Forecasting Ability, Firm Welfare and Managerial Skill

Abstract

We examine whether the ability to deliver high quality forecasts reflects greater managerial skills. We expect that managers are more likely to provide consistent forecasts when they can better anticipate future events in the business environment and their impact on earnings. Increased information processing ability as evidenced by greater forecast consistency should be associated with better corporate decisions and financial disclosures. Consistent with this view, we find that firms with CEOs who deliver more consistent forecasts experience higher profitability and higher valuation. We also find that this forecasting ability is, to a large extent, a CEO rather than a firm characteristic. Finally, we find that CEOs with greater forecasting skill experience better careers.

Key words: Managerial skills, Management Forecast, Firm performance, Variance analysis

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1. Introduction

Management earnings forecasts play an important role in capital markets. They are useful to set or alter market earnings expectations, to preempt litigation concerns, and to be a source of transparent and accurate reporting (Hirst, Koonce, and Venkataraman 2008). Trueman (1986) suggests that these voluntarily disclosed earnings forecasts are also useful to measure broader managerial skills. The basic intuition is that management forecasts reveal managers' knowledge of the firm's economic environment and their ability to forecast future business prospects. Consistent with the idea that managers draw on similar skills when generating external earnings forecasts and internal cash flow predictions for their investment decisions, Goodman et al. (2014) provide empirical evidence suggesting that the quality of management forecasts can be used as a valuable measure of managerial forecasting ability related to investment. We extend these studies by investigating the implications of management forecast skills for firm overall welfare and managerial career outcomes.

We first examine if greater forecasting ability leads to superior firm welfare. CEOs that demonstrate greater forecast quality should also have greater information processing ability, which in turn should reflect better quality corporate decisions. In particular, operational, investment, and financing decisions should be better for executives who can better calibrate their expectations. Consistent with this conjecture, Malmendier and Tate [2005, 2008] find that managerial overconfidence can account for corporate investment and mergers and acquisitions distortions. Ben-David, Graham, and Harvey [2010] also find that managerial miscalibration affects real investment. We expect that managers who understand the firm's future payoffs well enough to deliver high quality forecasts can run the firm more efficiently and thus deliver better firm performance.

Next, we examine whether forecasting ability is a distinctive organizational trait or a manager specific skill. We argue that management earnings forecast is important to an organization and its investors but likely secondary to the organization's core competencies. A core competency is a deep proficiency that enables a company to deliver unique value to customers and hence is essential or central to the overall performance and success of the firm (Prahalad and Hamel, 1990). It provides the foundation that allows a firm to be more profitable than its competitors (e.g., Honda's engine expertise). Such competencies are, by nature and by design, organizational traits. Firms may be tempted to protect competencies that provide consistent superior profit, but there is a limit to the number of core competencies an organization can develop and maintain (Prahalad and Hamel, 1990) and organizational overreach is costly (Bruch and Menges, 2010). To address this dilemma, one solution may be to rely on (distinctive) managerial skills instead of distinctive (organizational) competencies, that is, on the capacity of individuals to provide rare and valuable services instead of relying on institutional know-how. We argue that, in delivering high quality management forecasts, firms likely rely more on individual managerial skill rather than on organizational competency. Thus, we expect executive quality to matter more than organizational trait in this context.

Finally, to the extent that forecast quality is determined by managerial skill, we examine whether managers can extract the economic surplus associated with the supply of this skill. That is, are executives who possess this skill compensated for providing it, or is the organization that employs them the sole beneficiary? We consider three aspects of CEO welfare: the probability of finding another CEO appointment in case of departure, the probability of being replaced, and overall CEO compensation. In a broad cross-section of firms, Chang, Dasgupta, and Hilary (2010) find CEO performance to be positively correlated with both labor progress and compensation. If forecast ability is a positive and manager-specific attribute, we expect boards of directors to exert a greater effort to retain and attract more skilled CEOs. In turn, we expect CEOs who are skilled in making high-quality forecasts to receive higher compensation.

One challenge involved in our investigations is to find a good proxy for forecasting skill in a large sample of firms. To address this, we examine forecasts of their own earnings issued by firms and we rely on Bayesian theory which describes the quality of a forecast by measuring the informativeness of the signal. Building on recent work (Hilary and Hsu, 2013; Hilary, Hsu, and Wang, 2014) that provides an empirical application of this intuition, we use forecast consistency to measure forecast quality to determine whether forecasting is a predictor of firm performance in a large cross-section of firms.

Our empirical results are consistent with our hypotheses. We find that the ability to make superior forecasts is associated with greater firm performance, and that this ability is supported by managerial skill, and that firms compensate managers who provide it. First, firms that forecast their earnings more consistently experience higher profitability (measured by their ROA), higher productivity (measured using a data envelopment analysis) and higher valuation (measured by the firm Tobin's Q).

Second, we find that forecast ability is to a large extent a managerial characteristic. Specifically, past forecasting consistency of a CEO is a strong predictor of future consistency for the same CEO, even after controlling for firm characteristics. In addition, we find that CEO fixed effects significantly affect forecast consistency in a sample of executives who change employers. The CEO-specific factor is the largest contributor to the variance in forecasting quality (contributing close to 50 percent of the explained variance). Contrary to firm-fixed effects and other explanatory variables, this factor is reliably outside the range of values that could be obtained using random data (Fitza, 2014).

Finally, we find that CEOs who provide better forecasts are more likely to find another CEO position when they depart. This result supports the idea that the labor market attributes the capacity to issue consistent forecasts to managerial skill rather than to the firm's information environment. Consistent with the view that boards of directors value forecasting skill, we find that CEOs with greater forecast quality have a lower probability of dismissal and earn higher compensation. These results hold when we control for firm performance and financial distress.

We contribute to the existing literature by establishing a link between forecast quality and broad managerial skill. In particular, we show that firms managed by CEOs who can form better expectations of future earnings experience higher valuation and profitability. Goodman et al. (2014) find that managerial forecasting quality is positively associated with the quality of *investment* decisions. Our study extends their finding by establishing a link between firm overall welfare and managerial forecasting skill. Moreover, we demonstrate that managerial forecasting ability is, to a large extent, a CEO rather than a firm characteristic.

Our study also extends the literature that examines the relation between management forecast ability and managers' career development. Previous studies mainly use stated accuracy as a signal of managers' ability to adapt to future changes in the business environment (Zamora 2009; Lee, Matsunaga, and Park 2012). Our study shows that consistency is more important than accuracy in determining managerial turnover and subsequent progress in the labor market. Our results suggest that consistent managers are information suppliers and decision makers with greater information processing ability.

