# Capital Market Consequences of Managers' Voluntary Disclosure Styles

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Abstract:

This paper studies the capital market consequences of managers establishing an individual forecasting style. Using a manager-firm matched panel dataset, I examine whether and when manager-specific credibility matters. If managers' forecasting styles affect their perceived credibility, then the stock price reaction to forecast news should increase with managers' prior forecasting accuracy. Consistent with this prediction, I find that the stock price reaction to management forecast news is stronger when information uncertainty is high and when the manager has a history of issuing more accurate forecasts, indicating that individual managers benefit from establishing a personal disclosure reputation.



Key Words: Management Credibility, Earnings Guidance, Management Forecasts, Management Styles

## 1. Introduction

Research examining the credibility of management forecasts has shown that investors' and analysts' responses to management forecasts vary with firms' *overall* prior forecasting accuracy (Williams 1996; Hutton and Stocken 2009). These studies do not distinguish between manager- and firm-specific forecasting behavior because under both neoclassical economic and agency theories, managers' individual preferences should not have an effect on corporate decisions. In contrast, several recent studies in the accounting literature find that managers' individual preferences have an effect on firms' voluntary disclosure and financial reporting outcomes (Bamber, Jiang, and Wang 2010; DeJong and Ling 2010; Dyreng, Hanlon, and Maydew 2010; Ge, Matsumoto, and Zhang 2010). This study extends this line of research and investigates *whether* and *when* the stock price reaction to management forecasts news varies with an individual manager's forecasting behavior.[1]

If managers' forecasting styles affect their perceived credibility, then the stock price reaction to forecast news should increase with managers' prior forecasting accuracy and this effect is likely to be stronger when managers' individual differences are accentuated. Consistent with investors using managers' prior forecasting behavior to assess the credibility of their current forecasts and managers benefiting from establishing a personal disclosure reputation, I find that the market response to both good and bad news forecasts is stronger for managers with greater prior accuracy when there's higher uncertainty in the information environment.[2]

[1] I use the terms "forecasting style" and "forecasting behavior" interchangeably throughout the paper to refer to a manager-specific observed effect on firms' earnings forecasts.

[2] I focus on management earnings forecasts because 1) they are one of the most important and widely investigated forms of voluntary disclosure (Hirst, Koonce, and Venkataraman 2008), 2) they have information content, as suggested by the market reaction to these announcements (Baginski, Conrad, and Hassell 1993; Rogers and Stocken 2005; Anilowski, Feng, and Skinner 2007), and 3) management forecast truthfulness is easy to verify ex post, which

Ex ante, it is not clear whether investors should exert effort to understand differences between manager- and firm-specific forecasting behavior if they are only concerned about the firm's *overall* forecasting accuracy. However, prior research finds that investors and analysts tend to expect better performance from reputable CEOs (Malmendier and Tate 2009), indicating that manager-specific attributes do affect the beliefs of market participants. It thus follows that the market response to management forecasts could vary with manager credibility – one important attribute of a manager's overall reputation. Because past forecasting performance is a signal of the manager's forecasting skill and credibility (Mercer 2005), market participants should assign greater (less) weight to forecasts issued by managers with higher (lower) prior forecasting accuracy. Moreover, research in psychology and management finds that idiosyncratic personal differences are more likely to affect decision-making processes when individuals are faced with complex situations involving high uncertainty (Hambrick and Mason 1984; Caspi and Moffitt 1993; Hambrick 2007). This suggests that there are conditions under which manager-specific effects will play a more important role in determining forecast properties.

To address my research question, I follow the methodology introduced by Bertrand and Schoar (2003), which tracks managers across firms over time to identify a set of CEOs and CFOs who are employed by at least two firms during my sample period and also issued management forecasts during their tenure at each firm. This sample selection restriction makes it possible to separate the effects of managers from the stationary firm characteristics (firm fixed effects), time-specific cross-sectional effects (year fixed effects), and time-varying firm characteristics (control variables). Moreover, the advantage of the fixed-effect approach is that it generates parameter estimates of manager- and firm-specific forecast accuracy. Following prior research

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allows me to examine whether managers and firms can build a reputation by issuing accurate forecasts (Williams 1996; Stocken 2000; Hutton and Stocken 2009).

(Jennings 1987; Williams 1996; Rogers and Stocken 2005; Hutton and Stocken 2009), I measure forecast credibility as the stock price reaction to management forecast news. I first examine whether the market reaction is stronger for forecasts issued by managers with higher prior forecasting accuracy, and find that the market response to forecast news is positively associated with manager-specific forecasting accuracy. However, further tests show that this effect is subsumed when I control for firm-specific forecasting records. This result is consistent with Williams (1996) and Hutton and Stocken (2009), who find that security analysts and investors are more responsive to forecast news when *firms* develop a reputation for issuing more accurate forecasts in the past.

While the results discussed above suggest that investors do not distinguish between manager- and firm-specific forecasting styles unconditionally, research in management and psychology suggests that individual differences play a larger role in behavior when uncertainty is high. This suggests that investors should apply Bayesian updating and assign more weight to the highly skilled managers when they are uncertain about the overall precision of the forecast. In this analysis, I use principal components analysis to form two factors that capture different dimensions of uncertainty: information uncertainty and earnings uncertainty. The results show that when information uncertainty is high, the market response to both good and bad news forecasts is stronger for managers with the highest prior forecasting accuracy. I also find that the price reaction to bad news forecasts is stronger for firms with the highest prior forecasting accuracy when information uncertainty is high. However, while the stock price reaction varies with a firm's forecasting record when earnings uncertainty is high, it does not vary with the manager's forecasting record. Taken together, these results suggest that manager-specific credibility matters when individual-specific effects are likely to be accentuated.

Although I attempt to distinguish between manager- and firm-specific effects by following a methodology that has been employed in several recent studies, CEOs and CFOs are not assigned to firms randomly. A manager may be perceived as highly accurate because he/she happens to be at a firm with a record of issuing accurate forecasts. If this leads him/her to be hired by another firm that also wishes to initiate such a forecast policy even without hiring a new manager externally, then I would overestimate a high forecast accuracy fixed effect for that manager. Although I explicitly control for firm-specific forecast accuracy in the market reaction tests, the manager fixed effect estimates are still likely to be measured with error, and the results should be interpreted with this caveat in mind.

Subject to the limitation discussed above, this paper makes the following contributions: First, this is the first study to document the economic consequences of managers having a style of his/her own. While several studies in the economics, management, finance, and accounting literatures document the existence of individual manager styles, none of these studies examines whether the capital market responds to differences among individual managers' unique styles. My paper extends several recent accounting studies that employ a similar methodology to investigate whether managers have unique styles of their own that are reflected in their earnings forecasts, financial reporting, and tax avoidance choices of the firm for which they are employed at (Bamber et al. 2010; DeJong and Ling 2010; Dyreng et al. 2010; Ge et al. 2010).[3] I show that the persistence of the manager- and firm-specific forecast accuracy effects differ, which has implications for how investors incorporate managers' and firms' forecasting records into their responses to current management forecasts.

[3] Dyreng et al. (2010) examine the effects of managers on firms' effective tax rates and DeJong and Ling (2010) examine the effects of managers on firms' accruals. Ge et al. (2010) focus on CFOs and examine their effects on a range of corporate financial reporting choices and outcomes such as operating leases, earnings smoothing, the likelihood of meeting/beating analysts' forecasts, and the likelihood of accounting misstatements.

Second, to my knowledge, this paper provides the first evidence that managers develop a personal reputation via their disclosure behavior and is consistent with their concerns about establishing a personal reputation for accurate and transparent reporting (Graham, Harvey, and Rajgopal 2005). Although prior research has also examined the effect of management reputation on market responses to disclosures, these studies generally assume (implicitly) that a firm's disclosure history is attached to the firm or its management team and do not differentiate between the reputation of a firm and that of an individual manager (Williams 1996; Hutton and Stocken 2009). However, evidence from several recent studies on manager-specific effects suggests that there is reason to believe that it is important to distinguish between the two. Therefore, I identify settings where individual differences are accentuated and provide evidence that investors respond to manager-specific effects when management forecasts are more likely to reflect individual managers' forecasting styles.

My third contribution is a response to the Beyer, Cohen, Lys, and Walther (2010) call for research that considers management's tradeoff between high payoffs in the current period and reputation gains for a better understanding of the multi-period interaction between management and the users of corporate disclosures. My evidence is consistent with Stocken (2000), which argues that managers can build a reputation for reporting truthfully. The results presented suggest that managers with high prior forecasting accuracy benefit from a stronger market response to forecast news when information uncertainty is high.

The rest of the paper is organized as follows. Section two reviews prior literature and develops the hypotheses. Section three describes the data and research design. I discuss the empirical results in sections four and five. Section six discusses the robustness tests and section seven concludes.

## II. Hypotheses Development

This study draws from two streams of literature. I begin by reviewing research on manager-specific effects as it has evolved in the accounting literature. I then discuss the literature on the credibility of management forecasts.

### 2.1 Manager-Specific Effects

Under the neoclassical view of the firm, managers are homogeneous and selfless inputs which contribute to maximizing firm production. This implies that two firms with identical technologies and product market conditions will make similar choices, regardless of the differences in their top management teams. In contrast, standard agency models challenge this narrow view and assume that managers, instead of maximizing profit, maximize a utility function. Therefore, managers can use their discretion inside the firm to alter firm choices and pursue their own interest. Managers of firms with strong corporate governance would then be limited in their ability to exert their own influence on firm policies. Thus, prior empirical studies in accounting and finance often ignore the role of individual managers and attribute differences in firm behavior to variation in the strength of governance mechanisms across firms.

