-series predictions that we can test.[9]

[9] The difference between two forecasts made by the same manager in two periods is equal to

$F(X)_2 - F(X)_1 = [\alpha_2 E_m(a) + (1-\alpha_2) E_p(a) + b] - [\alpha_1 E_m(a) + (1-\alpha_1) E_p(a) + b] = (\alpha_2 - \alpha_1)(E_m(a) - E_p(a)) = (\alpha_2 - \alpha_1)\beta$. If β is positive, the manager becomes more over-optimistic as she becomes more overconfident (i.e., as α increases).

More specifically, to test our first hypothesis that managers become dynamically over-optimistic after a series of successes, we estimate the following model:

$$Optim_{i,t} = \alpha_i + \beta_1\, MBSTR_{i,t} + \gamma^k X^k_{i,t} + \varepsilon_{i,t}, \qquad (3)$$

where *Optim* is a measure of the bias in the managerial forecast estimated as follows. When we consider the consensus analyst forecast as a benchmark, our main proxy is *MFD* (signed management forecast deviation from consensus), defined as the management forecast minus the pre-existing consensus analyst forecast divided by the stock price two days before the issuance of the management forecast (multiplied by 1,000 for readability). We define the consensus forecast as the median analyst forecast over the 90 days prior to the issuance of the management forecast. We also consider *ACI,* an indicator variable that takes the value of one if the forecast made by CEO i in period t is greater than the pre-existing consensus analyst forecast before the issuance of the managerial forecast, and zero otherwise. When we consider the earnings realization as a benchmark, our main proxy is *MFE* (signed management forecast error), defined as the management forecast minus the earnings realization divided by the stock price two days before the issuance of the forecast (multiplied by 1,000 for readability). We also consider *OPI*, an indicator variable that takes the value of one if the forecast made by CEO i in period t exceeds the subsequent earnings realization, and zero otherwise. *MBSTR*, our measure of recent successes, and the vector of control variables X^k are defined below after Model (4).

To test our second hypothesis that firm performance increases after a series of successes, we estimate the following model:

$$Perf_{i,t} = \alpha_i + \beta_1\ MBSTR_{i,t} + \gamma_k\ X^k_{\ i,t} + \varepsilon_{i,t}, \tag{4}$$

where *Perf* represents performance as proxied by return on assets (ROA). We use two measures of ROA, namely, *ROA* and *OpROA*. *ROA* is defined as quarterly earnings before extraordinary items and discontinued operations divided by total assets at the beginning of the quarter. *OpROA*, operating ROA, is defined as quarterly operating income divided by total assets at the beginning of the quarter, where operating income is earnings excluding special or non-recurring items such as gain or loss from asset sales, asset write-downs, or write-offs.

MBSTR, the streak of recent successes, is our key independent variable. It counts the number of consecutive successes that CEO i enjoyed in the four quarters before the current forecast was announced. For example, if the streak of recent successes is 1, 0, 0, and 1 (counting backward from quarters t-1 to t-4), then *MBSTR* will be equal to one. If the streak is 1, 1, 0, and 1 (counting backward from quarters t-1 to t-4), then *MBSTR* will be equal to 2.[10] Initially, we define a success as an earnings realization that is above the manager's expectation (i.e., the mid-point of a range forecast or the forecast for a point estimate), but the sensitivity analysis reported in Section 3.4 shows that our results are not affected when we use multiple alternative proxies to define success. Our key prediction is that β_1 should be positive in both Models (3) and (4).

[10] We consider the last four quarters as prior literature suggests that this is the optimal period length for measuring short dynamics in biases (Hilary and Menzly (2006), Hilary and Hsu (2011)).

X^k represents a vector of k control variables suggested by prior literature. *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 (Johnson, Kasznik, and Nelson (2001)). *Size* is the log of total assets at the beginning of the quarter (Baginski and Hassell (1997)). *B-to-M* is the book value of equity divided by the market value of equity at the beginning of the quarter (Bamber and Cheon (1998)). *StdEarn* is the standard deviation of the quarterly return on assets over at least six of the preceding eight quarters. *RetVol* is the standard deviation of the stock return six months before the management forecast date. *Loss* is an indicator variable that takes a value of one if earnings are negative, and zero otherwise (Rogers and Stocken (2005)). *Cover* is the log of the number of analysts covering the firm in a given quarter (Hilary and Hsu (2011)). All continuous variables are winsorized at the 1% level.

2.3. Estimation procedure

We employ a panel (fixed-effect) technique to estimate the equations (i.e., we use CEO- specific intercepts α_i). The manager fixed-effect regression is particularly suitable for testing our hypotheses, which focus on the short-term dynamics of managers' forecasts, as it eliminates cross-sectional variation in the means of the variables while leaving the time-series dynamics of these forecasts intact. This approach allows us to treat over-optimism as a time-varying variable whereas most of the prior empirical literature has treated optimism as a fixed or at least slow moving characteristic. The use of manager fixed effects also provides a natural control for omitted variables. For example, constant differences in managerial skill levels, prediction bias, or constant firm characteristics such as industry classification are all controlled for. The prior literature (e.g., Hirshleifer, Low and Teoh (2012), Malmendier, Tate and Yan (2011), Campbell et al (2011)) typically draws on Malmendier and Tate (2005, 2008) and use the amount of unexercised options held by the CEO as a proxy for managerial optimism. Users of this measure have been thoughtful about the potential issues with this measure and have done multiple checks to ensure its construct validity. However, we believe that our approach provides a direct estimate of the change in optimism and reduces the need for these multiple robustness checks. In our main specifications, we employ CEO fixed effects (we revisit this issue in Section 3.2). 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 prior literature. For example, Lee, Matsunaga, and Park (2012) 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 our ordinary least squares specifications (the p-value is less than 0.01 in all cases).

We use an Ordinary Least Squares (OLS) approach when the dependent variable is continuous and a logit specification when the dependent variable is binary. The standard errors are calculated according to the procedure outlined in Cameron, Gelbach, and Miller (2011) and are groupwise heteroskedasticity-consistent (i.e., adjusted simultaneously for heteroskedasticity and the clustering of observations by CEO and year).

3. Empirical results

3.1. Sample and descriptive statistics

We obtain our management forecast data, which cover the 1998-2008 period, from the *FirstCall* database.[11] To increase data consistency, we focus on quarterly predictions and exclude forecasts made after the end of the fiscal period (i.e., pre-announcements). 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 only includes point and range forecasts, that is, we exclude qualitative forecasts that do not provide a numerical value of earnings per share. We also require that managers issued forecasts in at least four of the previous eight quarters and that the same CEO managed the firm at the time that these forecasts were made. Chuk, Matsumoto, and Miller (2013) document the presence of several problems with the First Call CIG database, but these are mitigated by both the time series and cross-sectional characteristics of our sample. First, Chuk, Matsumoto, and Miller (2013) indicate that the problems in the First Call database are largely concentrated in the pre-1998 period, while our sample period starts in 1998. Second, we require at least

[11] Although our initial sampling period starts in 1994 when the management forecast become available in the First Call database, our sample requirements are such that we get only 11 observations before 1998. Our results are not affected when we include these 11 observations.

five management forecasts for each CEO – it is unlikely that CIG omits a given CEO who issues a series of forecasts.