2. Measure of Forecast Quality and Sample Selection

2.1. Measure of Forecast Quality

We want to measure the quality of the private expectations that firms and their managers form (i.e., their private forecasts) about their own future earnings. However, this quality is not directly observable as earnings forecasts that are released are affected by different personal and firm incentives. Our approach to circumvent this issue is to follow Hilary and Hsu (2013) and Hilary et al. (2014) and to invert the quality of the private forecasts from the (biased) public ones. As these authors note, accuracy (the absolute forecast error), bias (the signed error), and consistency (the standard deviation of the signed error) are three different properties of forecasts. Hirst, Koonce, and Venkataram (2008) indicate that managers systematically and intentionally issue biased forecasts. These biases mechanically affect the stated accuracy of the forecast. In other words, accuracy is not only limited by the firm's or the CEO's ability to make accurate forecasts but also by their communication needs.[1] However, if users of these forecasts (e.g., financial market participants) can ‘undo’ predictable forecast biases, then these biases should not affect users’ predictions. A forecast that is a predictable transformation of the realization (e.g., realization minus three units) without a random error should be more informative to users than an unbiased forecast with a small unpredictable error, even if the biased forecast is less accurate. Potentially biased but consistent estimates should therefore have a greater impact on users’ expectations than estimates with inconsistent random errors. In essence, Hilary and Hsu (2013) and Hilary et al. (2014) argue that if users are Bayesian, forecast usefulness should be based on the extent to which a forecaster delivers consistent forecast errors, as captured by the volatility of unexpected errors. We follow their approach to invert the quality of private forecasts from the public ones.

[1] Specifically, managers may want to adjust investor expectations to lower cost of capital, to avoid legal liability, to signal their managerial ability, or to maximize their payoffs from stock-based compensation. Managers' ability to achieve any of these goals depends on being able to make their disclosures as persuasive and credible as possible but, as noted by Hilary et al. (2014), that does not necessarily mean as accurate as possible. A similar point can be made for other characteristics of public forecasts such as the choice of venue, time horizon, and the amount of supporting information provided.

According to previous studies, corporate transparency in general is important for the welfare of the firm (e.g., Jovanovic, 1982). Greater transparency and lower information asymmetry is viewed as economically desirable for firms because it is associated with higher liquidity (Diamond and Verrecchia, 1991) and a lower cost of capital (Leuz and Verrecchia, 2000). More specifically, it has been showed that managerial forecasts play an important economic role in financial markets. Hirst et al. (2008, p.2) note that, ‘‘they represent one of the key voluntary disclosure mechanisms by which managers establish or alter market earnings expectations, preempt litigation concerns, and influence their reputation for transparent and accurate reporting.’’ Firms therefore have incentives to provide optimal forecasts, as indicated by Hilary et al. (2014), who show that managers who issue consistent forecasts have a greater ability to influence investor and analyst, and Hilary and Hsu (2013), who show a similar result with analyst forecasts. Overall, their evidence suggests that the ability to deliver consistent forecasts improves the information environment surrounding the firm. Both studies show that, on average, consistency provides a more powerful measure of forecast quality than accuracy.

Following Hilary et al. (2014), we compute FQ^{firm}, our measure of forecast quality, as follows. First, we calculate a raw measure of forecast quality ($RawFQ^{firm}$) as the standard deviation of the management forecast errors over the last two years (with at least six non-missing observations) for firm i before the current actual earnings announcement, where forecast errors are calculated as the difference between realized earnings and the corresponding management forecast. The smaller $RawFQ^{firm}$ implies that the firm is more consistent. Second, we rank all firms by industry in quarter t based on the standard deviation of forecast errors scaled by the stock price at the beginning of the quarter. Finally, we compute a consistency ranking score using the formula: FQ^{firm} = 1 – (rank – 1) ⁄ (number of firms within the industry – 1). A higher FQ score thus implies that the firm is more consistent. Using a rank measure instead of a raw measure allows us to mitigate the effects of the common shocks affecting all of the managers within the same industry at a given point in time. However, using this coarser partition based on the ranking score (instead of the continuous variable) leads to a loss of information that may reduce the power of our tests.

2.2. Sample Selection

Our sample comes from the management forecasts of quarterly earnings per share (EPS) in the *FirstCall* database over the 1993 to 2010 period.[2] We obtain executive information from the *ExecuComp* database. To calculate our control variables, we intersect our sample with accounting data from the Compustat quarterly files and stock return data from the CRSP daily files. Following recent research literature (e.g., Hilary and Hsu, 2011; Hilary et al., 2014), we focus on the last forecast made by a given manager before the end of the fiscal period, and require that each firm in our sample issue forecasts for at least six quarters over the previous two years. This sampling procedure results in 7,321 firm-quarter observations from 525 firms spanning 34 industries.

3. Empirical Analyses

We conduct three sets of analyses. First, we consider if the ability to deliver high-quality forecasts benefits firm performance. Next, we investigate whether forecast ability is a managerial or organizational characteristic. Finally, we supplement our analysis by examining whether managers who issue high quality earnings forecasts are rewarded for such skill, or if the benefits mainly accrue to the organization employing them.

[2] The database starts coverage in 1993 and stops in early 2011. Chuk, Matsumoto, and Miller (2013) document the presence of several problems with the First Call CIG database, but these are mitigated by cross-sectional characteristic of our sample. We require at least six management forecasts for each CEO – it is unlikely that CIG omits a given CEO who issues a series of forecasts (Christensen, Merkley, Tucker and Venkataraman 2011 makes a similar point).

3.1. Forecast quality and firm performance

We hypothesize that firms that demonstrate greater forecast quality in a broad range of industries should benefit from this ability. First, as discussed earlier, informative forecasts are directly valued by the financial markets. Specifically, firms that issue management forecasts experience higher stock prices (Coller and Yohn, 1997) and access capital markets more often (Frankel, McNichols, and Wilson, 1995). In turn, cheaper and more flexible capital acquisition should lead to more profitable investments. Second, firms that have more informative forecasts should have a greater information processing ability and a greater capacity to understand the impact of their decisions on their welfare, which should make for better quality corporate decisions. For example, capital budgeting and deployment should be more efficient (Goodman et al., 2014). Better projects should be selected, while negative net present value (NPV) investments should be avoided. Production schedules should be optimized, leading to less inefficiency in the utilization of capital. As a consequence, the value of the firm, given the assets in place, should be higher. We expect that firms which understand their future payoffs well enough to deliver consistent forecasts will be more efficiently run and thus deliver better performance. This leads to our first hypothesis:

H1. Firms that release higher quality forecasts experience higher performance than firms releasing lower quality forecasts.