One of the first empirical papers in the economics literature that relaxes the manager homogeneity assumption is a study by Bertrand and Schoar (2003) that examines the effects of top managers on a range of corporate policies. The authors study differences in “style” for a set of 500 managers listed in the ExecuComp database from 1992 to 1999. The managers in their sample include CEOs, CFOs, and other top executives (e.g. vice presidents, chairmen, chief operating officers, etc.). They follow managers across different firms over time to examine whether systematic manager effects are correlated with a wide range of firm policies.

Specifically, they require that all managers be observed in at least two firms in their sample in order for them to disentangle the manager-specific behavior from the firm's. They then estimate how much of the unexplained variation in firm practices can be explained by adding manager fixed effects to a model that includes firm and year fixed effects, and other time-varying firm characteristics. Their results indicate that manager-specific effects explain a significant portion of the heterogeneity observed in firms' investing, financing, and organizational practices. They also find that a manager's style is related to his/her educational background and birth cohort, with MBA degree-holders being more aggressive and older managers being more conservative.

Since Bertrand and Schoar (2003), several recent studies in the accounting literature have also adopted their unique methodology to examine whether there are manager-specific effects on firms' voluntary disclosure, tax avoidance, and financial reporting decisions. Bamber et al. (2010) examine the role of managers on voluntary disclosures by using a sample of earnings forecasts issued between 1995 and 2005. Their results also indicate that managers have a significant impact on firms' forecasts and that, in most cases, CEOs matter more than CFOs. Bamber et al. (2010) also find that manager-specific forecast styles are correlated with observable managerial characteristics.[4] Their results indicate that managers born prior to World War II and managers with MBA degrees are more conservative. Dyreng et al. (2010) find that top managers also play a significant role in determining firms' tax rates. They argue that CEOs, CFOs, and other top executives can affect tax avoidance by setting the "tone at the top." They also show that there is not a strong association between an individual manager's tax avoidance behavior and the manager's other management "styles" or his/her biographical background. Lastly, Ge et al. (2010)

[4]While I am interested in manager-specific effects that are *not* attributable to economic incentives, it is very difficult empirically to separate the two. In untabulated tests, I find that the results are virtually identical when I control for the manager's equity compensation and the value of his/her shareholdings (Nagar et al. 2003). However, I do not control for these two variables in my main analyses because it would further reduce my sample size.

examine whether there are CFO-specific effects that are reflected in a wide range of firms' financial reporting decisions (e.g. discretionary accruals, operating leases, likelihood of meeting/beating analysts' forecasts, likelihood of accounting misstatement, etc.). Consistent with the studies above, they also find that CFOs matter and further tests suggest that the CFO-specific effects are unlikely to be attributable to his/her superior (i.e. the CEO). Overall, the results in these studies indicate that managers play a significant role in explaining firms' financial reporting and voluntary disclosure choices, and that they are likely to carry their "styles" from one firm to the other.[5]

2.2 Management Forecast Credibility

Prior research has examined the effect of overall management forecast credibility on both investors and analysts (Jennings 1987; Williams 1996; Rogers and Stocken 2005; Hutton and Stocken 2009). These studies predict and find that stock price reactions and analysts' forecast revisions to management forecasts vary with the magnitude of the forecast news *and* the credibility of the forecast. Specifically, forecasts issued by firms with greater prior forecasting accuracy or less predicted bias are likely to be more credible, and therefore elicit a stronger investor and analyst response per unit of news. These findings are consistent with reputation models in the economics literature that define reputation as the updated beliefs of a firm's type (Kreps and Wilson 1982; Milgrom and Roberts 1982). Firms that provide accurate forecasts are perceived as more credible by investors and analysts, and therefore enjoy the reputational benefits of having their forecast news being impounded into stock prices and analysts' forecast revisions more quickly (Williams 1996; Hutton and Stocken 2009).

[5] Unlike prior studies that are mainly interested in documenting the existence of managers' "styles", this paper focuses on an important economic attribute – forecasting accuracy – which allows me to develop testable capital market predictions.

Consistent with neoclassical economic and agency theories which argue that manager-specific effects do not affect corporate decisions, the studies above generally assume (implicitly) that a firm's disclosure history is attached to the firm or its management team and do not differentiate between the reputation of a firm and that of an individual manager. On the other hand, given the important role managers play in shaping corporate policies, as documented in recent research, it seems plausible that managers can build a personal reputation via their forecast decisions. This conjecture is also supported by survey evidence, which finds that over 90% of managers agree or strongly agree that establishing a reputation for accurate and transparent reporting is a key motivation for voluntary disclosures (Graham et al. 2005). However, whether or not investors' response to management forecast news varies with individual managers' prior forecasting accuracy remains an empirical question.

Prior research finds that investors and analysts tend to expect better performance from reputable CEOs (Malmendier and Tate 2009). This suggests that the market response to management forecasts is likely to vary with manager credibility – an important attribute of a manager's overall reputation.[6] Therefore, market participants should assign greater weight to forecasts issued by managers with higher prior forecasting accuracy, because past forecasting performance helps them evaluate a manager's forecasting skill and credibility (Mercer 2005). Following prior studies on forecast credibility, I measure forecast credibility as the stock price reaction per unit of forecast news (Jennings 1987; Williams 1996; Rogers and Stocken 2005; Hutton and Stocken 2009). This suggests that a manager's prior forecasting accuracy should

[6] For example, analysts stated that Honeywell's newly appointed CEO David Cote is "in the credibility penalty box" and is "having a hard time getting his hands around the business" when the company failed to meet their earnings guidance in 2002. Analysts also indicated that they had high expectations for Cote because of his twenty years of experience at General Electric and TRW prior to becoming the CEO of Honeywell in 2002 (BusinessWeek April 2003).

affect his/her perceived credibility and, as a result, the strength of the stock price reaction to his/her current forecasts. As such, my first hypothesis is stated as follows:

H1: The stock price reaction per unit of forecast news increases with an individual manager's prior forecasting accuracy.

## 2.3 Information Uncertainty

In this section, I develop cross-sectional predictions for *when* manager credibility is more likely to affect investors' responses to forecasts. Research in psychology suggests that individual differences are accentuated when individuals face ambiguous and uncertain events with insufficient information to allow adaptive behavior (Caspi and Moffitt 1993). The accentuation hypothesis suggests that these events bring forth responses that individuals are most familiar with and are more likely to reveal each person's salient disposition. Similarly, the upper echelons theory from the management literature argues that top managers often face complex situations that do not have calculable solutions. As such, managers are more likely to make strategic choices based on their personal experiences and backgrounds (Hambrick and Mason 1984; Hambrick 2007). Together, this suggests that manager-specific effects should be more pronounced when there is greater uncertainty.

In addition, research in finance also finds that investors tend to underweight firms' public signals when there is greater information uncertainty that stems from volatility in firms' underlying fundamentals and poor information (Daniel, Hirshleifer, and Subrahmanyam 1998, 2001; Zhang 2006). Firms with high innate volatility and poor internal accounting reports are also more likely to generate inaccurate forecasts (Waymire 1985; Feng, Li, and McVay 2009). Thus, for firms with greater uncertainty, their firm-specific component will be less useful in helping investors predict the firm's true value. I assume that investors act as Bayesian learners and will put less weight on the firm-specific effect when they are uncertain about the precision of the firm's forecast signal, which would make the manager-specific component relatively more informative. To summarize, I predict that investors will respond more strongly to forecasts issued by managers with a strong forecasting record when investors have greater difficulty valuing the business.

H2: The stock price reaction per unit of forecast news is more likely to increase with an individual manager's prior forecasting accuracy when uncertainty is high.

## III. Data and Research Design

### 3.1 Sample Selection

My initial sample consists of all managers listed in the ExecuComp database from 1996 to 2009.[7] I follow managers across firms and retain only those that held a CEO or CFO title in the old firm and became a CEO or CFO in the new firm.[8] This makes it possible for me to separate the manager fixed effects from firm fixed effects and other time-varying firm characteristics. If a manager stays with the same firm during my entire sample period, then the manager fixed effects would be perfectly correlated with the firm fixed effects. I then merge in the Company Issued Guidelines (CIG) dataset from First Call and match each firm-year with

[7] The sample period begins in 1996 to reflect the enactment of the Private Securities Litigation Reform Act on December 22, 1995. The Act was passed by Congress to strengthen the safe-harbor provision by reducing managers' liabilities to forward-looking disclosures not offered in good faith.

[8] I restrict the sample to CEO/CFO transfers because 1) CEOs and CFOs are more likely to be in the position to reflect their discretionary judgment on the firm's publicly issued forecast (Brochet, Faurel, and McVay 2009) and 2) CEOs and CFOs have more visibility than other top managers and are more likely to be recognized by the market, which is the main focus of this study.

both quarterly and annual management earnings forecasts reported in CIG.[9] This step results in a sample of 713 managers and 11,171 observations. I then merge in institutional investor data from Thomson 13F, analyst data from IBES, security returns data from CRSP, board composition data from RiskMetrics, and firm financials from Compustat to construct the control variables and to compute the market response to forecasts. The final sample includes 402 managers and 8,542 observations.[10] Of the full sample, I use the 6,491 forecasts issued during 1996 to 2005 to estimate firm- and manager-specific effects of forecast accuracy. The remaining 2,051 observations issued during 2006 to 2009 are used to verify the manager fixed-effect coefficient estimates and to examine the market response to forecasts. Table 1 provides a summary of the sample selection process.