We obtain CEO information from the *ExecuComp* database. We drop firms for which we are unable to obtain information such as the name of the CEO or the dates of her tenure. These sampling criteria yield 8,944 management forecasts, approximately 86% of which are range forecasts. We match the forecast data with the corresponding records of *FirstCall* reported earnings.[12] Accounting data come from Compustat's quarterly data files, and stock price and return data come from the daily files of the Center for Research in Security Prices.

Descriptive statistics are presented in Table 1. The mean and median values of *MFD* and *MFE* are reasonably close to zero (given that we multiply the values of these variables by 1,000). This suggests that managerial forecasts are reasonably well calibrated on average, albeit slightly below realization. However, this bias in reported forecasts is likely to be strategic as managers lowball their public forecasts to avoid negative earnings surprises (e.g., Tan, Libby, and Hunton (2010)). To the extent that this bias is constant over time, our fixed effect specifications will absorb it. The mean and median values of (quarterly) *ROA* and *OpROA* range between 1.7% and 1.9%.

Table 2 presents a correlation matrix. As expected, the correlation between *MFD* and *MFE* is positive but reasonably low (0.28). In addition, the (untabulated) correlation between *ACI* and *OPI* is only 0.05. This suggests that "relative" (i.e., compared to consensus) and "absolute" (i.e., compared to

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

realization) optimism are relatively independent phenomena. As expected, the correlation between *ROA* and *OpROA* is high (0.89). Our first hypothesis predicts a positive correlation between recent past successes and both our measures of optimism and our measures of performance. We find that the correlation between *MBSTR* and either *MFD, ROA* or *OpROA* is indeed positive. However, the correlation between *MBSTR* and *MFE* is negative, suggesting that managers who meet or beat with a longer streak in the past are more likely to meet or beat in the current quarter than those who meet or beat with a shorter streak. This result can be explained by the fact that some managers structurally display a greater ability to meet or beat forecasts than others. Our framework does not preclude (nor does it predict) cross-sectional differences in managers' abilities. Rather, it predicts that managers who experienced recent successes in meeting their own public forecasts will issue more optimistic forecasts than their characteristics would otherwise predict (that is, in the absence of the bias). In other words, our framework describes time-series rather than cross-sectional behavior. This finding highlights the importance of using fixed effects in our analysis and, as shown in Table 3, the correlation between *MBSTR* and *MFE* has the predicted direction in our panel specifications. When we consider the correlations among control variables, we observe that most of them are low, suggesting that multicolinearity is not an issue in our setting.

3.2. Dynamic over-optimism

The empirical results for the estimation of Model (3) are reported in Table 3. In the first column, we use the consensus analyst forecast as a benchmark. Results indicate that *MBSTR* is significantly associated with the degree of optimism relative to the consensus forecast. Specifically, *MBSTR* is significantly positive with a z-statistic equal to 5.49. The economic effect is such that the median value of *MFD* goes from -0.86 to -0.22 as *MBSTR* increases from 0 to 4. We reach similar conclusions when we use *ACI* as the dependent variable; in particular, we find that *MBSTR* is significantly positive with a z-statistic equal to 5.10 (untabulated). In the second column, we use the realization of the forecasted earnings as a benchmark. Results indicate that *MBSTR* is significantly associated with the degree of optimism relative to the subsequent realization. Specifically, *MBSTR* is significantly positive with a z-statistic equal to 4.77. The economic effect is such that the median value of *MFE* goes from 0.34 to 0.75 as *MBSTR* increases from 0 to 4. We reach a similar conclusion when we use *OPI* as the dependent variable, where *MBSTR* is significantly negative with a z-statistic equal to 3.60 (untabulated). Turning attention to the control variables, we do not observe a robust pattern across the two columns. One exception is *B-to-M,* which is negatively associated with the degree of optimism in both columns of Table 3. However, *B-to-M* is insignificant in the two untabulated logit specifications.

The above results continue to hold if we calculate *MBSTR* over three, five, or six quarters instead of four, or if we define *MBSTR* as the number of successes over the last four forecasts instead of the number of successes in a row. The results are also robust to using *SqrMFD* and *SqrMFE* (the square root of *MFD* and *MFE* while retaining their sign) to mitigate any skewness in the *MFD* and *MFE*, and to using the mean values of *MFD* and *MFE* by industry based on the Fama and French (1997) classification to control for industry shocks. Our results also continue to hold when we include several additional control variables. While the empirical literature on determinants of meeting or beating quarterly management forecasts is fairly limited, the literature on meeting or beating quarterly analyst forecasts suggests that, aside from fixed characteristics such as industry membership that we control for using fixed effects, factors such as a loss, special items, growth, prior stock return, and specific time period may matter. We already control for the existence of a loss in our baseline specification. However, we find that our conclusions are not affected if we control for the amount of special items reported in earnings, total accruals, sales growth, return momentum (i.e., the market-adjusted return over the six months prior to forecast issuance), forecast experience, and year (and fourth quarter) indicator variables.[13] Finally, our results continue to hold if we use firm fixed effects or Chief Financial Officer (CFO) fixed effects instead of CEO fixed effects.

[13] Results also hold if we control for a vector of largely cross-sectional variables that have been shown to affect managerial forecast characteristics (institutional ownership, number of outside directors, litigation risk, and internal control weaknesses).

3.3. Firm's welfare

Results reported in Table 4 confirm that *MBSTR* is positively correlated with both measures of performance. The respective statistics are 4.40 and 4.02. The economic effect is such that increasing *MBSTR* by one standard deviation increases *ROA* and *OpROA* by 3% to 4% of its median value. The positive coefficients associated with *MBSTR* are consistent with the presence of complementary effort. These results are robust to various specification checks. For example, they continue to hold if we calculate *MBSTR* over three, five, or six quarters instead of four, and if we define *MBSTR* as the number of successes over the last four forecasts instead of the number of successes in a row.

Further, they continue to hold if we use alternative dependent variables. Specifically, the results continue to go through if we use the change in *ROA* and in *OpROA* instead of the levels (the t-statistics are 4.11 and 4.26, respectively), if we use a binary variable equal to one if earnings are greater than prior-quarter earnings and zero otherwise (the z-statistics equal 5.49 for net earnings and 5.61 for operating earnings), or if we use a binary variable equal to one if the firm reports a profit and zero if it reports a loss (the z-statistics equal 3.59 for net profit and 3.42 for operating profit).[14] The results also hold when we control for the mean of *ROA* and *OpROA* by industry in the two regressions[15] and if we use firm fixed effects or CFO fixed effects instead of CEO fixed effects.

