Do Managers Always Know Better? An Examination of the Relative Accuracy of Management and Analyst Forecasts

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October 2011

Abstract

In this paper we examine the relative accuracy of management and analyst forecasts. We predict and find that analysts' information advantage resides at the macroeconomic level. They provide more accurate long-horizon earnings forecast than management when a firm's fortunes move in concert with macroeconomic factors such as gross domestic product and energy costs. In contrast, we expect and find that management's information advantage resides at the firm level. Their forecasts are more accurate than analysts when management's actions, which affect reported earnings, are difficult to anticipate by outsiders. Examples include when the firm's inventories are abnormally high, the firm has excess capacity, or is experiencing a loss. Interestingly, while analysts are commonly viewed as industry specialists, we fail to find evidence that analysts have an information advantage over managers at the industry level. Neither managers nor analysts have a forecasting advantage for firms with revenues that are more synchronous with their industries' revenues.

*****We are grateful to Mark Bradshaw, Mary Ellen Carter, Sugata Roychowdhury, the editor (Douglas Skinner), and an anonymous referee for their helpful comments and suggestions. We thank workshop participants at Columbia University, the University of Michigan and Boston College for useful comments and suggestions.

1. Introduction

Analysts' forecasts and management's forecasts are two important sources of information used by investors when developing firm-level earnings expectations. However, the importance investors should give to each (when both are provided, but differ) is unclear, given how little is known about the relative accuracy and information advantages of analyst and managers.[1]

One would expect that managers have a distinct advantage over analysts in forecasting earnings. They are insiders running the firm making key business decisions. As such, it is not surprising that much of the prior literature presumes that management has an information advantage over analysts (e.g., Diamond 1985, Altschuler 2009, Trueman and Versano 2010). However, given one of analysts' primary functions is to provide earnings forecasts and given the amount of resources devoted to this process, it is not a foregone conclusion that management's information set is superior.[2] In fact, Ruland (1978) and Hutton and Stocken (2010) document that management's forecasts are more accurate than analysts' forecasts only about 50% of the time. This empirical observation begs the question: *When are analysts' forecasts more accurate than management's forecasts, given the inside information managers possess?* In this paper we attempt to shed some light on this question by examining the relative accuracy of analyst and management annual earnings forecasts.[3]

[1] To identify relative information advantages of managers and analysts, this paper focuses on *relative forecast accuracy* rather than the relative level of optimism or pessimism (i.e., bias) in management's and analysts' forecasts. Thus, we classify a management forecast as more accurate than analysts' forecasts if management's forecast attempts to move the market's expectations (measured as the prevailing mean analyst forecast) closer to the ultimate realization of earnings for the fiscal year (see Williams 1996).
[2] Furthermore, it is also possible that management could have the dominant information set, but perhaps because of incentives chooses not to provide the most accurate forecast. We expect such incentives to play a more important role in short-horizon forecasts rather than long-horizon forecasts. Nevertheless, incentives affect forecasting behavior, and the issuance of intentionally biased forecasts by managers or analysts is a source of measurement error that may affect our results. We address this concern in section 5.
[3] We match up the management forecast with the prevailing non-stale individual analyst earnings forecasts issued for the same fiscal period. We define non-stale analyst forecasts as those made within 30 days *prior* to the management earnings forecasts. Our research design gives management the advantage, in that management's forecast is issued after the analysts' forecasts.

Drawing on the extant analyst forecast literature and management guidance literature, we conjecture when analysts' forecasts are likely to be more accurate than management's and vice versa. Specifically, we expect and find that analysts' information advantage resides at the macroeconomic level. When a firm's operations are highly exposed to forces outside managers' control (e.g., the business cycle, input prices, and regulation), analyst have the forecasting advantage. Analysts provide more accurate long-horizon earnings forecast when a firm's fortunes move with broad macroeconomic factors such as gross domestic product or depend on input prices that are often forecasted by macroeconomists, such as energy costs.

In contrast, we expect and find that managers' information advantage as insiders running the firm is most pronounced in situations where analysts find it hard to anticipate managers' response to unusual operating situations, such as when the firm faces abnormal inventory buildup, has excess capacity, or is experiencing an off-equilibrium loss year. Unable to anticipate management's response, analysts find it more difficult to anticipate the effect of management's response on reported earnings.

Finally, we explore whether analysts have an information advantage regarding industry-level factors that affect firm performance. One might expect analysts to have an information advantage at the industry level, as they are often viewed as industry specialists: organized along industry and sector lines within financial services firms and known to add value by identifying the winners and losers *within* an industry (see e.g., Boni and Womack 2006). However, analysts' information advantage at the industry level is not a foregone conclusion. Managers are also likely to have significant industry expertise and knowledge. They need to understand industry dynamics and demand to effectively run an operating firm. Thus, our prediction as to who has the information advantage at the industry level is not clear cut, and it is ultimately an empirical question whether managers or analysts have an information advantage regarding industry-level factors. Our empirical findings indicate that neither one has an advantage over the other: managers and analysts are well matched in forecasting earnings for firms with revenues or earnings that are highly synchronous with their industries.

We make several contributions to the literature: First, we highlight the fact that management's forecasts are more accurate than analysts' forecasts only about 50% of the time. By doing so we cast doubt on the premise in the literature that management has an information advantage over analysts that permits its earnings guidance to substitute for or subsume the private information acquired by analysts (Diamond 1985, Altschuler 2009, Trueman and Versano 2010). Second, we document the firm characteristics and operating situations associated with analysts providing more accurate long-horizon forecasts than management. Third, we document the circumstances under which management's information advantage leads to a clear forecasting advantage over sell-side analysts. These latter two findings ought to be useful for informing investors about the relative importance to assign to each type of forecast when forming their own earnings expectations.

The paper proceeds as follows: In section 2 we review the relevant literatures, outline our conjectures about the relative information advantage of managers versus analysts, and state our empirical predictions. Section 3 outlines our sample selection and variable definitions. Section 4 presents our empirical analysis; section 5 robustness tests; section 6 our conclusions.

2. Literature Review & Empirical Predictions

While the literatures on analyst forecasts and managerial earnings guidance are extensive, few prior research papers compare analyst and management forecasts. Instead, prior research often assumes that management forecasts are more accurate than analyst forecasts, because of the presumed information advantage of management. For instance, Altschuler (2009, p. 12) notes:

> *Even when management's forecasts are relatively inaccurate, it is unlikely that analysts can produce more accurate forecasts because of the information advantage managers have over analysts.*

Based on this presumption, Altschuler argues that the anticipation of a management forecast may reduce analysts' incentive to acquire private information because the information disclosed by management is a "substitute for otherwise costly acquisition of private information." More recently, Trueman and Versano (2010) simply assume that management's forecasts are *always* more accurate than analysts forecasts. See also Diamond (1985).

Prior literature shows that management forecasts are not always more accurate than analyst forecasts. Ruland (1978) provides descriptive statistics of the relative accuracy of analysts and managers, and documents that analysts are less accurate than managers 51% of the time. More recently, Hutton and Stocken (2010) document that for their sample of quarterly and annual management forecasts, managers are more accurate than the prevailing consensus analyst forecast only about 50% of the time.

This observation begs the question: *Under what circumstances and for which types of firms are analysts' forecasts more accurate than management's forecasts, given the inside information managers possess?* We search the extant analyst forecast literature and management guidance literature to develop conjectures about when analysts have an information advantage over management and thus when analysts' forecasts are likely to be more accurate than management's forecasts.

Our review of the literatures suggests that analysts' information advantage stems from their ability to be objective, their industry expertise (which enables them to survey a broad set of industry statistics and data), and finally their access to experts in macroeconomics. As a result, analysts are better positioned to forecast macroeconomic factors, and assess the likely impact of economy wide changes on the competitive environment (competitors, suppliers, or customers etc.) of the firm and thus on input and output prices. This gives them the edge when they issue earnings forecasts early in the fiscal year.

We hypothesize that when a firm's fortunes move with broad macroeconomic factors and depend on forces outside management's control (e.g., the business cycle, input prices, and regulation), analysts are better positioned to create a distinctive information advantage via their acquisition of private information. For these firms, management's forecasts are unlikely to be a close substitute for analysts' costly acquisition of private information.

Prior literature also points out when analysts' forecasting abilities are inadequate. For instance, they appear to have difficulty forecasting earnings for firms with high fixed costs, retail firms with abnormally high inventory growth, and complex firms that provide opaque disclosures (Weiss 2010, Kesavan and Mani 2010, Lehavy, Li and Merkley 2010). We expect that analysts' forecasting difficulty in these situations stems from the fact that they are outsiders trying to discern key information available only to insider. Their efforts are hampered when a firm's current situation involves substantial uncertainties, making it difficult for outsiders to anticipate managers' actions and the implications of these actions on forthcoming earnings. We conjecture that managers have the forecasting advantage in these situations, precisely because of their role as insiders in control of key operating decisions.

2.1. Management's Information Advantage

Managers are **Firm Specialists**, who have an *information advantage* because they run the firm making business decisions hourly and daily that ultimately affect reported earnings.

Because they have intimate knowledge of the firm's business strategy and its daily transactions, managers are entrusted with making the appropriate estimates and assumptions needed to prepare accrual-based financial statements. Early research exploring the usefulness of management earnings forecasts documents that analysts' forecast errors decrease more rapidly for firms that release management earnings forecasts than for firms that do not (Hassell, Jennings and Lasser 1988). This is not surprising, given that management makes key decisions regarding the timing and recognized amounts of business transactions. These accounting decision rights give management a clear information advantage in forecasting earnings, especially near-term earnings. Thus, we expect management forecasts to be more accurate than analysts' forecasts the shorter the horizon of the forecast. In fact, Baginski and Hassell (1990) find that analysts revise their forecasts to fall more in line with management's forecasts in the fourth quarter.

The unique information advantage that results from management holding key decision rights is likely to be most pronounced when the firm's current situation is unusual, for example in a loss year. Loss years are by their very nature off-equilibrium years, years when the firm is not operating within its band of steady state performance, making forecasting earnings based on historical performance particularly difficult. Prior research demonstrates that analysts' forecasts of losses are less accurate than their forecasts of profitable firm-years (Hwang et al. 1996). In loss years, management's inherent information advantage is enhanced by the difficulty outsiders face in anticipating what managers are likely to do in their turnaround efforts. Without knowing management's likely choice of action, it is more difficult for outsiders to forecast the implications of those actions for reported earnings. This disadvantage is particularly acute at the beginning of the fiscal year, before management has had a chance to communicate to outsiders its plans for dealing with the loss. Thus, we expect managers to provide more accurate forecasts than analysts when management is forecasting a loss for the year.[4]

Continuing to highlight circumstances when management's distinctive information advantage as insiders running the firm is likely to be most pronounced, we expect management's forecast to be more accurate than analysts' forecasts when the firm is experiencing abnormally high inventory buildup and when a firm with high fixed costs experiences a significant decline in its revenues (i.e., when the firm has excess capacity). Recent research documents shortcomings in analysts' forecasting abilities in these two situations.

First, Kesavan and Mani (2010) document the predictive power of abnormal inventory growth for retail firms' earnings and that analysts' forecasts fail to incorporate this relevant information. We simply extend their arguements and conjecture that management is in a better position to understand how abnormal inventory growth is likely to affect the firm's operating performance precisely because management is either directing the growth in anticipation of increased demand or is active in addressing it with impending markdowns or write-offs, the timing of which management controls.

Second, Weiss(2010) documents that analysts' forecasts are less accurate for firms with more sticky costs. He argues that these firms experience larger earnings decreases when activity levels decline but costs do not. This leads to greater earnings variability, making it more difficult for analysts to forecast accurately. We extend his arguments and conjecture that management is better positioned to assess how the drop in demand is likely to affect the firms's profitability because management has intimate knowledge of its plans to deal with the excess capacity. Thus,

[4] Loss years often involved the recognition of special items, exactly the types of accounting items whose timing and magnitudes depend on key estimates and assumptions made by management, giving them a clear advantage in forecasting earnings.

we expect management forecasts will be more accurate than analysts' forecasts when a firm's costs are largely fixed and the firm experiences a decline in revenues.

2.2 Analysts' Information Advantage

Given management's distinctive information advantage as insiders running the firm, what are the possible sources of analysts' information advantage? We argue that there are several.

First, analysts have access to macroeconomic expertise that affords them a distinctive information advantage in predicting economy-wide factors that lie outside management's control (such as GDP, interest rates, and energy costs). Specifically, analysts working at top tier investment banks have proprietary access to highly regarded macroeconomists (Jennings 1987). The morning conference calls taking place each day at these banks alert analysts to any forthcoming macroeconomic news and its implications.[5] Additionally, these macroeconomists provide analysts with detailed forecasts of commodity prices and interest rates, which ought to be useful for predicting the performance of many regulated firms: e.g., utilities whose profits depend on energy costs and commercial banks whose profits depend on the shape of the yield curve. As a specific example, the *Economic Research Group* at Goldman Saches **"**formulates macroeconomic forecasts for economic activity, foreign exchange rates and interest rates based on the globally coordinated views of its global and regional economists."[6] These are precisely the factors affecting firm operations that lie outside management's influence. The amount of resources devoted to macroeconomic research by these investment banks is significant, and any individual operating firm is unlikely to have access to the same level of resources and expertise.