### 3.2 Research Design

To examine whether investors respond to differences in manager-specific forecasting behavior requires an estimation of the manager-specific effects on forecasts. I first split my sample into two periods to avoid a look-ahead bias in the market response tests. I then follow Bamber et al. (2010) and estimate model (1) on a sample of forecasts issued during 1996 to 2005 to obtain the individual manager effects on forecast accuracy.[11]

$$ACCURACY = \sum \alpha_k X_{kit} + \sum \beta_t YEAR_t + \sum \gamma_m MGR_m + \sum \lambda_i FIRM_i + \varepsilon_{it} \quad (1)$$

[9] Following Bamber et al. (2010), I retain all observations with available data to estimate the firm-specific effect even if the firm has managers that are not observed in multiple firms. These observations are referred to as "filler years" in Ge et al. (2010). The manager fixed-effect coefficients are not estimable for these managers and thus not included in the market response tests.

[10] The number of managers in my sample is higher than Bamber et al. (2010) because I do not require managers to be with the company for at least three years to be in the final sample. I do not impose this requirement because it would further reduce the number of managers available in the market response tests. In untabulated robustness tests, I find that my results are not sensitive to relaxing this restriction.

[11] The tradeoff between an earlier and later cutoff is that an earlier year increases the power of the market response tests but decreases the number of observations available to obtain unbiased estimates of the manager- and firm-specific coefficient estimates. Using either 2004 or 2005 as a cutoff does not affect the tenor of the results.

ACCURACY is defined as the absolute difference between the management forecast and actual earnings multiplied by -1, scaled by beginning-of-period price.[12] Therefore, a less negative value of ACCURACY suggests higher forecasting accuracy. Because I include both quarterly and annual forecasts in my sample, I control for forecast periodicity where annual forecasts (ANNUAL) are coded as one, and zero otherwise. To assure comparability, I use actual earnings reported on the First Call Actuals file to compute forecast accuracy.[13] X is a vector of time-varying control variables that prior studies find is associated with management forecast accuracy. I control for firm size (SIZE) using the natural logarithm of market value of equity because prior studies find that larger firms tend to issue more accurate forecasts (Ajinkya, Bhojraj, and Sengupta 2005; Bhojraj, Libby, and Yang 2010). Firms that report losses may have more difficulty forecasting earnings, so I control for whether the firm reported a loss for the fiscal period. LOSS is an indicator variable equal to one for firms that report negative earnings in the fiscal period, and zero otherwise. Similarly, I control for return on assets (ROA) because prior research finds that disclosure is positively associated with firm performance. Ajinkya et al. (2005) hypothesize that institutional investors and outside directors serve as monitors for firms' disclosures and find that firms with greater institutional ownership and more outside directors issue forecasts that are more specific, accurate, and less optimistically biased. Therefore, I control for institutional ownership (INST) which is the percentage of the firm's aggregate common stock held by institutional investors and the percentage of outside directors on the board (OUTDIR). I also control for the number of analysts (ANALYSTS) following because Lang and Lundholm (1996) find that analyst following is associated with disclosure levels. Forecasts

[12] I follow the guidelines provided in Anilowski, Feng, and Skinner (2007) to identify forecasts as point, range, or open-ended.
[13] I use the mid-point (upper/lower bound) of range (open-ended) forecasts as the benchmark for calculating forecast accuracy because prior research suggests that investors use the mid-point when forming their expectations of earnings (Baginski, Conrad, and Hassell 1993).

issued earlier in the fiscal period when there is more uncertainty are likely to be less accurate (Baginski and Hassell 1997). Therefore, I include forecast horizon where HORIZON is the number of days between the forecast issuance date and the end of the fiscal period, divided by 365.[14] I also control for earnings volatility because firms with higher earnings volatility (EARNVOL) may issue more inaccurate forecasts. EARNVOL is the standard deviation of earnings per share for the prior four periods. I also control for market-to-book (MB) and litigation risk (LITRISK) as prior studies find that they are also important determinants of firms' forecast properties. Following Bamber et al. (2010), I also control for whether a firm engaged in restructurings or acquisitions during the period as firms that underwent these events may issue less accurate forecasts. RESTRUCTURE is an indicator variable equal to one if the firm engaged in a restructuring during the period. Similarly, ACQ is an indicator variable equal to one if the firm had a merger or acquisition during the period. Bamber and Cheon (1998) find that firms with greater product-market concentration, their proxy for proprietary costs, issue less specific forecasts. Therefore, *CONC* is the firm's product-market concentration ratio, defined as sales of the top-five firms in the two-digit SIC industry, divided by total sales in the same industry in year t.[15] Finally, I also control for research and development expenses (R&D) following Bamber et al. (2010).

I include an indicator variable for each firm, manager, and year in the model. The advantage of this research design is that it produces coefficient estimates that quantify each firm

[14] Preannouncements are excluded from my sample because they usually contain bad news and have different characteristics from forecasts issued prior to the fiscal period end. For example, preannouncements are usually issued before large negative earnings surprises and tend to be qualitative (Skinner 1994; Kasznik and Lev 1995; Bamber and Cheon 1998).

[15] Ali et al. (2009) find that industry competition measures constructed using Compustat data are subject to measurement error due to the exclusion of private companies. For robustness, I also use the natural log of entry costs and the natural log of industry sales as alternative proxies for industry competition, as suggested by Karuna (2007), and find identical results. Entry costs are defined as the weighted average of the gross value of property, plant, and equipment costs, weighted by market share.

and manager's forecasting accuracy over time for each firm and manager in my sample. I first conduct an out-of-sample test to examine 1) whether the firm- and manager-specific coefficient estimates capture forecast accuracy and 2) the persistence of firm- and manager-specific prior forecasting accuracy by estimating the following model on a sample of forecasts issued during 2006 to 2009.

$$ACCURACY = \sum \alpha_k X_{kit} + \sum \beta_t YEAR_t + \gamma_m FE\_MGR_m + \lambda_i FE\_FIRM_i + \varepsilon_{it} \quad (2)$$

FE_FIRM is each firm's fixed-effect coefficient estimate from model (1). Similarly, FE_MGR is the fixed-effect coefficient estimate for each manager. I also provide results using the quartile rank of FE_FIRM and FE_MGR to make the coefficients more easily interpretable. MGR and FIRM are the quartile ranks of the firm and manager fixed-effect coefficients. MGR (FIRM) ranges from 1 to 4 where managers (firms) in the top quartile are the most accurate, and vice versa. The control variables are the same as those used in model (1).

To examine whether market responses differ for firms and managers with higher forecasting accuracy, I then utilize the firm and manager fixed-effect estimates by estimating model (3) on a sample of forecasts issued during 2006 to 2009.

$$\begin{aligned} CAR(-1,+1) = {} & \beta_1 NEWS_{it} + \beta_2 MGR_m + \beta_3 MGR_m * NEWS_{it} + \beta_4 FIRM_i + \beta_5 FIRM_i * NEWS_{it} \\ & + \beta_6 SIZE_{it} + \beta_7 SIZE_{it} * NEWS_{it} + \beta_8 LOSS_{it} + \beta_9 LOSS_{it} * NEWS_{it} + \beta_{10} ROA_{it} \\ & + \beta_{11} ROA_{it} * NEWS_{it} + \beta_{12} HORIZON_{it} + \beta_{13} HORIZON_{it} * NEWS_{it} + \sum \beta_t YEAR_t \\ & + \varepsilon_{it} \quad (3) \end{aligned}$$

CAR (-1, +1) is the sum of the market-adjusted returns for the three-day trading window centered on the forecast date using the CRSP value-weighted index. NEWS is the management forecast surprise, defined as the management forecast minus prevailing analysts' mean consensus forecast, scaled by beginning-of-period price. I interact MGR and FIRM with news to examine whether investors respond more strongly per unit of forecast news for managers and firms with a stronger forecasting record. This specification is used in prior research to examine the credibility of forecasts (Jennings 1987; Williams 1996; Rogers and Stocken 2005; Hutton and Stocken 2009). A positive coefficient on FIRM*NEWS and MGR*NEWS indicates that the stock price reaction to forecast news is stronger for forecasts issued by managers and firms with greater prior forecasting accuracy, i.e., investors find these firms and managers to be more credible. I also control for whether the reaction is stronger for forecasts issued by larger firms (SIZE) and firms with better performance (ROA). I also expect forecasts issued earlier in the forecast period and forecasts issued by loss firms to be less credible because they are likely to be more inaccurate. Therefore, I predict a negative coefficient on LOSS*NEWS and HORIZON*NEWS.

## IV. Empirical Results

### 4.1 Summary Statistics

Panel A of Table 2 provides summary statistics for the variables used in my main analyses. The average three-day market response is negative (-0.003) while the median is positive (0.002). The probability of a loss is 13.5% and the average return on assets is 0.032. The average level of institutional ownership is 67.1% and the average percentage of outside directors on the board is 60.9%. The mean analyst following is 11.93 and less than 10% of firm-years had an acquisition or merger during my sample period. The average forecast is issued 161 days before the fiscal period end with an error of 1.3% of price. Overall, the statistics and firm characteristics are similar to prior studies that follow the Bertrand and Schoar (2003) methodology. The firms in my sample tend to be larger because I limit my sample to only managers who move between ExecuComp firms at the CEO or CFO level. Therefore, managers who move to private firms or to non-CEO/CFO positions within larger firms are dropped during my sample selection process. Panel B of Table 2 provides the Pearson correlation for the variables reported in Panel A. The correlations are consistent with prior studies with ACCURACY being positively associated with market reactions, size, and firm performance. Forecasts issued earlier in the period and by firms with reported losses and higher earnings volatility are less accurate.