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[14] We use a logit specification when the dependent variable is binary.

[15] We control for the mean of *ROA* and *OpROA* by industry to avoid confounding effects of macroeconomic shocks.

Turning our attention to the control variables, we find that firms with high book-to-market, negative earnings, large size, and (perhaps more surprisingly) large volatility of earnings observe lower growth in profitability. Our conclusions are also not affected if we control for the amount of special items reported in earnings, total accruals, sales growth, return momentum (i.e., the market-adjusted return for the six months prior to the forecast issuance), forecast experience, institutional ownership, number of outside directors, litigation risk, internal control weaknesses, fourth quarter and year indicator variables.

3.4. Alternative definitions of past successes and optimism

In our main specifications, we define a managerial success as a situation in which a manager announced earnings that were above her own expectations. Our results are also robust to alternative definitions of successes. Specifically, we consider six additional specifications for *MBSTR*. In the first (*STRMin*), we consider the lower bound of a range forecast (instead of the mid-point) to evaluate if a forecast is classified as "successful". In the second (*STRGrowth*), we define a success as a realization that is above the prior-quarter realization. In the third (*STRDebias*), we define a success as a realization that is above the forecast adjusted for the systematic bias in the managerial forecast (i.e., forecast minus average forecast error for the CEO over the entire sampling period). In the fourth, we define a success as a realization that is above the manager's forecast and is positive. In the fifth, we define a success as a realization that is greater than the prior-quarter realization and is positive. Finally, in the sixth, we define a success as a realization that is above both the manager's forecast and the prior-quarter realization.

When we re-estimate Models (3) and (4) using these six alternative measures of *MBSTR*, our conclusions are not affected: the z-statistics range between 3.27 and 8.69 when *MFD* is the dependent variable, between 2.19 and 5.21 when *MFE* is the dependent variable, between 3.18 and 4.74 when *ROA* is the dependent variable and between 3.25 and 6.07 when *OpROA* is the dependent variable. Results from Model (4) also hold if we use *MFD* instead of *MBSTR* as a more direct measure of over-optimism (the t-statistics are 6.52 and 8.88 for *ROA* and *OpROA*, respectively).[16]

One additional potential concern with the results in Table 3 is that they may be explained by mean reversion. In other words, it could be argued that there is a mechanical relationship between past forecast error and contemporaneous forecast error if the error process is mean-reverting. This concern is mitigated when we use a relative measure of optimism (*MFD* or *ACI*) that is weakly correlated with the absolute measure of optimism (*MFE* or *OPI*). As noted in Section 3.1, the correlation between *ACI* and *OPI* is only 0.05. This concern is also reduced when we use *STRGrowth* (the measure of past successes based on earnings growth described above) as a measure of success. The correlation

[16] We do not consider *MFE*, the difference between the managerial forecast and the earnings realization, as there is a mechanical relation between ROA (earnings scaled by assets) and earnings realizations.

between *STRGrowth* and either *MBSTR* or *STRDebias* is also reasonably low (34% and 17%, respectively). To further address this issue, we use *Tone*, a measure of the degree of optimism in the press release disclosing the forecast, as the dependent variable in Model (3). To calculate *Tone*, we rely on linguistic software to characterize the degree of optimism in press releases issued by the firm. We provide additional details on the construction of *Tone* in the Appendix. The correlation between *Tone* and either *MFD* or *MFE* is low (7% and 1%, respectively). The correlations between *Tone* with *ACI* or *OPI* are also low (2% and 4%, respectively). Untabulated results indicate that *MBSTR* is significantly positive with a z-statistic of 3.70 when we re-estimate Model (3). The fact that our baseline results go through using largely uncorrelated dependent variables suggests that we are not capturing a mechanical relationship induced by a mean-reverting forecast error.

4. Additional Analysis

4.1. Economic and cognitive models

Results in Table 3 (and 4) are consistent with the presence of dynamic over-optimism but, as noted in Section 2.1, dynamic over-optimism is consistent with both economic and cognitive models. To distinguish between these two (not necessarily mutually exclusive) frameworks, we conduct comparative statics analysis.

We first consider the two partitions suggested by the economic framework, namely, prior dispersion and experience.[17] As Van den Steen (2004) notes, over-optimism increases in the mean-preserving spread of the distribution of priors. Intuitively, noise will increase with more open disagreement with respect to the success of different actions. We proxy for this disagreement by calculating *Disp*, the dispersion in analyst forecasts (e.g., Diether, Malloy, and Scherbina (2002)), as the standard deviation of analyst forecasts 90 days prior to the issuance of a management forecast divided by price. We then split the sample based on the median value of *Disp* and re-estimate Model (3) using our two continuous variables (*MFD* and *MFE*) as the dependent variables in each sub-sample. Van den Steen (2004) also notes that the bias should weaken as managers gain more experience about the probability of success associated with different possible actions. The effect of experience results from a reduction in the heterogeneity of the priors rather than a decrease in the underlying mechanism that generates over-optimism. To investigate this possibility, we calculate *Exp* as the number of quarters for which a CEO has issued management forecasts prior to the current quarter. We then partition the sample using the median value of *Exp*. Results for the two partitions are reported in Panel A of Table 5. For brevity, we tabulate the coefficient and z-statistic for *MBSTR* and omit those for the other control variables. We also tabulate the p-value associated with the chi-square test that examines whether the difference between coefficients is statistically

[17] A last comparative static suggested by Van den Steen (2004) is the number of actions available to the manager. However, the effect of this partition is not easily testable in our setting for lack of good empirical proxy for the number of alternatives the manager faces.

significant across the two subsamples. As predicted by the economic framework, over-optimism is stronger when there is greater dispersion in analyst priors and when managers have less experience. Taken together, these results support an explanation based on the economic framework.

We next consider partitions suggested by the cognitive framework. Gilovich, Kerr, and Medvec (1993) find that predictions made well before actions are taken are more optimistic than predictions made immediately before actions are taken. We examine the effect of temporal proximity by splitting the sample based on the median value of forecast horizon (*Hor*). Armor and Taylor (2002) note that people appear to be more optimistically biased under conditions of greater uncertainty about the outcome. We examine the effect of uncertainty by splitting the sample based on the median value of earnings volatility (*StdEarn*). Note that uncertainty about the outcome realization is distinct from uncertainty about the outcome probability as measured by the dispersion of priors: in the former case, the outcome is uncertain but the distribution is known (*StdEarn*), whereas in the latter case the distribution itself is uncertain (*Disp*). Armor and Taylor (2002) also show that people display greater over-optimism when the accuracy of their predictions is less likely to be challenged and when they expect the consequence of being inaccurate to be less severe. We use the level of analyst coverage (*Cover*) to proxy for the likelihood of being challenged. We capture the severity of the consequences of being wrong using the earning response coefficient (*ERC*), where we estimate the *ERC* for each firm over the entire sample period (with at least eight observations for each firm) by regressing the market-adjusted, three-day buy-and-hold cumulative return (centered on the earnings announcement day) on the forecast error divided by stock price. *ERC* measures how important earnings news is for the stock price. We split the sample based on the median values of the partitioning variables and re-estimate Model (3) in each subsample. Results are reported in Panel B of Table 5.[18] The differences in coefficients typically take the predicted sign. However, they are not statistically different across subsamples and the p-values are typically above 0.50. The one exception is the split based on horizon when *MFD* is the dependent variable (but not when *MFE* is the dependent variable). In this case, the p-value is 0.07. Taken together, these results do not provide strong support for an explanation based on the cognitive framework.

