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MANAGERIAL MISCALIBRATION

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ABSTRACT

Using a unique 10-year panel that includes more than 13,300 expected stock market return probability distributions, we find that executives are severely miscalibrated, producing distributions that are too narrow: realized market returns are within the executives' 80% confidence intervals only 36% of the time. We show that executives reduce the lower bound of the forecast confidence interval during times of high market uncertainty; however, ex post miscalibration is worst during periods of high uncertainty. We also find that executives who are miscalibrated about the stock market show similar miscalibration regarding their own firms' prospects. Finally, firms with miscalibrated executives seem to follow more aggressive corporate policies: investing more and using more debt financing.

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I. INTRODUCTION

Miscalibration is the systematic underestimation of the range of potential outcomes. Evidence from psychology lab experiments indicates that subjects are generally miscalibrated. This happens either because most overestimate their ability to predict the future[1] or because they underestimate the volatility of random events.[2] But does this miscalibration apply to senior financial executives? In designing corporate policies, managers must routinely estimate future unknowns (e.g., demand, cash flows, and competition). We provide convincing evidence that top financial executives are severely miscalibrated.

There are theoretical reasons to believe that miscalibration may be prevalent among senior executives and that it may affect corporate policies. For example, Goel and Thakor (2008) argue that due to selection, overconfident managers who take a lot of risk either end up at the top or are fired, whereas other managers gravitate to the middle. Bernardo and Welch (2001) use a similar evolutionary argument to explain why overconfidence persists among entrepreneurs. In their model, overconfidence translates to excessive risk taking. Furthermore, recent research has documented a link between executive behavior and firm policies. Bertrand and Schoar (2003) show that there is a pronounced manager "fixed effect" in corporate decisions, but they do not study the behavioral traits and other characteristics of individual executives. Cronqvist, Makhija, and Yonker (2012) find a relation between CEOs' personal leverage and their firms' leverage.

Our article is the first to apply a laboratory approach to measure miscalibration in a population of thousands of real-world senior financial executives. Based on 10 years of quarterly surveys, we collect more than 13,300 forecasts of the S&P 500 made by finance professionals. In contrast to previous studies that mainly rely on student subjects, most of our respondents are the

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[1] Surveyed subjects typically provide confidence bounds for their predictions that are too narrow (Alpert and Raiffa 1982). Researchers also document that experts in a variety of professional fields overestimate the precision of their information, e.g., clinical psychologists (Oskamp 1965), and physicians and nurses (Christensen-Szalanski and Bushyhead 1981, Baumann, Deber, and Thompson 1991).

[2] Studies have shown that professionals such as engineers (Kidd 1970) and entrepreneurs (Cooper, Woo, and Dunkelberg 1988) are miscalibrated with regard to estimating the probabilities of random outcomes. Related to our study, Von Holstein (1972) documents that investment bankers provide miscalibrated forecasts of stock market returns; Deaves, Lüders, and Schröder (2010) find that stock market forecasters are miscalibrated on average and become more overconfident with previous successful forecasts; and Bar-Yosef and Venezia (2006) report that subjects (students and security analysts) in the laboratory exhibit miscalibration in their predictions of future accounting numbers. Deaves, Lüders, and Luo (2009) find that laboratory subjects who are miscalibrated also tend to trade excessively. None of these studies, however, link miscalibration to real actions in the corporate world.

chief financial officers (CFOs) of mid-size and large U.S. corporations.[3] We measure the extent to which financial executives are miscalibrated as well as the determinants of the miscalibration. We also link executives' miscalibration to their corporate actions. Specifically, we test whether miscalibration is related to the confidence interval of CFOs' forecasts of their own-firms' internal rate of return (IRR), to the intensity of corporate investment spending, and to corporate debt policy—all activities in which CFOs play a prominent role (Graham, Harvey, and Puri 2010, 2013).

Miscalibration is one form of overconfidence. In the psychology literature, overconfidence has several manifestations: miscalibration, the above-average effect, and the illusion of control. *Miscalibration* is defined as excessive confidence about having accurate information (Alpert and Raiffa 1982, Lichtenstein, Fischoff, and Phillips 1982, Ronis and Yates 1987, Kyle and Wang 1997, Daniel, Hirshleifer, and Subrahmanyam 1998, Odean 1998, 1999, Gervais and Odean 2001, Shefrin 2001, Moore and Healy 2008). Miscalibrated people overestimate the precision of their own forecasts or underestimate the variance of risky processes; in other words, their subjective probability distributions are too narrow. We use the terms *miscalibration* and *overprecision* interchangeably. In contrast, the *above-average effect* describes individuals who believe that they are better than their reference group on a particular attribute (Svenson 1981, Alicke 1985, Taylor and Brown 1988). The *illusion of control* refers to the tendency of individuals to overestimate their ability to control events over which they have limited influence (Langer 1975, Presson and Benassi 1996).

Theoretical models often distinguish between optimistic managers who overestimate the *mean* of their firms' cash flows (Shefrin 2001, Heaton 2002, Hackbarth 2008), which we refer to as optimism, and miscalibrated managers who underestimate the *volatility* of their firms' future cash flows (e.g., Shefrin 2001, Hackbarth 2008). Our data allow us to disentangle respondents' biases in the first and second moments of expectations. In other words, we can separate optimism from overprecision. To our knowledge, this article is the first to directly measure both miscalibration and optimism and link these constructs to firms and their actions.

[3] Our population of executives is different from groups previously studied in the behavioral economics field. Deaves, Lüder, and Luo (2009) test overconfidence with students. Deaves, Lüders, and Schröder (2010) study overconfidence among financial market practitioners in Germany. Bar-Yosef and Venezia (2006) explore the overconfidence of accounting students. Malmendier and Tate (2005, 2008) and Malmendier, Tate, and Yan (2011) study overconfidence (in the sense of "above average") indirectly in the population of CEOs by looking at their personal portfolio holdings.

From June 2001 to March 2011, we surveyed U.S. CFOs on a quarterly basis. We asked them to predict one- and 10-year market-wide stock returns and to provide an 80% confidence interval for their predictions. According to the confidence bounds that they provided, the CFOs are severely miscalibrated: the realized one-year S&P 500 returns fall within their 80% confidence intervals only 36.3% of the time. Even during the least volatile quarters in our sample, only 59% of realized returns fall within the 80% confidence intervals provided. We also explore the degree of overprecision by comparing the size of the CFOs' confidence intervals to the distribution of historical one-year returns. Though CFOs provide an average confidence interval of 14.5%, the difference between the 10th and 90th return percentiles from the realized distribution of the one-year S&P 500 returns is 42.2%. We find that only 3.4% of CFOs provide confidence intervals wider than 42.2%. Ten-year average return forecasts are also miscalibrated, albeit to a lesser degree.

We do not require executives to provide symmetric confidence intervals (we ask separate questions for the upper and lower bounds), which allows us to study the upper and lower ranges separately. Our findings suggest that respondents translate high market uncertainty into substantial downside risk.[4] Nevertheless, CFOs do not sufficiently adjust their confidence intervals to account for the high market uncertainty. In other words, we find that ex post overprecision (i.e., the percentage of CFOs who had an S&P 500 realization outside the 80% confidence interval) is more severe during episodes of high uncertainty.

CFOs appear somewhat less miscalibrated when making long-term forecasts. Two factors contribute to the relatively wider long-term confidence intervals. First, we find that during periods in which there is a greater dispersion of opinions among CFOs about long-term expected returns, the long-term confidence intervals are wider. This result is consistent with a model of parameter uncertainty (see Pastor and Stambaugh 2012): long-term forecasts should have wider confidence intervals to allow for the forecasters' uncertainty about long-term expected returns. Second, there is weak evidence that the long-term confidence intervals are linked to forecasts of greater longer-term volatility.

We also provide evidence that overprecision permeates corporate planning and forecasting. First, CFOs provide internal rate of return (IRR) distributions for own-firm projects

[4] This behavior is consistent with the evidence of Arnold (1986), March and Shapira (1987), and Kahneman and Lovallo (1993), who argue that managers focus on downside risk.

that reflect extremely low anticipated volatility relative to reasonable benchmarks such as the volatility of a CFO's own-firm return on invested capital. Second, CFOs who are miscalibrated with regard to market-wide returns are also miscalibrated about their own firms' projects.

We also explore the link between overprecision and corporate policies. We provide suggestive evidence that more miscalibrated managers invest more and tolerate higher leverage. This aggressive behavior is consistent with our earlier results showing that managers are miscalibrated regarding their own firms' prospects.

We also examine corporate investment and debt around the date when the CFO takes office (for the subset of CFOs who volunteer their identity). We use hand-collected data to track these critical dates. We perform an event-study analysis around the dates the CFOs join their firms. Our results show that the investment level increases in the years following the start-date of miscalibrated CFOs. Although these results are consistent with overprecision impacting corporate investment, given our data, we are not able to conclude that the relation is causal.