### 4.2 Estimation of Manager and Firm Fixed Effects

I first replicate Bamber et al. (2010) to obtain the manager and firm fixed-effect coefficient estimates on forecast accuracy. Table 3 Panel A provides results on tests of model (1). I first examine a variation of model (1) that includes manager fixed effects, year fixed effects, and a vector of control variables. Column 1 reports that the R-square for this specification is 19.54%. However, column 2 shows that the R-square for a model with firm fixed effects, year fixed effects, and control variables, is 23.85%. Finally, the R-square for a model that includes both manager and firm fixed effects, in addition to year fixed effects and control variables, is 27.14%. This suggests that the incremental increase in explanatory power is 39% when firm fixed effects are added to a model that controls for manager-specific effects. Moreover, the incremental increase in explanatory power is only 14% when manager fixed effects are added to a model that does not control for manager-specific effects.[16] While it is not surprising that firm-

[16] Bamber et al. (2010) examine the incremental effect of individual managers on five management forecast attributes: frequency, precision, news, bias, and error. They show that the raw percentage increase is 10% when adding manager-specific effects to a base model that explains forecast error. The raw percentage increase I find (3%) is lower than that reported in their study because I also include quarterly forecasts in my sample. In untabulated tests, I find that the raw percentage increase in adding manager-specific effects is approximately 8% when I limit my sample to annual forecasts like in Bamber et al. (2010). I am unable to compare the incremental increase in adding firm-specific effects because this test is not performed in their study.

specific effects have a bigger influence than manager-specific disclosure behavior on forecasting properties, this result is important for interpretations of the market response tests. Columns 4 and 5 report how managers in the CEO or CFO positions contribute to the increase in explanatory power. Similar to Bamber et al. (2010), I find that the increase in explanatory power is higher for CEOs than for CFOs. However, untabulated Vuong tests indicate that the differences are not significant at conventional levels.[17]

Table 3 Panel B reports the distribution of the manager and firm fixed-effect coefficients estimated from a model that includes firm, manager, year fixed effects and control variables. Because the fixed effects capture deviations from average levels of the variables, the distribution of the estimates should be centered around zero by construction. Indeed, the means (medians) of the manager and firm fixed-effect estimates for the entire forecast sample are close to zero at 0.016 (0.017) and -0.027 (-0.020). While Bamber et al. (2010) do not report the distribution of their firm-specific estimates, my manager-specific estimates are comparable to the mean (median) of 0.03 (0.01) reported in their study. There is also variation in the fixed-effect estimates, with managers and firms in the 75$^{th}$ percentile issuing forecasts that are more accurate by 2 to 4.7% of price than those issued by managers and firms in the 25$^{th}$ percentile. The last two rows report the distribution of the fixed-effect estimates for the managers and firms that remain in the 2006 to 2009 sample for the market reaction tests. The number of managers and firms that continued to issue forecasts in the latter years of my sample period is approximately 40% of the original sample size, but the mean (median) manager and firm fixed-effect coefficients are similar to that of the main sample. I also examine whether the F-statistics are driven by only a few significant

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[17] Following Bamber et al. (2010), I use the XTREG command in STATA to calculate the adjusted R-squares. As pointed out in Bamber et al. (2010), this approach generates more conservative R-squares but the same coefficient estimates as using an OLS estimation with explicit dummy variables for each firm, manager, and year.

coefficients in my sample. Figure 1 presents the frequency of managers with statistically significant fixed effects. Because there are 402 managers in my forecast sample, under the null hypothesis that managers do not have a significant influence on forecasting decisions, the expected frequency of managers with significant fixed-effect coefficients at the 1%, 5%, and 10% level should be 4, 20, and 40, respectively. In my regressions results, 192, 237, and 273 managers have coefficients significant at the 1%, 5%, and 10% level. This suggests that the effects are not attributable to only a few managers in my sample. Moreover, the percentage of managers with significant coefficients is higher than that reported in Bamber et al. (2010). This is likely due to the significantly larger sample size I have, which increases the power of my tests.

[Insert Table 3]

[Insert Figure 1]

I also perform an out-of-sample test to verify that the fixed-effect estimates are positively associated with forecast accuracy for the latter years of my sample period. Table 4 provides results estimating model (2) where I regress ACCURACY on the manager and firm fixed-effect coefficients and the control variables. Consistent with my prediction, I find that MGR and FIRM are positively and significantly associated with ACCURACY. Moreover, the coefficient on MGR (FIRM) is 0.002 (0.007) and suggests that ACCURACY increases by 0.2% (0.7%) of price for each quartile rank increase. The results using the raw fixed-effect coefficients are also similar. Combined with the earlier result on the incremental explanatory power of firm-specific effects, this finding suggests that firm-specific effects are more persistent and should affect investors' responses to forecast news. The signs on the control variables are largely consistent with prior research. I find that firm size (SIZE), performance (ROA), institutional ownership (INST), and research and development expenditures (R&D) are positively associated with forecast accuracy. Forecasts issued earlier in the fiscal period (HORIZON) and forecasts issued by loss firms (LOSS) or firms with higher earnings volatility (EARNVOL) have lower accuracy. High market-to-book firms and firms in more concentrated industries with higher proprietary costs also issue less accurate forecasts. However, I do not find that annual forecasts are more inaccurate as the sign on ANNUAL is not significant. Overall, these results suggest that my measures of firm- and manager-specific forecasting behavior are correlated with ex-post forecasting properties, which should have an effect on the market reactions to forecasts.

[Insert Table 4]

4.3 Market Response to Manager and Firm Effects

Thus far, I have established that managers and firms both play a significant role in determining firms' forecasting behavior and that the fixed-effect coefficients are associated with ex-post forecast accuracy. Next, I use the coefficient estimates as proxies for firm- and manager-specific forecasting accuracy to examine whether the market distinguishes between firm- and manager-level forecasting behavior. Table 5 provides the results for the regression analysis of the market response tests using a sample of forecasts issued during 2006 to 2009. I first report results including only MGR*NEWS and several control variables. The coefficient on MGR*NEWS is positive and significant which suggests investors find managers with higher prior forecasting accuracy to be more credible. Because MGR is the quartile rank of the fixed-effect coefficient estimates, this suggests that the market response for forecasts issued by a manager in a higher accuracy quartile is 30.2% stronger per unit of news. I also find that investors find firms with better performance to have higher credibility as the coefficient on ROA*NEWS is also positive and significant. The next column provides results controlling for firm-specific forecasting accuracy. Interestingly, I find that the effect of MGR*NEWS is subsumed once I control for firm-level effects. The coefficient on MGR*NEWS becomes negative though insignificant. Moreover, the coefficient on FIRM*NEWS is positive and significant at the 1% level. This suggests that investors do not respond stronger to forecasts issued by managers with higher prior forecasting accuracy once the firm's forecasting record is controlled for. I also find that forecasts issued by larger firms and firms with higher return on assets elicit a stronger response. The coefficients on SIZE*NEWS and ROA*NEWS are both positive and significant. However, contrary to my predictions, the coefficient on LOSS*NEWS is also positive. In untabulated tests, I also examine whether the results are similar when I use the raw fixed-effect estimates. Consistent with the results using manager quartiles, I find that the coefficient on a variable interacting the manager fixed-effect coefficient with NEWS is positive and significant at the 1% level but becomes insignificant when I control for firm-specific effects. Overall, this finding is consistent with the results discussed in the prior section, which indicate that 1) firm-specific forecasting accuracy is more persistent and 2) firm-level effects are stronger determinants of forecast properties. However, it is unlikely that the market does not respond to individual managers' disclosure styles given that they play such an important role in firms' voluntary disclosure and financial reporting decisions (Bamber et al. 2010; DeJong and Ling 2010; Dyreng et al. 2010; Ge et al. 2010). Therefore, I next examine whether the stock price reaction to forecast news varies with manager forecasting credibility when the information environment is more uncertain and when forecasts are likely to reflect greater manager discretion.

[Insert Table 5]

## V. Cross-Sectional Tests of Market Responses to Manager and Firm Effects

5.1 Uncertainty Factors

In this section, I perform principal components analysis (PCA) to form factors that capture different dimensions of uncertainty. In this procedure, individual variables are reduced into a smaller number of factors that account for most of the variance in the observed variables. Eight variables that are likely to capture uncertainty are included in this analysis. I include return volatility (RETVOL), measured as the standard deviation of returns over the 30-day period prior to forecast issuance to proxy for uncertainty in the information environment among investors. I also control for share turnover (TURNOVER), measured as the daily trading volume divided by shares outstanding, averaged over the 30-day period prior to forecast issuance.[18] Leverage (LEVERAGE) and market-to-book (MB) are included because highly levered firms and high market-to-book firms have greater information asymmetry. ROA and EARNVOL capture uncertainty in earnings, the underlying signal forecasted. Following prior research (Lang and Lundholm 1996; Barron, Kim, Lim, and Stevens 1998), I also proxy for uncertainty about firms' future earnings or disagreement among market participants using analyst forecast dispersion (DISP). Last, I control for litigation risk (LITRISK) because the information environment is likely to be significantly different for high-litigation-risk firms.