4.2. Increase in over-optimism or decrease in over-pessimism?

The results from Table 3 are consistent with the presence of dynamic over-optimism. However, it could be argued that these results reflect a decrease in over-pessimism rather than an increase in over-optimism. We investigate this possibility by turning our attention to analyst reactions. If there is a reduction in pre-existing (suboptimal) over-pessimism, managerial forecasts should come closer to optimality and financial analysts should give more weight to forecasts after a streak of successes. To test this conjecture, we regress *REV* on *MBSTR* and our usual control variables, where *REV* is defined as the ratio of an individual

[18] Other mediating variables have been suggested by the behavioral literature, for instance, anxiety or dysphoria. However, the effects of these partitions are difficult to measure in our setting.

analyst forecast revision to the difference between the management forecast and the consensus forecast before the issuance of a new management forecast,[19] and an individual analyst forecast revision is defined as the difference between an analyst's first forecast issued within 30 days after the management forecast date and the latest forecast issued within 90 days before the management forecast date. In untabulated results, we find the coefficient associated with *MBSTR* is significantly negative with a z-statistic of -2.72. This finding indicates that analysts give less weight to these forecasts, which suggests that these forecasts are further from optimality than the managerial forecasts unaffected by past successes. In other words, the positive effect of *MBSTR* on our measures of optimism reflects an increase in over-optimism rather than a decrease in over-pessimism.

4.3. Over-optimism and overconfidence

Our results so far indicate that CEOs become dynamically over-optimistic. As explained above several times, over-optimism and overconfidence are two distinct notions. However, a key part of the underlying mechanism is a biased attribution that leads the agent to become dynamically overconfident in her skill and gradually puts more weight on both her own information and her own

[19] 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).

actions.[20] Although our focus is on over-optimism (i.e., the belief that future events are more likely to be positive than is justified), we investigate the importance of dynamic overconfidence in our setting. Specifically, we examine whether past successes affect three measures of overconfidence (defined as placing too much weight on the accuracy of private information and an excessive belief in personal skills): the likelihood of issuing a forecast (*ISSUE*) in the current quarter, the range of the forecast (*RANGE*), and the likelihood of being more accurate than the consensus forecast (*ACCD*). To do this, we estimate the following model:

$$Conf_{\mathrm{i,t}} = \alpha_{\mathrm{i}} + \beta_1\, MBSTR_{i,t} + \gamma^k X^k_{i,t} + \varepsilon_{i,t,} \qquad (5)$$

where *Conf* represents the measure of overconfidence (*ISSUE, RANGE,* and *ACCD*). *ISSUE* equals one if the manager issues a management forecast in the current quarter (and we have sufficient data to estimate *MBSTR*), and zero if the firm has issued forecasts in the past (i.e., we have sufficient data to estimate *MBSTR*) but not in the current quarter. *RANGE* is the absolute value of the difference between the upper and lower bounds of the forecast divided by the stock price (point estimates have a range of zero). *ACCD* equals one if the management forecast is more accurate than the consensus analyst forecast and zero otherwise. *MBSTR* is our previously defined measure of prior successes and X^k is the vector of control variables.

[20] We note that this bias attribution is also widely studied by the cognitive literature (see, for example, Kunda (1990) for a review) and thus is not limited to the economic framework we consider here.

The untabulated results are consistent with dynamic overconfidence increasing with over-optimism. In particular, *MBSTR* is positively associated with the likelihood of issuing a forecast (z-statistic=7.25), negatively associated with the range of the forecast (z-statistic=-5.18), and negatively associated with the likelihood of being more accurate than the consensus analyst forecast (z-statistic=-2.79). In other words, after a series of successes, managers are more likely to issue a forecast that is more precise but less accurate. As noted by prior literature (e.g., Hilary and Hsu (2011)), this pattern can be explained by dynamic overconfidence paralleling the dynamic over-optimism that we identify in Section 3.2.

4.4. Is the improvement in performance genuine?

As noted above, results from Table 4 are consistent with the idea that optimism and effort are complements. However, an alternative explanation is that managers manipulate reporting to deliver on the optimistic forecast once it has been announced. This could be done through either accrual manipulation or real earnings management. To investigate these possibilities, we first look for evidence of manipulation. We then examine whether markets take the improvement in performance to be genuine.

To determine whether there is evidence of manipulation, we regress a measure of accrual management (*AccrMgt*) and a measure of real earnings management (*RealMgt*) on *MBSTR* and our usual control variables:

$$Mgt_{i,\mathrm{t}} = \alpha_{\mathrm{i}} + \beta_1\, MBSTR_{\mathrm{i,t}} + \gamma^{\mathrm{k}}\, X^{k}_{\mathrm{i,t}} + \varepsilon_{i,t,} \qquad (6)$$

where *Mgt* represents earnings management as proxied by *AccrMgt* or *RealMgt.* We calculate *AccrMgt* as the residual from a specification that regresses total accruals on assets, change in sales minus change in accounts receivables, and plant, property, and equipment (e.g., Brown and Pinello (2007)). We calculate *RealMgt* as a combination of the abnormal levels of cash flow from operations (OCF), discretionary expenses, and production costs (e.g., Roychowdhury (2006)). We provide additional details on the construction of *AccrMgt* and *RealMgt* in the Appendix.

Results for Model (6) are presented in the first two columns of Table 6. Inconsistent with the presence of manipulation, the coefficients on *AccrMgt* and *RealMgt* are insignificantly different from zero in both regressions, with z-statistics of 0.33 and 0.23, respectively. We also use a performance-adjusted abnormal accrual measure for *AccrMgt*. For each quarter-industry (two-digit SIC code) pair, we create four portfolios by sorting the data into quartiles of ROA measured four quarters prior to the quarter of portfolio formation. The abnormal accrual for a given firm is the unexplained accrual for that firm minus the average (excluding the sample firm). Our conclusions are not affected by this alternative measure of *AccrMgt*. Our results are also similar when we use the three individual real earnings management proxies (*R_OCF*, *R_PROD,* and *R_DISX*) in our test.