To test this hypothesis, we measure firm performance from three different perspectives. First, we examine if firms with more consistent forecasts have higher operating performance, measured by return on assets (ROA). In addition to measuring profitability, we also examine the effect on productivity using data envelopment analysis (DEA). The DEA-based firm efficiency score provides an ordinal ranking of efficiency relative to the Pareto-efficient frontier—the best performance that a firm can practically achieve. Finally, we explore the association between management forecast quality and valuation. We expect firms that are able to release higher quality forecasts to successfully identify and capitalize on investment opportunities, and thus our forecast ability measure to be positively associated with profitability, productivity, and valuation.

We estimate the following three regressions to test this hypothesis:

$$AROA_{i,t} = a_0 + a_1 FQ^{firm}{}_{i,t} + \sum a_k CONTROLS_{i,t} + \varepsilon_{i,t} \quad (1)$$

$$FIRMEFF_{i,t} = b_0 + b_1 FQ^{firm}{}_{i,t} + \sum b_k CONTROLS_{i,t} + \varepsilon_{i,t} \quad (2)$$

$$ATOBINQ_{i,t} = c_0 + c_1 FQ^{firm}{}_{i,t} + \sum c_k CONTROLS_{i,t} + \varepsilon_{i,t}, \quad (3)$$

where *AROA* is return on assets (adjusted for industry median), *FIRMEFF* is within-industry ranking of firm efficiency score based on DEA (Demerjian et al., 2012), and *ATOBINQ* is the market-to-book ratio of total assets (adjusted for industry median).[3] Our results are not affected if we use an industry ranking approach for the three dependent variables similar to one used for *FQ* (untabulated results). If the ability to deliver high quality forecasts is related to firm performance, we expect a_1, b_1, and c_1 to be positive in Models (1) – (3).

The vector *CONTROLS* contains those variables identified in previous studies that are related to information environment, management forecast characteristics, and firm performance. Following prior literature (e.g., Bourgeois, 1985; Chaganti and Damanpour, 1991; Gentry and Shen, 2013; Nielsen and Nielsen, 2013), we control for firm size (*SIZE*), leverage (*LEV*), analyst following (*COVER*), earnings volatility (*EARNVOL*), stock return

[3] Following Demerjian et al. (2012), we conduct a DEA and calculate firm efficiency score by excluding financial services firms (banks, insurance, real estate, and finance companies) because of the uniqueness of their asset structure and earnings generating process as well as utility companies because of regulation of the output price. As a result, the sample size is reduced to 6,380 when we use *FIRMEFF* as the dependent variable in Model (2).

(*RET*), forecast horizon (*HOR*), and institutional ownership (*INSTO*). We also include a control for growth opportunities (*BTM*) when *AROA* or *FIRMEFF* is the dependent variable. In addition, we include *ROA* (return on assets) in Models (2) and (3) (our results are not affected if this variable is excluded). We calculate *AROA*, *FIRMEFF*, *ATOBINQ*, and *CONTROLS* as moving averaged values over the last two years but our conclusions are not affected if we consider the value at the end of the last quarter. These variables are defined in greater detail in the Appendix. Except for the ranking variables, all of our variables are winsorized at one percent in either tail of the distribution to remove the effects of outliers and extremely misrecorded data. We adjust the standard errors for heteroskedasticity and the clustering observations by firm and quarter (Cameron, Gelbach, and Miller, 2011).

[Insert Table 1 here]

We present the descriptive statistics in Table 1. Most means and medians are close to each other, suggesting that skewness is not an issue in our setting. The one exception is *ATOBINQ*. Our results are not affected when we replicate our tests using the log of *TOBINQ*.

[Insert Table 2 here]

We present the univariate correlations in Table 2. Consistent with hypothesis H1, FQ^{firm} is positively and significantly (at less than the one percent level) associated with our three measures of firm performance (*AROA*, *FIRMEFF*, and *ATOBINQ*). The correlation between the different control variables is reasonably low, suggesting that multicollinearity is not an issue in our setting. The exception is the correlation between *COVER* and *SIZE* that is predictably high (0.6).

[Insert Table 3 here]

We present the results from the estimation of Models (1) – (3) in Table 3. They indicate that firms releasing higher quality forecasts experience higher performance, supporting H1. Specifically, FQ^{firm} is positively associated with *AROA*, *FIRMEFF* and *ATOBINQ*, with z-statistics of 2.42, 2.20, and 6.83, respectively. The economic effect of FQ^{firm} on *AROA* is approximately 25 percent of the effect of *LEV*, one of the most significant drivers of *AROA*. Similarly, the economic effect of FQ^{firm} on *FIRMEFF* is approximately 80 percent of the effect of *LEV* while the effect on *ATOBINQ* is five percent greater than the effect of *LEV*.[4] Untabulated results indicate that FQ^{firm} is positively associated with the profit margin (*PM*) of the firm (z-statistic of 2.40). We also re-estimate Models (1) – (3) using $RawFQ^{firm}$ instead of FQ^{firm}. Untabulated results indicate that our conclusions are not affected (z-statistics of -2.10, -2.37, and -2.05, respectively).

To ensure that our results are not driven by earnings management, we regress a measure of accrual management (*ACCRMGT*, Brown and Pinello, 2007) and a measure of real earnings management (*REALMGT*, Roychowdhury, 2006) on FQ^{firm} and our control variables. See the Appendix for a detailed description of the variables. Untabulated coefficients on FQ^{firm} are insignificantly different from zero in both regressions, which do not support a manipulation explanation.

[4] Since the mean and median values of *ROA* are close to zero, we cannot meaningfully estimate the economic effect by comparing the effect of *FQ* to these statistics. We can, however, compare the effect of *FQ* to the effect of other significant control variables. The effect of *FQ* on *AROA* is 25 percent of the effect of *LEV* (we multiply the coefficient on *FQ* by the standard deviations of the respective variables divided by the product of the coefficient on *LEV* and its standard deviation). Specifically, the economic effect of *FQ* on *AROA* is based on the following ratio: (0.003×0.345) / (0.028×0.149) = 0.248. The comparable ratios for *FIRMEFF* and *ATOBINQ* are (0.039×0.345)/(0.113×0.149) = 0.799; and (0.497×0.345)/(1.097×0.149) = 1.049, respectively.

3.2. Is forecast quality a managerial characteristic?

We next investigate whether forecast ability is a managerial characteristic. As discussed in the introduction, we expect there to be a limit to what a firm can handle as an organization. Prahalad and Hamel (1990) note (p. 83) that “few companies are likely to build world leadership in more than five or six fundamental competencies.” Bruch and Menges (2010) argue that organizational overstretch is costly. They argue that many organizations increase the number and speed of their activities, raise performance goals, shorten innovation cycles, and introduce new management technologies or organizational systems; while this frenzy of activity may initially be successful, it quickly generates organizational overload, dilutes the company’s focus, and severely weakens the organization. As a consequence, we expect companies to rely on individual managers to acquire important but non-core competencies such as the issuance of high quality management forecasts. Results in Table 3 indicate that superior forecasting ability generates superior firm performance, but they do not disentangle the individual effects of organizational competency and managerial forecasting skill. Our theory posits that firms will rely on managerial skill to obtain this ability.