I use a combination of the eigenvalue method and the scree test to determine the number of factors to retain (Jolliffe 2002). This results in two factors that are retained for an oblique rotation.[19] Table 6 reports the factor loadings of the eight individual variables on the two retained factors. As is common in the PCA procedure, I consider a factor loading to be large if its absolute value is greater than 0.5. The Earnings Uncertainty (EU) factor captures volatility in a

[18] While differences in information facilitate trading among investors, it is likely that differences in how investors interpret the same set of information they hold also contribute to share turnover.
[19] I choose an oblique rotation over an orthogonal rotation because the prior does not require the factors to be independent. However, the results are not sensitive to using an orthogonal rotation.

firm's earnings predictability. Firms with high EU scores have higher earnings volatility (EARNVOL) and analyst dispersion (DISP), and lower firm performance (ROA) and market-to-book (MB). The Information Uncertainty (IU) factor captures uncertainty in a firm's information environment. Firms with high IU scores have higher return volatility (RETVOL) and share turnover (TURNOVER) 30 days prior to their forecast issuance.

[Insert Table 6]

5.2 Market Responses to Manager and Firm Effects Conditional on Uncertainty

To examine whether the market responds to manager- and firm-specific effects conditional on the information environment, I estimate model (4) below with the sample partitioned on the two uncertainty factors.

$$
\begin{aligned}
CAR(-1,+1) = {} & \beta_1 MGR1_m * GOODNEWS_{it} + \beta_2 MGR1_m * BADNEWS_{it} \\
& + \beta_3 FIRM1_i * GOODNEWS_{it} + \beta_4 FIRM1_i * BADNEWS \\
& + \beta_5 GOODNEWS_{it} + \beta_6 BADNEWS_{it} + \beta_7 MGR1_m + \beta_8 FIRM1_i \\
& + \beta_9 SIZE_{it} + \beta_{10} SIZE_{it} * NEWS_{it} + \beta_{11} LOSS_{it} + \beta_{12} LOSS_{it} * NEWS_{it} + \beta_{13} ROA_{it} \\
& + \beta_{14} ROA_{it} * NEWS_{it} + \beta_{15} HORIZON_{it} + \beta_{16} HORIZON_{it} * NEWS_{it} + \sum \beta_t YEAR_t \\
& + \varepsilon_{it} \qquad (4)
\end{aligned}
$$

Because I expect managers with the strongest forecasting record to benefit from a stronger market response, managers in the top ACCURACY quartile are coded as MGR1, and zero otherwise. I also separate forecasts into good and bad news forecasts because prior research finds that there is an asymmetric market reaction to good and bad news forecasts (Skinner 1994; Anilowski, Feng, and Skinner 2007; Kothari et al. 2009). I examine whether the coefficients on MGR1*GOODNEWS and MGR1*BADNEWS vary for the different uncertainty subsamples. I expect $\beta_1$ and $\beta_2$ to be more positive for the high uncertainty group because idiosyncratic manager styles play a bigger role and investors are more likely to consider the manager's prior forecasting record when they are uncertain about the precision of the forecast signal.

The results of tests examining the market response to manager and firm effects conditional on the two uncertainty factors are presented in Table 7. Consistent with hypothesis 2, the coefficients on MGR1*GOODNEWS and MGR1*BADNEWS are positive and significant for the high information uncertainty group. When there is more uncertainty in the information environment, the stock price reaction to forecast news is stronger for managers with greater forecasting accuracy. The results also suggest that, when there is greater uncertainty in the information environment, investors perceive bad news forecasts issued by firms with a stronger forecasting record to be more credible. Consistent with prior studies, the market response is also positively associated with forecast news. In contrast, all of the coefficients on the interaction terms are not significant for the low information uncertainty group.[20] In untabulated results, I also examine whether the market response is linear by replacing MGR1 with MGR in the news interaction terms and find that the coefficients are positive but not significantly different from zero for both good and bad news forecasts. This suggests that investors only perceive forecasts to be credible if issued by a manager with sufficient prior forecasting accuracy and is consistent with managers' concerns about establishing a reputation for accurate reporting (Graham et al. 2005). Last, consistent with IU capturing the underlying construct of interest, the coefficients on MGR1*GOODNEWS and MGR1*BADNEWS continue to be insignificant when I sort the sample based on high and low earnings uncertainty. Overall, the results from the cross-sectional tests partitioned on uncertainty suggest that the market response to management forecasts varies

[20] Coefficients on the control variables interacted with NEWS have been suppressed.

with manager-specific forecasting credibility when there is greater uncertainty in the information environment.

[Insert Table 7]

## VI. Robustness Tests

6.1 Bundled Forecasts

Several studies find that that the percentage of firms issuing management forecasts in conjunction with earnings announcements has increased over the recent years (Anilowski et al. 2007; Rogers and Van Buskirk 2009). This suggests that the market reaction variable (CAR (-1, +1)) used in my market response tests could also be capturing investor responses to earnings announcement news. To address this issue, I identify forecasts that are issued within a three-day window of an earnings announcement and code them as BUNDLED=1, and zero otherwise. Because it would not be feasible to delete all the bundled forecasts, I explicitly control for them in the following specification:

$$\begin{aligned} CAR(-1,+1) = {} & \beta_1 NEWS_{it} + \beta_2 MGR_m + \beta_3 MGR_m * NEWS_{it} + \beta_4 FIRM_i + \beta_5 FIRM_i * NEWS_{it} \\ & + \beta_6 SIZE_{it} + \beta_7 SIZE_{it} * NEWS_{it} + \beta_8 LOSS_{it} + \beta_9 LOSS_{it} * NEWS_{it} + \beta_{10} ROA_{it} \\ & + \beta_{11} ROA_{it} * NEWS_{it} + \beta_{12} HORIZON_{it} + \beta_{13} HORIZON_{it} * NEWS_{it} + \beta_{14} BUNDLED_{it} \\ & + \beta_{15} BUNDLED_{it} * NEWS_{it} + \sum \beta_t YEAR_t + \varepsilon_{it} \qquad (5) \end{aligned}$$

Model (5) includes an indicator variable for whether the forecast is issued in the three-day earnings announcement window and an interaction variable BUNDLED*NEWS. The results for estimating model (5) are presented in Table 9. Consistent with the results discussed in section 4.3, I find that the coefficient on MGR*NEWS becomes insignificant when I control for firm-specific effects. The coefficient on FIRM*NEWS continues to be positive and significant. The coefficient on BUNDLED is positive and suggests that bundled forecasts tend to elicit a positive market reaction, but investors do not find bundled forecasts to be more credible. In untabulated tests, I also find that controlling for bundled forecasts does not affect the cross-sectional analyses partitioning on uncertainty.

[Insert Table 8]

6.2 Controlling for Firms that Discontinued Guidance

Chen, Matsumoto, and Rajgopal (2011) find that poor performance, increases in return volatility, and decreases in analyst following are associated with firms' decisions to discontinue providing forecasts. This suggests that the firms and managers that continue to issue forecasts during my latter sample period are likely to be different from those that are dropped out of my analyses because they stopped providing forecasts. I conduct two robustness tests to address this sample selection concern. First, I compare the manager and firm fixed-effect estimates of the two groups and do not find any significant differences in their forecasting behavior. Next, I control for the estimated likelihood of a firm stopping guidance using coefficient estimates from the logit model provided in Chen et al. (2011); see Appendix A for further details. I create a variable STOP that captures the likelihood of a firm discontinuing guidance during my sample period and include it as an additional control variable in model (2). Untabulated results from this specification suggest that while STOP is negatively associated with ACCURACY, the coefficients on MGR and FIRM continue to be positive and significant at the 5% and 1% level, respectively. While the results (untabulated) for the market reaction tests are also similar, it is important to note that my analysis is limited to a subsample of firms that choose to continue providing guidance. Therefore, my results may not apply to the universe of firms that are covered by CIG.

### 6.3 Incompleteness of the CIG Database

Recent research on management forecasts suggests that there is an increase in the number of management forecasts provided in the CIG database in 1998 (Anilowski et al. 2007) and that firm coverage is associated with analyst following and prior firm performance (Chuk, Matsumoto, and Miller 2009). These findings suggest that the sample of management forecasts used in the current study may be incomplete prior to 1998, or in general. I conduct two tests to examine the robustness of the results. First, untabulated tests indicate that the results are virtually identical when I carry out my analyses using a sample period that commences in 1998. Second, I generate a random sample of 100 firm-years from my sample firms and hand-collect press releases for this random sample.[21] A comparison of the hand-collected press releases with the CIG sample suggests that the match rate between the two samples is approximately 87%. That is, I was able to find 515 earnings forecasts in my CIG sample for the 592 respective press releases issued by the random sample of firm-years. Not surprisingly, this ratio is much higher than that reported in Chuk et al. (2009) because the firms in my sample are larger firms with higher analyst following. Moreover, Chuk et al. (2009) find that EPS forecasts, the main interest of this study, are more likely to be covered by CIG compared to forecasts related to sales, cash flow, etc.

## VII. Conclusion

[21] Following Chuk et al. (2009), I search in LexisNexis for company press releases issued via Business Wire or PR Newswire using the following search string: (forecast or guidance or outlook or expectation or expect or guide or anticipate or expected or anticipated) w/25 (earnings or profit or loss or income or EBITDA). Because I am only interested in EPS forecasts, I modify their search string and remove the words sales, revenue, and cash flows from the search term.