Finally, our results are reinforced by an out-of-sample analysis in a new study by Inoue, Kato, and Yamasaki (2012). Their study replicates many of our tests on a different sample. Using 50 years of survey data, the authors find that Japanese CEOs are similarly miscalibrated. They also find that executives link market uncertainty to downside risk.

Our paper is organized as follows. Section II details the methods we use to collect the miscalibration data and construct the variables; it also presents some summary statistics. In Section III, we provide evidence on the miscalibration of CFO expectations. Section IV explores the determinants of miscalibration. Section V studies the association between short-term and long-term forecasts. Section VI tests the relations between CFO miscalibration and optimism, and corporate forecasts and corporate investment policy. Some concluding remarks are offered in the final section.

II. DATA

II.A. Executive survey

Our study is based on a unique set of stock market predictions made by senior finance executives, the majority of whom are CFOs. The data were collected in 40 quarterly surveys conducted by Duke University between June 2001 and March 2011. Each quarter, we poll between 2,000 and 3,000 financial officers with a short survey on important topical issues (see Graham and Harvey (2011) for a detailed description of the survey). The usual response rate for the quarterly survey is 5% to 8%; most of the responses arrive within the first two days of the survey invitation date.[5] The survey usually contains eight questions about the U.S. economy, firm policies, and short-term corporate expectations. Some of the questions are identical for each survey; others change over time, depending on economic conditions. Historical surveys as well as aggregated responses can be accessed at http://www.cfosurvey.org.

We base our miscalibration proxies on two survey questions. The first question is:

Over the next year, I expect the annual S&P 500 return will be:
- There is a 1-in-10 chance the actual return will be less than ___%
- I expect the return to be: ___%
- There is a 1-in-10 chance the actual return will be greater than ___%

The second question is similar but relates to annualized stock market return forecasts over the next 10 years. The initial words change to *"Over the next 10 years, I expect the average annual S&P 500 return will be."*[6]

In contrast to most studies that use survey data, we are able to examine the characteristics of a sizable fraction of the respondents. Although the survey does not require CFOs to identify themselves, about half of the respondents voluntarily provide such information, and about a quarter of the respondents confirm that they are employed by U.S. public companies.

Overall, our sample includes 13,346 one-year expected returns and 13,058 10-year expected returns both with 10th and 90th percentile information. For most CFOs, we have information about their firm's characteristics (e.g., size, industry, private/public ownership). Of this sample, 4,287 observations are from self-reported public companies, and of them, we are able to match 3,335 observations (1,061 unique firms) to data in CRSP and Compustat. For 2,587 observations (757 unique firms), there is a full set of survey responses and accounting and market data.

[5] The bulk of our tests exploit variation within the respondent group, yet the overall response rate of 5% to 8% could potentially lead to a non-response bias in the inference of some tests (e.g., in Section III). We explore this issue further in Section II.F. and in Online Appendix A-II.
[6] The first question has appeared in its current form since 2001Q2. The current form of the second question dates from 2002Q1.

II.B. Imputing CFOs' individual volatility estimates

Our overprecision measure maps each CFO's 10th and 90th percentile predictions into an individual probability distribution. Wide distributions reflect high subjective uncertainty about the estimated variable, whereas narrow distributions reflect subjective confidence. From an empirical point of view, asking respondents to predict a widely followed variable like the S&P 500 index is better than asking them to predict their own firms' performance. Private information would play a greater role in the latter, and responses are difficult to compare across managers due to differences in the subjective definition of performance.

One way to assess the quality of CFOs' predictions is to benchmark their estimations with the distributional properties of the S&P 500. To do so, we convert their confidence intervals into individual volatility estimates. Starting with the confidence interval information, we use the Davidson and Cooper (1976) method to recover respondent *i*'s individual probability distribution, based on the normal distribution. The imputed individual volatility is calculated as:

$$\hat{\sigma}_i = \frac{x(0.90) - x(0.10)}{Z}, \qquad (1)$$

where $x(0.90)$ and $x(0.10)$ represent the 90th and 10th percentile of the respondent's distribution, and Z is the number of standard deviations within the confidence interval. For confidence intervals of 80% in a normal distribution, Z equals 2.65. Keefer and Bodily (1983) show that given information about the 10th and 90th percentiles, this simple approximation is the preferred method for estimating the standard deviation of the probability distribution of a random variable. We test the statistical properties of S&P 500 returns and find that they are reasonably close to that of a normal distribution.[7]

This method can be used for short-term volatility estimates, but it needs to be slightly modified for long-term volatility estimates. CFOs provide the *average* annual S&P 500 return and confidence bounds for this average return. We are interested, however, in the *annualized* volatility of long-term returns. To transform the imputed volatility of *average* long-term returns

[7] Alternatively, we could use logged gross returns. To evaluate this possibility, we examine the statistical properties of one-year S&P 500 simple returns over the period 1950 to 2000 (computed at a daily frequency). We find that the distribution of simple returns better fits the normal distribution than does the logged returns (where gross returns are one plus simple returns). Z is estimated as 2.64 for simple returns versus 2.60 for logged gross returns. Also, the distribution of simple returns is more symmetric than that of the logged gross returns (a skewness of -0.078 vs. -0.483).

into the *annualized* volatility of long-term returns, we multiply the volatility of the *average* long-term returns by the square root of 10—the number of years.

II.C. Measuring miscalibration

Our measure of overprecision is obtained through two steps. First, we multiply the individual's imputed volatility by -1, so that low individual volatility will correspond to higher miscalibration. Second, because overprecision should be determined at a particular point in time (because market conditions change over time), we standardize the variable to have a mean of zero and a standard deviation of one within each survey date. Given that CFOs provide estimates for short-term (one-year) S&P 500 returns and long-term (10-year) S&P 500 average returns, we create short- and long-term overprecision variables: *Miscalibration ST* and *Miscalibration LT*. Although we measure "relative" miscalibration, we use the more general term "miscalibration" because the majority of CFOs provide responses that would be considered miscalibrated by any reasonable metric (see discussion in Section III).

Overprecision is very persistent.[8] Consider an objective measure of volatility such as the volatility index (VIX, an index of implied volatility on the S&P 500). We identify 1,185 pairs of sequential responses (at least four quarters apart) for a given CFO, and we benchmark the imputed individual volatility to VIX.[9] We find that if the CFO's imputed volatility is less than VIX in the first period, there is a 98.3% chance in the next period that the same CFO's imputed volatility will be less than VIX. We also calculate the persistence of our relative overprecision measure. We find that the correlation between sequential *Miscalibration ST* (*Miscalibration LT*) observations is 0.53 (0.29).

II.D. Measuring optimism

Our survey data have the advantage of allowing us to measure overprecision while simultaneously controlling for optimism in expected returns. Similar to our measure of miscalibration, we measure relative optimism by standardizing each CFO's forecast of the

[8] Jonsson and Allwood (2003) and Glaser, Langer, and Weber (2012) also report that miscalibration persists over time.

[9] VIX is an index that reflects the average of implied volatility across traded options in the S&P 500 futures index, traded on the Chicago Board of Options Exchange (CBOE). We note that VIX is a risk neutral measure of volatility. Conversely, realized volatility contains a risk premium. This should not matter much for our analysis since the imputed volatility is significantly lower than VIX.

expected return (subtracting the cross-sectional mean at each point in time and dividing by the cross-sectional standard deviation). Our optimism measures are also persistent. The correlation between sequential relative *Optimism ST* (*Optimism LT*) observations is 0.40 (0.34).

II.E. Company and market data

Throughout the analysis, we use several databases with firm-level information. A detailed description of the variables is provided in Appendix Table A.1. First, we retrieve accounting data from Compustat for the subset of firms that we can identify as being public; these data include industry classification (Standard Industrial Classification (SIC)), book leverage, market leverage, the asset market-to-book ratio, profitability, collateralized assets, net investments scaled by lagged assets, and indicator variables for repurchases, as well as dividend payments.[10] We merge the survey observations with annual Compustat data, matching by the nearest fiscal end-of-year date. Second, we use CRSP to compute one-year past returns for firms. Third, we use Yahoo! Finance for historical S&P 500 dividend-adjusted prices and for volatility index (VIX) data.

We also use Execucomp (1993 to 2010) to identify CFOs' transitions into and out of their jobs. Since Execucomp is limited to the S&P 1500 firms, we complement the dataset with CFO names extracted from 10-K reports since 2000 (the CFO signs the reports). This process requires a careful hand-matching procedure to account for nicknames and partial names. Then, for each firm, we identify cases in which CFOs change over time. We manually verify that changes are not due to variations in CFOs' names. We then match CFO names to our survey data so that each survey observation is matched with information about the date when the CFO joined and left the firm.