We view analysts' information advantages with respect to macro factors as two-fold: the ability to forecast the macroeconomic factors early in the fiscal year, and the ability to figure out

[5] In contrast, managerial earnings guidance has been shown to *lag* macroeconomic news (see Anilowski, Feng and Skinner, 2007).
[6] http://www2.goldmansachs.com/services/research/gir/research-and-analysis.html.

the implications of these macro forecasts for the firm, its customers, suppliers and competitors. We conjecture that analysts' objectivity and ability to work with large amounts of proprietary data enables them to better assess the impact of economy-wide changes on the competitive environment of the firm, such as input and output prices, giving them the edge when they issue earnings forecasts early in the fiscal year for firms whose profits are highly dependent on macroeconomic factors.[7]

Second, analysts are **Industry Specialists**. Financial institutions commonly organize analysts by industry and sector and analysts routinely benchmark a firm's performance against its direct competitors (see Ramnath 2002). Clement (1999) and Jacob et al. (1999) show that analysts' forecast accuracy improves with industry specialization, while Gilson et al. (2001) show that the composition of analyst coverage changes after spin-offs and equity carve-outs. Finally, Boni and Womack (2006) demonstrate that analysts' expertise lies in their ability to rank stocks *within* the industries in which they specialize. Together, these results suggest that analysts' comparative advantage lies in interpreting specific industry and market sector trends and improving intra-industry information transfers. Of course, managers are also industry specialist. Most managers spend their entire career working within the confines of one or perhaps two related industries. To rise to the position of CFO or CEO (the top managers most likely involved in creating the firm's earnings forecasts), managers must have a great deal of knowledge about the firm's key competitors and the workings of its industry dynamics. It is

[7] We note, however, that if analysts' information advantages stem mainly from their foresights regarding future demand shocks, then our prediction regarding analysts' macroeconomic advantages is predicated on a timing difference in their information acquisition. That is, analysts are informed about the upcoming demand shocks early in the year, while managers eventually recognize the changes later and take actions in response to the demand shocks. However, analyst's advantages could also stem from their ability to forecast input and output prices, which impacts a firm's profitability in the absence of management's response to a demand shock.

ultimately an empirical question whether analysts' information advantage is superior to that of managers regarding industry-level factors.

Existing empirical evidence supports these conjectures: Piotroski and Roulstone (2004) find that stock return synchronicity is positively associated with analyst forecasting activities, consistent with analysts increasing the amount of *industry* and *market-level* information in prices. Conversely, they find that stock return synchronicity is negatively related to greater levels of insider trading, indicating that the net contribution of managers' trading activities is to increase the relative amount of *firm-specific* information in stock prices.

3. **Sample Selection and Variable Definitions**

We use the *First Call* database of "Company Issued Guidance" (*CIG)* to identify a sample of 31,275 annual management earnings forecasts issued between January 2001 and December 2007. Our sample period begins after the passage of Regulation Fair Disclosure (RegFD). Prior to RegFD, managers could communicate their forecasts privately to analysts, making our analysis of the relative accuracy of the earnings forecasts by these two groups difficult.[8] The sample includes only point, range, or one-sided directional forecasts; it excludes qualitative managerial forecasts not specific enough to determine numerical earnings per share (EPS) forecasts. To determine a numeric value for each management forecast, we use the value of the point and one-sided directional forecasts and mid-point of the range forecasts.[9]

[8] Regulatory and legal environment affects management forecasting behavior (see Baginski, Hassell and Kimbrough 2002; Heflin, Subramanyam and Zhang 2003). To control for these effects, we restrict our sample to forecasts issued after the implementation of Reg FD on October 23, 2000.

[9] Prior research suggests that investors use the mid-point of a range forecast when forming their earnings expectations (e.g., Baginski, Conrad, and Hassell 1993; Hirst, Koonce, and Miller 1999). In some cases, however, the *CIG* database indicated that EPS would be at the low (high) end of the range based on CIG code. In these instances, we used the low (high) end of the range as the value for management's EPS estimate.

We then merged our *First Call* sample with the *I/B/E/S* detailed file of individual analyst earnings estimates and with the *I/B/E/S* actual earnings.[10] We conduct our analysis on the *first* annual management earnings forecast issued after the release of the prior year's earnings. We expect that the relative accuracy of analysts and managers early in the year is more likely driven by their comparative information advantage. The relative accuracy of management forecasts issued late in the fiscal year, on the other hand, is confounded by other factors, such as management's ability and incentives to meet their or analyst forecasts via expectations management or earnings manipulation (see Matsumoto 2002; Kasznik 1999). We delete management forecasts that are not the first annual forecasts issued after the prior year's earnings announcement (13,704) and those that are the first annual forecasts but issued in the fourth quarter (79).

For each management forecast, we gather all earnings forecasts for the same fiscal year made by individual analysts within the previous 30 days to ensure that the analyst forecasts are not stale.[11] The timeline of management forecasts and the corresponding analyst forecasts is presented in Figure 1. Management forecasts that do not have any corresponding I/B/E/S analyst forecasts made within the 30 day window are deleted (11,976). If a management forecast is made *within* 30 days after the prior year's earnings announcement, we adjust the window for gathering analyst forecasts to start two days after the prior year's earnings announcement. This adjustment ensures that the analysts have also observed the prior year's earnings. Finally, we

[10] We choose to use the analyst forecasts and actuals in I/B/E/S instead of those in First Call for a few reasons. First, I/B/E/S likely has more comprehensive coverage of brokers/analysts. For example, in our sample, the mean number of analysts is 4.6 using I/B/E/S (see Table 2) while the mean number of analysts is 3.2 using First Call. Second, management forecasts from CIG are historical and unadjusted for splits (taken directly from actual press releases of management forecasts), while First Call analyst forecasts and actuals are adjusted for splits. This creates measurement errors due to rounding (Payne and Thomas 2003). In contrast, the I/B/E/S's historical database provides unadjusted analyst forecasts and unadjusted actuals.

[11] We note that our inferences are conditional on firms with both management forecasts and analyst forecasts. Managers with inaccurate information set might choose not to issue forecasts, and these firms will not be in our sample. This limits the generalizability of our results.

merge the sample of *First Call* earnings forecasts with financial data from *Compustat,* and delete observations with missing *Compustat* data (1,472). The sample development is summarized in Table 1.[12] The final sample consists of 4,044 management forecasts made by 1,476 firms during the sample period January 2001 and December 2007. Range forecasts make up 84.4% of the management forecasts included in our final sample, 11.7% are point estimates, and over three percent are one-sided directional or confirming estimates.

3.1. Earnings Realization Issues and the Construction of a "Clean" Sample

We base earnings realizations on I/B/E/S actuals, which are adjusted by I/B/E/S to be consistent with the EPS construct used by the majority of analysts following a firm.[13] While the I/B/E/S actuals are consistent with analyst forecasts, they may not be consistent with the EPS construct forecast by management (Gu and Chen 2004, Barth, Gow and Taylor 2010).[14]

To ensure that our results are not affected by this measurement error, we construct a "clean" sample where there is little doubt that managers and analysts are forecasting the same EPS construct. Panel B of Table 1 summarized our sample selection procedure for the "clean" sample. We begin by identifying the sub sample of observations for which the I/B/E/S actual EPS is equal to one of the four EPS numbers reported on Compustat (including or excluding extraordinary items, diluted or basic). It is less likely that there are significant differences in the EPS construct focused on by managers and analysts for this sub sample, as analysts are forecasting a GAAP number. There are 1,341 forecasts that meet this criterion.

[12] We recognize that our sample excludes a substantial proportion of non-quantitative management forecasts; see Pownall, Wasley, and Waymire (1993) and Bamber and Cheon (1998). Additionally, our sample is not a complete set of all quantitative forecasts made by all firms, as the CIG data base is known to be incomplete, systematically excluding smaller firms with fewer analysts following them; see Chuk, Matsumoto and Miller (2010) for details.
[13] In addition, I/B/E/S also adjusts individual analyst's forecasts, if they were inconsistent with the majority, to conform to the construct used by the majority.
[14] The same is true for the *First Call* analyst estimates and actuals.

However, systematic differences may still remain between the EPS constructs focused on by the managers and by analysts if, for instance, management is forecasting a non-GAAP number (e.g., managers may exclude stock-based compensation expense). Thus, we further refine our "clean" sample by hand-collecting the press releases of the annual *earnings* announcements for these 1,341 observations.[15] We read each press release to determine whether the actual EPS construct reported in I/B/E/S is also the most prominent EPS number in the company's earnings press release.[16]

In 1,133 of the observations, the I/B/E/S EPS number is clearly the most prominent EPS number in the company's press release. We delete 22 observations because the I/B/E/S actual number is not in the earnings release. In the remaining 186 cases, the I/B/E/S EPS construct appears in the press release, but is not the focus of management's discussion, largely because management does not highlight a specific EPS number. In these cases, we use the details in the financial statements embedded in the earnings release to help us identify the specific earnings construct reported as the I/B/E/S actual (e.g., earnings after discontinued operations; earnings before the cumulative effect of an accounting change) and then search *Factiva* for the management forecasts (MF) release or conference call scripts to identify the EPS construct forecast by management. In 119 instances the MF press release is sufficiently detailed to identify the particular EPS construct forecast by management; we delete the 67 observations with

[15] We focus our hand-collection of data on the *earnings announcement* press release, because by reading this one release we are able to identify (1) the EPS construct focused on by management and (2) the IBES actual EPS number (e.g., diluted earnings after discontinued operations; basic earnings before the cumulative effect of an accounting change etc.). This allows us to make a reasonable assessment of whether the two are the same. One might think a potential alternative approach would be to examine the management *forecast* press release. However management forecast press releases do not provide insight on which construct analysts are forecasting and they often times do not provide sufficient detail regarding the construct management is forecasting.

[16] Our approach assumes that the EPS number that is unambiguously the focus of management's press release is the EPS construct that management forecasts. We define the most prominent EPS number as the one that either appears in the headline or is the first EPS number discussed by management. To verify our assumption, we randomly select 50 observations from the sample where the I/B/E/S actual is unambiguously the focus of management's earnings announcement press. In all but 3 cases, we were able to confirm that the most prominent EPS number in the company's earnings announcement matched the earnings construct management forecast.

insufficient detail in the MF release. In 74 (45) of the cases with sufficient detail, the EPS construct forecast by managers is consistent (inconsistent) with the I/B/E/S construct. We delete the 45 inconsistent observations. Our final "clean sample" consists of 1,207 firm years. For this sub sample we feel confident that management and analysts are forecasting the same EPS construct and that the I/B/E/S actual EPS number is the correct earnings realization against which to assess the accuracy of analysts' and management's forecasts.

While the clean sample enables us to assess whether our main results are affected by the measurement errors in the earnings realizations, focusing on this sub sample alone limits the generalizability of our results. A significant body of research employs I/B/E/S actual EPS as a proxy for management's 'pro forma' earnings reported in firms' press releases (e.g., Brown and Sivakumar 2003; Bradshaw and Sloan 2002; Doyle et al 2003). Doyle et al (2003) articulate reasons the I/B/E/S actual EPS is a good proxy for what firms report in their earnings announcements. First, I/B/E/S uses the earnings announcement press release as its source of the actual EPS. Second, given the close relation between managers and analysts, it is difficult to believe that the two parties are not focused on the same earnings definition; otherwise, what would it mean to beat analyst forecasts? Third, Johnson and Schwartz (2005) and Bhattacharya et al (2003) identify the EPS number that the firm emphasizes the most in a sample of press releases, and conclude it closely corresponds to the actual EPS reported in I/B/E/S or Zacks.

To increase our confidence in our sample, we randomly selected 100 observations from the firm-years where the I/B/E/S actual differs from the GAAP earnings constructs reported on COMPUSTAT. We require a firm to have the press releases for both the earnings announcement and the management forecast. Using the company's earnings announcement release, we first identify the I/B/E/S EPS construct.[17] Then we search the management forecast release to see whether the earnings construct being forecast by management is consistent with the I/B/E/S actual. In 71 cases, the EPS construct in the management forecast is consistent with the EPS construct used by analysts.[18] In light of the findings in prior literature and in our own sample, we continue to use the I/B/E/S actual EPS as a proxy for earnings realization in our main tests.

3.2. Variable Definitions: Analysts' Information Advantage

As discussed earlier, analysts' information advantage in predicting firm-level earnings comes from their access to experts in macroeconomic forecasting and from their expertise as industry specialists. Thus, we expect analysts' forecasts to be more accurate than management's when a firm's fortunes move with the broad economy or with its industry. We define industries based on the Fama and French 48 industry portfolios (Fama and French 1997). As discussed in section 5 (robustness check), we also use an alternative industry definition, with similar results.

To capture the extent to which a firm's earnings move with the broad economy, we compute *Cyclicality*, a measure of the ability of Gross Domestic Product (GDP) to explain firm-level earnings. Specifically, for each firm-year observation, we regress the firm's quarterly earnings over the prior 12 quarters on the corresponding quarterly Gross Domestic Product:

$$EARN_{i,t} = \alpha_0 + \alpha_1\, GDP_t + \varepsilon_{i,t}$$

where *EARN* is defined as income before extraordinary item and *GDP* is the nominal quarterly Gross Domestic Product.[19] We define *Cyclicality* as the coefficient of determination (R^2) from the estimation of the above regression. A high *Cyclicality* value indicates that the variability of a firm's earnings is well explained by the variability in the overall economy; the measure will be

[17] Examples of the EPS constructs in our sample include operating income per share, EPS from continuing operations, adjusted earnings excluding one-time items and special charges, and cash earnings per share.
[18] In the remaining 29 cases, either the EPS construct used by managers is inconsistent with the I/B/E/S actual (8 cases), or there were insufficient details to assess whether the two EPS constructs are the same (21 cases).
[19] GDP data is available from the Bureau of Economic Analysis (http://www.bea.gov/national/index.htm#gdp).

high when the firm's earnings is highly cyclical or highly counter cyclical. In either case, analysts ought to have an information advantage over management, since they have access to experts who provide detailed forecasts of macroeconomic conditions. Thus, we expect analyst forecasts to be more accurate when a firm's *Cyclicality* measure is high.[20]

Appendix 2 reports the mean and median *Cyclicality* across the Fama and French (1997) 48 industries. There is substantial variation in the *Cyclicality* measure across the 48 industries. The two industries that have the lowest mean *Cyclicality* are Tobacco Products and Candy and Soda. The five industries that have the highest mean *Cyclicality* are Electrical Equipment, Construction, Defense, Healthcare, and Shipbuilding and Railroad. This is consistent with our intuition. For example, Construction is a classic cyclical industry; 'housing starts' vary substantially with the state of the economy.