The goal of this paper is to examine whether market responses to management forecasts vary with managers' forecasting credibility, where credibility is captured by manager-specific prior forecasting accuracy. Following several recent studies that adapt an empirical design by Bertrand and Schoar (2003), I separate firms' overall forecasting records into a firm- and a manager-specific component. I first show that the firm- and manager-specific estimates are differentially associated with forecasting accuracy in an out-of-sample test. I then examine the market response to forecasts and show that the effect of the manager's forecasting behavior is subsumed once the firm's forecasting record is controlled for. However, I also find that investors respond more strongly to forecasts issued by managers with the highest prior forecasting accuracy when information uncertainty is high. This finding suggests that managers do benefit from establishing a strong forecasting record and is also consistent with managers' concerns about establishing a reputation for accurate reporting.

This paper extends recent studies (Bamber et al. 2010; DeJong and Ling 2010; Dyreng et al. 2010; Ge et al. 2010) that provide evidence of significant manager effects on an array of firms' accounting and financial reporting choices and is the first to document the capital market consequences to managers for establishing an individual forecasting style. While prior and concurrent research (William 1996; Hutton and Stocken 2009) has only examined the effect of management reputation at the firm level, I provide evidence that individual manager styles also matter to capital market participants. However, it is important to note that because CEOs and CFOs are not assigned to firms randomly, the manager fixed-effect estimates may also be capturing a firm's change in disclosure policy, rather than the manager's active influence on the firm's forecasting decision. Although I explicitly control for firm-specific forecast accuracy in the market reaction tests, the manager fixed-effect estimates are still likely to be measured with error, and the results should be interpreted with this caveat in mind.

Future studies can examine whether the labor market for top executives is also efficient in recognizing differences in managers' disclosure styles. Are individual managers' forecasting styles correlated with their other financial reporting or operating styles? Moreover, are managers with higher forecasting accuracy more likely to be employed because they've signaled their talent? These are some questions related to this line of research that can lead to further insights.

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## Appendix A

The probability of a firm discontinuing guidance (STOP) is estimated from the cumulative distribution function:

$$G\begin{pmatrix} -0.79*\text{BHRET}-1.09*\Delta\text{PMBAF}+0.22*\Delta\text{STD}+0.26*\Delta\text{DISP}-0.08*\Delta\text{AF} \\ +0.54*\Delta\text{PINST}-14.18*\Delta\text{LTPINST}+0.43*\text{LAWSUIT}-0.02*\text{LNMV}-0.00*\text{MB} \\ -1.49*\text{LNCT}-1.15*\text{REGFD} \end{pmatrix}$$

Coefficient estimates for the independent variables are obtained from Chen et al. (2011). BHRET is the market-adjusted buy-and-hold returns for the 12 months beginning from month -12 ending month-1, with month 0 being the management forecast month. ΔPMBAF is the difference between the percentage of quarters that firm earnings meet or beat consensus analyst forecasts in the eight quarters preceding the management forecast quarter, quarters -1~-4 minus quarters -5~-8. ΔSTD is the difference in the standard deviation of raw returns during 252 days prior to the management forecast date, days -252~-1 minus days -504~-253. ΔDISP is the difference in the standard deviation of pre-earnings announcement analyst forecasts scaled by beginning price, quarter -1 minus quarter -8, or the next available quarter if quarter -8 is missing. ΔAF is the difference in number of analysts following the firm at the beginning of the quarter, quarter -1 minus quarter -8, or the next available quarter if quarter -8 is missing. ΔPINST is the difference between institutional ownership at the beginning of the quarter, quarter -1 minus quarter -4. ΔLTPINST is the difference between long-term institutional ownership at the beginning of the quarter, quarter -1 minus quarter -4. Long-term institutional investors are defined based on the turnover methodology reported in Bushee (1998). LAWSUIT is an indicator variable equal to one if a firm is sued within the [-24, -1] month window of the management forecast date, zero otherwise. Lawsuit occurrences are obtained from Stanford's Securities Clearing House website. LNMV is the natural logarithm of the beginning of quarter market value of equity. MB is the beginning of quarter market-to-book. LNCT is the natural logarithm of (1+CT), where CT is the number of management quarterly EPS forecasts issued up till quarter -1. REGFD is an indicator variable coded as one if a firm's initial appearance on the CIG database occurs after Regulation FD (October 23, 2000), zero otherwise.

## Appendix B

| | |
|---|---|
| ACCURACY | Absolute difference between the management forecast and actual earnings multiplied by -1, scaled by beginning-of-period price |
| CAR (-1,+1) | Market-adjusted returns for the three-day trading window centered on the forecast date using the CRSP value-weighted index |
| FE_MGR (FE_FIRM) | Manger (Firm) fixed effect coefficient estimated from regressing ACCURACY on firm-, manager-, and year-specific fixed effects and a vector of control variables |
| MGR (FIRM) | Quartile rank variable of FE_MGR (FE_FIRM) |
| MGR1 (FIRM1) | Indicator variable equal to one if the firm is in the top quartile rank of FE_MGR (FE_FIRM); zero otherwise |
| NEWS | Management forecast minus analysts' mean consensus forecast prior to forecast issuance, scaled by beginning-of-period price |
| GOODNEWS | Equal to NEWS if NEWS is greater than zero; zero otherwise |
| BADNEWS | Equal to NEWS if NEWS is less than zero; zero otherwise |
| Control Variables | |
| SIZE | Natural logarithm of market value at beginning-of-period |
| LOSS | Indicator variable equal to one if the firm reported a loss for the fiscal period forecasted; zero otherwise |
| ROA | Return on beginning-of-period assets |
| INST | Percentage of aggregate institutional ownership at beginning-of-period |
| ANALYSTS | Number of analysts following the firm prior to management forecast issuance |
| HORIZON | Number of days between the forecast date and the end of the fiscal period, divided by 365 |
| EARNVOL | Standard deviation of earnings per share for the prior four periods |
| ANNUAL | Indicator variable equal to one for annual forecasts; zero otherwise |
| OUTDIR | Percentage of outside directors on the board |
| MB | Market-to-book at beginning-of-period |
| CONC | A firm's product-market concentration ratio, defined as sales of the top-five firms in the two-digit SIC industry, divided by total sales in the same industry in year t |
| LITRISK | Indicator variable equal to one if firm is in of the following high-litigation-risk industries: SIC codes 2833-2836 (biotechnology), 3570-3577 and 7370-7374 (computers), 3670-3674 (electronics), 5200-5961 (retailing), and 8731-8734 (R&D service), and suffers a 20 percent or greater decrease in earnings; zero otherwise |
| RESTRUCTURE | Indicator variable equal to one if the firm engaged in a restructuring in the fiscal period; zero otherwise |
| ACQ | Indicator variable equal to one if the firm has a merger or acquisition in the fiscal period; zero otherwise |
| R&D | Expenditures on research and development in the fiscal period |
| BUNDLED | Indicator variable equal to one if forecast is issued within a three-day window of the earnings announcement |

## Table 1 Sample Selection Process

This table reports the effect of the sample selection criteria on the number of observations that constitute the sample. Strict CEO/CFO external transfer refers to a CEO/CFO leaving one firm in ExecuComp for a CEO/CFO position in another firm in ExecuComp. The sample period is from 1996 to 2009.

| **Sample selection step** | **Number of managers** | **Number of observations** |
|---|---|---|
| Number of strict CEO/CFO external transfers in ExecuComp | 926 | |
| Data available on CIG file | 713 | 11,171 |
| Data available for control variables from Compustat, CRSP, Thomson 13F, RiskMetrics, and IBES | 402 | 8,542 |
| Managers whose fixed-effect coefficients are estimable and also provide forecasts in 2006 to 2009 | 172 | 2,051 |

## Table 2 Summary Statistics of Full Sample

**Panel A Descriptive Statistics**

| Variable | Mean | P25 | Median | P75 | Std Dev |
|---|---|---|---|---|---|
| CAR(-1,1) | -0.003 | -0.037 | 0.002 | 0.039 | 0.092 |
| SIZE | 8.148 | 6.991 | 7.982 | 9.241 | 1.529 |
| LOSS | 0.135 | 0.000 | 0.000 | 0.000 | 0.342 |
| ROA | 0.032 | 0.010 | 0.027 | 0.058 | 0.085 |
| INST | 0.671 | 0.572 | 0.711 | 0.818 | 0.197 |
| ANALYSTS | 11.927 | 6.000 | 11.000 | 16.000 | 6.707 |
| HORIZON | 0.442 | 0.175 | 0.289 | 0.688 | 0.364 |
| EARNVOL | 0.765 | 0.180 | 0.407 | 0.852 | 1.119 |
| ANNUAL | 0.610 | 0.000 | 1.000 | 1.000 | 0.488 |
| OUTDIR | 0.609 | 0.500 | 0.750 | 0.846 | 0.323 |
| MB | 1.866 | 1.199 | 1.544 | 2.123 | 1.114 |
| CONC | 0.444 | 0.339 | 0.397 | 0.520 | 0.168 |
| LITRISK | 0.359 | 0.000 | 0.000 | 1.000 | 0.480 |
| RESTRUCTURE | 0.383 | 0.000 | 0.000 | 1.000 | 0.486 |
| ACQ | 0.090 | 0.000 | 0.000 | 0.000 | 0.287 |
| R&D | 0.009 | 0.000 | 0.000 | 0.014 | 0.014 |
| ACCURACY | -0.013 | -0.009 | -0.003 | -0.001 | 0.035 |
| NEWS | 0.001 | -0.002 | 0.000 | 0.002 | 0.024 |

This table reports descriptive statistics for the full sample of 8,542 quarterly and annual management forecasts issued over the period 1996 to 2009. See Appendix B for variable definitions.