H2. Forecasting ability is a managerial characteristic.

To test this hypothesis, we focus on the role played by CEOs. Anecdotal evidence suggests that forecasting ability is a managerial skill, and more specifically a CEO skill. For example, after General Electric (GE) missed an earnings forecast, Jack Welch (former chairman and CEO) stated in an April 16, 2008 interview on CNBC that ‘‘Jeff [Immelt, GE’s current CEO; emphasis added] has a credibility issue.’’ Similarly, Daniel Vasella, CEO of Novartis, indicated "The practice by which CEOs [emphasis added] offer guidance about their expected quarterly earnings performance […] is an old one.” James Hesket, writing his

Harvard Business School blog, asked "Should CEOs [emphasis added] of Public Companies Offer Earnings Guidance?" Brochet, Faurel, and McVay (2011) indicate that the decision to follow a policy of issuing earnings guidance or not is largely a CEO decision and that CFOs have little effect on this decision.[5]

To investigate H2, we first consider a sample of CEOs who leave a firm to take up an executive position at another firm. We define forecast quality for the CEO, FQ^{ceo} ($RawFQ^{ceo}$), as the analog of FQ^{firm} ($RawFQ^{firm}$) based on the executive tenure. The key difference between FQ^{ceo} ($RawFQ^{ceo}$) and FQ^{firm} ($RawFQ^{firm}$) is that we require that the CEO does not change during the time these forecasts (at least six over the previous two years) were made when we calculate FQ^{ceo} ($RawFQ^{ceo}$). We then regress our measure of forecast quality on a vector of time-varying explanatory variables (*SIZE*, *BTM*, *LEV*, *COVER*, *EARNVOL*, *ROA*, *RET*, *HOR*, and *INSTO*), industry and year fixed effects, as well as on CEO and firm fixed effects. We use the method proposed by Abowd, Kramarz, and Margolis (1999).[6] Our sample includes 43 different "connected" CEOs and 877 observations. However, we note that the discrete and bounded nature of *FQ* may create additional econometric issues in this case. Thus, we focus on *RawFQ* for this test. The untabulated F-test indicates that the CEO

[5] Bamber, Jiang, and Wang (2010) establish the presence of CEO fixed effects on forecast accuracy and biases. Our approach differs from theirs in several aspects. First, and most important, our goal is to show that managerial effects are larger than firm effects, while theirs is merely to establish the presence of managerial fixed effects. Second, we focus on forecast consistency rather than on forecast accuracy or bias. Hilary and Hsu (2013) and Hilary et al. (2014) suggest that consistency is a better measure than accuracy and biases to capture forecast quality and informativeness. This is not an issue for the Bamber et al. (2010) study as it attempts to establish the presence of managerial styles rather than the managerial effect on forecast quality. However, their tests yield a different interpretation from ours. Lastly, Fitza (2014) suggests that the CEO effect can be exaggerated by sheer luck. The benefit of that study was not available to Bamber et al. (2010), but we address this issue in Table 4.

[6] Abowd et al. (1999) (AKM) lever the potentially small number of mover observations (i.e., managers who move across companies) to deduce information about non-movers who work in firms that have employed at least one mover (i.e., the "connected" managers). Using the AKM method allows us to separate firm and manager fixed effects not only for movers but also for some non-movers, which increases the sample size and power (e.g., Bertrand and Schoar, 2003). This method has been used in previous studies (e.g., Graham, Li, and Qiu, 2012).

fixed effects are jointly significant with an F-value of 9.36. For completeness, we repeat the procedure using FQ^{ceo} and find the F-value to be 14.62 (we do not include industry and year fixed effects when we use FQ^{ceo} as this variable is estimated at the industry-year level).

Next, we re-estimate models (1) – (3) using FQ^{ceo} instead of FQ^{firm}. Results (untabulated) indicate that we reach similar conclusions. However, both the economic and statistical significance increase when we use FQ^{ceo} instead of FQ^{firm} (the point estimates of the coefficient increase by approximately 30 percent on average and the z-statistics by 6 percent on average). These results are consistent with the notion that forecasting ability is a managerial skill rather than a firm characteristic.

[Insert Table 4 here]

Finally, we perform a variance decomposition analysis (e.g., Abowd et al., 1999) in Table 4. We again note the potential econometric issues created by the discrete and bounded nature of FQ^{ceo} and focus on $RawFQ^{ceo}$ for this decomposition. However, as discussed below, we obtain similar estimates if we use FQ^{ceo} instead of $RawFQ^{ceo}$ in this test. Following Fitza (2014), we also replace $RawFQ^{ceo}$ as dependent variable with a randomly created variable based on 100 draws from a normal distribution with the same mean and standard deviation as $RawFQ^{ceo}$. This procedure allows us to estimate the range of explanatory power we could obtain by sheer luck. Results in Table 4 indicate that that CEO fixed effects is the main explanatory variable to explain variations in forecast quality. The managerial fixed effects contribute 49 percent of the explained variance (47 percent of the overall variance). In contrast, the contribution of firm-fixed effects is 50 percent smaller (33 percent of the explained variance) while other explanatory variables (including the year and industry fixed effects) contribute only 18 percent to the explained variance. When we compare the estimate to the simulated data, we observe that only the effect from the managerial fixed effects is materially outside the 90 percent confidence interval (47 percent of total variance versus an upper bound of 29 percent for the confidence interval). In contrast, the value obtained for the firm fixed effects is within the 90 percent confidence interval (31 percent of total variance versus an upper bound of 46 percent). Thus we cannot reject the hypothesis that the contribution of the firm fixed effects is obtained by sheer luck. For completeness, we also consider a similar analysis using FQ^{ceo} and obtain similar estimates.[7] These results support the notion that CEOs matter more for forecast quality than firm-specific capital.

Next, H2 suggests that, since forecasting is a managerial skill, its quality should be consistent (i.e., not a by-product of luck) and independent of firm characteristics. To further investigate these claims, we regress the current forecast quality (FQ^{firm} or FQ^{ceo}) on the past forecast quality ($LagFQ^{firm}$ or $LagFQ^{ceo}$) for the same firm or CEO-firm. We consider only non-overlapping observations of eight quarters and use the value lagged by one period (i.e., eight quarters) to define past consistency. We also control for the current value of our usual variables (*SIZE*, *BTM*, *LEV*, *COVER*, *EARNVOL*, *ROA*, *RET*, *HOR*, and *INSTO*) as well as industry and year fixed effects.[8] Specifically, we next estimate the following two models:

$$FQ^{firm}_{i,t} = a_0 + a_1\, LagFQ^{firm}_{i,t} + \sum a_k\, CONTROLS_{i,t} + \varepsilon_{i,t} \tag{4a}$$

$$FQ^{ceo}_{i,t} = a_0 + a_1\, LagFQ^{ceo}_{i,t} + \sum a_k\, CONTROLS_{i,t} + \varepsilon_{i,t} \tag{4b}$$

[Insert Table 5 here]

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7 Only the effect from the managerial fixed effects is materially outside the 90 percent confidence interval (44 percent versus an upper bound of 32 percent for the confidence interval). The value for the firm fixed effects is only slightly higher than the 90 percent confidence interval (38 percent versus an upper bound of 37 percent) and within the 95 percent confidence interval.