II.F. Summary statistics

We present summary statistics for survey responses and the characteristics of the respondents' firms in Table I, Panels A to C. Panel A presents summary statistics for the key

[10] To ensure that our results are not driven by outliers and consistent with the practice of many studies that use similar data, we winsorize our survey data within each survey date at the 1% level. Similarly, we ensure that the corporate policy results are not driven by outliers by winsorizing variables calculated from Compustat data at 1%. Our results remain qualitatively the same when we apply a tighter winsorization of 2%.

variables used in the analysis. Additional statistics are presented in Online Appendix Tables A-I through A-III.[11]

An important issue is the representativeness of the sample. In Table I, Panel B, we compare the attributes of the portion of our sample for which we have Compustat data to the attributes of the pooled population of Compustat firms between 2001 and 2010. Note that if our sample mirrored Compustat, we would expect 20% in each cell. The results show that we have larger and thereby more economically influential firms. Our sample is fairly representative in terms of other dimensions.

One might wonder whether the key variables of interest—optimism and miscalibration—affect the likelihood of a CFO responding to our survey or whether they are somehow related to the likelihood that we are able to identify a firm and include it in our analysis. For example, perhaps CFOs are more likely to respond to a survey if they are optimistic or if their firms are performing particularly well. We do not find evidence that this is a material issue in our sample. First, Panel B shows that the past five-year sales growth for our sample firms is representative of historic sales growth for Compustat firms. Second, we compute the means of the miscalibration and optimism variables in different subsamples (tabulated in Online Appendix Table A-III, Panel C). Optimism appears to be statistically similar across subsamples (i.e., the full sample, the public firms sample, and the identified firms sample). Importantly, the economic variation in miscalibration across the different subsamples suggests that CFOs in larger firms (with sales greater than $1bn) are less miscalibrated. Third, we conduct an additional selection test, described in Online Appendix Section AII. This analysis uses firm characteristics to predict the miscalibration and optimism variables for all Compustat firms. We then test whether there is a selection into the sample. We find no evidence that miscalibrated or optimistic CFOs are more likely to respond to the survey. Also, we fail to find an association between entering or exiting the sample and current or future performance.

In sum, although it is not possible to eliminate all possible concerns about sample representativeness, we do not find that our sample should affect the generalizability of the results. Indeed, given large- and mid-cap firms, which we know are less miscalibrated, our sample is tilted against finding evidence of miscalibration.

[11] In Online Appendix Table A-III, Panel B, we present a breakdown by industry and revenues. The results demonstrate that industry composition is similar in the full and identified samples.

III. ARE CFOs MISCALIBRATED?

In this section, we use two methods to assess whether CFO respondents are, on average, miscalibrated.[12]

III.A. Ex ante predictions versus ex post realizations

In this test, we exploit the fact that our data are based on a series of 40 surveys. If CFOs are well calibrated, then in 80% of the cases, S&P 500 realizations should fall within the confidence intervals they provided.

We judge whether CFOs are miscalibrated by examining whether ex post market realizations fall within the ex ante confidence intervals. Panel A of Table II shows that only 36.6% of the stock market return realizations are within the 80% confidence bounds estimated by CFOs (also see Figure I).[13] The statistical standard error around the mean of 36.6% is 7.8%, after accounting for overlapping observations using the Newey-West (1987) procedure; hence, the difference of the measured mean from the 80% benchmark is statistically significant at the 1% level.[14] Statistics broken down by each quarterly survey are presented in Online Appendix Table A-II.

This degree of overprecision is consistent with other studies that request subjects in experiments (mostly students) to estimate 80% confidence bounds (Lichtenstein, Fischoff, and Phillips 1982, Russo and Schoemaker 1992, Klayman, Soll, Gonzales-Vallejo, and Barlas 1999, Soll and Klayman 2004). Even during relatively stable stock market periods (e.g., between 6/2003 and 11/2006), the percent of stock market return realizations that fall in the 80% confidence interval does not exceed 60%. In a recent replication of our study, Inoue, Kato, and Yamasaki (2012) find that 36.3% of Japanese CEO's one-year forecasts fall in the 80% confidence interval in the 2000 to 2011 period.

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[12] A third method—based on VIX as a proxy for the market's expectation of future volatility—is provided in Online Appendix Section AI.

[13] CFOs at large firms (>$500m sales) are less miscalibrated than CFOs at small firms (38.0% vs. 34.2%, respectively).

[14] We estimate the standard error using the Newey-West procedure with four lags.

III.B. Historical volatility and return distributions

Next, we consider the distribution of historical volatility and compare it to the distribution of the imputed individual volatility. Figure IIA shows the distribution of historical volatility computed in a one-year rolling window of monthly returns in the presurvey period of 1950 to 2011. The figure shows that the distribution is centered at 12% and that most of the distribution lies between 8% and 25%. In addition, we present the distribution of the individual volatility imputed from the CFOs' forecasts. The imputed individual volatilities are centered at 4%, and that most of the distribution lies between 1% and 15%. Fifty-eight percent of the imputed individual volatilities of CFOs are lower than 5.1%—the lowest historical one-year volatility over the past 60 years. Overprecision is also evident in the long-term annualized volatility, although to a lesser degree (see Figure IIB).

Another approach is to compare the 10th and 90th return percentiles as reported by CFOs to the historical unconditional distributions of S&P 500 one-year and 10-year annualized returns. Again, we examine historical return distributions from 1950 until 2011 (Table II, Panel B). For the one-year returns, the 10th and 90th percentiles are -13.4% and 28.8%, respectively. Thus, the confidence interval based on historical returns is 42.2%. In contrast, the average confidence interval across responses is only 14.5% (Table II, Panel B), and only 3.4% of CFOs provided a one-year confidence interval wider than 40.3%. A comparable analysis in Inoue, Kato, and Yamasaki (2012) shows that only 1.0% of CEOs provided a one-year confidence interval wider than the expected confidence interval based on historical stock market volatility in Japan (58.8%).

We repeat the same exercise for the annualized 10-year return forecasts in Table II, Panel B. The 10th and 90th percentiles of the annualized forecasted 10-year S&P 500 returns are 2.2% and 11.6%, respectively. The size of the confidence interval provided by CFOs is 9.4%. The 80% confidence range for actual annualized 10-year returns is 12.4% (based on a sample of monthly S&P 500 returns from 1950 to 2011). We find that only 18.0% of CFOs provide a range that is wider than the historical 12.4%. Although CFOs are miscalibrated in their long-term forecasts, they are less miscalibrated than in their short-term forecasts. In Section V, we discuss the relation between one-year and 10-year forecasts.

III.C. Do CFOs provide narrow confidence intervals because of innumeracy?

Our evidence shows that CFOs' confidence intervals are too narrow. Narrow confidence intervals could result from respondents' weakness in generating estimates rather than an innate behavioral bias. Indeed, many studies find that survey respondents have trouble with estimation tasks (e.g., Tversky and Kahneman 1971, 1973, 1983).

To explore the possibility that our results could reflect an innumeracy problem among CFOs rather than miscalibration, we perform an innumeracy experiment in our 2011Q1 survey, in which CFOs are requested to provide an estimate to a math question. The usual innumeracy questions asked in experimental settings of students are fairly simple, and we worried that asking too simple a question could be interpreted as insulting to a CFO and might even lead the CFO to abandon the survey. We therefore chose a question that deals with discounting and that has been previously studied, but that would also be moderately challenging to CFOs. Our goal was to obtain a cross-sectional measure of relative innumeracy. We asked the following question:

> *You are presented with a hypothetical investment that will double your money each year (all reinvested). You start with $1. How many years would you need to accumulate $1 million? No calculators please.*

Of the respondents, 54% provide guesses that are between 19 and 21 years (the correct answer is 20). A large estimation error would suggest that the respondent might have poor estimation skills and perhaps even have hyperbolic discounting (Laibson 1997), which could mean that they would also provide too small confidence intervals for the S&P 500 forecast question. However, we find that there is no significant relation between the estimation error in the innumeracy question and overprecision (see Online Appendix Table A-V).

III.D. Miscalibration and CFO characteristics

We test the relation between miscalibration and CFO characteristics collected in various surveys. In 2003Q4 and 2004Q1, we gathered information about CFO education and age; in 2008Q1 we asked CFOs about their age; and in all surveys we asked CFOs about their optimism regarding their firms' financial prospects.[15] The results are presented in Table III. Our analysis shows that long-term miscalibration increases with the level of education and with age, and that

[15] This question reads: "Rate your optimism about the financial prospects for your own company on a scale from 0–100, with 0 being the least optimistic and 100 being the most optimistic."

both short- and long-term miscalibration are positively correlated with managers' optimism about their firms' financials.