**Panel B Correlations**

| | CAR(-1,1) | SIZE | LOSS | ROA | INST | ANALYSTS | HORIZON | EARNVOL | MB | CONC | ACCURACY | NEWS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CAR(-1,1) | 1.00 | **0.06** | -0.09 | **0.11** | **0.06** | 0.00 | **0.03** | 0.00 | **0.08** | **0.02** | **0.12** | **0.13** |
| SIZE | **0.06** | 1.00 | -0.22 | **0.19** | **-0.23** | **0.60** | **0.11** | -0.01 | **0.23** | -0.01 | **0.17** | **0.08** |
| LOSS | **-0.09** | **-0.22** | 1.00 | **-0.41** | **-0.03** | **-0.07** | 0.00 | **0.27** | **-0.13** | **-0.07** | **-0.28** | **-0.17** |
| ROA | **0.11** | **0.19** | **-0.41** | 1.00 | **0.06** | **0.10** | **0.09** | **-0.22** | **0.26** | **0.06** | **0.21** | **0.14** |
| INST | **0.06** | **-0.23** | **-0.03** | **0.06** | 1.00 | **-0.08** | 0.01 | **0.02** | 0.02 | **0.13** | 0.01 | **0.04** |
| ANALYSTS | 0.00 | **0.60** | **-0.07** | **0.10** | **-0.08** | 1.00 | **0.08** | 0.01 | **0.22** | **0.04** | 0.00 | **0.04** |
| HORIZON | **0.03** | **0.11** | 0.00 | **0.09** | 0.01 | **0.08** | 1.00 | **0.23** | **-0.06** | **-0.06** | **-0.24** | **0.08** |
| EARNVOL | 0.00 | -0.01 | **0.27** | **-0.22** | **0.02** | 0.01 | **0.23** | 1.00 | **-0.16** | **-0.03** | **-0.33** | 0.01 |
| MB | **0.08** | **0.23** | **-0.13** | **0.26** | 0.02 | **0.22** | **-0.06** | **-0.16** | 1.00 | 0.02 | **0.16** | **0.03** |
| CONC | **0.02** | -0.01 | **-0.07** | **0.06** | **0.13** | **0.04** | **-0.06** | **-0.03** | 0.02 | 1.00 | **-0.03** | **0.03** |
| ACCURACY | **0.12** | **0.17** | **-0.28** | **0.21** | 0.01 | 0.00 | **-0.24** | **-0.33** | **0.16** | **-0.03** | 1.00 | **-0.16** |
| NEWS | **0.13** | **0.08** | **-0.17** | **0.14** | **0.04** | **0.04** | **0.08** | **0.01** | **0.03** | **0.03** | **-0.16** | 1.00 |

This table presents Pearson correlations for the sample of 8,542 management forecasts over the period 1996 to 2009. See Appendix B for variable definitions. The correlations marked in bold are significant at least at the 5% level.

## Table 3

## Test of Manager Fixed Effects on Management Forecast Accuracy, 1996-2005

**Panel A. Significance of Manager and Firm Fixed Effects**

| | Column 1: Manager and Year Fixed Effects and Controls | Column 2: Firm and Year Fixed Effects and Controls | Column 3: Manager, Firm and Year Fixed Effects and Controls | Column 4: CEO, Firm and Year Fixed Effects and Controls | Column 5: CFO, Firm and Year Fixed Effects and Controls |
|---|---|---|---|---|---|
| Firm Fixed Effects | | 13.06 | 13.04 | 12.93 | 13.04 |
| | | ($p<0.001$) | ($p<0.001$) | ($p<0.001$) | ($p<0.001$) |
| Manager Fixed Effects | 7.05 | | 6.41 | 6.47 | 6.36 |
| | ($p<0.001$) | | ($p<0.001$) | ($p<0.001$) | ($p<0.001$) |
| Adjusted Rsq | 19.54% | 23.85% | 27.14% | 26.18% | 25.40% |
| Percentage improvement in adjusted Rsq relative to Column 1 | | | 38.89% | | |
| Percentage improvement in adjusted Rsq relative to Column 2 | | | 13.79% | 10.00% | 6.50% |

Panel A reports F-statistics for the firm and manager fixed effects and adjusted R-squares from regressions with management forecast accuracy as the dependent variable. Management forecast accuracy is defined as the absolute difference between the management forecast and actual earnings multiplied by -1, scaled by beginning-of-period price. The sample includes 6,491 quarterly and annual management forecasts issued during 1996 to 2005. The vector of control variables includes: SIZE, LOSS, ROA, INST, ANALYSTS, HORIZON, EARNVOL, ANNUAL, OUTDIR, MB, CONC, LITRISK, RESTRUCTURE, ACQ, R&D. See Appendix B for variable definitions. The adjusted R-squares are calculated based on the within R-squares from XTREG, FE in STATA with robust standard errors.

**Panel B. Distribution of Manager and Firm Fixed Effects**

| | N | Mean | P25 | Median | P75 | Min | Max |
|---|---|---|---|---|---|---|---|
| Forecast Sample | | | | | | | |
| Manager Fixed Effects | 402 | 0.016 | 0.006 | 0.017 | 0.026 | -0.267 | 0.197 |
| Firm Fixed Effects | 679 | -0.027 | -0.048 | -0.020 | -0.001 | -0.275 | 0.108 |
| Main Sample | | | | | | | |
| Manager Fixed Effects | 172 | 0.017 | 0.010 | 0.019 | 0.026 | -0.099 | 0.172 |
| Firm Fixed Effects | 168 | -0.030 | -0.055 | -0.021 | -0.001 | -0.189 | 0.033 |

Panel B reports descriptive statistics for the manager and firm fixed-effect coefficients from estimating the following model on 6,491 quarterly and annual management forecasts issued during 1996 to 2005:

$$\textit{Management Forecast Accuracy} = \sum \alpha_k X_{kit} + \textit{Year Fixed Effects} + \textit{Firm Fixed Effects} + \textit{Manager Fixed Effects} + \varepsilon_{it}$$

The forecast sample includes all firms and managers for which the fixed-effect coefficients are estimable. The main sample includes all firms and managers that are used in the market reaction tests. N is the number of unique firms and managers.

**Table 4**
**Out-of-Sample Test: OLS Regression Analysis of Forecast Accuracy on Manager and Firm Effects, 2006-2009**

| | Predicted Sign | Dependent Variable: ACCURACY | |
|---|---|---|---|
| FE_MGR | + | 0.072** | |
| | | (0.034) | |
| FE_FIRM | + | 0.228*** | |
| | | (0.045) | |
| MGR | + | | 0.002** |
| | | | (0.001) |
| FIRM | + | | 0.007*** |
| | | | (0.001) |
| SIZE | + | 0.012*** | 0.012*** |
| | | (0.002) | (0.002) |
| LOSS | - | -0.008** | -0.009** |
| | | (0.004) | (0.003) |
| ROA | + | 0.101** | 0.100** |
| | | (0.042) | (0.041) |
| HORIZON | - | -0.014*** | -0.014*** |
| | | (0.002) | (0.002) |
| INST | + | 0.060*** | 0.063*** |
| | | (0.009) | (0.009) |
| ANALYSTS | + | -0.001*** | -0.001*** |
| | | (0.000) | (0.000) |
| EARNVOL | - | -0.012*** | -0.012*** |
| | | (0.002) | (0.002) |
| ANNUAL | - | -0.002 | -0.001 |
| | | (0.003) | (0.003) |
| OUTDIR | + | -0.000 | -0.001 |
| | | (0.002) | (0.002) |
| MB | - | -0.007*** | -0.007*** |
| | | (0.002) | (0.002) |
| CONC | - | -0.018*** | -0.019*** |
| | | (0.005) | (0.004) |
| LITRISK | + | 0.003 | 0.003 |
| | | (0.001) | (0.001) |
| RESTRUCTURE | - | -0.001 | 0.000 |
| | | (0.001) | (0.001) |
| ACQ | - | -0.004 | -0.003 |
| | | (0.002) | (0.002) |
| R&D | ? | 0.228*** | 0.193*** |
| | | (0.048) | (0.047) |
| Year Fixed Effects | | Y | Y |
| Observations | | 2051 | 2051 |
| R-squared | | 0.391 | 0.389 |

This table presents results from regressions of forecast accuracy on manager and firm effects reported in Table 3. The sample includes 2,051 management forecasts issued during 2006 to 2009. ACCURACY is defined as the absolute difference between the management forecast and actual earnings multiplied by -1, scaled by beginning-of-period price. FE_MGR (FE_FIRM) is the manager (firm) fixed effect coefficient estimated from regressing ACCURACY on firm-, manager-, and year-specific fixed effects and a vector of control variables. MGR is the quartile rank of FE_MGR. FIRM is the quartile rank of FE_FIRM. See Appendix B for control variable definitions. Robust standard errors adjusting for heteroscedasticity are reported in parentheses. *** and ** indicate significance at the 0.01 and 0.05 level, respectively, based on two-tailed tests.