8 Controlling for the additional variables used by Gong, Li, and Wang (2011), including *ZSCORE*, *HHI*, *XFINQ*, *NETSALES*, *LITIG*, *LOSS*, and *ACCRUAL* (all of which are defined in the Appendix), does not affect our conclusions.

Results indicate that past consistency is a strong predictor of current consistency, even after controlling for firm characteristics. This is true in both columns of Table 5, but the effect is stronger when we focus on the definition based on CEO tenure in column (2) rather than on the definition based on the firm-level. In column (1), when FQ^{firm} is the dependent variable, the coefficient on past values of FQ^{firm} is 0.288 with a z-statistic of 10.40. In Column (2), when FQ^{ceo} is the dependent variable, the coefficient on past values of FQ^{ceo} increases to 0.333 with a z-statistic of 10.79.[9] These results indicate that forecast quality is persistent. The fact that the results hold after controlling for firm characteristics is consistent with the notion that forecast quality is an individual executive skill. For completeness, we define $RawFQ^{ceo}$ as the analog of $RawFQ^{firm}$ and regress $RawFQ^{ceo}$ on $LagRawFQ^{ceo}$ (and our standard control variables). Results (untabulated) are not affected. Taken together, our results from various tests discussed above support hypothesis H2.

Naturally, CEOs do not complete the process of preparing forecasts alone. Management forecasts are the output of a lot of work within firms (e.g., data from different departments are aggregated and projected). Forecasting skill comprises the ability to organize the firm in such way that the different functions provide high quality information and the capacity to synthesize the information collected by the different functions. Our results suggest that it is managerial skill rather than firm functional quality that has a first-order effect on forecast quality, suggesting that the first element is more significant than the second. Consistent with this view, Simon (1973, 270) argues that "…the scarce resource is not information; it is processing capacity to attend to information."

[9] This specification is the only one in which the VIFs are above the conventional level. In untabulated specifications, we drop the industry and year fixed effects. Doing this reduces the average VIF to 1.51 and the highest one to 2.10). Our conclusions are not affected. The point estimates of the coefficient slightly increase from 0.288 to 0.305 for FQ^{firm} and from 0.333 to 0.363 for FQ^{ceo}. The z-statistics change from 10.40 to 10.16 for FQ^{firm}, and from 10.79 to 11.99 for FQ^{ceo}.

3.3. Forecasting ability and CEO welfare

Finally, we ask whether CEOs who issue high-quality earnings forecasts are rewarded for such skill. If forecasting skills are rare and valuable and are provided by managers, we expect this to be the case (Geletkanycz, Boyd, and Finkelstein, 2001). In contrast, if the ability to provide high-quality forecasts is part of the organizational capital, managers running the firm may not be able to extract the economic surplus for themselves. We consider three aspects of CEO welfare; the probability of finding another CEO appointment in case of departure, the probability of being replaced, and overall CEO compensation. In a broad cross-section of firms, Chang et al. (2010) find CEO performance to be positively correlated with both labor progress and compensation. If forecast ability is a positive and manager-specific attribute, we expect boards of directors to exert a greater effort to retain and attract more skilled CEOs. In turn, we expect CEOs who are skilled in making high-quality forecasts to receive higher compensation. This leads to the following set of hypotheses:

H3a. The probability that a CEO who leaves one firm to work as a CEO for another is positively related to management forecast consistency.

H3b. The probability of CEO turnover is negatively related to management forecast consistency.

H3c. CEO compensation is positively related to management forecast consistency.

To test H3a, we compare the CEOs who left one firm to work as a CEO for another (covered by the *ExecuComp* database) with the same number of CEOs who also left a firm but did not find similar employment. We then estimate the following model for manager i in quarter t:

$$NEWJOB^{ceo}_{i,t} = a_0 + a_1 FQ^{ceo}_{i,t} + \sum a_k CONTROLS_{i,t} + \varepsilon_{i,t}, \quad (5)$$

where $NEWJOB^{ceo}$ is a binary variable equal to one if the CEO found a new appointment as CEO of a listed firm after leaving the firm, and zero if she did not.[10] We focus on *FQ* instead of *RawFQ* because prior research (e.g., Antle and Smith, 1986) suggests that relative performance evaluation (RPE) is a key element of CEO selection and evaluation. We control for size (*SIZE*), growth opportunities (*BTM*), leverage (*LEV*), analyst following (*COVER*), earnings volatility (*EARNVOL*), forecast horizon (*HOR*), institutional ownership (*INSTO*), profitability (*ROA*), and stock performance (*RET*). We calculate *CONTROLS* as moving averages over the last two years but our conclusions are not affected if we consider the value at the end of the previous quarter. Our results are not affected if we use a propensity score matching procedure to obtain our control sample. The score is based on the control variables defined above (*CONTROLS*) (naturally excluding FQ^{ceo}). H3a predicts the coefficient on FQ^{ceo}, a_1, to be positive.

To test H3b, we estimate the following model for manager *i* in quarter *t*:

$$Prob(TURNOVER^{ceo}_{i,t+1}=1) = b_0 + b_1 FQ^{ceo}_{i,t} + \sum b_k\, CONTROLS_{i,t} + \varepsilon_{i,t}, \qquad (6)$$

where $TURNOVER^{ceo}_{i,t+1}$ is an indicator variable that equals one if CEO *i* is replaced in quarter *t*+1, otherwise zero.[11] Our results are not affected if we extend the measurement window of the turnover to four quarters in the future (i.e. from quarter *t*+1 to *t*+4). In Model (6), we control for our standard set of variables. H3b predicts the coefficient on FQ^{ceo}, b_1 to be negative.

To test Hypothesis 3c, we estimate the following model for manager *i* in quarter *t*:

10 We calculate the value of FQ^{ceo} in the final years before the CEO leaves her position, i.e., there is only one observation per CEO-firm. Our results do not change when we set *NEWJOB* to one if the new position is either as CEO or a Chairperson of a listed firm.