We consider two additional macro-level factors likely to affect firm-level performance: energy prices and interest rate spreads. To assess the extent to which a firm's earnings move with these two variables, we compute *Energy* and *Spread* in an analogous fashion to *Cyclicality*: for each firm-year observation, we regress the firm's quarterly earnings over the prior 12 quarters on the corresponding quarterly factor: energy prices or interest rate spread:

$$EARN_{i,t} = \alpha_0 + \alpha_1\, Factor_t + \varepsilon_{i,t}$$

[20] As noted earlier, if analysts' forecasts are *predicated* on management changing operating decisions in response to changing macroeconomic factors, it must be the case that as the year progresses management also recognizes the changing macroeconomic conditions and adjusts their operating plans in response; otherwise analysts' forecasts would not be more accurate than management's. To validate this assumption, we examine whether, over the course of the fiscal year, managers of highly cyclical firms are more likely to revise their forecasts to align with analysts' forecasts. This is, in fact, what we observe. Furthermore, the cost structures of the cyclical firms that revise their forecasts are more variable (vs. fixed), suggesting that it is easier for these firms to adjust their output in response to changing macroeconomic conditions.

where *EARN* is defined as income before extraordinary item and *Factor* is either energy costs or the spread between the 30-year mortgage rate and the t-bill rate.[21] We define *Energy* and *Spread* as the coefficient of determination (R^2) from the estimation of the respective regression. A high *Energy* or *Spread* value indicates that the variability of a firm's earnings is well explained by variability in overall energy costs or interest rate spreads (positively or negatively), suggesting an information advantage for analysts, since they have access to experts who provide detailed forecasts of energy costs and interest rates. Thus, we expect analyst forecasts to be more accurate when a firm's *Energy* or *Spread* measure is high.

Appendix 2 reports the mean and median of *Energy* and *Spread* across the 48 industries and highlights the 10 industries with the highest mean for each of the three macro-factors. Not surprising, there is considerable overlap of the top ten industries for the various macro-factors. For instance, Construction, Electronic Equipment, Electrical Equipment, Steel Works and Shipbuilding & Railroad are in the top ten for each factor.

In addition to their expertise at the macroeconomic level, we argue that analysts are also industry experts highly capable of forecasting and interpretation of industry demand and dynamics. We expect this expertise to translate into an information advantage for analysts when forecasting earnings for firms whose product demand moves in synch with its industry. To identify firms for which this analyst information advantage is likely, we compute a *Revenue Synchronicity* measure that captures how a firm's sales growth is correlated with the underlying

[21] We use monthly commodity fuel (energy) index as our proxy for energy prices. Energy includes crude oil (petroleum), natural gas, and coal price indices. The data is obtained from International Monetary Fund (http://www.imf.org/external/np/res/commod/index.asp). We also use monthly crude oil prices, with essentially the same results. For interest spread, we use the monthly time series of 30 year fixed mortgage rates, obtained from Freddie Mac (http://www.freddiemac.com/pmms/pmms30.htm), minus the one year constant maturity U.S. Treasury rate (http://www.federalreserve.gov/releases/h15/data.htm).

industry growth. Specifically, *Rev Sync* is measured as the R^2 from the firm-level estimation of the model over the prior 12 quarters:

$$REV_{i,t} = \alpha_0 + \alpha_1\, INDREV_t + \varepsilon_{i,t}$$

$REV_{i,t}$ is defined as revenue for firm i in quarter t scaled by revenue in quarter t-4, and *INDREV* is the sum of revenue for all firms in the industry (excluding firm i) in quarter t divided by the same measure in quarter t-4.[22] If analysts have an information advantage over managers in forecasting industry level demand shocks, then we expect analysts' forecasts to be more accurate when a firm's sales growth is highly synchronous with its industry.

Firms in regulated industries face common constraints, and the resulting commonality among these firms likely benefits analysts' private information acquisition. In addition, the performance of regulated firms tends to depend on input prices regularly forecast by macroeconomists. For example, financial institutions' profits often depend on the shape of the yield curve, while utilities' profits depend on the costs of their main inputs, energy prices. If analysts enjoy an information advantage afforded them by macroeconomists' detailed forecasts of energy costs and interest rates, then their forecasts for regulated firms are likely to be more accurate than those of management.

Consistent with the prior literature, we define *Regulated* industries as financial institutions and utilities. Specifically, we define a dummy variable, equal to one if a firm's four-digit SIC code fall between 4900-4999 (utilities), 6000-6099, 6100-6199 (banking), and 6200-6299, 6700-6799 (financial institutions), and zero otherwise.

[22] For the synchronicity measure we focus on the growth in sales revenues because existing evidence suggests that analysts' industry level expertise provides them with an enhanced ability to forecast sales growth, but not necessarily bottom line profits (Givoly, Hayn and D'Souza 1999, Fairfield, Ramnath and Yohn 2009).

3.3. Variable Definitions: Managers' Information Advantage

Managers have an information advantage because they run the firm and make key business decisions that ultimately affect reported earnings. As discussed earlier, the information advantage that results from management holding key decision rights is likely to be most pronounced when the firm's current situation is unusual, making it particularly difficult for analysts to anticipate the actions managers will take and the implications of these actions for reported earnings. Specifically, uncertainties regarding possible managerial actions are likely to arise in loss years, in years when the firm has a buildup of excessive inventory, and in years when the firm has excess capacity.

We define a firm-year as a *Loss* year when the EPS forecast by management is negative; we expect managers to provide more accurate forecasts than analysts in these years.

Identification of firms with excess inventory buildup is done in four steps: (1) we compute for each firm-year days inventory, where days inventory is equal to (inventory /cost of goods sold) * 365; (2) we compute the average days inventory for each industry-year; (3) we compute abnormal inventory (*ABI*) as a normalized deviation from the industry average days inventory, measured as (DI_{it} – Industry mean DI_t) /Industry standard deviation of DI_t; (4) we isolate firm-years where inventory is a significant asset class, defining *High Inventory* as the subsample of firm-years ranking in the top quintile of the ratio of inventory to assets. Since we expect management's information advantage to be most pronounced for the subset of high inventory firms experiencing abnormal inventory buildup, we interact the two variables (*High Inventory* and *ABI*) in the regression analysis presented below.

To identify firm-years with excess capacity, we focus on firms with high fixed costs that also experience a demand drop. To measure a firm's *Cost Structure*, we estimate the following firm-level regression using data from the prior 12 quarters (similar to Anderson et al., 2003):

$$LOG(EXP_t / EXP_{t-1}) = \beta_0 + \beta_1 LOG(REV_t / REV_{t-1}) + \varepsilon_{i,t}$$

where *REV* is defined as revenue and *EXP* is defined as revenue minus income before extraordinary item. A high value of β_1 indicates that a firm's costs are sensitive to its revenue, suggesting that the costs are mostly variable. Conversely, a low value of β_1 indicates that a firm's costs do not vary much with the revenue, suggesting that its costs are largely fixed.

Firms with relatively high fixed costs are more likely to experience excess capacity when there is an unanticipated decline in product demand, Such firm-years likely pose a forecasting challenge for analysts as they are uncertain how management will respond to the excess capacity and how the response will affect reported earnings.[23] We employ two measures to capture the unanticipated decline in demand. The first is an *ex-ante* measure, revenue volatility (*Std Rev*), which is intended to capture the probability of an unanticipated demand drop and is measured as the standard deviation of the revenue over the prior 12 quarters, scaled by the average revenue over the same period.[24] The second is an *ex post* measure, *Negative Demand Shocks*, which is an indicator variable set to one if (Actual Revenue – Analyst Consensus Revenue Forecast) <0 and

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[23]We focus on excess capacity versus demand in excess of existing capacity, as firms with high fixed costs are not able to respond quickly to dramatic increases in demand, since such a response is more long-term requiring the building of new production capacity. In contrast, when demand drops for firms with high fixed costs, forthcoming earnings are likely to be dramatically affected by management's near-term decisions. Management will find ways to utilize the excess capacity, perhaps by finding another firm wishing to outsource its production or by decreasing prices to increase demand. Alternatively, management may allow revenues and earnings to drop, without decreasing prices in the hope that the demand shock is temporary. Such managerial actions could significantly affect forthcoming earnings.

[24] Our first tests use an *ex-ante* measure of the *probability* of an unanticipated demand drop, rather than an *ex post* measure of an actual demand drop. Having all of the variables observable *ex ante* would permit investors to use our analysis to inform the relative weights they place on analyst and management forecasts when forming their own earnings expectations. The use of the revenue volatility to proxy for the *probability* of ex post demand drop can be viewed as analogous to using stock return volatility as a proxy for the *probability* of a large stock price drop in the securities litigation literature.

zero otherwise, where the analyst consensus revenue forecast is measured in the month prior to the management forecast.

To capture the interactive effect of cost structure and a decline in demand, we interact *Cost Structure* with *High Std Rev* (set to one for firm-years in the top quintile of *Std Rev* and zero otherwise), and with *Negative Demand Shocks.* Assuming managers know how they plan to address the excess capacity and the consequences for earnings, we expect that high fixed costs coupled with a decline in demand gives management an information advantage over analysts.

Finally, we expect management to have a forecasting advantage over analysts for shorter horizon forecasts. Analysts' information advantages in forecasting macroeconomics variables and industry demand shocks are likely to dissipate as the forecast horizon shortens and the end of the fiscal year approaches. This is because later in the fiscal year many of the macro- and industry-level shocks would have been observed by managers.[25] We measure *Horizon* as the number of days between the management forecast date and the end of the fiscal year.

3.4. Control Variables

We control for a number of variables that are related to a firm's general information environment, and therefore likely to affect forecast accuracy in general as well as the relative forecast accuracy of managers vs. analysts. However, we do not predict the signs of the control variables, as for most the effect on the *relative accuracy* of management and analyst is unclear.

Prior work finds that firm *Size* is an important determinant of analyst following (Lang and Lundholm 1996; Barth, Kasznik and McNichols, 2001). Larger firms tend to have better information environments but potentially more complex operations, both of these are likely to

[25] An alternative story that leads to the same prediction is that managers have incentives to manage earnings toward their own forecasts (Kasznik, 1999). If their incentives to engage in such behavior are stronger for short horizon forecasts, managers might appear to be more accurate with regard to short horizon forecasts. While we cannot rule out this explanation, we explore the effects of earnings management in Section 5.

affect forecast accuracy. We measure firm *Size* as the natural logarithm of total assets, measured at the end of the prior fiscal year.

We control for a firm's market to book ratio, *MB*, defined as the market value of equity divided by the book value of equity measured at the end of the prior year. Firm with high market to book ratios are likely to have more growth opportunities. High-growth firms tend to attract greater analyst following due to greater visibility, but analysts are also expected to have greater difficulty in accurately forecasting earnings for high growth firms (Barth et al., 2001).

Leverage can also affect the information environment of a firm. For firms with more debt, the scrutiny and monitoring by debt holders potentially improves the firm's information environment. *Leverage* is defined as total assets divided by book value of equity measured at the end of the prior fiscal year.

We expect the number of analysts following a firm to affect our measure of the relative accuracy of management and analyst forecasts. First, greater analyst following subjects a firm to greater scrutiny and affects a firm's information environment. Second, assuming individual analysts' information sets are not perfectly correlated, averaging across a greater number of analysts' forecasts will lead to a more accurate mean analyst forecast. Such that one could argue that our research design inherently biases in favor of analysts by comparing the *average* forecast across *N* analysts' forecasts to a *single* management earnings forecast.[26] However, this would only be true if the management forecast is drawn from the same distribution as all the individual analyst forecasts, which is unlikely.[27] Nevertheless, we control for the number of analysts in the

[26] We re-ran our analysis using only a single analyst forecast, the most recent analyst forecast, as the benchmark to compare against management's forecast. The tenor of the findings is unaffected.

[27] Given management's information set is distinct from that of analysts, earnings forecasts by the two parties are from different distributions. We used the Kolmogorov-Smirnov two sample test to examine the equality of the two distributions. The null hypothesis that the distributions are similar is rejected (p-value < 0.001). In addition, our research design gives management an inherent "advantage" because the management forecast is issued *after*

cross sectional regression analysis. *Analyst Following* is the natural logarithm of the number of analysts forecasts issued within the thirty days prior to the management forecast.

We control for a firm's overall complexity and forecasting difficulty using the *Dispersion* of analyst forecasts and the *Fog Index* (Li, 2008). Greater forecast dispersion reflects the general difficulty in forecasting earnings for a specific firm. *Dispersion* is measured as the standard deviation of the analyst forecasts scaled by the mean consensus analyst forecast, both measured in the month prior to the management forecast. We also use the *Fog Index* (Li 2008) as a control variable.[28] This measure captures the readability of the firm's prior period's 10-K filings, and is a comprehensive measure of the firm's overall complexity. Lehavy et al. (2010) document that a higher *Fog Index* is associated with lower analyst forecast accuracy.

We control for industry structure. The more concentrated an industry, the more likely the performance of its members are inter-related, which suggests that analysts ought to have an information advantage, as they are better at objectively assessing industry outlook. However, managers in concentrated industries are also highly vested in learning about their competitors, making the relative information advantage between the two hard to predict. We measure industry concentration using the *Herfindahl Index*, defined as $\sum_{i=1}^{N} MKTSHARE_i^2$ where *MKTSHARE* is the market share for each firm in the industry. Market share for firm i is measured as the revenue for firm i divided by total revenue for all firms in the industry.[29]

Finally, we include control variables for the type of management forecasts (e.g. point vs. range and good news vs. bad news). The *Point* dummy variable is one for a point forecast and

management observes the N analyst forecasts. So the management forecast is effectively based on a total of N analyst forecasts plus the manager's own information set.

[28] We are grateful to Feng Li for generously providing us with the data on the *Fog Index*.

[29] We recognize that ours is a noisy proxy for industry concentration because *Compustat* covers only U.S. publicly held firms. See Ali, Klasa, and Yeung (2009) for details.

zero otherwise; The *Good News* dummy variable is one if management's earnings forecast is greater than the average of the non-stale analyst forecasts, and zero otherwise.