**Table 5**
**OLS Regression Analysis of the Market Response to Manager and Firm Effects, 2006-2009**

| | Predicted Sign | Dependent Variable: CAR (-1, 1) | |
|---|---|---|---|
| NEWS | + | 1.488 | 3.701** |
| | | (0.958) | (1.465) |
| MGR | ? | 0.002 | 0.003 |
| | | (0.002) | (0.002) |
| MGR*NEWS | + | 0.302** | 0.196 |
| | | (0.133) | (0.134) |
| FIRM | ? | | 0.006** |
| | | | (0.003) |
| FIRM*NEWS | + | | 0.839*** |
| | | | (0.184) |
| SIZE | ? | -0.000 | 0.003 |
| | | (0.001) | (0.002) |
| SIZE*NEWS | + | -0.136 | 0.362** |
| | | (0.128) | (0.166) |
| LOSS | ? | -0.005 | -0.001 |
| | | (0.006) | (0.006) |
| LOSS*NEWS | - | -0.149 | 1.035** |
| | | (0.465) | (0.528) |
| ROA | ? | 0.039 | 0.023 |
| | | (0.032) | (0.032) |
| ROA*NEWS | + | 4.626** | 4.491** |
| | | (2.122) | (2.110) |
| HORIZON | ? | -0.002 | -0.002 |
| | | (0.004) | (0.004) |
| HORIZON*NEWS | - | 0.358 | 0.095 |
| | | (0.337) | (0.340) |
| Year Fixed Effects | | Y | Y |
| Observations | | 2051 | 2051 |
| R-squared | | 0.031 | 0.044 |

This table presents results from regressions of three-day cumulative adjusted returns on manager and firm effects reported in Table 3. The sample includes 2,051 management forecasts issued during 2006 to 2009. CAR (-1, +1) is the three-day cumulative market-adjusted return centered on forecast issuance date. MGR (FIRM) is the quartile rank of manager (firm) fixed effect coefficients estimated from regressing ACCURACY on firm-, manager-, and year-specific fixed effects and a vector of control variables. See Appendix B for control variable definitions. Robust standard errors adjusting for heteroscedasticity are reported in parentheses. *** and ** indicate significance at the 0.01 and 0.05 level, respectively, based on two-tailed tests.

## Table 6

## Factor Analysis: Uncertainty Factors and Factor Loadings

| | Factor Loadings | |
|---|---|---|
| | Earnings Uncertainty | Information Uncertainty |
| Components | | |
| RETVOL | 0.053 | **0.595** |
| TURNOVER | -0.088 | **0.671** |
| LEVERAGE | 0.431 | -0.248 |
| MB | **-0.565** | 0.123 |
| ROA | **-0.507** | -0.073 |
| EARNVOL | **0.522** | 0.113 |
| DISP | **0.518** | 0.218 |
| LITRISK | 0.292 | -0.032 |
| | | |
| Variance Explained | 59.03% | 40.97% |
| Correlation between Factors | 0.1978 | |

This table reports the factor loadings on each of the individual uncertainty variables. Factors are computed using exploratory components analysis. Two factors with an eigenvalue greater than unity are retained: Earnings Uncertainty and Information Uncertainty. RETVOL is the standard deviation of daily returns over the 30-day period prior to forecast issuance. TURNOVER is daily trading volume divided by shares outstanding, averaged over the 30-day period prior to forecast issuance. LEVERAGE is total debt divided by total assets. MB is market-to-book at beginning-of-period. ROA is return on beginning-of-period assets. EARNVOL is the standard deviation of earnings per share for the prior four periods. DISP is analyst dispersion at beginning-of-period. LITRISK equals one if firm is in one of the following high-litigation-risk industries: SIC codes 2833-2836 (biotechnology), 3570-3577 and 7370-7374 (computers), 3670-3674 (electronics), 5200-5961 (retailing), and 8731-8734 (R&D service), and suffers a 20 percent or greater decrease in earnings; zero otherwise.

**Table 7**

**OLS Regression Analysis of the Market Response to Manager and Firm Effects Conditional on Uncertainty, 2006-2009**

| | Dependent Variable: CAR(-1,1) | | | |
|---|---|---|---|---|
| | INFORMATION UNCERTAINTY | | EARNINGS UNCERTAINTY | |
| | HIGH | LOW | HIGH | LOW |
| MGR1*GOODNEWS | 2.495** | 0.093 | 0.602 | 3.379 |
| | (1.138) | (0.979) | (1.284) | (2.584) |
| MGR1*BADNEWS | 4.062*** | -2.960 | 1.000 | 2.280 |
| | (1.128) | (1.687) | (1.116) | (2.539) |
| FIRM1*GOODNEWS | 2.615 | 0.372 | 1.650 | 1.120 |
| | (1.524) | (0.906) | (1.031) | (1.377) |
| FIRM1*BADNEWS | 3.235*** | 0.946 | 3.220*** | 6.500*** |
| | (0.936) | (2.494) | (0.899) | (2.280) |
| GOODNEWS | 1.920 | 1.807 | 2.227 | 2.246 |
| | (2.324) | (3.292) | (2.295) | (2.609) |
| BADNEWS | 2.595 | 4.389 | 2.847 | 2.236 |
| | (2.306) | (4.060) | (2.323) | (2.831) |
| MGR1 | 0.021*** | -0.002 | 0.006 | 0.012 |
| | (0.008) | (0.005) | (0.006) | (0.007) |
| FIRM1 | 0.014** | 0.010 | 0.010 | 0.022*** |
| | (0.007) | (0.009) | (0.008) | (0.008) |
| Year Fixed Effects | Y | Y | Y | Y |
| Observations | 1050 | 1001 | 1009 | 1042 |
| R-squared | 0.107 | 0.065 | 0.095 | 0.075 |

This table presents results from regressions of three-day cumulative adjusted returns on manager and firm effects conditional on high and low uncertainty. The sample includes 2,051 management forecasts issued during 2006 to 2009. CAR (-1, +1) is the three-day cumulative market-adjusted return centered on forecast issuance date. MGR1 (FIRM1) is an indicator variable equal to one if the manager is in the top quartile rank of manager (firm) fixed effect coefficients estimated from regressing ACCURACY on firm-, manager-, and year-specific fixed effects and a vector of control variables. The sample is split into high and low uncertainty at the median of the Information Uncertainty and Earnings Uncertainty factors. GOODNEWS (BADNEWS) equals NEWS if NEWS is greater (less) than zero. Robust standard errors adjusting for heteroscedasticity are reported in parentheses. *** and ** indicate significance at the 0.01 and 0.05 level, respectively, based on two-tailed tests.

**Table 8**
**OLS Regression Analysis of the Market Response to Manager and Firm Effects Controlling for Bundled Forecasts, 2006-2009**

| | Predicted Sign | Dependent Variable: CAR (-1, 1) | |
|---|---|---|---|
| NEWS | + | 2.814*** | 2.463 |
| | | (1.055) | (1.642) |
| MGR | ? | 0.002 | 0.003* |
| | | (0.002) | (0.002) |
| MGR*NEWS | + | 0.253* | 0.175 |
| | | (0.134) | (0.135) |
| FIRM | ? | | 0.006** |
| | | | (0.003) |
| FIRM*NEWS | + | | 0.773*** |
| | | | (0.190) |
| SIZE | ? | -0.000 | 0.003 |
| | | (0.001) | (0.002) |
| SIZE*NEWS | + | -0.229 | 0.257 |
| | | (0.130) | (0.174) |
| LOSS | ? | -0.005 | -0.001 |
| | | (0.006) | (0.006) |
| LOSS*NEWS | - | -0.057 | 1.008* |
| | | (0.464) | (0.528) |
| ROA | ? | 0.045 | 0.030 |
| | | (0.032) | (0.032) |
| ROA*NEWS | + | 5.214** | 5.058** |
| | | (2.123) | (2.113) |
| HORIZON | ? | -0.002 | -0.002 |
| | | (0.004) | (0.004) |
| HORIZON*NEWS | - | 0.326 | 0.129 |
| | | (0.339) | (0.341) |
| BUNDLED | ? | 0.011*** | 0.012*** |
| | | (0.004) | (0.004) |
| BUNDLED*NEWS | ? | -0.863 | -0.495 |
| | | (0.531) | (0.341) |
| Year Fixed Effects | | Y | Y |
| Observations | | 2051 | 2051 |
| R-squared | | 0.040 | 0.050 |

This table presents results from regressions of three-day cumulative adjusted returns on manager and firm effects reported in Table 3. CAR (-1, +1) is the three-day cumulative market-adjusted return centered on forecast issuance date. MGR (FIRM) is the quartile rank of manager (firm) fixed effect coefficients estimated from regressing ACCURACY on firm-, manager-, and year-specific fixed effects and a vector of control variables. BUNDLED equals one for bundled forecasts; zero otherwise. See Appendix B for control variable definitions. Robust standard errors adjusting for heteroscedasticity are reported in parentheses. *** and ** indicate significance at the 0.01 and 0.05 level, respectively, based on two-tailed tests.

## Figure 1

## Frequencies of Significant Manager Fixed Effects

This figure reports the frequency of significant manager fixed effects for the forecast and main sample relative to what would be expected under the null hypothesis if the model in Table 3 Panel B is well-specified. The calculations are performed at the 1 percent, 5 percent, and 10 percent significance level, respectively. The forecast sample includes all managers for which the fixed effect coefficients are estimable. The main sample includes managers that are used in the market reaction tests.