IV. UNDERSTANDING CFO FORECASTS AND MISCALIBRATION

In this section, we identify the variables that explain the level of overprecision. Our goal is to better understand the mechanism through which executives use available information when forming their predictions.

IV.A. Can CFOs predict future returns?

Although CFOs might be miscalibrated in terms of having imputed individual volatilities that are much lower than reasonable benchmarks, their return forecasts could still be accurate. However, in Panel A of Table IV, the evidence is inconsistent with forecasts having any predictive power. The table shows no significant relation between S&P 500 future one-year realizations and CFOs' forecasts. We also test whether S&P 500 forecasts can predict CFOs' own-firm returns (results available upon request). We find no relation between the forecasts and executives' own-firm future returns.

IV.B. Variation of miscalibration over time

Next, we examine the relation between the CFO return forecasts and both past returns and contemporaneous expected volatility (measured by VIX). The motivation for studying these variables comes from experimental and empirical results that show that forecasters develop estimates by extrapolating past events (e.g., Kahneman and Tversky 1974, Alba, Hutchison, and Lynch 1991, De Bondt 1993, Vissing-Jorgensen 2004, Soll and Klayman 2004).[16] Another motivation is that CFOs' confidence intervals are likely to be correlated with expected market volatility, approximated by VIX.

[16] Other research points to past performance affecting predictions about own-firm future performance. Kahneman and Tversky (1972) propose that the "representativeness" of past events leads people to forecast similar patterns in the future. In models by Einhorn and Hogarth (1978) and Van den Steen (2004), decision makers "learn" about their decision-making ability by observing the outcomes of past decisions, while ignoring exogenous determinants of these outcomes. Following favorable outcomes, decision makers become more confident about their judgment through a self-attribution mechanism, even if the outcome was independent of their prior decisions. In applying this idea to trading behavior, Gervais and Odean (2001) argue that traders become overconfident after observing a series of past successes that they then attribute to their own abilities. As an extension of this reasoning, Hilary and Menzly (2006) find that security analysts exhibit greater aggressiveness following success in predicting earnings.

The results in Table IV, Panel B, show that the one-year return forecasts are not affected by past returns. However, confidence bounds widen in periods of increased volatility and the lower bound is particularly sensitive to contemporaneous volatility. A one standard deviation change in contemporaneous volatility (a change of 9.4% in VIX) is associated with a 2.2 percentage-point wider confidence interval (a 15% increase in the average confidence interval). This pattern is depicted in Figure III. The chart presents survey averages of the upper bound, expected return, and lower bound, in addition to the contemporaneous VIX (inverted). The chart demonstrates that the average lower bound of CFOs' S&P 500 estimations co-moves with the inverted VIX. In contrast, the average upper bound does not move as much with VIX. The disparity between the upper and lower bounds causes confidence intervals to widen during times of stress. Note, however, that Table II, Panel A, shows that widening the confidence interval during times of high market stress does not improve calibration: in quarters with an above-median VIX, only 24.1% of the time do one-year-ahead S&P 500 realizations fall within the 80% confidence interval that CFOs provide.

V. SHORT-TERM VERSUS LONG-TERM FORECASTS

In Section III.B., we noted that the confidence interval for long-term forecasts is materially wider than that of short-term forecasts. It is interesting to understand the factors that affect short-term versus long-term forecasts, as executives are often required to plan for different time horizons. In this section, we test two possible explanations for the difference in confidence intervals between short- and long-term predictions.

V.A. The confidence interval and dispersion of opinions among respondents

The first potential explanation for the difference in confidence intervals suggests that confidence intervals are wider for multi-period predictions because forecasters allow for larger mistakes over long horizons (errors due to unknown model parameters accumulate over the forecast horizon). Thus, in a multi-period setting, wider confidence intervals are needed (see Pastor and Stambaugh 2012).

We test this explanation by regressing the difference between the long-term and short-term imputed volatilities (at the survey level) on the difference in the long-term and short-term dispersion of opinions. *Dispersion of opinions* is defined as the cross-sectional standard deviation of the expected return estimates by CFOs at each point in time. High dispersion could reflect low quality signals that CFOs are receiving and using to make their forecasts.

The results are presented in Table V, Panel A. The panel shows that a higher dispersion of opinions is correlated with higher average imputed volatility. The evidence shows that a higher relative dispersion of beliefs (long-term minus short-term) is associated with higher long-term relative imputed volatility. We also show that the level of long-term dispersion is important.

V.B. Term structure of volatility

Another potential and non–mutually exclusive explanation for why long-term predictions appear to have wider confidence intervals is that CFOs might believe volatility will increase in the future. To provide evidence for this conjecture, we asked CFOs in the March 2011 survey to estimate the two-year-ahead volatility:

> *In 2010, the volatility of S&P 500 returns was 12.6%. What do you think the volatility of S&P 500 returns will be in 2012?*

We regress the difference between the long-term and the short-term imputed volatilities on respondents' forecasts of two-year-ahead volatility. In contrast to Panel A, this test exploits cross-sectional variation in forecasts and is limited to a single survey. As a result, we cannot include time-varying controls like past returns. The coefficients of expected volatility in Table V, Panel B, are positive albeit statistically insignificant (p = 0.12).[17] The positive sign potentially indicates that CFOs with higher relative long-term imputed volatility anticipate higher volatility two years ahead.

VI. MISCALIBRATION AND CORPORATE ACTIONS

We now consider corporate actions. First, we examine the relation between miscalibration in S&P 500 return forecasts and miscalibration concerning own-firm project returns. Second, we examine the effects of executive overprecision on corporate investment. Third, we extend the analysis and test the relation between CFO miscalibration and financing policy.

[17] In these regressions, we cluster errors by one-digit SIC industry classification, which is self-reported by executives. To account for the potential bias created due to the small number of clusters, we use bootstrapped standard errors based on Cameron, Gelbach, and Miller (2009).

VI.A. Miscalibration regarding own-firm projects

Our first test examines whether S&P 500 miscalibration is related to firm-level planning. Specifically, we query executives about their firms' expected internal rates of return (IRRs) (i.e., the expected return on the firm's own investment projects) and IRR confidence intervals. We determine the correlation between CFOs' overprecision in S&P 500 forecasts and the overprecision when forecasting the returns on their own firms' projects.

To implement this test, we asked CFOs in the 2007Q2 survey to provide mean estimates and 10th and 90th percentiles for the return distributions of their own firms' investments in the future:

> *For the investments that your company makes this year, what do you expect the internal rate of return (IRR) to be?*
>
> *- There is a 1-in-10 chance that the actual IRR will be less than ___%*
>
> *- I expect the IRR to be ___%*
>
> *- There is a 1-in-10 chance that the actual IRR will be greater than ___%*

In addition, we surveyed respondents about the degree to which they personally affect investment decisions in their firms on a scale of 1 (not at all) to 7 (a lot).

We compute the imputed individual volatility of own-firm IRR and assess whether CFOs are overprecise. Although we cannot observe the true distribution of the IRR outcomes of individual firms, it is possible to compare the imputed individual volatilities of own-firm IRR to public firms' market and accounting returns. We find that the average annualized imputed volatility of own-firm IRR is surprisingly small, only 5.3% (5th percentile: 1.1%, 95th percentile: 11.3%). These estimates seem to grossly underestimate volatility relative to several benchmarks: (1) the average of the historical (1950–2011) S&P 500 volatility of 13.9% (Table II, Panel B); (2) the 47.4% volatility of individual company stock returns in 2001–2007 (before the time of the survey question); and (3) the volatility of the ROIC (return on invested capital) of Compustat firms in 2001–2007, which was 36.5%.

Given this result, that most CFOs appear to be overprecise when judging their own-firm projects, we calculate an own-firm miscalibration variable (*Own-firm IRR Miscalibration*) according to the procedure used in Section II.C. As with the S&P 500-based miscalibration variables, *Own-firm IRR Miscalibration* reflects the standardized perceived volatility of own-firm investment returns (multiplied by -1): a high value of *Own-firm IRR Miscalibration* reflects high miscalibration.

Next, we test whether own-firm overprecision is correlated with S&P 500 overprecision. In Table VI, columns (1) and (2), we find that firm-based overprecision is significantly correlated with both the short-term and long-term miscalibration variables (lending some credibility to our relating these latter miscalibration variables to corporate actions below). Although the power of the regression is low due to the small sample and to our conservative clustering approach (standard errors are bootstrapped based on Cameron, Gelbach, and Miller (2009)), the magnitude of the coefficients is large: a one standard deviation shift in short-term (long-term) market miscalibration is associated with a shift of 41.7% (27.5%) of one standard deviation of own-firm IRR miscalibration. The correlation is even stronger for the subset of CFOs who are more involved in their companies' investment decisions (columns (3) and (4)).