4. **Empirical Results**

Table 2 provides descriptive statistics for the 4,044 management earnings forecasts. Since we focus on the first annual forecast, the horizon of the management forecasts (measured relative to the end of the fiscal year) is relatively long, with an average of 224 days, and a median of 248 days. Consistent with existing literature, management earnings forecasts tend to be issued by large firms with significant analyst following: the sample firms have an average total asset of $7.07 billion dollars and a median of $1.62 billion dollars; the mean number of analysts following is 4.6, the median is three. Also consistent with prior research, management earnings forecasts are predominately bad news: for 55% of the forecasts in our final sample management's forecast is lower than the mean of non-stale analysts' forecasts. We also note however that only 2% of the management forecasts are of a *Loss*. While *Regulated* firms make up 13.9% of the sample firms, they offer only 11.7% of the management forecasts.

In Table 3, we provide descriptive statistics for two subsamples: those where management forecasts are more accurate and those where the mean analyst forecasts are more accurate. We define a management forecast as more accurate if the absolute value of the management forecast error (measured as the management forecast less realized earnings per share) is smaller than the absolute value of the mean forecast error of the analyst forecasts (measured as the corresponding mean analyst forecasts less realized earnings per share), that is,

$$|\textit{Mean Analyst Estimate} - \textit{Realized EPS}| > |\textit{Management Forecast} - \textit{Realized EPS}|.$$

As seen in Table 3, management forecasts in our sample are more accurate than the mean analyst forecast less than 50% of the time (1,996 out of 4,044), consistent with prior research (Rutland 1978; Hutton and Stocken 2010).

Comparing the two subsamples presented in Table 3, several firm characteristics differ as predicted. Specifically, the sample of firms where analyst forecasts are more accurate exhibit greater *Cyclicality*; the difference in the means of *Cyclicality* between the two subsamples is highly significant. These firms also have higher mean *Energy* and *Spread*; the corresponding management forecasts have a longer forecast *Horizon*. These univariate results are consistent with our conjectures that analysts' information advantage resides at the macro-level, and when the forecast horizon is relatively long. However, the results cast doubt on analysts' information advantage over managers at the industry level as analysts do not provide more accurate forecasts than managers for firms with high *Revenue Synchronicity*, or in regulated industries.

For the subsample of firms where managers' forecasts are more accurate, they are more likely to be *Loss* years, years with *Negative Demand Shocks* and more likely to be *Retail* firm. As for the control variables, they tend to be statistically indifferent between the two subsamples, with the exception of the number of analysts and the *Good News* dummy variable.

The mean (median) of the forecast difference (*MF – AF*) is -0.010 (0.0002) for the subsample where management's forecasts are more accurate; the mean (median) difference is 0.004 (-0.003) for the subsample where analysts' forecast are more accurate. While the difference in means across the two subsamples is significant at the 1% level; the difference in the medians is not. For the subsample where managers are more accurate, analyst forecasts are systematically optimistic, perhaps indicating that management's forecasts are more accurate when they are issued to reign in overly optimistic analyst forecasts (Larocque 2010). In contrast, for the subsample where analysts are more accurate, the mean forecast difference (0.004) is insignificantly different from zero, indicating that there is no systematic bias in management's earnings forecasts compared to analysts' forecasts for this subsample.

Table 4 provides the correlations among our variables of interest and all the control variables. The table reports Pearson correlation on the upper diagonal and the Spearman correlation on the lower diagonal. While many of the variables are significantly correlated, several are correlated at levels greater than 30% raising concerns about multi-collinearity. For instance, the correlation between *Cyclicality* and *Spread* is 66.4%; the correlation between *Cyclicality* and *Energy* is 37.5%; the correlation between *Energy* and *Spread* is 37.9%.[30]

Table 5 presents the main regression analysis that includes our variables of interest as well as the control variables. The dependent variable is one if the management forecast is more accurate than the average prevailing, non-stale analysts' forecasts, and zero otherwise.[31] We present the predicted signs of the coefficients for our variables of interest, the coefficient estimates, and the Z-statistics. The standard errors are clustered by firm. The magnitude and the standard error of the interaction terms are estimated based on Ai and Norton (2003). For ease of interpretation, we also present the marginal impact of each variable.[32]

Panel A presents the results using the general sample. We present two different models. Model 1 presents the results with the *ex- ante* measure of the probability of a negative demand shock, i.e., revenue volatility, and model 2 presents the results using the *ex post* measure, i.e., a

[30] Our main regression analysis includes all three macro factors in one regression. However, we also include only one of the three at a time. Each macro-factor increases in significance in the absences of the other two.

[31] For our dependent variable to be set to one, management's forecast must be strictly more accurate than analysts' forecast. However, we also re-ran out analysis after deleting all observations where management's and analysts' forecasts are equally accurate. The tenor of the findings is unaffected.

[32] The marginal impact is the expected change in the probability of having a more accurate management forecast resulting from an increase in the independent variable from the 25th to the 75th percentile of the sample distribution when it is a continuous variable, from 0 to 1 if it is an indicator variable, and from one standard deviation below the mean to one standard deviation above the mean when the variable is an interaction between an indicator variable and a continuous variable, while holding all other independent variables at their means.

dummy variable highlighting actual negative demand shock. The results are similar across the two models, so we focus our discussion on model 1. The relative accuracy of management and analyst forecasts is predictably related to our main variables of interest. Specifically, the coefficients on *Cyclicality*, *Energy*, *Regulated* and *Horizon* are all negative and significant, indicating that analysts have an information advantage (i.e. managers are less accurate) when a firm's fortunes move with the broad economy (GDP) and energy costs, when the firm is either a utility or financial services institution, and when the managerial earnings forecast is issued earlier in the year.[33]

Also consistent with our predictions, managers are more accurate than analysts when it is harder for analysts to anticipate managements' actions. Specifically, the interaction between *Cost Structure* and *High Std Rev* is negative and significant in model 1, so is the interaction between *Cost Structure* and *Negative Demand Shock* in model 2. Unable to anticipate exactly how managers will respond to the change in product demand, it is difficult for analysts to anticipate the effects of high fixed costs and highly variable revenues on reported earnings.[34]

In addition, the coefficient on *Loss* is positive and significant, suggesting that managers are more accurate when they are anticipating a loss. As insiders running the firm, management

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[33]To verify our interpretation of the *Cyclicality* result, we examine the sign of management's and analysts' forecast errors in boom and bust times. If management lacks foresight at the macro level, managers might under-estimate in boom times and over-estimate in recessions for *highly cyclical* firms. We document results partially consistent with the above conjecture. Specifically, in a boom year (2004) managers tended to underestimate earnings relative to the actual earnings realization and relative to analyst forecasts. However, managers did not significantly overestimate earnings in a bust year (2001). We identify 2004 (2001) as the boom (bust) year because it has the highest (lowest) GDP growth in our sample period. We thank the referee for this suggestion.

[34]A slightly different interpretation is that analysts have a relative advantage at forecasting earnings for firms that can more easily increase or decrease production, i.e., those with largely variable costs and no capacity constraint. Conditional on demand volatility, analysts find it easier to extrapolate directly from their information advantaged forecasts of macro factors to forecasts of earnings when a firm's costs are largely variable.

knows its plans for addressing the underlying reasons for the loss and presumably the implications of its plans for reported earnings.[35]

Finally, the coefficient on the interaction between *High Inventory* and abnormal inventory (*ABI)* is positive and significant. This suggests that for firms where inventory is a significant asset class, excess inventory buildup results in an information advantage for managers. Management has either been building the inventory in anticipation of increased demand or will decide how to deal with the excess inventory through markdowns or write-offs. Management knows it plans and can anticipate better the likely effect on reported earnings.

Regarding the control variables, the coefficient on *Good News* is positive and significant. This suggests that management forecasts are more accurate (than the prevailing analysts' forecasts) when management raises investor expectations about forthcoming earnings, consistent with managers' litigation and reputation concerns. The coefficient on *LOG(Analyst)* is positive, suggesting that managers are more accurate when there is greater analyst following. Analyst forecast *Dispersion* and the *Fog Index*, which proxy for difficulty forecasting earnings and firm complexity, are not significant.[36]

To ensure that our results are unaffected by the possible measurement error that could result from management and analysts forecasting different EPS constructs, we rerun our regression using a "clean sample" where we have little doubt that the EPS constructs forecast by managers and analysts are the same. The results are presented in Table 5, Panel B; our main variables of interest remain significant in the predicted directions.

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[35]An alternative interpretation of the positive coefficient on LOSS is that analysts have incentives to avoid forecasting losses and thus are intentionally less accurate in their forecasts. See section 5.2.2 below for a more complete discussion of how incentives to issue biased forecasts affects our inferences.

[36] Instead of using the Fog Index to proxy for firm complexity, we also use two other proxies based on prior literature. The first is a measure of the amount of intangibles in a firm (Barth et al. 2001), measured as the ratios of research and development expense and advertising expense to total operating expenses for a given year, less the respective industry average ratio for that year. The second measure uses segment data to calculate firm level diversification as a measure of complexity. Neither of these alternative measures of firm complexity is significant.

Overall, inferences based on the regression analysis are consistent with our expectations: Analysts appear to have an information advantage at the macro level, for regulated firms and for longer-horizon forecasts. In contrast, managers have an information advantage because they hold key decision rights, and their relative advantage is enhanced in situations where analysts find it difficult to anticipate managers' actions and the resulting implications for forthcoming earnings. Interestingly, while analysts are commonly viewed as industry specialists, we fail to find evidence that analysts have an information advantage over managers at the industry level. Neither managers nor analysts have a forecasting advantage for firms with revenues that are more synchronous with their industries' revenues.

5. Additional Analysis and Robustness Checks

5.1 Alternative Proxies and Variables

We redefine the variable that identifies firm-years with abnormal inventory build-up. Instead of using *High Inventory* firms from all industries, we focus on retail firms as in Kesavan and Mani (2010). We interact *ABI* with a dummy variable *Retail* set to one for firms in the two-digit SIC codes 52 through 57 and 59; zero otherwise. The results (untabulated) lend support to our interpretation of coefficient on *ABI * High Inventory* and are consistent with the findings presented in Kesavan and Mani (2010).

While we argue analysts' information advantage resides at the macro level, their advantage is likely to vary across firms. Specifically, their relative advantage at the macro level should be attenuated for larger firms, as larger firms are likely to expend significant resources on forecasting macro-economic effects to improve their operational decisions. Consistent with this conjecture, when we include an interaction term: *Cyclicality* LOG(Total Assets),* the coefficient on the interaction term is positive (0.065) and significant ($p<0.01$); while the coefficient on Cyclicality remains negative (coefficient = -0.659, $p<0.01$).

Our measure of *Revenue Synchronicity* controls for seasonality by scaling sales revenue in quarter t by revenue in quarter t-4. However, if we redefine *Revenue Synchronicity* ignoring seasonality (i.e., measuring changes in revenue quarter over quarter), the tenor of the results is unaffected. Additionally we explored whether cross sectional variation in firms' *Earnings Synchronicity* with their industries is related to the relative accuracy of management's and analysts' earnings forecasts. The findings are similar to those for *Revenue Synchronicity*: neither managers nor analysts appear to have a forecasting advantage.

We perform our main analysis using Fama and French (1997) 48 industries. However, prior research indicates that alternative methods of industry classification can significantly affect tests of industry influences (Bhojraj, Lee, and Oler, 2003). To check the robustness of our findings, we redefine revenue synchronicity and other industry related variables based on the Global Industry Classification Standard (GICS). The untabulated results are very similar; all of our main inferences remain unchanged.

5.2. Measurement Error

In this paper we use *relative forecast accuracy* of analyst and management annual earnings forecasts to infer how their *information advantages* differ in relation to firm characteristics and specific firm circumstances. If the relative forecast accuracy of analysts and management is measured with error, our cross-sectional inference will be affected. Our cross-sectional regression analysis will suffer from a lack of power if the measurement error is random, however it will produce biased coefficient estimates if the measurement error is correlated with our main variables of interest. Thus, we need to specify the potential sources of the measurement error and conduct robustness checks to ensure that our inferences are valid.

Focusing on our measure of relative forecast accuracy:

|*Mean Analyst Estimate – Realized EPS*| - | *Management Forecast – Realized EPS*|,

we are able to identify the most likely sources of measurement error: First, mis-measurement of *Realized EPS* could result from managers and analysts forecasting different EPS constructs or from managers manipulating reported earnings. Second, mis-measurement of the forecasts themselves would result from analysts or management issuing intentionally biased forecasts. We address each of these in turn below.

5.2.1. Measurement error in Realized EPS

We have already addressed one possible way *Realize EPS* could be mis-measured – if the EPS construct forecast by management differs from the one forecast by analysts. We demonstrate in section 4 (Table 5 Panel B) that our results are not sensitive to this measurement error by re-estimating our cross-sectional regressions using a "clean sample", one where it is highly likely that management and analysts are focused on the same EPS construct.

Realized EPS could also be mis-measured if management manipulates reported EPS. That is, earnings management would affect our measure of relative accuracy and cause it to measure with error the relative information advantage of management and analysts. Indeed, prior research documents that managers manipulate reported earnings at year-end to meet their own forecasts (Kasznik, 1999).

To mitigate this concern, we re-run our analysis after deleting all management earnings forecasts that are not revised at least once during the fiscal year (1,264 initial forecasts are not revised). The idea behind this sub sample analysis is that managers who do not revise their initial forecasts are more likely to be beholden to their first forecasts and thus are more likely to manage earnings to meet that initial forecasts. On the other hand, managers who revise their forecasts during the fiscal year need not manage earnings to meet their initial forecast. Table 6 Panel A presents this sub sample analysis. Our main inferences remain unchanged except for the *LOSS* variable which is now insignificant. In this sub sample only 1% of the firms (compared to 2% in the full sample) experience a loss, reducing the power of the test. While this sub sample analysis does not eliminate all observations where reported earnings are likely to be manipulated, it eliminates those where the manipulation is most likely to bias our measure of relative accuracy in favor of management's first forecast of the year.