To examine whether markets take the improvement in performance to be genuine, we regress *AdjRet*, the buy-and-hold market-adjusted return for the quarter, on *MBSTR* and our usual control variables:

$$AdjRet_{i,t} = \alpha_i + \beta_1 \, MBSTR_{i,t} + \gamma^k X^k_{i,t} + \varepsilon_{i,t.} \qquad (7)$$

If the improvement in performance is genuine, we expect *MBSTR* to be significantly positive.

The results, presented in Column 3 of Table 6, are consistent with this prediction. In particular, the coefficient on *MBSTR* is positive and significant with a t-statistic equal to 4.64. The economic effect is such that increasing *MBSTR* by one unit increases the quarterly adjusted return by 0.8%. The results continue to hold if we use raw returns or if we start the return accumulation period after the management forecast announcement. They also hold if we define *MBSTR* as the number of successes over the last four forecasts instead of the number of successes in a row. Overall, the lack of evidence in support of managerial manipulation and the presence of positive returns suggest that the improvement in performance is genuine.

4.5. How persistent is the increase in profitability?

In our final set of analyses, we examine whether the positive effect of over-optimism on firm performance is short lived or persistent. To this end, we regress two measures of future performance (*Future*) on *MBSTR* and our usual control variables:

$$Future_{i,t} = \alpha_i + \beta_1 \, MBSTR_{i,t} + \gamma^k X^k_{i,t} + \varepsilon_{i,t,} \qquad (8)$$

where *Future* is the sum of our performance measures over quarters t+1 to t+4. Our two measures of future performance are *FutureROA,* which is earnings before extraordinary items and discontinued operations summed over four quarters starting with quarter t+1, divided by average total assets from quarter t+1 to quarter t+4, and *FutureOpROA,* which is defined in a similar way except that we use operating income instead of earnings before extraordinary items and discontinued operations in the calculation.

The results, reported in Table 7, indicate that the effect of over-optimism on performance remains for at least a year. When *FutureROA* and *FutureOpROA* are dependent variables, the z-statistics associated with *MBSTR* are 2.88 and 3.57, respectively. The economic effect is such that increasing *MBSTR* by one unit increases *FutureROA* and *FutureOpROA* by 25% to 30% of its median value. *Size*, *B-to-M,* and *Loss* remain negatively associated with the growth in future profitability. In contrast, *StdEarn,* which was significant in Table 4, ceases to be significant (at least in Column 2), while *RetVol,* which was insignificant in Table 4 (at least in Column 2), becomes significantly negative. When we consider each of the four subsequent quarters separately instead of considering the cumulative effect over the next year (as in Table 7), untabulated results indicate that the coefficients and z-statistics associated with *MBSTR* are approximately constant across the four quarters, that is, the positive effect of optimism on firm performance is not short lived and persists at least over the mid-term. When we define *FutureROA* over quarters t+5 to t+8 (instead of t+1 to t+4), *MBSTR* ceases to be significant. *MBSTR* remains significant when we consider *FutureOpROA* but the point estimate of the coefficient is reduced to 1.14 compared to the 1.68 reported in Table 7.

5. Conclusion

Human inference and estimation is subject to systematic biases. In particular, there is a long literature showing that overconfidence due to cognitive biases can lead to sub-optimal decisions. We depart from this research by showing empirically that a) optimism is a related but different bias, b) it can emerge dynamically in a rational framework rather than because of cognitive biases, and c) it can improve firm's welfare.

Specifically, we show that managers of firms that have experienced recent successes are more likely to subsequently issue forecasts that are more optimistic than they would have been absent this bias. Further, press releases become increasingly optimistic as the firm experiences short-term successes. Comparative statics suggest that these results are better explained by an economic framework than by a cognitive one. In particular, consistent with Van den Steen (2004), optimism increases with the diffusion of managerial priors and decreases with managerial experience.

Importantly, we also find that managers appear to exert greater effort to meet their over-optimistic forecasts: contemporaneous performance increases as the number of recent prior successes rises. This is true for both ROA and market returns. In contrast, contemporary measures of accruals or real earnings management are not affected by past performance, suggesting that the increase in performance is genuine and not the byproduct of managerial manipulation. In addition, future ROA performance over the next four quarters is also positively affected, suggesting that the effect is persistent, at least over the mid-term.

Appendix

Estimation of *Tone, AccrMgt,* and *RealMgt*

Tone

Tone is the *Optimism* score for the text of management's forecast press release as generated by *DICTION software* (www.dictionsoftware.com). Diction uses dictionaries (word lists) to search a text for qualities such as certainty, realism, and optimism and scores these qualities based on occurrence. The dictionary approach to textual analysis is well established, dating back several decades (see, for example, the Harvard-IV-4 and Lasswell dictionaries used in the General Inquirer: www.wjh.harvard.edu/~inquirer). Diction is a more recent application of this approach and has been applied in various scholarly fields to examine a wide variety of public communications, including newspaper articles, political speeches, corporate filings, and company press releases (for a list of scholarly research employing the Diction language analysis program, see www.dictionsoftware.com/files/dictionresearch.pdf). Full texts of earnings forecast press releases are obtained from Factiva. We average *Optimism* scores where more than one press release occurred on the same day for the same company.

AccrMgt

We follow Brown and Pinello (2007) to calculate *AccrMgt* as the residual from the following regression estimated with quarterly data for all COMPUSTAT firms in each industry-year (industry and firm subscripts omitted):

$$TA_t\,/\,Assets_{t\text{-}1} = \beta_1(1\,/\,Assets_{t\text{-}1}) + \beta_2[(\Delta SALE_t - \Delta REC_t)\,/\,Assets_{t\text{-}1}] +$$
$$\beta_3(PPE_t\,/\,Assets_{t\text{-}1}) + \varepsilon_t, \qquad \text{(a)}$$

where TA_t is total accruals for quarter t, defined as earnings before extraordinary items and discontinued operations. $Assets_{t\text{-}1}$ represents total assets at the beginning of the quarter. $\Delta SALE_{it}$ is the change in revenues from quarter t-1 to quarter t. ΔREC_t is the change in accounts receivable from quarter t-1 to quarter t, and PPE_t is net property, plant, and equipment at the end of quarter t. We require at least 15 observations to estimate the regression.