VI.B. Miscalibration and corporate investment

We now study the corporate policies of companies run by miscalibrated executives. Do companies invest more when their executives are miscalibrated and optimistic? We regress investment intensity (the dependent variable), computed as the annual net investments scaled by lagged total assets, on overprecision, optimism, and firm controls.

The results are presented in Table VII, columns (1) and (2). We find a positive relation between corporate investment and long-term overprecision as well as long-term optimism; for short-term optimism and overprecision, we observe a positive but insignificant relation. Since miscalibration and optimism are standardized, we can assess the economic magnitude directly from the regression coefficients. A one standard deviation shift in long-term overprecision is associated with a shift of 0.6 of a percentage point (t = 2.7) in corporate investment (relative to a mean of 8.7 percentage points and a median of 5.4 percentage points).

This evidence resonates with Kahneman and Lovallo (1993), who theorize that executives are often optimistic and overconfident about their managerial skills and their ability to mitigate risk. Also, Heaton (2002) shows that optimistic managers invest more because they perceive negative net present value (NPV) projects to be good projects.

VI.C. Miscalibration and corporate debt

CFOs play an important role in decision making about the financing of the firm. Hackbarth (2008) argues that a miscalibrated manager chooses a higher level of debt because she overestimates her firm's ability to meet its liabilities. We test Hackbarth's prediction in Table VII, columns (3) and (4). We regress firm leverage (total interest-bearing liabilities scaled by total book asset value) on short-term and long-term miscalibration variables in addition to firm variable controls and industry and survey date fixed effects. The results show that both short- and long-term miscalibration variables are positively associated with debt leverage (t = 3.6 and t = 1.3, respectively). A one standard deviation shift in short-term miscalibration is associated with a moderate increase of 1.3% in leverage, relative to a sample mean of 22.5%; the effect of long-term miscalibration is about half of that of short-term miscalibration.[18]

Although our tests cannot identify the direction of causality and the economic magnitude of the results is modest, the findings are consistent with Hackbarth's (2008) hypothesis that overprecise managers tend to have higher leverage.

VI.D. Change in corporate policies when CFOs take office

Given the correlation between overprecision and corporate investment and debt policies, we search for hints about the direction of causality: high miscalibration might induce high investment and leverage, or, perhaps, high investment and debt induce selection and cause executives to be overprecise. Related to this, one wonders whether miscalibrated CFOs are selected (or self-select) to work in firms with high corporate investment and debt.

To shed some light on the direction of causality, we exploit within-firm variation through time. In particular, we examine how corporate investment behaves in the years surrounding a CFO's hiring. We extract the dates when CFOs join firms from Execucomp data and by hand-collecting data from 10-K filings (Section II.E. provides further details on the process). A CFO is considered to take office in a firm when she/he first signs the financial reports. In addition, we match corporate investment and characteristics from Compustat for the year of taking office. The dependent variable in our regressions is the difference between the average corporate investment in the two years following the CFO taking office and the average corporate investment in the two years prior to the event.

[18] The results are similar, although slightly weaker, when we use market leverage instead of book leverage.

The regression results in Table VIII, column (1) indicate no significant relation between our short-term measure of miscalibration and corporate investment. However, corporate investment increases for firms in the long-term miscalibration of hired CFOs (column (2)). A one standard deviation increase in CFO long-term overprecision is associated with a 0.7 percentage-point (t = 2.0) (column (2)) higher investment intensity (relative to the average investment intensity of 8.7 percentage points).

To summarize, we find a weak correlation between investment and debt policies and miscalibration around the year when a new CFO takes office. Although we cannot rule out reverse causality, our findings are consistent with CFO miscalibration leading to a change in corporate policies.

VII. CONCLUSION

Over the past 10 years, we collected more than 13,300 S&P 500 forecasts, including 80% confidence intervals, from CFOs. We study the abilities of CFOs to estimate probabilities over time and in the cross-section and examine how these abilities affect the corporate policies at the CFOs' firms.

We use several methods to show that CFOs are, on average, severely miscalibrated: their confidence intervals are far too narrow. For example, the 80% confidence interval for their one-year forecasts contains only 36.6% of the realized returns. We find that confidence intervals are wider in periods of high market-wide uncertainty, but during these periods, CFOs are even more miscalibrated. We also show that the size of the confidence intervals is related to the dispersion of forecasts across CFOs.

We find evidence that CFO overprecision appears to be related to corporate decision making. We show that the overprecision measure, based on predicting the S&P 500 returns, is significantly correlated with overprecision in own-firm investment return predictions. Moreover, we find modest evidence that firms with miscalibrated or optimistic executives invest more and have more debt, on average.

Knowing that executives are miscalibrated has important implications for investors, regulators, and other corporate stakeholders who rely on corporate data and forecasts. We look forward to future research that examines how such data should be best used and also that determines how miscalibrated employees should be compensated and motivated.

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APPENDIX TABLE A.1

VARIABLE DEFINITIONS

Variables from CFO Survey

One-year (10-year annualized) return estimate: lower bound (%)	Survey response for the level of S&P 500 return for which there is a 1-in-10 chance of its being lower. Applies to short-term (1-year) and long-term (10-year) returns.
One-year (10-year annualized) return estimate: expected value (%)	Survey response for the (average) expected return of the S&P 500. Applies to short-term (1-year) and long-term (10-year) returns.
One-year (10-year annualized) return estimate: upper bound (%)	Survey response for the level of S&P 500 return for which there is a 1-in-10 chance of its being higher. Applies to short-term (1-year) and long-term (10-year) returns.
One-year (10-year annualized) return estimate: imputed individual volatility (%)	$\frac{upper\ bound - lower\ bound}{2.65}$. Applies to short-term (one-year) and long-term (10-year) forecasts. For 10-year forecasts, we multiply by sqrt(10).
Confidence interval (%)	Upper bound minus lower bound.
Miscalibration ST (LT)	Miscalibration (or overprecision) is the negative imputed individual volatility, standardized within each survey date. We calculate the mean of the imputed individual volatility within each survey date and subtract it from the imputed individual volatility. Then, we multiply the result by -1 and divide by the standard deviation of the imputed individual volatilities within the survey date. We apply the same procedure to short-term (1-year) and long-term (10-year) forecasts.
Dispersion volatility (%)	Standard deviation of mean forecasts (expected returns) within the survey date. Applies to short-term (1-year) and long-term (10-year) forecasts.
Optimism ST (LT)	Standardized expected returns: we subtract the mean within each survey date from the expected return estimate and divide by the standard deviation within the survey date. Applies to short-term (1-year) and long-term (10-year) forecasts.
Forecast error (%)	One year realized S&P 500 return minus the expected S&P 500 return for the same period.
IRR estimate: lower bound (%)	Survey response for the level of internal rate of return (IRR) for which there is a 1-in-10 chance of its being lower. Question was asked in the 2007Q2 survey.
IRR estimate: expected value (%)	Survey response for the (average) expected internal rate of return (IRR). Question was asked in the 2007Q2 survey.
IRR estimate: upper bound (%)	Survey response for the level of internal rate of return (IRR) for which there is a 1-in-10 chance of its being higher. Question was asked in the 2007Q2 survey.
Own-firm IRR miscalibration	The negative imputed individual volatility about own-firm IRR, standardized within the survey date. We calculate the mean of the imputed individual IRR volatility within each survey date, and subtract it from the imputed individual volatility observations. Then, we multiply it by -1 and divide by the standard deviation of the imputed individual volatilities within the survey date.
Involved in investments	Response to the question: To what degree do you personally affect the investment decisions of your firm? (1) Not at all, to (7) A lot. Question was asked in the 2007Q2 survey.
2012 volatility estimate (%)	Volatility estimates made by survey participants (2011Q1) for volatility in 2012.

Math estimation error	The absolute value of the log difference between the right answer to the math problem and the answer respondents provided. Question was asked in the 2011Q1 survey.
Optimistic about own firm	Response to the question: “Rate your optimism about the financial prospects for your own company on a scale from 0-100, with 0 being the least optimistic and 100 being the most optimistic.”

Variables from Compustat

Market leverage (%)	Total debt / market assets = sum(item DLTT, item DLC) / sum(CRSP item SHROUT * CRSP abs(PRC), item AT, – item CEQ).
Book leverage (%)	Total debt / total assets = sum(item DLTT, item DLC) / sum(item AT).
log(Sales)	Logged annual sales in millions of USD (log(item SALE)).
Asset market-to-book (M/B)	Total assets at market values / total assets = sum(CRSP item SHROUT * abs(CRSP item PRC), total assets (item AT), – book value of equity(item CEQ)) / total assets at book values (item AT).
Profitability (%)	Operating profit (item OIBDP) / lag(total assets at book values (item AT)).
Five-year sales growth (annualized)	(item SALE / lag5(item SALE))$^{1/5}$ – 1.
Return on invested capital (ROIC)	Earnings before interest and taxes (EBIT) * (1 – %tax) / lag(invested capital) = item EBIT * (1 – 0.35) / lag(item ICAPT).
Repurchases	1 if repurchased common and preferred stock is greater than 1% of equity, and zero otherwise. I(item PRSTKC / CRSP item SHROUT * CRSP item abs(PRC)) > 0.01.
Dividends	1 if firm declared dividends in previous year, and 0 otherwise. I(item DV > 0).
Investment intensity (%)	Net investments / lag(total assets at book values) = (capital expenditures (item CAPX) + change in investments (item IVCH) + acquisitions (item AQC) – sales of property, plant and equipment (item SPPE) – sale of investments (item SIV)) / lag(total assets at book values (item AT)).