Another strategy management may follow is to manipulate reported earnings to meet / beat the mean analyst forecasts, while still ensuring that the reported EPS number falls within their range forecasts. To ensure that our results are not affected by this strategy, we re-run our analysis after deleting all management earnings forecasts for which (i) the earnings realization falls within the range of management's forecast, (ii) the actual earnings meets or beats the analyst forecast, and (iii) analyst forecast is more accurate than management forecast. Table 6 Panel B presents this sub sample analysis; our main inferences remain unchanged suggesting that such a strategy of manipulating reported earnings is unlikely to be driving our results.[37]

5.2.2. Measurement error in the forecasts – intentional bias

A second form of measurement error arises if analysts or managers intentionally biased their earnings forecasts. For instance, if analysts face incentives to avoid issuing or updating forecasts of firm losses (McNichols and O'Brien 1997), this could be an alternative explanation for the positive coefficient on *LOSS* in Table 5. Thus, we add a caveat in footnote 36.

[37] When we delete observations that meet criteria (i) and (ii) only, we obtain very similar results.

Prior research also indicates that both analysts' and managers' forecasts tend to be optimistic at the beginning of the fiscal year (with a walk down throughout the year, e.g., Richardson, Teoh and Wysocki 2004). Thus, our relative comparison of management's and analysts' forecasts made at the beginning of the year affords at least a partial correction for the bias in their forecasts. Still, we acknowledge that our relative comparison would only result in a full correction for the bias in the forecasts if the bias in the two forecasts is of the same magnitude, which is unlikely to be the case.

Prior research indicates that expectations management appears to be a primary motive for management's issuance of public earnings forecasts (e.g., Cotter Tuna and Wysocki 2006). Given negative earnings surprises are costly to firms (e.g. Matsumoto 2002, Skinner and Sloan 2002), it is conceivable that in some cases management will forecast in less than a forthright fashion and 'low ball' their estimates.

To control for this bias in management forecasts, we use two different approaches. First, we include another control variable in our main regression – the level of analysts' optimism measured at the beginning of the fiscal year (prior to the management forecasts), as analyst optimism is shown to be a key determinant of management forecast decisions (Cotter et al. 2006). Our main results remain unchanged. Second, to address the concern that managers could compromise their forecast accuracy (i.e. issue a less accurate forecast) in order to guide down overly optimistic analysts' forecasts, we also re-run our primary analysis after deleting "suspect" observations, i.e., where (i) analyst forecasts are optimistic, (ii) management forecasts are pessimistic, and (iii) management forecasts are less accurate than analyst forecasts.[38] Again, results are similar to those in our main findings.

Overall, the additional analyses conducted in this section indicate that measurement error in *Relative Accuracy* is not driving our results and that our inferences are sound.

5.3. *Alternative Specification*

Our main tests use a logit specification to focus on which party provides more accurate forecast. However, the magnitude of relative forecast errors is also informative about the relative information advantage of managers vs. analysts. To examine how the magnitude of the relative forecast errors varies with firm characteristics, we run an OLS regression with the same independent variables as in our main regression (Table 5), but redefine our dependent variable to be a continuous variable: *DIFF*= [Abs(AFE/Stock price)-Abs(MFE/Stock price)] × 100. Note that this variable is directionally consistent with the dependent variable in Table 5: when managers are more accurate, *DIFF* is positive; and when analysts are more accurate, *DIFF* is negative. Thus, our signed predictions are the same as those for Table 5.

Untabulated results are similar to Table 5 for our main variables of interest, with the exception of *Energy* and *Regulated*. The coefficient on *Energy* and *Regulated* become insignificant.[39] The coefficient on *Cyclicality* continues to be negative and significant, consistent with our expectation that analysts' advantage resides at the macro level. Variables proxying for managers' comparative advantage are also significant with the predicted signs. Interestingly, *Rev Sync* is positive and significant, indicating that analyst forecast errors are larger than management forecast errors for firms whose revenues move in synch with the industry revenues.

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[38] The three criteria are meant to capture cases where management intentionally compromises forecast accuracy in an attempt to "low ball" earnings estimates, which in turn biases our measure of relative accuracy in favor of analysts. However, if we delete observations that meeting criteria (i) and (ii) only, we obtain similar results.
[39] When ENERGY is the only macro factor included in the regression, it is significant (coefficient=-0.054, p=0.06).

While the magnitude test adds a new dimension to our analysis as it incorporates the size of the forecast errors, it assumes a linear relation between the variables of interest and the magnitude of the differences in forecast errors. Given the lack of theory on how managerial and analyst expertise at the macro, industry and firm levels affect their *relative* forecast accuracy, we are more comfortable with a less restrictive test. The logit model accommodates non-linear relations between the variables of interest and relative forecast accuracy without specifying the form of non-linearity. In addition, when the dependent variable is defined as who is more accurate, we do not have to select a scalar for the forecast errors, which is known to introduce complications in measurement (see e.g. Cheong and Thomas, 2010).

6. **Conclusion**

To our knowledge, we are the first to examine the information advantages that lead to relative accuracy of management and analyst forecasts. Our strongest finding is that analysts' forecasts are more accurate than management's when a firm's fortunes move in concert with broad macroeconomic factors. This includes not only cyclical firms, but regulated firms whose performance depends on such macro factors as interest rates and energy prices.

In contrast, management's forecasts are more accurate when the firm is experiencing unusual circumstances, such as a loss, abnormal inventory buildup, or excess capacity. In these situations, management's near-term decisions undertaken in response to the unusual circumstance greatly affect forthcoming earnings. Thus, analysts are at a disadvantage because it is difficult for them to anticipate how management will respond to the unusual situation and even more difficult for them to assess the effect of management's response on reported earnings.

We highlight and investigate the fact that management's forecasts are more accurate than analysts' forecasts only about 50% of the time. By doing so we rebuff the premise in the literature that management has an information advantage over analysts that permits its earnings guidance to substitute for the private information acquired by analysts (Diamond 1985, Altschuler 2009). Analysts bring something unique to the table, an ability to incorporate in a sophisticated and objective manner macro-level information into firm-level earnings forecasts. Thus, our empirical evidence ought to be useful to investors when forming their own earnings expectations; it suggests putting more weight on analysts' forecasts for cyclical firms, firms exposed to energy costs and regulated firms. On the other hand, investors should put more weight on management's forecasts when the firm is facing unusual circumstances, such as a loss, abnormal inventory buildup or excess capacity.

This work also suggests some future research: Early research exploring the usefulness of management earnings forecasts documents that analysts' forecast errors decrease more rapidly for firms that release management forecasts than for firms that do not (Hassell, Jennings and Lasser (1988). Our findings suggest an extension of this early line of inquiry: one could use the cross-sectional findings in this paper to propose when management forecasts are likely to be most useful in reducing analysts' forecast errors. Similarly, our evidence on when management's forecasts are more accurate can be extended to investigate cross-sectional differences in stock price reactions to management forecasts and possible trading strategies.

REFERENCES

Ai, C. and E. Norton. "Interaction Terms in Logit and Probit Models." *Economic Letters* 80 (2003): 123-129.

Ali, A., S. Klasa, E. Yeung. "The Limitations of Industry Concentration Measures Constructed with Compustat data: Implications for Finance Research. *Review of Financial Studies* 22 (2009): 3839-3871.

Anilowski, C., M. Feng and D. Skinner. "Does Earnings Guidnace Affect Market Returns? The nature and information content of aggregate earnings guidance." *Journal of Accounting and Economics*, 44 (2007): 36-63.

Altschuler, D. "Anticipation of Management Forecasts and Analysts' Incentives to Acquire Private Information." *Working Paper* (2009), Loyola University Chicago.

Anderson, M., R. Banker and S. Janakiraman. "Are Selling, General, and Administrative Costs "Sticky"?" *Journal of Accounting Research* 41 (2003): 47-63.

Baginski, S.P., E.J. Conrad, and J.M. Hassell. "The Effects of Management Forecast Precision on Equity Pricing and on the Assessment of Earnings Uncertainty." *The Accounting Review*, 68, 4 (1993): 913-27.

Baginski , S. and J. Hassell. "Determinants of Management Forecast Precision." *The Accounting Review* 72 (1997): 303-312.

Baginski, S., J. Hassell and M. Kimbrough. "The Effect of Legal Environment on Voluntary Disclosure: Evidence from Management Earnings Forecasts Issued in U.S. and Canadian Markets." *The Accounting Review* 77 (2002): 25-50.

Barth, M., R. Kasznik and M. McNichols. "Analyst Coverage and Intangible Assets." *Journal of Accounting Research* 39 (2001):1-34.

Barth, M., I. Gow and D. Taylor. "Non-GAAP and Street Earnings: Evidence from SFAS 123R." *Working Paper* (2010), Stanford University.

Bhattacharya, E. Black, T. Christensen and C. Larson. "Assessing the relative informativeness and permanence of pro forma earnings and GAAP operating earnings." *Journal of Accounting and Economics* 36 (2003): 285–319.

Ben-David, I., J. Graham and C. Harvey. "Managerial Overconfidence and Corporate Policies." *NBER Working Paper* (2007), University of Chicago and Duke University.

Bhojraj, S., C. Lee and D. Oler. "What's My Line? A Comparison of Industry Classification Schemes for Capital Market Research." *Journal of Accounting Research* 41 (2003): 745-774.

Boni, L. and K. Womack. "Analysts, Industries and Price Momentum." *Journal of Financial and Quantitative Analysis* 41 (2006): 85-109.

Bradshaw, M. and R. Sloan. "GAAP versus The Street: An Empirical Assessment of Two Alternative Definitions of Earnings." *Journal of Accounting Research* 40 (2002): 41-66.

Brown, L. and K. Sivakumar. "Comparing the Value Relevance of Two Operating Income Measures." *Review of Accounting Studies* 8 (2003): 561-572

Chen, H., M. Frank and O. Wu. "What Actually Happened to the Inventories of American Companies Between 1981 and 2000?" *Management Science* 51 (2005): 1015-1031.

Cheong, F., and J. Thomas. "Why Do EPS Forecast Error and Dispersion Not Vary with Scale? Implications for Analyst and Managerial Behavior." *Journal of Accounting Research* 49 (2011): 359-401.

Chuk, E., D. Matsumoto and G. Miller. "Assessing Methods of Identifying Management Forecasts: CIG vs. Researcher Collected" *Working Paper* (2009), University of Michigan.

Clement, M. "Analyst Forecast Accuracy: Do Ability, Resources, and Portfolio Complexity Matter?" *Journal of Accounting and Economics* (1999): 285-303.

Diamond, D. "Optimal Release of Information by Firms." *Journal of Finance* 40 (1985): 1071-1094.

Doyle, J., R. Lundholm and M. Soliman. " The Predictive Value of Expenses Excluded from Pro Forma Earnings." *Review of Accounting Studies* 8 (2003): 145-174.

Englmaier, F. "A Strategic Rationale For Having Overconfident Managers." *Working Paper* (2004), University of Munich.

Fairfield, P., S. Ramnath and T. Yohn. "Do Industry-Level Analyses Improve Forecasts of Financial Performance?" *Journal of Accounting Research* 47 (2009): 147-178.

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

Gilson, S., P. Healy and K. Palepu. "Analysts Specialization and Conglomerate Stock Breakups." *Journal of Accounting Research* 39 (2001): 565-582.

Givoly, D., C. Hayn and J. D'Souza. "Measurement Errors and Information Content of Segment Reporting." *Review of Accounting Studies* 4 (1999): 15-43.

Gu, Z., and T. Chen. "Analysts' treatment of nonrecurring items in street earnings." *Journal of Accounting and Economics* 38 (2004) : 129–170.

Hassell, J., R. Jenning and D. Lasser. "Management Earnings Forecasts: Their Usefulness as a Source of Firm-Specific Information to Security Analysts." *The Journal of Financial Research* 11 (1988): 303-320.

Heaton, J. "Managerial Optimism and Corporate Finance." *Financial Management* Summer (2002): 33-45.

Heflin, F., K.R. Subramanyam and Y. Zhang. "Regulation FD and the Financial Information Environment: Early Evidence." *The Accounting Review* 78 (2003): 1-37.

Hirshleifer, D., A. Low and S.H. Teoh. "Are Overconfident CEOs Better Innovators?" *Working Paper* (2010), University of California Irvine and Nanyang Technological University.

Hirst, D.E., L. Koonce, and J. Miller. "The Joint Effect of Management's Prior Forecast Accuracy and the Form of its Financial Forecasts on Investor Judgment." *Journal of Accounting Research*, 37, Supplement (1999): 101-24.

Hribar, P. and H. Yang. "Does CEO Overconfidence Affect Management Forecasting and Subsequent Earnings Management?"*Working Paper* (2010), University of Iowa and University of Pennsylvania.

Hutton, A. and P. Stocken. "Prior Forecasting Accuracy and Investor Reaction to Management Earnings Forecasts." *Working Paper* (2010), Boston College and Dartmouth College.

Hwang, L., C. L. Jan, and S. Basu. "Loss Firms and Analysts' Earnings Forecast Errors." *Journal of Financial Statement Analysis* 1 (1996): 18-30.

Jacob, J., T. Lyz and M. Neale. "Expertise in Forecasting Performance of Security Analysts." *Journal of Accounting and Economics* 28 (1999): 51-82.

Jennings, R. "Unsystematic Security Price Movements, Management Earnings Forecasts, and Revisions in Consensus Analyst Earnings Forecasts." *Journal of Accounting Research* 25 (1987): 90-110.

Johnson, B. and W. Schwartz. ''Are Investors Misled by Pro Forma Earnings?'' *Contemporary Accounting Research* 22 (2005): 915-963.

Kasznik, R. "On the Association between Voluntary Disclosure and Earnings Management." *Journal of Accounting Research*, Vol. 37, No. 1 (1999): 57-81.

Kesavan, S. and V. Mani. "The Predictive Power of Abnormal Inventory Growth: Application to Earnings Forecasting for Retailers." *Working Paper* (2010), University of North Carolina at Chapel Hill.

Lang, M. and R. Lundholm. "Corporate Disclosure Policy and Analyst Behavior." *The Accounting Review* 71 (1996): 467-492.

Larocque, S. "Do Managers Issue Guidance to Correct Analysts' Forecast Errors That Are Unpredicted by the Market?" *Working Paper* (2010), University of Notre Dame.

Lehavy, R., R. Li and K. Merkley. "The Effect of Annual Report Readability on Analyst Following and the Properties of Their Earnings Forecasts." *The Accounting Review*, Forthcoming.