RealMgt

We follow Roychowdhury (2006) to calculate *RealMgt.* Specifically, we consider the abnormal levels of cash flow from operations (OCF), production costs, and discretionary expenses. We estimate the normal level of OCF using the following cross-sectional regression for each industry-year:

$$OCF_t\,/\,Assets_{t\text{-}1} = \beta_1(1\,/\,Assets_{t\text{-}1}) + \beta_2(SALE_t)\,/\,Assets_{t\text{-}1} +$$
$$\beta_3(\Delta SALE_t\,/\,Assets_{t\text{-}1}) + \varepsilon_t. \qquad \text{(b)}$$

We estimate the normal level of production costs as:

$$PROD_t / Assets_{t-1} = \beta_1(1 / Assets_{t-1}) + \beta_2(SALE_t) / Assets_{t-1} + \beta_3(\Delta SALE_t / Assets_{t-1})$$
$$+ \beta_4(\Delta SALE_{t-1}) / Assets_{t-1}] + \varepsilon_t. \qquad \text{(c)}$$

The normal level of discretionary expenses can be expressed as a linear function of sales:

$$DiscExp_t / Assets_{t-1} = \beta_1(1 / Assets_{t-1}) + \beta_2(SALE_{t-1}) / Assets_{t-1} + \varepsilon_{t.} \qquad \text{(d)}$$

In the above equations *OCF* is cash flow from operations in quarter t; *Prod* represents production costs in quarter t, defined as the sum of the cost of goods sold and the change in inventories; and *DiscExp* represents discretionary expenditures in quarter t, defined as the sum of R&D expenses and SG&A. Abnormal OCF (*R_OCF*), abnormal production costs (*R_PROD*), and abnormal discretionary expenses (*R_DISX*) are computed as the difference between the actual values and the normal levels predicted from equations (b), (c), and (d). We require at least 15 observations to estimate each regression.

We compute *RealMgt* by summing the three individual real earnings management variables. Specifically, we multiply *R_OCF* and *R_DISX* by negative one so the higher the amount of *R_OCF* and *R_DISX*, the more likely it is that the firm is engaging in sales manipulation through price discounts and discretionary expense reductions. We do not multiply *R_PROD* by negative one since higher production costs, as noted earlier, are indicative of overproduction to reduce cost of goods sold.

References

Addis, Donna Rose, Alana T. Wong, and Daniel L. Schacter, 2007, Remembering the past and imagining the future: Common and distinct neural substrates during event construction and elaboration, *Neuropsychologia* 45, 1363-1377.

Armor, David A. and Shelley E. Taylor, 2002, When predictions fail: The dilemma of unrealistic optimism, in *Heuristics and Biases, The psychology of Intuitive Judgment*, Editor, Thomas Gilovich, Dale Griffin and Daniel Kahneman, Cambridge University Press, 334-347.

Baginski S. P. and J. M. Hassell, 1997, Determinants of management forecast precision, *The Accounting Review* 72, 303-312.

Bamber L. S. and Y. S. Cheon, 1998, Discretionary management earnings forecast disclosures: antecedents and outcomes associated with forecast venue and specifity choices, *Journal of Accounting Research* 36, 167-190.

Benabou, Roland and Jean Tirole, 2002, Self-confidence and personal motivation, *Quarterly Journal of Economics* 117, 871-915.

Benoit, J-P and J. Dubra, 2011, Apparent overconfidence, *Econometrica* 79, 1591-1625.

Brown, L. D. and A. S. Pinello, 2007, To what extent does the financial reporting process curb earnings surprise games? *Journal of Accounting Research* 45, 947-981.

Calderon, T.G., 1993, Predictive properties of analysts' forecasts of corporate earnings, *The Mid-Atlantic Journal of Business* 29, 41-58.

Campbell, Jennifer D. and Patricia J. Fairey, 1985, Effects of self-esteem, hypothetical explanations, and verbalization of expectancies on future performance, *Journal of Personality and Social Psychology* 48, 1097-1111.

Campbell, T. Colin, Michael Gallmeyer, Shane A. Johnson , Jessica Rutherford, and Brooke W. Stanley, 2011, CEO optimism and forced turnover, *Journal of Financial Economics* 101, 695-712.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller, 2011, Robust inference with multi-way clustering", *Journal of Business and Economic Statistics* 29, 238-249.

Chuk, E., D. Matsumoto, and G. S. Miller, 2013, Assessing methods of identifying management forecasts: CIG vs. researcher collected. *Journal of Accounting and Economics* 55, 23–42.

Compte, Olivier and Andrew Postlmaite, 2004, Confidence-enhanced performance, *American Economic Review* 94, 1536-1557.

Cooper, Arnold C. and Kendall W. Artz, 1995, Determinants of satisfaction for entrepreneurs, *Journal of Business Venturing* 10, 439-457.

Diether, Karl, Christopher J. Malloy and Anna Scherbina, 2002, Differences of opinion and the cross section of stock returns, *Journal of Finance* 57, 2113-2141.

Dunning, D., Heath, C. and J. Suls, 2004, Flawed self-assessment: implications for health, education, and the workplace, *Psychological Science in the Public Interest* 5, 69-106.

Einhorn, H. J., & Hogarth, R. M., 1978, Confidence in judgment: Persistence of the illusion of validity, *Psychological Review* 85, 395-416.

Fama, E. and K. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153-193.

Gervais, S., Odean, T., 2001, Learning to be overconfident, *Review of Financial Studies* 14, 1-27.

Gervais, Simon, J.B. Heaton and Terrance Odean, 2007, Overconfidence, investment policy, and manager welfare", *working paper*.

Gilovich, T., Kerr, M., & Medvec, V.H., 1993, The effect of temporal perspective on subjective confidence, *Journal of Personality and Social Psychology* 64, 552-560.

Glaser, Markus and Martin Weber, 2010, Overconfidence, *Behavioral Finance*, Kolb Series in Finance, Wiley, H. Kent Baker and John R. Nofsinger, editors, pp. 241-258.

Hackbarth, Dirk, 2008, Managerial traits and capital structure decisions, *Journal of Financial and Quantitative Analysis* 43, 843-881.

Heaton, J.B., 2002, Managerial Optimism and Corporate Finance, *Financial Management* 31, 33 - 45

Hilary, Gilles, and Charles Hsu, 2011, Endogenous overconfidence in managerial forecasts, *Journal of Accounting and Economics* 51, 300-313.

Hilary, Gilles, and Charles Hsu, 2013, Analyst forecast consistency, *Journal of Finance* 68, 271-297.

Hilary, Gilles, and Lior Menzly, 2006, Does past success lead analysts to become overconfident?, *Management Science* 52, 489-500.

Hirshleifer, David, Angie Low, and Siew Hong Teoh, 2012, Are overconfident CEOs better innovators?, *The Journal of Finance* 67, 1457-1498.

Johnson, M., R. Kasznik and K. Nelson, 2001, The impact of Securities Litigation Reform on the disclosure of forward-looking information by high technology firms, *Journal of Accounting Research* 3, 297-327.

Klaaren, K. J., S. D. Hodges, and T. D. Wilson, 1994, The role of affective expectations in subjective experience and decision making, *Social Cognition* 12, 77-101.

Kunda, Z., 1990, The case for motivated reasoning, *Psychological Bulletin* 108, 480-498.

Lee, S., S. R. Matsunaga, and C. W. Park, 2012, Management forecast accuracy and CEO turnover, *Accounting Review* 87, 2095-2122.

Lord, C., L. Ross, M. Lepper. 1979, Biased assimilation and attitude polarization: The effects of prior theories on subsequently considered evidence, *Journal of Personality Social Psychology* 37, 2098-2109.