11 Our results are not affected when we identify involuntary turnover events (instead of turnover for any reason).

$$ACOMP^{ceo}{}_{i,t} = c_0 + c_1\, FQ^{ceo}{}_{i,t} + \sum c_k\, CONTROLS_{i,t} + \varepsilon_{i,t}, \tag{7}$$

where $ACOMP^{ceo}$ is the natural logarithm of the overall compensation of the CEO (adjusted for the industry median).[12] We calculate $ACOMP^{ceo}$ as moving averaged values over the last two years but our conclusions are not affected if we consider the value at the end of the last quarter. Our conclusions do not change if we use an industry ranking approach for $ACOMP^{ceo}$ similar to the one used for FQ^{ceo}. The variables FQ^{ceo} are as previously defined. *CONTROLS* are our standard set of variables. H3c predicts the coefficient on FQ^{ceo}, c_1, to be positive.

Before considering the regression results, we split the sample based on whether $NEWJOB^{ceo}$ is equal to 1 or to 0. Untabulated results indicate that FQ^{ceo} is 25 percent larger in the former than in the latter (t-statistic of 2.14). We then repeat the procedure with CFOs but fail to find support for the hypothesis that CFOs who are able to deliver high quality forecasts have better career development than CFOs who are not. These preliminary results are consistent with the idea that the labor market attributes high forecast consistency to CEO skill rather than to the managerial environment or to CFO skill. By separating the CEO-firm from the CFO-firm observations we gain further confidence that the effect is driven by the CEOs rather than by the characteristics of the firms they manage.

[Insert Table 6 here]

We report the results of estimating Model (5) in Column 1 of Table 6. Consistent with H3a, the coefficient associated with FQ^{ceo} is positive (3.949) and significant at the one percent level. The marginal effect is approximately four percent. Column 2 of Table 6

[12] Executive compensation ($ACOMP^{ceo}$) is an annual item. Therefore, we only include the fourth quarter of each fiscal year to estimate Model (6). This reduces our sample to 1,558 CEO-years. Our results are not affected if we include all quarters.

reports the results of testing Model (6). The coefficient on FQ^{ceo} is negative (-0.398) and significant at less than the five percent level (z-statistic of -2.31). The untabulated marginal effect of FQ^{ceo} on quarterly turnover is approximately two percent. These results support H3b. Column 3 of Table 5 reports the results of testing Model (7). Consistent with H3c, the coefficient on FQ^{ceo} is 0.222 and is significant at less than five percent level (z-statistic of 2.39). The economic effect of FQ^{ceo} is such that it represents approximately 14 percent, 50 percent, and 45 percent of the effects of *SIZE*, *RET*, and *INSTO* respectively, probably the most important determinants of compensation. Results (untabulated) indicate that our conclusions are not affected if we define FQ^{ceo} using five or seven quarters, or if we omit all the control variables. Untabulated results show that our conclusions in Table 6 are not affected if we control for financial stress by including *LOSS* (an indicator variable that equals one if the firm is reporting a loss, zero otherwise) or if we use an extended list of controls (*DUAL*, *HHI*, *AGE*, *EXPERIENCE* and *MBAF*). [13]

Overall, our results suggest that employers reward managers for their forecasting skill. We note that this effect is incremental to standard drivers of compensation. To obtain further confidence that this result is not driven by the superior performance of firms associated with high-quality forecasts, we further control for profitability, productivity and valuation by including *PM* (profit margin, *ROA* is already included), *FIRMEFF*, and Tobin's Q (we drop *BTM* in this case). Results (untabulated) indicate that FQ^{ceo} remains significant (z-statistics of 2.60, -2.08, and 1.94, respectively), consistent with the notion that forecasting skills are directly rewarded. More generally, they are consistent with the notion that firms acquire forecast competences by hiring and compensating managers who can directly provide them.

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13 The additional variables are defined in the Appendix. Our conclusions are not affected if we control for current total compensation ($COMP^{ceo}$) and include a fourth quarter indicator (*Q4*) to control for year-end effects in Model (6).

4. Conclusions

We examine whether the ability to deliver high quality forecasts reflects greater managerial skill. We expect that managers are more likely to provide consistent forecasts when they can better anticipate future events in the business environment and their impact on earnings. Increased information processing ability as evidenced by greater forecast consistency should be associated with better corporate decisions and financial disclosures. Consistent with this view, we find that firms with CEOs who deliver more consistent forecasts experience higher profitability and higher valuation.

Next, our results suggest that forecast consistency is, to a large extent, a CEO rather than a firm characteristic. We find that past forecast consistency is a strong predictor of future forecast consistency, even after controlling for firm characteristics. In addition, we find that CEO fixed effects significantly affect forecast consistency in a sample of executives who change employers. The CEO-specific factor is the largest contributor to the variance in forecasting quality (contributing close to 50 percent of the explained variance). Contrary to firm-fixed effects and other explanatory variables, this factor is reliably outside the range of values that could be obtained using random data (Fitza, 2014). We do not find a comparable effect for CFOs, however, suggesting that the consistency of the forecasts is attributed to CEOs rather than to CFOs.

Lastly, we investigate whether managers are rewarded for providing consistent forecasts. We expect that information processing ability should be an important attribute of a manager's quality that is valued by a firm's board of directors. Our empirical results are consistent with this prediction and indicate that CEOs who provide better forecasts are more likely to find another CEO position when they depart. This result supports the idea that the labor market attributes the capacity to issue consistent forecasts to managerial skill rather than to the firm's information environment. Consistent with the view that boards of directors value forecasting skill, we find that CEOs with greater forecast quality have a lower probability of dismissal and earn higher compensation. These results hold when we control for firm performance and financial distress.

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Appendix: Variable Definitions

Variables	Definitions
FQ^{firm}	Measure of consistency for a firm based on the industry ranking. We first calculate the standard deviation of the management forecast errors over the last two years for firm *i* in quarter *t*. We then rank all of the firms by industry (4-digit SIC codes) in quarter t based on the standard deviation of forecast errors scaled by stock price two days before the management forecast. Finally, we obtain a consistency ranking score using the formula (Hilary, Hsu, and Wang, 2014): 1 – (rank – 1) ⁄ (number of CEOs within the industry – 1). Management forecast error is the difference between the management forecast and the realized earnings.
FQ^{CEO}	Measure of consistency for a CEO based on the industry ranking. We first calculate the standard deviation of the management forecast errors over the last two years for CEO *i* in quarter *t*. We then rank all of the CEOs by industry (4-digit SIC codes) in quarter t based on the standard deviation of forecast errors scaled by stock price two days before the management forecast. Finally, we obtain a consistency ranking score using the formula ((Hilary et al., 2014): 1 – (rank – 1) ⁄ (number of CEOs within the industry – 1).
ACCRMGT	Abnormal accruals, measured 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 (Brown and Pinello, 2007).
ACCRUAL	Total accruals, measured as the difference between income before extraordinary items and operating cash flows, deflated by average total assets.
MBAF	The frequency of meeting or beating consensus analyst forecasts over the previous two years before the current management forecast date, divided by the total number of forecasts issued by CEO *i* over the two-year period.
AGE	The current age of a CEO.
$ACOMP^{ceo}$	The natural logarithm of total annual compensation for a CEO, adjusted for the industry-median (based on Fama French 48 industries).