Li, F. "Annual Report Readability, Current Earnings and Earnings Persistence." *Journal of Accounting and Economics* 45 (2008): 221-247.

Malmendier, U. and G. Tate. "CEO Overconfidence and Corporate Investment." *Journal of Finance* 60 (2005): 2661-2700.

Malmendier, U., G. Tate and J. Yan. "Corporate Financial Policies with Overconfident Managers." *NBER Working Paper* (2007).

Matsumoto, D. "Management's Incentives to Avoid Negative Earnings Surprises." *The Accounting Review* 77 (2002): 483-514.

McNichols, M. and P. C. O'Brien. "Self-selection and Analyst Coverage" *Journal of Accounting Research* 35 (1997): 167-199

Piotroski, P. and D. Roulstone. "The Influence of Analysts, Institutional Investors, and Insiders on the Incorporation of Market, Industry, and Firm-Specific Information into Stock Prices." *The Accounting Review* 79 (2004): 1119-1151.

Ramnath, S. "Investor and Analyst Reactions to Earnings Announcements of Related Firms: An Empirical Analysis." *Journal of Accounting Research* 40 (2002): 1351-1376.

Ruland, W. "The Accuracy of Forecasts by Management and by Financial Analysts." *The Accounting Review* 53 (1978): 439-447.

Schrand , C. and S. Zechman. "Executive Overconfidence and the Slippery Slope to Fraud." *Working Paper* (2010), University of Pennsylvania and University of Chicago.

Schultz, P. and M. Zaman. "Do the Individuals Closest to Internet Firms Believe They Are Overvalued." *Journal of Financial Economics* 59 (2001): 347-381.

Trueman, B. and T. Versano. "The Impact of Analyst Industry Expertise on Market Prices." *Working Paper* (2010), University of California, Los Angles.

Weiss, D. "Cost Behavior and Analysts' Earnings Forecasts." *The Accounting Review* 85 (2010): 1441-1471.

Williams, P. "The Relation Between a Prior Earnings Forecast by Management and Analyst Response to a Current Management Forecast." *The Accounting Review* 71 (1996): 103-113.

TABLE 1
Sample Selection

Panel A: General Sample

	No. of Forecasts
First Call CIG dataset of annual earnings per share forecasts, January 2001 through December 2007	31,275
Less:	
Firms that do not have any I/B/E/S analysts' forecasts 30 days before the management forecast	11,976
Management forecasts that are not the first forecast made after last period's earnings announcement	13,704
Management forecasts announced in the last quarter of the year	79
Missing data for variables used in the regression	1,472
FINAL	**4,044**

Panel B: "Clean" Sample

	No. of Forecasts
Subsample where I/B/E/S actual is equal to one of the four *Compustat* EPS	1,341
Less:	
I/B/E/S actual not in the earnings announcement press release	22
EPS construct focused on by managers in the earnings press release is inconsistent with I/B/E/S actual	45
Insufficient data for determination	67
FINAL	**1,207**

Note to Table 1:
The sample includes only point, range, one-sided directional and confirming forecasts. Figure 1 presents a diagram showing the timing of the management and analyst forecasts used in our sample.

TABLE 2

Descriptive statistics for the entire sample: 4,044 firm-year observations, 2001 to 2007

Variable	N	Mean	Std dev	25%	Median	75%
CYCLICALITY	4044	0.294	0.283	0.051	0.205	0.473
ENERGY	4044	0.222	0.240	0.029	0.129	0.343
SPREAD	4044	0.215	0.231	0.026	0.129	0.345
REVENUE SYNCHRONICITY (REVSYNC)	4044	0.175	0.199	0.021	0.096	0.265
REGULATED (0/1)	4044	0.117	0.322	0.000	0.000	0.000
COST STRUCTURE	4044	0.881	0.416	0.768	0.911	1.016
REVENUE VOLATILITY (STD REV)	4044	0.184	0.128	0.096	0.149	0.233
HIGH STD REV (0/1)	4044	0.199	0.399	0.000	0.000	0.000
*COST STRUCTURE * HIGH STD REV (0/1)*	4044	0.167	0.375	0.000	0.000	0.000
LOSS (0/1)	4044	0.020	0.140	0.000	0.000	0.000
ABNORMAL INVENTORY (ABI)	4044	-0.071	0.394	-0.240	-0.101	-0.019
INVENTORY	4044	0.116	0.144	0.005	0.069	0.166
HIGH INVENTORY (0/1)	4044	0.198	0.398	0.000	0.000	0.000
*ABI * HIGH INVENTORY (0/1)*	4044	0.026	0.222	0.000	0.000	0.000
HORIZON	4044	224	72	218	248	257
TOTAL ASSETS	4044	7072	16274	509	1623	5088
MB	4044	3.418	3.371	1.735	2.593	4.031
LEVERAGE	4044	3.226	3.213	1.598	2.197	3.239
ANALYST	4044	4.613	4.926	1.000	3.000	6.000
DISPERSION	4044	0.034	0.050	0.011	0.021	0.039
FOG INDEX	4044	19.531	1.591	18.454	19.302	20.370
HERFINDAHL	4044	0.052	0.047	0.031	0.040	0.056
POINT ESTIMATE (0/1)	4044	0.117	0.322	0.000	0.000	0.000
MF-AF	4044	-0.003	0.128	-0.030	-0.001	0.025
GOODNEWS (0/1)	4044	0.450	0.498	0.000	0.000	1.000
DEMANDSHOCK	4044	-0.002	0.124	-0.028	0.005	0.042
NEGATIVE DEMANDSHOCK (0/1)	4044	0.432	0.495	0.000	0.000	1.000
*COST STRUCTURE * NEGATIVE DEMANDSHOCK*	4044	0.372	0.506	0.000	0.000	0.859

Notes to Table 2:
All variables are defined in Appendix 1. Indicator variables are identified with a (0/1) after the names. All continuous variables are winsorized at the extreme 1%.

TABLE 3

Descriptive statistics after splitting firm-year observations based on whether management or analyst forecasts are more accurate (smaller absolute forecast error)

	Mean or Difference in Proportions			
Variable	**Management forecasts are more accurate (1)**	**Analyst forecasts are more accurate (2)**	**(1) – (2)**	**Predicted Sign**
No. of observations	1,966	2,078		
CYCLICALITY	0.281	0.307	-0.026***	-
ENERGY	0.210	0.234	-0.024***	-
SPREAD	0.210	0.221	-0.011*	-
REVENUE SYNCHRONICITY (REV SYNC)	0.177	0.174	0.004	+/-
REGULATED (0/1)	0.110	0.124	-0.014	-
COST STRUCTURE	0.872	0.889	-0.017	
REVENUE VOLATILITY (STD REV)	0.186	0.182	0.003	
HIGH STD REV (0/1)	0.209	0.188	0.021**	
*COST STRUCTURE * HIGH STD REV (0/1)*	0.164	0.170	-0.006	-
LOSS (0/1)	0.026	0.014	0.012***	+
ABNORMAL INVENTORY (ABI)	-0.067	-0.076	0.009	
INVENTORY	0.118	0.113	0.005	
HIGH INVENTORY (0/1)	0.188	0.194	-0.007	
*ABI * HIGH INVENTORY (0/1)*	0.034	0.019	0.016***	+
HORIZON	218	231	-13***	-
DEMANDSHOCK	-0.006	0.002	-0.008**	
NEGATIVE DEMANDSHOCK (0/1)	0.464	0.401	0.063***	
*COST STRUCTURE * NEGATIVE DEMANDSHOCK*	0.376	0.368	0.008	-
Control variables				
TOTAL ASSETS	6881	7254	-373	
MB	3.360	3.473	-0.113	
LEVERAGE	3.153	3.296	-0.143	
ANALYST	4.786	4.448	0.338***	
DISPERSION	0.034	0.034	0.001	
FOG INDEX	19.547	19.516	0.031	
HERFINDAHL	0.052	0.053	-0.002	
POINT ESTIMATE (0/1)	0.120	0.114	0.006	
GOODNEWS (0/1)	0.519	0.385	0.133***	
MF-AF	-0.010	0.004	-0.014***	

Notes to Table 3
All variables are defined in Appendix 1. Indicator variables are identified with a (0/1) after the names. All continuous variables are winsorized at the extreme 1%. *, ** and *** represent significance at 10%, 5% and 1% respectively (2-tailed). In the column (1)-(2), we test the differences in means of continuous variables using the t-test and the differences in proportions of indicator variables using the chi-square test.

TABLE 4
Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1. CYCLICALITY		0.375	0.664	0.022	0.003	0.047	0.002	-0.003	-0.041	-0.037	0.016	-0.031	0.087	0.023	0.027	-0.066	0.042	0.028	0.013	-0.005	-0.097
		(0.000)	(0.000)	(0.154)	(0.851)	(0.003)	(0.877)	0.826)	(0.011)	(0.019)	(0.306)	(0.046)	(0.000)	(0.135)	(0.081)	(0.000)	(0.008)	(0.076)	(0.403)	(0.758)	(0.000)
2. ENERGY	0.282		0.379	0.014	-0.016	0.050	-0.012	0.009	-0.025	-0.030	0.036	-0.009	0.083	-0.021	0.059	-0.045	0.066	0.021	-0.013	-0.010	0.000
	(0.000)		(0.000)	(0.370)	(0.306)	(0.002)	(0.461)	(0.545)	(0.111)	(0.053)	(0.023)	(0.573)	(0.000)	(0.173)	(0.000)	(0.004)	(0.000)	(0.174)	(0.411)	(0.532)	(0.979)
3. SPREAD	0.623	0.260		0.038	0.031	0.046	0.008	0.006	-0.025	-0.008	0.035	-0.019	0.065	0.056	0.025	-0.023	0.007	0.012	0.007	0.000	-0.038
	(0.000)	(0.000)		(0.016)	(0.045)	(0.004)	(0.608)	(0.700)	(0.117)	(0.620)	(0.024)	(0.237)	(0.000)	(0.000)	(0.116)	(0.143)	(0.646)	(0.456)	(0.652)	(0.992)	(0.017)
4. REV SYNC	0.008	0.015	0.021		0.089	-0.003	0.045	0.016	-0.031	-0.027	0.010	0.036	-0.002	0.013	0.004	0.050	0.009	-0.062	0.019	0.013	-0.010
	(0.622)	(0.354)	(0.180)		(0.000)	(0.851)	(0.005)	(0.322)	(0.050)	(0.090)	(0.530)	(0.024)	(0.906)	(0.416)	(0.823)	(0.001)	(0.589)	(0.000)	(0.236)	(0.409)	(0.536)
5. REGULATED	-0.017	-0.018	0.012	0.064		0.000	0.092	-0.030	0.018	-0.152	-0.056	0.313	-0.115	0.474	-0.086	-0.015	0.095	-0.191	0.002	0.045	0.054
	(0.288)	(0.246)	(0.445)	(0.000)		(0.999)	(0.000)	(0.056)	(0.267)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.324)	(0.000)	(0.000)	(0.876)	(0.004)	(0.000)
6. COST	0.102	0.092	0.083	-0.006	0.033		-0.033	-0.137	0.011	0.033	0.043	0.139	-0.032	0.056	0.048	-0.051	-0.008	0.002	-0.051	-0.008	-0.147
	(0.000)	(0.000)	(0.000)	(0.723)	(0.033)		(0.038)	(0.000)	(0.486)	(0.036)	(0.006)	(0.000)	(0.043)	(0.000)	(0.002)	(0.001)	(0.594)	(0.899)	(0.001)	(0.605)	(0.000)
7. HIGH STD REV	-0.021	-0.047	-0.021	0.041	0.092	-0.057		0.134	0.101	0.060	-0.060	-0.145	0.030	-0.060	-0.018	0.030	-0.005	-0.033	0.059	0.010	-0.004
	(0.191)	(0.003)	(0.171)	(0.010)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.053)	(0.000)	(0.249)	(0.053)	(0.751)	(0.037)	(0.000)	(0.515)	(0.804)
8. LOSS	-0.001	0.008	0.007	0.021	-0.030	-0.119	0.134		-0.026	-0.038	-0.096	-0.135	0.009	-0.059	-0.017	-0.201	0.010	-0.013	0.035	-0.005	0.043
	(0.944)	(0.601)	(0.635)	(0.173)	(0.056)	(0.000)	(0.000)		(0.099)	(0.016)	(0.000)	(0.000)	(0.584)	(0.000)	(0.277)	(0.000)	(0.506)	(0.422)	(0.024)	(0.741)	(0.006)
9. ABI	-0.064	-0.033	-0.035	-0.045	0.001	-0.025	0.107	-0.032		0.259	0.002	-0.037	-0.004	0.014	0.023	0.000	-0.052	-0.076	0.023	0.036	0.037
	(0.000)	(0.036)	(0.030)	(0.005)	(0.961)	(0.124)	(0.000)	(0.043)		(0.000)	(0.887)	(0.020)	(0.804)	(0.378)	(0.157)	(0.992)	(0.001)	(0.000)	(0.146)	(0.024)	(0.021)
10. HIGH INV	-0.031	-0.037	-0.001	-0.011	-0.152	0.039	0.060	-0.038	0.263		0.009	-0.125	-0.079	-0.121	0.048	0.000	-0.118	0.031	-0.014	0.000	0.049
	(0.047)	(0.018)	(0.966)	(0.503)	(0.000)	(0.012)	(0.000)	(0.016)	(0.000)		(0.551)	(0.000)	(0.000)	(0.000)	(0.002)	(0.985)	(0.000)	(0.046)	(0.367)	(0.985)	(0.002)
11. HORIZON	0.021	0.027	0.035	0.025	-0.025	0.048	-0.057	-0.096	0.020	0.040		0.163	0.038	-0.002	0.067	0.004	0.015	0.025	-0.067	0.027	-0.036
	(0.186)	(0.081)	(0.027)	(0.112)	(0.114)	(0.002)	(0.000)	(0.000)	(0.203)	(0.010)		(0.000)	(0.015)	(0.876)	(0.000)	(0.780)	(0.343)	(0.104)	(0.000)	(0.081)	(0.020)
12. SIZE	-0.025	-0.010	-0.020	0.019	0.310	0.196	-0.140	-0.129	-0.037	-0.128	0.193		-0.034	0.440	0.330	-0.074	0.089	-0.004	-0.021	-0.012	-0.012
	(0.107)	(0.531)	(0.205)	(0.239)	(0.000)	(0.000)	(0.000)	(0.000)	(0.020)	(0.000)	(0.000)		(0.029)	(0.000)	(0.000)	(0.000)	(0.000)	(0.816)	(0.190)	(0.446)	(0.430)
13. MB	0.145	0.142	0.120	0.000	-0.156	-0.031	0.013	-0.009	-0.038	-0.117	0.108	-0.018		0.204	0.131	-0.062	-0.019	0.049	0.046	-0.042	-0.019
	(0.000)	(0.000)	(0.000)	(0.984)	(0.000)	(0.048)	(0.400)	(0.588)	(0.018)	(0.000)	(0.000)	(0.245)		(0.000)	(0.000)	(0.000)	(0.237)	(0.002)	(0.003)	(0.007)	(0.222)
14. LEVERAGE	-0.041	-0.080	-0.007	0.039	0.404	0.142	-0.071	-0.093	-0.067	-0.077	0.039	0.554	-0.055		0.002	-0.004	0.024	-0.067	0.005	0.019	0.050
	(0.009)	(0.000)	(0.660)	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.014)	(0.000)	(0.000)		(0.895)	(0.794)	(0.131)	(0.000)	(0.747)	(0.222)	(0.001)
15. ANALYST	0.027	0.053	0.022	-0.001	-0.084	0.062	-0.016	-0.018	0.050	0.047	0.093	0.321	0.205	0.013		-0.013	0.032	-0.004	0.015	-0.029	-0.026
	(0.089)	(0.000)	(0.153)	(0.940)	(0.000)	(0.000)	(0.321)	(0.251)	(0.002)	(0.003)	(0.000)	(0.000)	(0.000)	(0.400)		(0.392)	(0.039)	(0.776)	(0.335)	(0.061)	(0.093)
16. DISPERSION	-0.073	-0.046	-0.041	0.032	-0.013	-0.046	0.074	-0.163	0.005	0.000	-0.048	-0.031	-0.139	-0.008	0.034		0.037	-0.008	-0.009	0.061	0.032
	(0.000)	(0.003)	(0.009)	(0.044)	(0.390)	(0.004)	(0.000)	(0.000)	(0.770)	(0.987)	(0.002)	(0.051)	(0.000)	(0.598)	(0.030)		(0.018)	(0.616)	(0.559)	(0.000)	(0.039)
17. FOG INDEX	0.029	0.063	-0.006	0.018	0.091	-0.008	-0.007	0.022	-0.035	-0.140	-0.019	0.078	-0.007	0.048	0.036	0.031		-0.015	0.008	-0.018	-0.026
	(0.063)	(0.000)	(0.719)	(0.260)	(0.000)	(0.594)	(0.670)	(0.159)	(0.028)	(0.000)	(0.228)	(0.000)	(0.658)	(0.002)	(0.023)	(0.048)		(0.349)	(0.608)	(0.255)	(0.100)
18. HERF	0.008	0.011	-0.005	-0.095	-0.381	-0.009	-0.079	0.001	-0.121	0.067	0.044	-0.116	0.152	-0.174	-0.009	-0.029	-0.041		0.026	-0.038	-0.041
	(0.605)	(0.467)	(0.761)	(0.000)	(0.000)	(0.585)	(0.000)	(0.958)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.582)	(0.067)	(0.009)		(0.096)	(0.015)	(0.008)
19. POINT	0.008	-0.010	0.000	0.008	0.002	-0.067	0.059	0.035	-0.004	-0.014	-0.044	-0.020	0.054	-0.032	0.013	-0.030	0.005	0.022		0.020	-0.010
	(0.606)	(0.540)	(0.996)	(0.607)	(0.876)	(0.000)	(0.000)	(0.024)	(0.792)	(0.367)	(0.005)	(0.213)	(0.000)	(0.044)	(0.397)	(0.057)	(0.753)	(0.164)		(0.210)	(0.531)
20. GOODNEWS	-0.001	-0.003	0.009	0.016	0.045	0.000	0.010	-0.005	0.019	0.000	0.030	-0.008	-0.063	0.015	-0.028	0.055	-0.010	-0.018	0.020		-0.011
	(0.927)	(0.849)	(0.547)	(0.311)	(0.004)	(0.991)	(0.515)	(0.741)	(0.229)	(0.986)	(0.057)	(0.626)	(0.000)	(0.344)	(0.078)	(0.000)	(0.528)	(0.256)	(0.210)		(0.490)
21. NEG	-0.092	-0.012	-0.033	-0.004	0.054	-0.075	-0.004	0.043	0.022	0.049	-0.026	-0.009	-0.067	0.050	-0.028	0.000	-0.015	-0.049	-0.010	-0.011	
DEMANDSHOCK	(0.000)	(0.439)	(0.037)	(0.777)	(0.000)	(0.000)	(0.804)	(0.006)	(0.178)	(0.002)	(0.092)	(0.570)	(0.000)	(0.002)	(0.077)	(0.996)	(0.349)	(0.002)	(0.531)	(0.490)	