Malmendier, Ulrike, and Geoffrey A. Tate, 2005, CEO overconfidence and corporate investment, *Journal of Finance* 60, 2660-2700.

Malmendier, Ulrike, and Geoffrey A. Tate, 2008, Who makes acquisitions? CEO overconfidence and the market's reaction, *Journal of Financial Economics* 89, 20-43.

Malmendier, Ulrike, Geoffrey A. Tate, and Jon Yan, 2011, Overconfidence and early-life experiences: The effect of managerial traits on corporate financial policies, *Journal of Finance* 66, 1687-1733.

Moore, D. A. and P. J. Healy, 2008, The trouble with overconfidence, *Psychological Review* 115, 502-517.

Peake P.K. and D. Cervone, 1989, Sequence anchoring and self-efficacy: primacy effects in the considerations of possibilities, *Social Cognition* 7, 31-50.

Puri, Manju and David T. Robinson, 2007, Optimism and economic choice", *Journal of Financial Economics* 86, 71-99.

Rabin, Matthew, and Joel L. Schrag, 1999, First impressions matter: A model of confirmatory bias, *Quarterly Journal of Economics* 114, 37-82.

Rogers, Jonathan L. and Philip C. Stocken, 2005, Credibility of management forecasts, *The Accounting Review* 80, 1233-1260.

Roychowdhury, S., 2006, Earnings management through real activities manipulation, *Journal of Accounting and Economics* 42, 335-370.

Scheier, M. F., and Carver, C. S., 1985, Optimism, coping, and health: Assessment and implications of generalized outcome expectancies, *Health Psychology* 4, 219-247.

Scheier, M. F., Carver, C. S., and Bridges, M. W., 1994, Distinguishing optimism from neuroticism (and trait anxiety, self-mastery, and self-esteem): A Reevaluation of the life orientation test, *Journal of Personality and Social Psychology* 67, 1063-1078.

Sharot, Tali, Alison M. Riccardi, Candace M. Raio and Elizabeth A. Phelps, 2007, Neural mechanisms mediating optimism bias, *Nature* 450, 102-106.

Sherman, Steven J., 1980, On the self-erasing nature of errors of prediction, *Journal of Personality and Social Psychology* 39, 211-221.

Sherman, Steven J., Richard B. Skov, Esther F. Hervitz and Caryl B. Stock, 1981, The effects of explaining hypothetical future events: From possibility to probability to actuality and beyond, *Journal of Experimental Social Psychology* 17, 142-158.

Tan, H. T., R. Libby, and J. E. Hunton. 2010, When do analysts adjust for biases in management guidance? Effects of guidance track record and analysts' incentives, *Contemporary Accounting Research* 27, 187–208.

Van den Steen, E., 2004, Rational overoptimism (and other biases), *The American Economic Review* 94, 1141-115.

Weinstein, Neil D., 1980, Reducing unrealistic optimism about illness susceptibility, *Health Psychology* 2, 11-20.

Weinstein, Neil D., 2003, Exploring the links between risk perceptions and preventive health behavior, In J. Suls & K. Wallston (Eds.), Social psychological foundations of health and illness (22-53). Maiden, MA: Blackwell.

Table 1
Descriptive Statistics.

MFD is the management forecast minus the pre-existing analyst consensus forecast divided by the stock price two days before the issuance of management forecast (multiplied by 1,000 for readability). *MFE* is the management forecast minus earnings realization divided by the stock price two days before the issuance of the forecast (multiplied by 1,000 for readability). *ROA* is defined as the earnings before extraordinary items and discontinued operations divided by total assets at the beginning of the quarter. *OpROA* is defined as operating income divided by total assets at the beginning of the quarter, where operating income is earnings excluding special or non-recurring items such as gain or loss from asset sales, asset write-downs or write-offs. *MBSTR* is the number of consecutive successes that CEO i enjoyed over 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 fiscal period. Size is the log of the 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 six of the preceding eight 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, standard deviations, medians, and all other statistics are computed for the entire sample, which begins in the first quarter of 1998 and finishes in the last quarter of 2008.

Variable	N	Mean	Median	Std. Dev.
MFD	8,448	-1.10	-0.29	4.37
MFE	8,944	-0.75	-0.68	4.40
ROA	8,940	0.02	0.02	0.02
OpROA	8,940	0.02	0.02	0.02
MBSTR	8,944	2.69	4.00	1.60
Hor	8,944	3.84	4.13	0.70
Size	8,944	7.44	7.34	1.47
B-to-M	8,944	0.42	0.37	0.26
StdEarn	8,944	0.01	0.01	0.02
RetVol	8,944	0.02	0.02	0.01
Cover	8,944	1.55	1.61	0.87
Loss	8,944	0.05	0.00	0.21

Table 2
Correlation table.

MFD is the management forecast minus the pre-existing analyst consensus forecast divided by the stock price two days before the issuance of management forecast. *MFE* is the management forecast minus earnings realization divided by the stock price two days before the issuance of the forecast. *ROA* is defined as the earnings before extraordinary items and discontinued operations divided by total assets at the beginning of the quarter. *OpROA* is defined as operating income divided by total assets at the beginning of the quarter, where operating income is earnings excluding special or non-recurring items such as gain or loss from asset sales, asset write-downs or write-offs. *MBSTR* is the number of consecutive successes that CEO i enjoyed over 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 fiscal period. Size is the log of the 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 six of the preceding eight 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 Pearson correlations in bold are significant at the 5% level or less.

	MFD	*MFE*	*ROA*	*OpROA*	*MBSTR*	*Hor*	*Size*	*B-to-M*	*StdEarn*	*RetVol*	*Cover*
MFE	**0.28**										
ROA	**0.26**	**-0.14**									
OpROA	**0.26**	**-0.13**	**0.89**								
MBSTR	**0.09**	**-0.13**	**0.16**	**0.16**							
Hor	**0.04**	**0.03**	0.00	0.00	0.01						
Size	**0.08**	0.02	**-0.04**	**-0.05**	**0.07**	**-0.06**					
B-to-M	**-0.14**	**0.05**	**-0.47**	**-0.51**	**-0.20**	-0.01	**-0.05**				
StdEarn	**-0.13**	0.01	**-0.23**	**-0.13**	**-0.05**	0.00	**-0.20**	**0.06**			
RetVol	**-0.15**	-0.01	**-0.20**	**-0.16**	**-0.11**	0.01	**-0.37**	**0.24**	**0.39**		
Cover	0.02	0.00	**0.07**	**0.09**	**0.03**	**-0.18**	**0.37**	**-0.16**	**0.04**	0.01	
Loss	**-0.32**	**0.21**	**-0.43**	**-0.43**	**-0.14**	-0.02	**-0.10**	**0.24**	**0.30**	**0.26**	**-0.02**

Table 3
Dynamic over-optimism**.**

This table reports regressions of managerial optimism (*MFD* and *MFE*) on the number of past successes. Variables are defined in Table 1. CEO fixed effects are included. The z-statistics, which are reported in parentheses, are calculated using double clustering by CEO and year to control for heteroskedasticity-consistent standard errors.