AROA	Return on a firm's assets adjusted for the industry-median (based on Fama French 48 industries) over the last three months.
ATOBINQ	The market-to-book ratio of total assets adjusted for the industry-median (based on Fama French 48 industries) over the last three months.
BTM	Book-to-market ratio, measured as book value of equity divided by market value of equity.
$COMP^{ceo}$	The natural logarithm of the total annual compensation for a CEO.
COVER	The natural logarithm of one plus the number of analysts covering the firm in a quarter. If the number of analysts covering the firm in a quarter is missing, we set it as zero.
DUAL	Indicator variable that equals one if a CEO is also holding the position of Chairman within a firm, and zero otherwise.
EARNVOL	The standard deviation of the quarterly return on assets over the preceding eight quarters.
EXPERIENCE	Forecast experience of a CEO, measured as the natural logarithm of one plus the number of quarters in which a CEO has issued forecasts before the current management forecast.
HHI	Industry concentration, measured by the Herfindahl-Hirschman index and calculated as the sum of the squares of the market shares of the firms' sales within each 4-digit SIC industry.
HOR	The natural logarithm of one plus the number of days between the issuance of the forecast and the fiscal period end.
LEV	Leverage ratio, measured as total liability over book value of equity.
LITIG	Indicator variable that equals one for litigious industries, including Biotechnology (SIC 2833 to 2836), Computer Hardware (SIC 3570 to 3577), Electronics (SIC 3600 to 3674), Retailing (SIC 5200 to 5961) and Computer Software (SIC 7371 to 7379), and zero otherwise.
LOSS	Indicator variable that equals one if the firm is reporting a loss, zero otherwise.
MFE	Management forecast errors, measured as the management forecast of quarter t earnings per share minus quarter *t* realized earnings per share scaled by the stock price at the beginning of quarter *t*.
NETSALES	Net sales (in millions of shares) from open market transactions by CEOs during the 30-day period following management forecasts.

$NEWJOB^{ceo}$	Indicator variable equal to one if the CEO found a new CEO appointment after leaving the firm, zero if she did not.
PM	Profit margin, measured as income before extraordinary items divided by sales.
Q4	Indicator variable that equals one for the 4th quarter, and zero otherwise.
ROA	Return on a firm's assets over the last three months, measured as income before extraordinary items divided by total assets.
REALMGT	A combination of the abnormal levels of cash flow from operations (*ABOCF*), discretionary expenses (*ABDE*), and production costs (*ABPC*) (-1×(*ABOCF*+*ABDE*)+*ABPC*) (Roychowdhury, 2006).
RET	The raw stock return of a firm over the last three months.
SIZE	Natural logarithm of market value of equity.
$RawFQ^{ceo}$	The standard deviation of the management forecast errors over the last two years for a CEO, scaled by the stock price.
$RawFQ^{firm}$	The standard deviation of the management forecast errors over the last two years, scaled by the stock price.
$TURNOVER^{ceo}$	Indicator variable that equals one if CEO *i* is replaced in quarter *t*+1, and zero otherwise.
XFINQ	External financing, measured as the sum of net equity financing and net debt financing scaled by total assets.
ZSCORE	Altman's Z-score.

Table 1
Summary statistics

variable	N	MEAN	STD	MEDIAN
AROA	7,321	0.003	0.022	0.002
FIRMEFF	6,380	0.765	0.213	0.800
ATOBINQ	7,321	0.473	1.126	0.142
FQ^{firm}	7,321	0.551	0.345	0.571
SIZE	7,321	7.744	1.480	7.544
BTM	7,321	0.427	0.242	0.375
LEV	7,321	0.178	0.149	0.172
COVER	7,321	1.814	0.602	1.816
EARNVOL	7,321	0.015	0.019	0.008
RET	7,321	0.034	0.067	0.031
HOR	7,321	3.902	0.374	4.020
INSTO	7,321	0.761	0.171	0.793

All of the variables are defined in the Appendix.

Table 2
Correlations

	AROA	*FIRMEFF*	*ATOBINQ*	*FQ^{firm}*	*SIZE*	*BTM*	*LEV*	*COVER*	*EARNVOL*	*RET*	*HOR*
FIRMEFF	**0.260**										
ATOBINQ	**0.476**	**0.149**									
FQ^{firm}	**0.233**	**0.235**	**0.305**								
SIZE	**0.167**	**0.521**	**0.217**	**0.318**							
BTM	**-0.408**	**-0.216**	**-0.651**	**-0.336**	**-0.392**						
LEV	**-0.180**	**0.084**	**-0.303**	**-0.068**	**0.103**	**0.029**					
COVER	**0.076**	**0.271**	**0.154**	**0.137**	**0.595**	**-0.192**	**-0.040**				
EARNVOL	**-0.094**	**-0.092**	**0.044**	**-0.168**	**-0.139**	**0.127**	**-0.077**	**0.062**			
RET	**0.274**	**0.080**	**0.115**	**0.089**	**-0.096**	**-0.136**	-0.016	**-0.125**	**-0.040**		
HOR	-0.019	-0.016	**0.038**	-0.016	**-0.079**	**-0.026**	**-0.100**	**-0.247**	0.021	-0.005	
INSTO	-0.015	**0.036**	**-0.093**	**0.040**	**-0.044**	**0.096**	**-0.050**	**0.135**	**-0.032**	**-0.135**	**0.053**

All of the variables are defined in the Appendix. The Pearson correlations in bold are significant at the 5% level or less.