Variable from CRSP

Past 12-month firm returns (%)	Stock-level cumulative returns over the 12 months preceding the survey date.

Variables from Yahoo!

12-month S&P 500 returns (%)	S&P 500 total returns, accumulated over 12 months.
12-month S&P 500 volatility (%)	S&P 500 volatility, computed over 12 months using daily data.
VIX (%)	An index for the implied volatility on 30-day options. The index is constructed by the Chicago Board Options Exchange (CBOE) from a wide range of S&P 500 (S&P 100 until August 2003) index options (both calls and puts). The index reflects the anticipated volatility in the next 30 days. VIX represents a risk neutral volatility. Realized volatility, in contrast, may contain a risk premium. See http://www.cboe.com/micro/vix/vixwhite.pdf for further details.

TABLE I

SUMMARY STATISTICS

PANEL A: SAMPLE SUMMARY STATISTICS

	Obs	Mean	Std Dev	5th pctl	Median	95th pctl
One-year S&P 500 return forecasts (all surveys 2001Q2-2011Q1)						
Imputed individual volatility (%)	13,346	5.52	4.41	1.1	3.8	15.1
Confidence interval (%)	13,346	14.64	11.70	3.0	10.0	40.0
Optimism about own firm	11,457	65.60	19.68	30.0	70.0	90.0
10-year S&P 500 return forecasts (all surveys 2002Q1-2011Q1)						
Imputed individual volatility (%)	13,058	11.44	9.25	3.6	9.5	25.1
Confidence interval (%)	13,058	9.59	7.75	3.0	8.0	21.0

PANEL B: DISTRIBUTION RELATIVE TO THE COMPUSTAT UNIVERSE

	Compustat quintiles				
Variable	Q1 (smallest)	Q2	Q3	Q4	Q5 (largest)
Sales	3.5%	5.9%	9.3%	20.1%	61.2%
Controlling for year, sales quintile, and 2-digit SIC:					
Asset market-to-book	14.3%	23.6%	23.7%	21.9%	16.5%
Profitability	16.3%	22.6%	23.1%	20.9%	17.1%
Five-year sales growth	19.2%	25.6%	22.9%	19.7%	12.7%
Market leverage	20.2%	20.5%	21.7%	20.2%	17.3%
Investment intensity	15.6%	21.0%	23.2%	22.5%	17.7%
Return on invested capital (ROIC)	14.5%	23.2%	21.9%	20.8%	19.6%

Panel A presents summary statistics for the select variables used in the study, based on the sample of CFO responses, aggregated CFO responses at the survey level, and Compustat variables for survey firms that could be identified as Compustat firms. (Online Appendix Tables A-I and A-III provide additional summary statistics.) Panel B compares the distribution of key attributes of the sample firms to those from the Compustat universe from 2001 to 2010. The columns represent Compustat quintiles, and the numbers report the percentage of sample observations that fall within each quintile. Sales are reported in raw form. For other variables, we split the universe of Compustat firms into sales quintiles, by year, and by 2-digit SIC industry classification, and we report the distribution of survey firms along these thresholds. Variable definitions are provided in Appendix Table A.1. *, **, *** denote two-tailed significant difference from zero at the 10%, 5%, and 1% levels, respectively.

TABLE II

AGGREGATE FORECASTS AND CONFIDENCE INTERVALS

PANEL A: AGGREGATE FORECASTS AND S&P 500 REALIZATIONS

		S&P 500 realizations		
	Avg. forecast error (%) (realized - forecasted)	% below 10th percentile	% between 10th and 90th percentiles	% above 90th percentile
All quarters	-3.1%	30.5%	36.3%	33.2%
6/2003-11/2006 (low volatility period)	2.8%	5.3%	59.1%	35.5%
Quarters with above-median VIX	-5.2%	40.8%	23.0%	36.2%
Quarters with below-median VIX	-0.8%	19.1%	51.0%	29.9%

PANEL B: AGGREGATE FORECASTS

	One-year return		10-year annualized return	
	CFO Forecasts	S&P 500 (1950-2011)	CFO Forecasts	S&P 500 (1950-2011)
# surveys	40		37	
Average # respondents	334		353	
Average lower bound (10th percentile)	-2.7%	-13.4%	2.2%	0.1%
Average expected (realized) returns	5.8%	8.4%	7.5%	7.2%
Average upper bound (90th percentile)	11.8%	28.8%	11.6%	12.5%
80% confidence interval	14.5%	42.2%	9.4%	12.4%
Average imputed individual volatility	5.5%	13.9%	11.2%	14.3%
Average dispersion volatility	4.7%		3.6%	

Panel A compares survey S&P 500 forecasts to S&P 500 realized returns. Panel B shows summary statistics of the CFO forecasts over 2001–2011 and S&P 500 realized returns and volatility over 1950–2011. Variable definitions are provided in Appendix Table A.1.

TABLE III

MISCALIBRATION AND PERSONAL CHARACTERISTICS

PANEL A: SUMMARY STATISTICS

Survey variables	Obs	Mean	Std Dev	5th pctl	Median	95th pctl
CFO has MBA	401	0.57	0.50	0.0	1.0	1.0
CFO has PhD	401	0.05	0.23	0.0	0.0	1.0
Age 40-49	775	0.43	0.50	0.0	0.0	1.0
Age 50-59	775	0.39	0.49	0.0	0.0	1.0
Age 60+	775	0.08	0.27	0.0	0.0	1.0
Optimism about own firm	11,457	65.60	19.68	30.0	70.0	90.0

PANEL B: MISCALIBRATION AND CFO CHARACTERISTICS

Dependent variable →	Miscalibration ST			Miscalibration LT		
	(1)	(2)	(3)	(4)	(5)	(6)
CFO has MBA	0.004			0.134		
	[0.860]			[0.390]		
CFO has PhD	0.207			0.533**		
	[0.185]			[0.090]		
Age 40-49		-0.127			0.046	
		[0.475]			[0.475]	
Age 50-59		0.131			0.217**	
		[0.595]			[0.050]	
Age 60+		0.055			0.282***	
		[0.650]			[<0.001]	
Optimism about own firm			0.004***			0.001**
			[<0.001]			[<0.001]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	399	781	11,343	401	775	11,457
Adj R^2	-0.018	0.008	0.018	0.003	0.005	0.003

The table explores whether miscalibration is determined by personal characteristics. Panel A provides summary statistics. Panel B presents the regressions. All regressions are OLS. Variable definitions are provided in Appendix Table A.1. All regressions include one-digit SIC industry fixed effects and intercepts that are not presented. Standard errors are clustered by one-digit SIC and bootstrapped following Cameron, Gelbach, and Miller (2009). *p*-values are presented in square brackets. *, **, *** denote two-tailed significance at the 10%, 5%, and 1% levels, respectively.

TABLE IV

DETERMINANTS OF FORECASTS AND INDIVIDUAL CONFIDENCE INTERVALS

PANEL A: FUTURE S&P 500 RETURNS AND AVERAGE FORECASTS

Dependent variable →	12-month future S&P 500 return (%)	
	(1)	(2)
One-year average lower bound (%)		-8.236*
		(4.110)
One-year average expected returns (%)	0.698	16.065
	(3.574)	(11.342)
One-year average upper bound (%)		-5.278
		(7.006)
Intercept	-1.040	-50.514
	(24.179)	(43.402)
Observations	40	40
Adj. R^2	-0.023	0.123

PANEL B: AVERAGE FORECASTS AND PAST S&P 500 RETURNS AND VIX

Dependent variable →	One-year forecasts (%): Average of…				10-year forecasts (%): Average of…			
	Lower bound	Expected return	Upper bound	Confidence interval	Lower bound	Expected return	Upper bound	Confidence interval
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Current VIX (%)	-0.225***	-0.075***	0.009	0.234***	-0.058**	-0.014	0.005	0.063***
	(0.043)	(0.025)	(0.026)	(0.043)	(0.024)	(0.011)	(0.009)	(0.023)
12-month past S&P 500 return (%)	-0.005	0.002	-0.003	0.002	-0.023	-0.011	-0.011**	0.012
	(0.029)	(0.017)	(0.016)	(0.024)	(0.016)	(0.008)	(0.005)	(0.014)
Intercept	2.234***	7.418***	11.479***	9.246***	3.461***	7.696***	11.322***	7.862***
	(0.687)	(0.616)	(0.789)	(0.824)	(0.332)	(0.204)	(0.243)	(0.388)
Observations	40	40	40	40	37	37	37	37
Adj. R^2	0.629	0.210	-0.048	0.588	0.073	0.015	0.162	0.157

The sample comprises averages of CFO estimates aggregated at the survey level in addition to market data. Panel A presents regressions of future S&P 500 returns on the average lower bound, the average expected return, and the average upper bound. Panel B shows regressions of average forecasts on current VIX and past S&P 500 returns. Observation units in Panels A and B are the means of survey responses within a given quarter (measured in percentage points). The regressions in Panels A and B are weighted by the square root of the number of observations of each survey date, and standard errors in the OLS regressions (in parentheses) are adjusted for autocorrelation using the Newey and West (1987) procedure with four lags. Variable definitions are provided in Appendix Table A.1. *, **, *** denote two-tailed significance at the 10%, 5%, and 1% levels, respectively.