Notes to Table 4:
This table reports the Pearson (Spearman) correlation on the upper (lower) diagonal. Two tailed p-values are presented in parentheses. All variables are defined in Appendix 1. All continuous variables are winsorized at the extreme 1%.

TABLE 5
Logistic regressions modeling the probability that management's annual earnings forecasts are more accurate than analysts' forecasts

Panel A: General Sample

$Pr(MGR_{i,t}=1) = f\,(CYCLICALITY_{i,t-1}, ENERGY_{i,t-1}, SPREAD_{i,t-1}, REV\ SYNC_{i,t-1}, REGULATED_{i,t}, COST\ STRUCTURE_{i,t-1}, X_{i,t-1}, COST\ STRUCTURE{*}\ X_{t-1}, LOSS_{i,t}, ABI_{i,t-1}, HIGH\ INVENTORY_{i,t-1}, ABI{*}\ HIGH\ INVENTORY_{i,t-1}, HORIZON_{i,t}, LN(TOTAL\ ASSETS)_{i,t-1}, MB_{i,t-1}, LEVERAGE_{i,t-1}, LN(ANALYST)_{i,t}, DISPERSION_{i,t-1}, FOG\ INDEX_{i,t-1}, HERFINDAHL_{i,t}, POINT\ ESTIMATE_{i,t}, GOODNEWS_{i,t})$

Variable	Predicted Sign	(1) Coeff	(1) Z-stat	(1) Marginal Impact	(2) Coeff	(2) Z-stat	(2) Marginal Impact
INTERCEPT		-0.262	-0.57		-0.480	-1.04	
CYCLICALITY	-	-0.335**	-2.07	-0.033	-0.350**	-2.32	-0.034
ENERGY	-	-0.314**	-2.08	-0.023	-0.296*	-1.85	-0.022
SPREAD	-	0.268	1.34	0.020	0.244	1.24	0.018
REV SYNC	+/-	0.135	0.83	0.008	0.030	0.17	0.002
REGULATED (0/1)	-	-0.254**	-1.97	-0.061	-0.210*	-1.66	-0.050
COST STRUCTURE		-0.012	-0.14	-0.001	0.164	1.55	0.009
HIGH STD REV (0/1)		0.235**	2.09	0.054			
*COST STRUCTURE * HIGH STD REV*	-	-0.071**	-2.26	-0.012			
NEGATIVE DEMANDSHOCK (0/1)					0.585***	3.55	0.134
*COST STRUCTURE * NEGATIVE DEMANDSHOCK*	-				-0.107**	-2.39	-0.025
MF LOSS (0/1)	+	0.441*	1.74	0.096	0.432*	1.71	0.094
ABI (ABNORMAL INVENTORY)		-0.095	-0.97	-0.005	-0.069	-0.69	-0.004
HIGH INVENTORY (0/1)		-0.086	-0.87	-0.020	-0.098	-1.01	-0.023
*ABI * HIGH INVENTORY*	+	0.098**	2.10	0.010	0.096**	2.07	0.010
HORIZON	-	-0.002***	-4.54	-0.017	-0.002***	-4.24	-0.018
LOG(TOTAL ASSETS)		-0.031	-1.16	-0.017	-0.033	-1.25	-0.018
MB		-0.007	-0.70	-0.004	-0.010	-0.93	-0.005
LEVERAGE		0.000	0.01	0.000	-0.004	-0.29	-0.002
LOG(ANALYST)		0.139***	3.29	0.166	0.140***	3.33	0.168
DISPERSION		0.059	0.08	0.000	-0.314	-0.44	-0.002
FOG INDEX		0.035	1.60	0.016	0.034	1.59	0.015
HERFINDAHL		-0.794	-0.96	-0.005	-0.715	-0.88	-0.004
POINT (0/1)		-0.059	-0.55	-0.014	-0.036	-0.34	-0.008
GOODNEWS (0/1)		0.621***	7.93	0.143	0.603***	7.66	0.139
N		4,044			4,044		
Pseudo R^2		2.92%			3.06%		

Notes to Table 5 Panel A:

In the regression equation, X = *HIGH STD REV* in column (1) and X = *NEGATIVE DEMANDSHOCK* in column (2). All variables are defined in Appendix 1. Indicator variables are identified with a (0/1) after the names. All continuous variables are winsorized at the extreme 1%. *, ** and *** represent significance at 10%, 5% and 1% (2-tailed). Standard errors are clustered by firm. The magnitude and standard error of *COST STRUCTURE * HIGH STD REV* and *ABI*HIGH INVENTORY* are estimated based on Ai and Norton (2003). Marginal impact is the expected change in the probability of having a more accurate management forecast (MGR=1) resulting from an increase in each independent variable from the 25th to the 75th percentile of the sample distribution when it is a continuous variable, from 0 to 1 if it is an indicator variable, and from one standard deviation below the mean to one standard deviation above the mean when the variable is an interaction between an indicator variable and a continuous variable, while holding all other independent variables at their means.

TABLE 5 (CONTINUED)

Logistic regressions modeling the probability that management's annual earnings forecasts are more accurate than analysts' forecasts

Panel B: Clean Sample

$Pr(MGR_{i,t}=1) = f$ ($CYCLICALITY_{i,t-1}$, $ENERGY_{i,t-1}$, $SPREAD_{i,t-1}$, $REV\ SYNC_{i,t-1}$, $REGULATED_{i,t}$, $COST\ STRUCTURE_{i,t-1}$, $X_{i,t-1}$, $COST\ STRUCTURE* X_{t-1}$, $LOSS_{i,t}$, $ABI_{i,t-1}$, $HIGH\ INVENTORY_{i,t-1}$, $ABI* HIGH\ INVENTORY_{i,t-1}$, $HORIZON_{i,t}$, $LN(TOTAL\ ASSETS)_{i,t-1}$, $MB_{i,t-1}$, $LEVERAGE_{i,t-1}$, $LN(ANALYST)_{i,t}$, $DISPERSION_{i,t-1}$, $FOG\ INDEX_{i,t-1}$, $HERFINDAHL_{i,t}$, $POINT\ ESTIMATE_{i,t}$, $GOODNEWS_{i,t}$)

Variable	Predicted Sign	(1) Coeff	(1) Z-stat	(1) Marginal Impact	(2) Coeff	(2) Z-stat	(2) Marginal Impact
INTERCEPT		1.735**	2.16		1.512*	1.83	
CYCLICALITY	-	-0.657**	-2.16	-0.083	-0.761**	-2.41	-0.096
ENERGY	-	-0.531**	-2.09	-0.048	-0.422*	-1.83	-0.038
SPREAD	-	-0.108	-0.32	-0.010	-0.119	-0.36	-0.011
REV SYNC	+/-	-0.015	-0.05	-0.001	-0.032	-0.10	-0.002
REGULATED (0/1)	-	-0.687*	-1.67	-0.168	-0.747*	-1.83	-0.183
COST STRUCTURE		-0.115	-0.52	-0.006	0.105	0.35	0.005
HIGH STD REV (0/1)		1.113*	1.88	0.259			
*COST STRUCTURE * HIGH STD REV*	-	-0.303***	-2.58	-0.054			
NEGATIVE DEMANDSHOCK (0/1)					0.416	1.16	0.103
*COST STRUCTURE * NEGATIVE DEMANDSHOCK*	-				-0.159*	-1.87	-0.039
MF LOSS (0/1)	+	1.133*	1.68	0.250	1.275*	1.93	0.271
ABI (ABNORMAL INVENTORY)		0.175	0.87	0.011	0.145	0.76	0.009
HIGH INVENTORY (0/1)		-0.386**	-2.11	-0.096	-0.428**	-2.34	-0.107
*ABI * HIGH INVENTORY*	+	0.168**	2.20	0.018	0.172**	2.38	0.018
HORIZON	-	-0.004***	-4.72	-0.038	-0.004***	-4.66	-0.038
LOG(TOTAL ASSETS)		-0.091**	-1.80	-0.050	-0.087*	-1.78	-0.047
MB		0.028	1.30	0.016	0.027	1.41	0.015
LEVERAGE		-0.031	-1.17	-0.010	-0.034	-1.28	-0.011
LOG(ANALYST)		-0.010	-0.12	-0.004	-0.006	-0.08	-0.002
DISPERSION		0.939	0.59	0.006	0.711	0.45	0.004
FOG INDEX		0.003	0.08	0.001	0.008	0.22	0.004
HERFINDAHL		-1.528	-1.30	-0.010	-1.459	-1.22	-0.010
POINT (0/1)		0.403*	1.81	0.099	0.368*	1.69	0.090
GOODNEWS (0/1)		0.675***	4.74	0.166	0.659***	4.64	0.162
N		1,207			1,207		
Pseudo R^2		8.57%			8.53%		

Notes to Table 5 Panel B:

In the regression equation, *X* = *HIGH STD REV* in column (1) and *X* = *NEGATIVE DEMANDSHOCK* in column (2). All variables are defined in Appendix 1. Indicator variables are identified with a (0/1) after the names. All continuous variables are winsorized at the extreme 1%. *, ** and *** represent significance at 10%, 5% and 1% (2-tailed). Standard errors are clustered by firm. The magnitude and standard error of *COST STRUCTURE * HIGH STD REV* and *ABI*HIGH INVENTORY* are estimated based on Ai and Norton (2003). Marginal impact is the expected change in the probability of having a more accurate management forecast (MGR=1) resulting from an increase in each independent variable from the 25th to the 75th percentile of the sample distribution when it is a continuous variable, from 0 to 1 if it is an indicator variable, and from one standard deviation below the mean to one standard deviation above the mean when the variable is an interaction between an indicator variable and a continuous variable, while holding all other independent variables at their means.