	Dependent Variable	
	MFD	*MFE*
MBSTR	**0.25**	**0.12**
	(5.49)	**(4.77)**
HOR	0.14	0.20
	(1.53)	(1.97)
SIZE	-1.13	0.39
	(-4.52)	(1.37)
B-to-M	-4.04	-3.01
	(-4.69)	(-4.63)
Loss	-5.71	5.51
	(-10.54)	(6.68)
StdEarn	-8.93	6.74
	(-1.24)	(1.00)
RetVol	-39.76	-13.76
	(-3.01)	(-1.77)
Cover	-0.03	0.06
	(-0.44)	(0.97)
Number of observations	8,448	8,944
R-square	45.75	41.01

Table 4
Contemporaneous performance.

This table reports regressions of contemporaneous firm performance (*ROA* and *OpROA*) on the number of past successes. Variables are defined in Table 1. 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.

	Dependent Variable	
	ROA	*OpROA*
MBSTR	**0.60**	**0.50**
	(4.40)	**(4.02)**
HOR	0.73	0.37
	(2.15)	(1.58)
SIZE	-5.57	-4.89
	(-4.08)	(-3.39)
B-to-M	-52.35	-40.25
	(-12.76)	(-10.16)
Loss	-31.62	-26.05
	(-13.68)	(-13.52)
StdEarn	-265.58	-60.92
	(-2.78)	(-2.46)
RetVol	-104.11	-49.47
	(-2.07)	(-1.38)
Cover	0.47	0.79
	(1.51_	(4.81)
Number of observations	8,940	8,940
R-square	63.01	70.06

Table 5
Comparative statics.

This table reports regressions of managerial optimism (*MFD* and *MFE*) on the number of past successes using partitions suggested by the economic framework and the cognitive framework. The regression models with *MFD* and *MFE* as dependent variables are same as those reported in columns (1) and (2) in Table 3. *Exp* is the number of quarters for which a CEO has issued management forecasts prior to the current management forecast. *Disp* is the standard deviation of analyst forecasts 90 days prior to the issuance of management forecast divided by price. *StdEarn* is the standard deviation of the quarterly return on assets over at least six of the preceding eight 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 fiscal period. *Cover* is the log of the number of analysts covering the firm in a quarter. We estimate the *ERC* for each firm over the entire sample period by regressing the market-adjusted, three-day buy-and-hold cumulative return, centered on the earnings announcement day, on forecast error divided by stock price. The z-statistics, which are reported in parentheses, are calculated using double clustering by CEO and by year to control for heteroskedasticity-consistent standard errors.

Panel A: Economic Framework

	Dependent Variable					
	MFD			*MFE*		
	High	*Low*	*χ^2 test p-val.*	*High*	*Low*	*χ^2 test p-val.*
Exp	0.23 (3.29)	0.35 (7.74)	**0.07**	0.10 (3.10)	0.46 (8.73)	**<0.01**
Disp	0.31 (4.29)	0.15 (3.66)	**0.08**	0.19 (4.09)	0.04 (1.50)	**0.06**

Panel B: Cognitive Framework

	Dependent Variable					
	MFD			*MFE*		
	High	*Low*	*χ^2test p-val.*	*High*	*Low*	*χ^2test p-val.*
Hor	0.29 (7.77)	0.19 (2.73)	**0.07**	0.09 (2.20)	0.12 (3.17)	**0.42**
StdEarn	0.32 (5.14)	0.23 (6.68)	**0.40**	0.15 (3.79)	0.13 (3.58)	**0.65**
Cover	0.27 (5.91)	0.29 (4.20)	**0.58**	0.11 (2.72)	0.13 (3.17)	**0.80**
ERC	0.27 (8.58)	0.24 (3.44)	**0.63**	0.12 (4.90)	0.10 (2.16)	**0.74**

Table 6
Is the performance genuine?

This table reports regressions of earnings management measures (*AccrMgt* and *RealMgt*) and the market-adjusted return (*AdjRet*) on the number of past successes. *AccrMgt* is the residual from a specification that regress total accruals on assets, change in sales minus change in accounts receivable and plant, property and equipment. *RealMgt* combines three normalized metrics: the abnormal levels of cash flow from operations, of discretionary expenses, and of production costs. *AdjRet* is the market adjusted return for the quarter. Other variables are defined in Table 1. CEO fixed effects are included. For readability, all of the coefficients in the first two columns are multiplied by 1,000 and 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 to control for heteroskedasticity-consistent standard errors.

	Dependent Variable		
	AccrMgt	*RealMgt*	*AdjRet*
MBSTR	**0.11**	**0.15**	**0.75**
	(0.33)	**(0.23)**	**(4.64)**
HOR	-0.79	-2.06	1.33
	(-1.79)	(-1.93)	(5.13)
SIZE	-1.51	31.29	-10.22
	(-0.99)	(6.30)	(-9.16)
B-to-M	-34.64	35.18	65.88
	(-3.47)	(2.20)	(12.22)
Loss	-22.05	16.47	-11.70
	(-6.08)	(3.22)	(-7.22)
StdEarn	-298.86	-136.34	-8.10
	(-2.05)	(-2.99)	(-0.24)
RetVol	141.35	-442.53	-43.63
	(2.17)	(-3.65)	(-1.04)
Cover	-2.13	-7.16	-0.39
	(-3.30)	(-5.99)	(-1.61)
Number of observations	8,715	8,250	8,944
R-square	29.67	77.32	20.13

Table 7
Future performance.

This table reports regressions of future firm performance (*FutureROA* and *FutureOpROA*) on the number of past successes. *FutureROA* is the earnings before extraordinary items and discontinued operations summed over four quarters starting with quarter q+1, divided by average total assets from quarter t+1 to quarter t+4. *FutureOpROA* is defined in a similar way except that we use operating income instead of earnings before extraordinary items and discontinued operations in the calculation. Other variables are defined in Table 1. 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.

	Dependent Variable	
	FutureROA	*FutureOpROA*
MBSTR	**1.88**	**1.68**
	(2.88)	**(3.57)**
HOR	0.17	0.62
	(0.14)	(0.74)
SIZE	-35.70	-26.63
	(-6.89)	(-6.70)
B-to-M	-145.69	-96.83
	(-4.26)	(-6.05)
Loss	-26.04	-33.19
	(-6.37)	(-5.48)
StdEarn	612.99	142.82
	(2.46)	(0.95)
RetVol	-852.38	-485.13
	(-3.20)	(-2.69)
Cover	0.32	0.10
	(0.24)	(0.11)
Number of observations	8,640	8,640
R-square	71.02	79.58

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