TABLE V

DETERMINANTS OF LONG-TERM INDIVIDUAL VOLATILITY

PANEL A: AVERAGE FORECASTS AND DISPERSION VOLATILITY

Dependent variable →	Avg. imputed 10-year volatility - Avg. imputed one-year volatility (%)	
	Survey average responses	
	(1)	(2)
10-year dispersion volatility - One-year dispersion volatility (%)	0.325***	0.365***
	(0.063)	(0.073)
10-year dispersion volatility (%)		0.415***
		(0.135)
Intercept	6.199***	5.073***
	(0.259)	(0.385)
Industry FE	No	No
Observations	37	37
Adj. R^2	0.139	0.273

PANEL B: TERM STRUCTURE OF VOLATILITY

Dependent variable →	Imputed 10-year volatility - Imputed one-year volatility (%)	
	(1)	(2)
Two-year volatility estimate (%)	0.361	0.368
	[0.125]	[0.120]
Intercept	3.472***	3.390***
	[<0.001]	[<0.001]
Industry FE	No	Yes
Observations	375	375
Adj. R^2	0.023	0.025

Panel A shows results from a sample of aggregated data at the survey level. The panel presents regressions of the difference in average long-term and short-term imputed volatilities on the difference in survey-level dispersion of opinions of short-term and long-term forecasts. OLS errors in Panel A are adjusted for autocorrelation using the Newey and West (1987) procedure with 7 lags. Panel B uses individual forecasts from the 2011Q1 survey. The panel presents results from a regression of the difference in long-term and short-term imputed volatility on the two-year expected volatility. The regressions include one-digit SIC industry fixed effects. In Panel B, OLS errors are clustered by one-digit SIC industry and bootstrapped following Cameron, Gelbach, and Miller (2009). *p*-values are presented in square brackets. Variable definitions are provided in Appendix Table A.1. *, **, *** denote two-tailed significance at the 10%, 5%, and 1% levels, respectively.

TABLE VI

OWN-FIRM IRR MISCALIBRATION AND S&P 500 MISCALIBRATION

Dependent variable →	Own-firm IRR Miscalibration			
Sample →	All respondents		Involved in investments	
	(1)	(2)	(3)	(4)
Miscalibration ST	0.418***		0.445***	
	[0.000]		[0.000]	
Optimism ST	0.009		0.041	
	[0.846]		[0.528]	
Miscalibration LT		0.293***		0.382***
		[0.000]		[0.000]
Optimism LT		-0.043		-0.002
		[0.454]		[0.822]
Industry FE	Yes	Yes	Yes	Yes
Observations	331	331	214	214
Adj. R^2	0.184	0.093	0.195	0.108

The sample contains individual CFO's forecasts from the 2007Q2 survey. In columns (1) and (2), the sample includes all respondents. In columns (3) and (4), the sample is restricted to respondents who reported that they are involved in investments ("involved in investments" question = [5, 6, 7]). The regressions include one-digit SIC industry fixed effects. OLS errors are clustered by one-digit SIC industry and bootstrapped following Cameron, Gelbach, and Miller (2009). *p*-values are presented in square brackets. Variable definitions are provided in Appendix Table A.1. *, **, *** denote two-tailed significance at the 10%, 5%, and 1% levels, respectively.

TABLE VII

MISCALIBRATION, OPTIMISM, AND CORPORATE POLICIES

Dependent variable →	Investment intensity (%)		Leverage (%)	
	(1)	(2)	(3)	(4)
Miscalibration ST	0.235		1.324***	
	(0.257)		(0.358)	
Optimism ST	0.336		-0.027	
	(0.384)		(0.454)	
Miscalibration LT		0.600**		0.538
		(0.242)		(0.450)
Optimism LT		0.837*		0.227
		(0.418)		(0.632)
Firm characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Survey Date FE	Yes	Yes	Yes	Yes
Observations	2,547	2,511	2,601	2,565
Adj R^2	0.114	0.116	0.316	0.310

The sample includes all observations that could be identified and merged with Compustat. The dependent variables are investment intensity (net investment / total assets) and book leverage (total debt / total assets), expressed in percentage points. Firm characteristics include log(sales), asset market-to-book, profitability, a repurchase indicator, a dividend indicator, and 12-month past firm returns. Columns (1) and (2) also include market leverage as a control. Summary statistics are in Online Appendix Table A-III, Panel A. Industry fixed effects are based on the two-digit SIC level classification. OLS standard errors are clustered at the two-digit SIC level. Variable definitions are provided in Appendix Table A.1. *, **, *** denote two-tailed significance at the 10%, 5%, and 1% levels, respectively.

TABLE VIII

CHANGE IN CORPORATE POLICIES WHEN NEW CFOS TAKE OFFICE

Dependent variable →	Change in investment intensity Avg(t-2, t-1) → Avg(t+1, t+2) (%)		Change in leverage Avg(t-2, t-1) → Avg(t+1, t+2) (%)	
	(1)	(2)	(3)	(4)
Miscalibration ST	-0.026		0.169	
	(0.348)		(0.495)	
Optimism ST	0.340		-0.065	
	(0.334)		(0.411)	
Miscalibration LT		0.724*		0.154
		(0.369)		(0.412)
Optimism LT		0.318		0.300
		(0.547)		(0.525)
Firm characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year of taking office FE	Yes	Yes	Yes	Yes
Observations	939	929	1,052	1,045
Adj R^2	0.341	0.342	0.356	0.363

The sample includes one observation per survey response for which we could identify an event in which the CFO took office. The dependent variable is the change between the average investment intensity (or book leverage, in columns (3) and (4)) in the two years preceding the CFO taking office (t-2, t-1) and the average investment intensity (or book leverage) in the two years following the CFO taking office (t+1, t+2). The dependent variable is expressed in percentage points. All regressions are OLS and include controls for firm characteristics measured at the year of being hired (log(sales), asset market-to-book, profitability, repurchases, dividends, 12-month past firm return, industry fixed effects (two-digit SIC level), year fixed effects that correspond with the date of the investment and corporate characteristics, and year fixed effects that correspond with the year when the CFO took office. Columns (1) and (2) also include market leverage as a control. Summary statistics are in Online Appendix, Table A-III, Panel A. Standard errors are clustered at the two-digit SIC level. Variable definitions are provided in Appendix Table A.1. *, **, *** denote two-tailed significance at the 10%, 5%, and 1% levels, respectively.