Table 3
Managerial forecast ability and firm performance

	(1) *AROA*	(2) *FIRMEFF*	(3) *ATOBINQ*
FQ^{firm}	**0.003****	**0.039****	**0.497*****
	(2.42)	**(2.20)**	**(6.83)**
SIZE	0.000	0.077***	0.028
	(0.41)	(11.38)	(0.78)
BTM	-0.034***	0.097**	
	(-13.08)	(2.32)	
LEV	-0.028***	0.113**	-1.097***
	(-7.07)	(2.33)	(-4.54)
COVER	-0.000	-0.009	0.152*
	(-0.42)	(-0.61)	(1.91)
EARNVOL	-0.252***	0.577	16.197***
	(-6.69)	(1.41)	(8.49)
RET	0.025***	0.343***	0.204
	(3.96)	(4.26)	(0.54)
HOR	-0.003***	0.024	0.284***
	(-2.80)	(1.26)	(4.12)
INSTO	0.005	0.074	-0.541**
	(1.39)	(1.58)	(-2.08)
ROA		1.884***	38.768***
		(4.01)	(12.05)
N	7,321	6,380	7,321
adj. R^2	0.446	0.311	0.537

This table reports of the relationship between managerial forecast ability and firm performance. The estimation results are based on the following models:

$$AROA_{i,t}=a_0 + a_1FQ^{firm}_{i,t} + \sum a_kCONTROLS_{i,t} + \varepsilon_{i,t} \quad (1)$$
$$FIRMEFF_{i,t}=b_0 + b_1FQ^{firm}_{i,t} + \sum b_kCONTROLS_{i,t} + \varepsilon_{i,t} \quad (2)$$
$$ATOBINQ_{i,t}=c_0 + c_1FQ^{firm}_{i,t} +\sum c_kCONTROLS_{i,t} + \varepsilon_{i,t} \quad (3)$$

All of the variables are defined in the Appendix. The constant terms are included, but not tabulated. z-statistics, which are reported in parentheses, are corrected for heteroskedasticity and are adjusted for clustering of observations by firm and quarter. Coefficients that are significant at the 10, 5, and 1% levels are marked with *, ** and ***, respectively.

Table 4
Variance analysis

Components	(1) $RawFQ^{ceo}$
Managerial fixed effects	0.47 (0.01-0.29)
Firm fixed effects	0.31 (0.01-0.46)
Explanatory variables	0.17 (0.09-0.65)
Unexplained variance	0.05 (0.21-0.65)

This table reports results of the variances analysis on $RawFQ^{ceo}$ using the connectedness sample (i.e., the sample that includes all the CEOs who have worked in the firms that have hired at least one mover) (Abowd, Kramarz, and Margolis, 1999). Column 1 presents the covariance between $RawFQ^{ceo}$ and each of the components, normalized by the variance of $RawFQ^{ceo}$, respectively. The normalized covariance (excluding "unexplained variance") can be interpreted as decomposition of model R^2. Explanatory variables include year and industry indicator variables. The results in parentheses indicate the 90% interval of the variances based on randomly created numbers (Fitza, 2014).

Table 5
The Persistence of Management Forecast Quality

	(1) FQ^{firm}	(2) FQ^{ceo}
LagFQ^firm^	**0.288***** **(10.40)**	
LagFQ^ceo^		**0.333***** **(10.79)**
SIZE	0.056*** (6.45)	0.040*** (4.14)
BTM	-0.243*** (-4.68)	-0.232*** (-4.33)
LEV	-0.136** (-1.96)	-0.012 (-0.18)
COVER	-0.047*** (-2.60)	-0.025 (-1.21)
EARNVOL	-1.567*** (-3.48)	-1.997*** (-3.63)
ROA	0.302 (0.44)	0.310 (0.42)
RET	0.848*** (6.61)	0.901*** (6.87)
HOR	-0.011 (-0.45)	-0.012 (-0.46)
INSTO	0.173*** (2.70)	0.187*** (2.77)
N	3,987	2,986
adj. R^2	0.309	0.322

This table reports persistence of management forecast quality. The estimation results are based on the following regression models:

$$FQ^{firm}_{i,t}=a_0 + a_1 LagFQ^{firm}_{i,t} + \sum a_k CONTROLS_{i,t} + \varepsilon_{i,t} \quad (4a)$$
$$FQ^{ceo}_{i,t}=a_0 + a_1 LagFQ^{ceo}_{i,t} + \sum a_k CONTROLS_{i,t} + \varepsilon_{i,t} \quad (4b)$$

All of the variables are defined in the Appendix. The constant terms, industry and year fixed effects are included, but not tabulated. All of the continuous variables are winsorized at the 1st and 99th percentiles. Column (1) reports the estimation results of Model (4a). Column (2) reports the estimation results of Model (4b). z-statistics, which are reported in parentheses, are corrected for heteroskedasticity and are adjusted for clustering of observations by CEO and quarter. Coefficients that are significant at the 10, 5, and 1% levels are marked with *, ** and ***, respectively.

Table 6
Managerial forecast ability and welfare

	(1) *NEWJOB*^{ceo}	(2) *TURNOVER*^{ceo}	(3) *ACOMP*^{ceo}
FQ^{ceo}	**3.949*****	**-0.398****	**0.222****
	(2.68)	**(-2.31)**	**(2.39)**
SIZE	0.250	0.205*	0.377***
	(0.31)	(1.93)	(6.29)
BTM	1.689	-0.199	0.055
	(1.63)	(-0.46)	(0.24)
LEV	-16.114**	0.424	0.593
	(-2.08)	(0.52)	(1.62)
COVER	-2.228	-0.290	-0.094
	(-1.11)	(-1.28)	(-0.95)
EARNVOL	-2.562	4.229	0.285
	(-0.24)	(0.95)	(0.16)
ROA	-1.687	-20.505**	-0.515
	(-0.13)	(-2.08)	(-0.15)
RET	6.185**	-1.480	2.223***
	(2.07)	(-1.22)	(2.69)
HOR	-1.457***	0.102	-0.259*
	(-5.71)	(0.32)	(-1.69)
INSTO	0.236	0.263	1.029***
	(0.06)	(0.33)	(3.54)
N	628	5,415	1,558
adj. R^2 (pseudo R^2)	0.436	0.050	0.204

This table reports the effect of managerial forecast ability on CEO welfare. The estimation results are based on the following regression models:

$$Prob(NEWJOB^{ceo}_{i,t}=1)=c_0 + c_1FQ^{ceo}_{,t} +\sum c_kCONTROLS_{i,t} + \varepsilon_{i,t} \quad (5)$$
$$Prob(TURNOVER^{ceo}_{i,t+1}=1)=b_0 + b_1FQ^{ceo}_{,t} +\sum a_kCONTROLS_{i,t} + \varepsilon_{i,t} \quad (6)$$
$$ACOMP^{ceo}_{i,t}=a_0 + a_1FQ^{ceo}_{i,t} +\sum a_kCONTROLS_{i,t} + \varepsilon_{i,t} \quad (7)$$

All of the variables are defined in the Appendix. In Model (4), we only keep one observation per CEO-firm. The constant terms, year and industry fixed effects are included in Columns (1) and (2), but not tabulated. The constant term is included in Column (3), but not tabulated. z-statistics, which are reported in parentheses, are corrected for heteroskedasticity and are adjusted for clustering of observations by industry and quarter (Column (1)), by CEO and quarter (Columns (2)), or by CEO and year (Column (3)). Coefficients that are significant at the 10, 5, and 1% levels are marked with *, ** and ***, respectively.