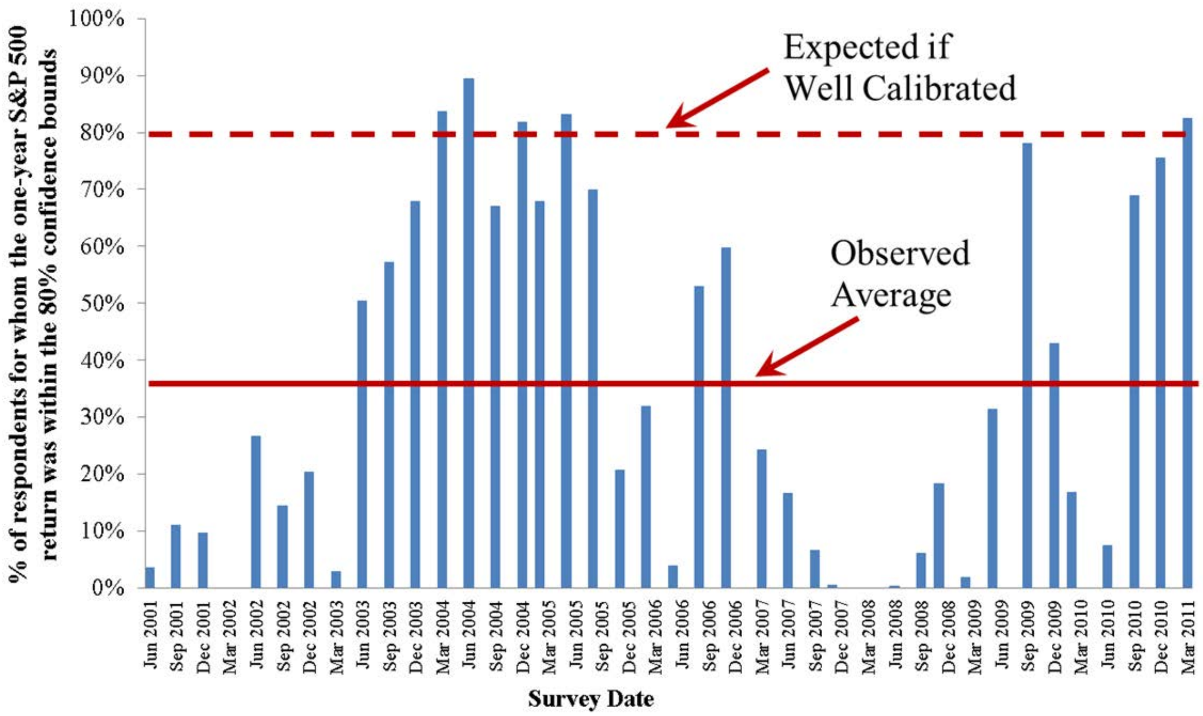

FIGURE I

TIME-SERIES OF CFO MISCALIBRATION

The figure presents the percentage of CFOs whose S&P 500 realized returns fall within the 80% confidence interval, by survey quarter. The horizontal dashed line represents the 80% line; if executives are well calibrated, the percentage of respondents for whom the actual return is within the 80% confidence bounds should be 80%. The horizontal line represents the sample average across surveys.

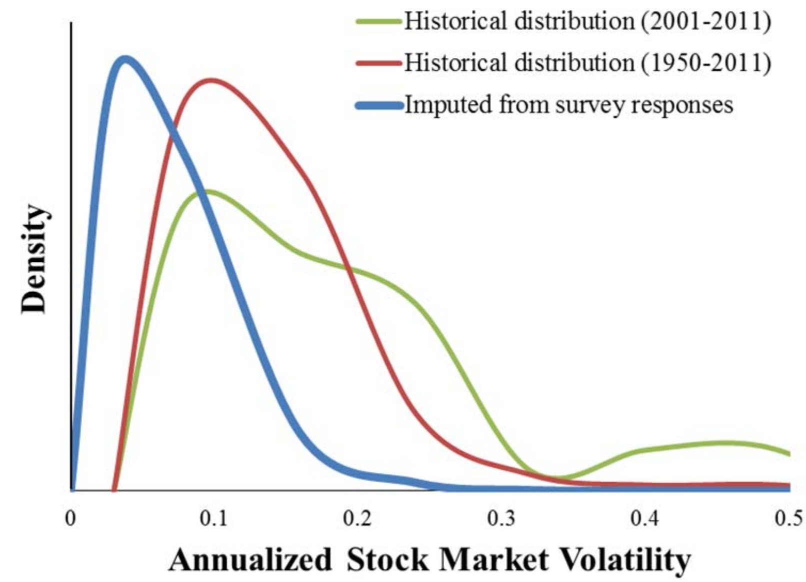

FIGURE IIA

ONE-YEAR IMPUTED INDIVIDUAL S&P 500 VOLATILITY VERSUS HISTORICAL DISTRIBUTION

The kernel density of the one-year S&P 500 return volatility for the period of 1950–2000 (or 2001–2011), and the kernel density of the imputed one-year S&P 500 individual volatility derived from CFOs' predictions.

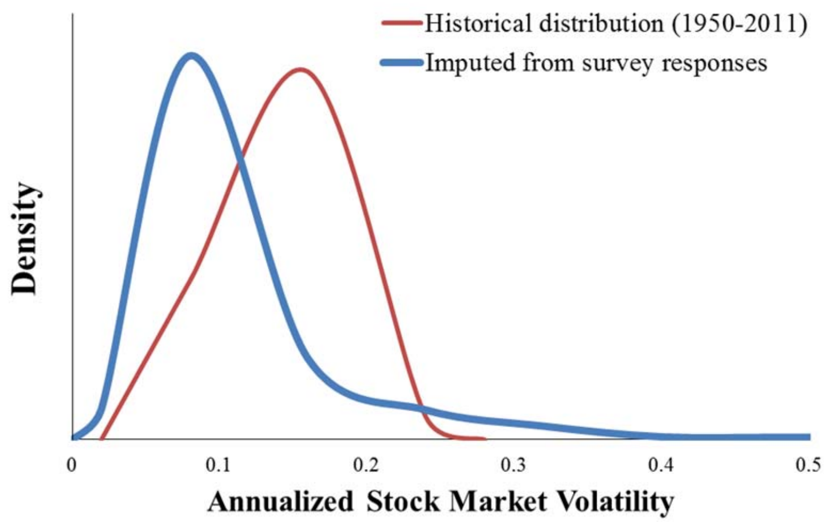

FIGURE IIB

10-YEAR IMPUTED INDIVIDUAL S&P 500 VOLATILITY VERSUS HISTORICAL DISTRIBUTION

The kernel density of the 10-year S&P 500 annualized return volatility for the period of 1950 to 2000 and the kernel density of the imputed 10-year S&P 500 annualized individual volatility derived from CFOs' predictions.

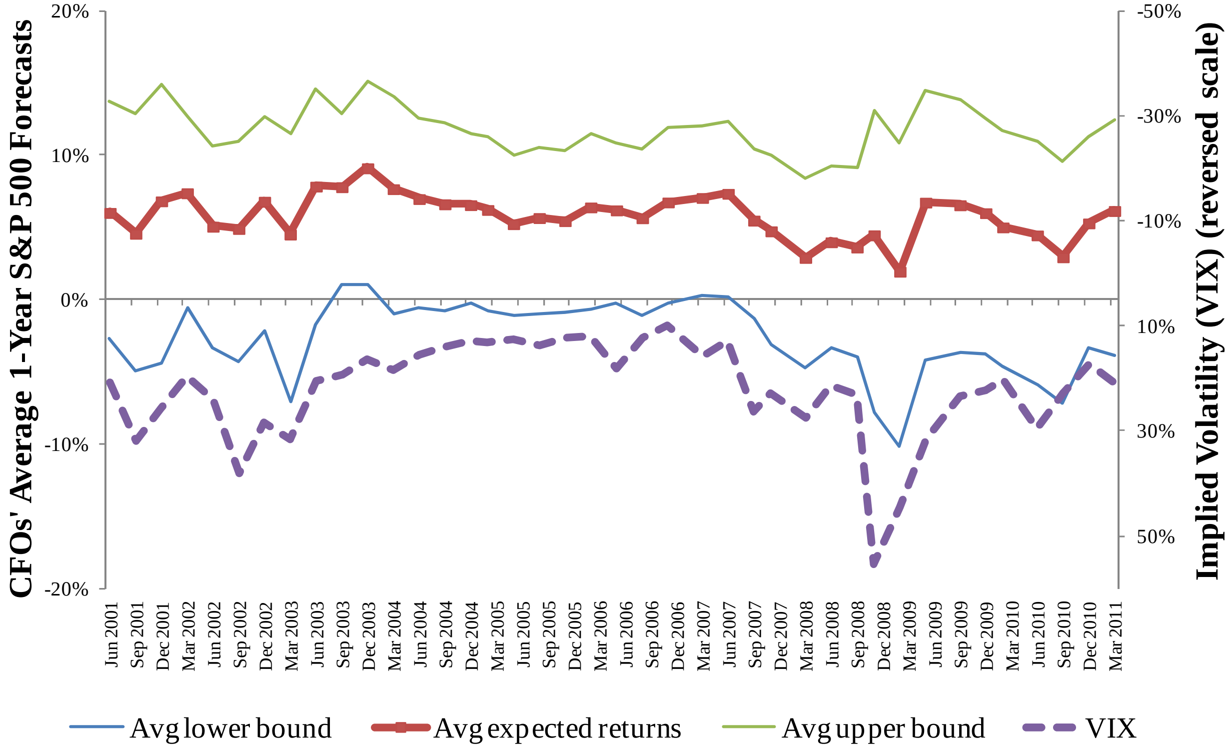

FIGURE III

AVERAGE S&P 500 FORECASTS AND MARKET IMPLIED VOLATILITY, BY SURVEY

The chart shows the average lower bound, the average expected returns, and the average upper bound for one-year S&P 500 return predictions, per survey date (left-hand scale). In addition, the chart includes the S&P 500 option implied volatility (VIX index) on the survey date (reversed right-hand scale).