TABLE 6
Logistic regressions modeling the probability that management's annual earnings forecasts are more accurate than analysts' forecasts

Panel A: Sample of firms where managers revise their earnings forecasts

$Pr(MGR_{i,t}=1) = f\,(CYCLICALITY_{i,t-1}, ENERGY_{i,t-1}, SPREAD_{i,t-1}, REV\ SYNC_{i,t-1}, REGULATED_{i,t}, COST\ STRUCTURE_{i,t-1}, HIGH\ STD\ REV_{i,t-1}, COST\ STRUCTURE{*}\ HIGH\ STD\ REV_{t-1}, LOSS_{i,t}, ABI_{i,t-1}, HIGH\ INVENTORY_{i,t-1}, ABI{*}\ HIGH\ INVENTORY_{i,t-1}, HORIZON_{i,t}, LN(TOTAL\ ASSETS)_{i,t-1}, MB_{i,t-1}, LEVERAGE_{i,t-1}, LN(ANALYST)_{i,t}, DISPERSION_{i,t-1}, FOG\ INDEX_{i,t-1}, HERFINDAHL_{i,t}, POINT\ ESTIMATE_{i,t}, GOODNEWS_{i,t})$

Variable	Predicted Sign	(1) Coefficient	(1) Z-stat	(2) Coefficient	(2) Z-stat
INTERCEPT		-0.298	-0.55	-0.528	-0.97
CYCLICALITY	-	-0.401**	-2.19	-0.442**	-2.41
ENERGY	-	-0.394**	-2.04	-0.340*	-1.75
SPREAD	-	0.370	1.49	0.366	1.48
REV SYNC	+/-	0.056	0.28	0.059	0.30
REGULATED (0/1)	-	-0.356**	-2.22	-0.338**	-2.14
COST STRUCTURE		0.014	0.14	0.209	1.59
HIGH STD REV (0/1)		0.318**	2.36		
*COST STRUCTURE * HIGH STD REV*	-	-0.076**	-2.02		
NEGATIVE DEMANDSHOCK (0/1)				0.579***	2.95
*COST STRUCTURE * NEGATIVE DEMANDSHOCK*	-			-0.117**	-2.18
MF LOSS (0/1)	+	0.046	0.10	0.102	0.24
ABI (ABNORMAL INVENTORY)		-0.159	-1.32	-0.037	-0.32
HIGH INVENTORY (0/1)		-0.043	-0.37	-0.166	-1.37
*ABI * HIGH INVENTORY*	+	0.166***	2.91	0.169***	2.98
HORIZON	-	-0.003***	-4.47	-0.003***	-4.32
LOG(TOTAL ASSETS)		-0.030	-0.97	-0.035	-1.17
MB		-0.008	-0.71	-0.009	-0.76
LEVERAGE		0.004	0.25	0.001	0.08
LOG(ANALYST)		0.137***	2.71	0.141***	2.80
DISPERSION		0.045	0.05	-0.090	-0.10
FOG INDEX		0.047*	1.86	0.046*	1.84
HERFINDAHL		-1.428*	-1.80	-1.344*	-1.70
POINT (0/1)		0.240*	1.71	-0.211	1.53
GOODNEWS (0/1)		0.787***	8.58	0.781***	8.44
N		2,780		2,780	
Pseudo R^2		4.17%		4.29%	

Notes to Table 6 Panel A:
In this table we only use observations where managers revise their forecasts, where managers have provided more than one forecasts during the year and $MF_j \neq MF_i$. All variables are defined in Appendix 1. All continuous variables are winsorized at the extreme 1%. *, ** and *** represent significance at 10%, 5% and 1% (2-tailed). Standard errors are clustered by firm. The magnitude and standard error of *COST STRUCTURE * HIGH STD REV* and *ABI*HIGH INVENTORY* are estimated based on Ai and Norton (2003).

TABLE 6

Logistic regressions modeling the probability that management's annual earnings forecasts are more accurate than analysts' forecasts

Panel B: Sample excluding firm-years when actual earnings falls within the MF range, actual earnings >=AF and AF is more accurate than MF

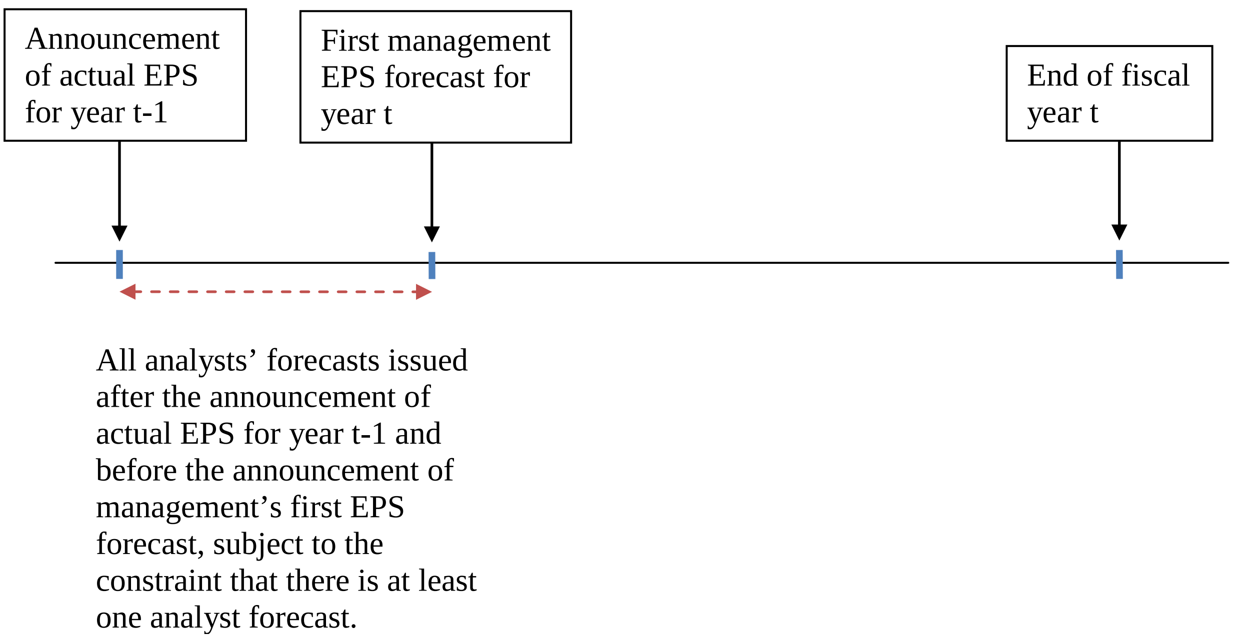
$Pr(MGR_{i,t}=1) = f\,(CYCLICALITY_{i,t-1}, ENERGY_{i,t-1}, SPREAD_{i,t-1}, REV\ SYNC_{i,t-1}, REGULATED_{i,t}, COST\ STRUCTURE_{i,t-1}, HIGH\ STD\ REV_{i,t-1}, COST\ STRUCTURE^*\ HIGH\ STD\ REV_{t-1}, LOSS_{i,t}, ABI_{i,t-1}, HIGH\ INVENTORY_{i,t-1}, ABI^*\ HIGH\ INVENTORY_{i,t-1}, HORIZON_{i,t}, LN(TOTAL\ ASSETS)_{i,t-1}, MB_{i,t-1}, LEVERAGE_{i,t-1}, LN(ANALYST)_{i,t}, DISPERSION_{i,t-1}, FOG\ INDEX_{i,t-1}, HERFINDAHL_{i,t}, POINT\ ESTIMATE_{i,t}, GOODNEWS_{i,t})$

Variable	Predicted Sign	(1) Coefficient	(1) Z-stat	(2) Coefficient	(2) Z-stat
INTERCEPT		-0.235	-0.50	-0.478	-1.00
CYCLICALITY	-	-0.360**	-2.17	-0.334**	-2.03
ENERGY	-	-0.263*	-1.71	-0.288*	-1.78
SPREAD	-	0.257	1.25	0.246	1.21
REV SYNC	+/-	0.133	0.80	0.133	0.80
REGULATED (0/1)	-	-0.239*	-1.83	-0.248*	-1.92
COST STRUCTURE		-0.002	-0.02	0.146	1.33
HIGH STD REV (0/1)		0.233**	2.05		
*COST STRUCTURE * HIGH STD REV*	-	-0.267**	-2.29		
NEGATIVE DEMANDSHOCK (0/1)				0.525***	3.10
*COST STRUCTURE * NEGATIVE DEMANDSHOCK*	-			-0.326**	-1.96
MF LOSS (0/1)	+	0.491*	1.92	0.478*	1.87
ABI (ABNORMAL INVENTORY)		-0.084	-0.84	-0.094	-0.94
HIGH INVENTORY (0/1)		-0.080	-0.79	-0.092	-0.91
*ABI * HIGH INVENTORY*	+	0.348**	1.96	0.365**	2.06
HORIZON	-	-0.003***	-4.99	-0.003***	-4.86
LOG(TOTAL ASSETS)		-0.027	-1.00	-0.028	-1.06
MB		-0.004	-0.35	-0.004	-0.37
LEVERAGE		-0.004	-0.28	-0.006	-0.44
LOG(ANALYST)		0.115***	2.69	0.115***	2.68
DISPERSION		0.104	0.14	-0.082	-0.11
FOG INDEX		0.040*	1.80	0.040*	1.81
HERFINDAHL		-0.830	-0.97	-0.783	-0.92
POINT (0/1)		-0.133	-1.23	-0.114	-1.06
GOODNEWS (0/1)		0.602***	7.56	0.595***	7.41
N		3,939		3,939	
Pseudo R^2		2.85%		3.04%	

Notes to Table 6 Panel B:
In this table we exclude observations where the actual earnings realization falls within the manager's forecast range, actual earnings is greater than or equal to analyst forecast and AF is more accurate than MF. All variables are defined in Appendix 1. All continuous variables are winsorized at the extreme 1%. *, ** and *** represent significance at 10%, 5% and 1% (2-tailed). Standard errors are clustered by firm. The magnitude and standard error of *COST STRUCTURE * HIGH STD REV* and *ABI*HIGH INVENTORY* are estimated based on Ai and Norton (2003).

FIGURE 1
Timing of Management and Analyst Forecasts

Management's first EPS forecast for year t issued *after* the announcement of actual EPS for year t-1.



APPENDIX 1

Variable definitions (Compustat data items in parentheses):

MGR	Indicator variable set to 1 when the absolute value of the management forecast error is smaller than the absolute value of the analyst forecast error. Management forecast error is measured as the first management earnings forecast for year t issued after the announcement of earnings for year t-1, minus the actual earnings for year t. Analyst forecast error is measured as the mean of all analyst forecasts issued thirty days before the first management forecast minus the actual earnings. The variable is set to 0 otherwise.
CYCLICALITY	Cyclicality is measured as the R^2 from the firm-level estimation of the model over the prior 12 quarters: $EARN_{i,t} = \alpha_0 + \alpha_1\ GDP_t + \varepsilon_{i,t}$ where *EARN* is defined as income before extraordinary item (ibq) and *GDP* is the nominal quarterly Gross Domestic Product.
ENERGY	Energy is measured as the R^2 from the firm-level estimation of the model over the prior 12 quarters: $EARN_{i,t} = \alpha_0 + \alpha_1\ ENERGY_t + \varepsilon_{i,t}$ where *EARN* is defined as income before extraordinary item (ibq) and *ENERGY* is the nominal energy price index.
SPREAD	Spread is measured as the R^2 from the firm-level estimation of the model over the prior 12 quarters: $EARN_{i,t} = \alpha_0 + \alpha_1\ SPREAD_t + \varepsilon_{i,t}$ where *EARN* is defined as income before extraordinary item (ibq) and *SPREAD* is defined as the 30-year mortgage rate minus the 1-year U.S. Treasury bill rate.
REVENUE SYNCHRONICITY (REV SYNC)	Revenue synchronicity is measured as the R^2 from the firm-level estimation of the model over the prior 12 quarters: $REV_{i,t} = \alpha_0 + \alpha_1\ INDREV_t + \varepsilon_{i,t}$ where *REV* is defined as revenue (saleq) divided by lagged four-quarter revenue for firm i and *INDREV* is the sum of revenue (saleq) for all firms in the industry (excluding firm i) divided by lagged four-quarter revenue for all firms (excluding firm i) in the industry. The industry classification is based on Fama and French (1997).
REGULATED	Indicator variable set to 1 if the firm operates in a regulated industry, defined as the four-digit SIC codes 4900-4999 (utilities), 6000-6099, 6100-6199 (banking), and 6200-6299, 6700-6799 (financial institutions), 0 otherwise.
COST STRUCTURE	Cost structure is measured as the estimated coefficient (β_1) from the firm-level regression using the prior 12 quarters: $LOG(EXP_t\ /\ EXP_{t-1}) = \beta_0 + \beta_1 LOG(REV_t\ /REV_{t-1}) + \varepsilon_{i,t}$. The model is based on Anderson et al. (2003) where *REV* is defined as revenue (saleq) and *EXP* is defined as revenue (saleq) minus income before extraordinary item (ibq).
REVENUE VOLATILITY (STD REV)	Standard deviation of revenue (saleq) measured over the prior 12 quarters scaled by the mean revenue over the same time period.
HIGH STD REV	Indicator variable set to 1 if the firm-year is in the top quintile of *REVENUE VOLATILITY* and 0 otherwise.
LOSS	Indicator variable set to 1 if the management forecast is less than 0 and 0 otherwise.
INVENTORY	Inventory (invt) divided by total assets (at).
HIGH INVENTORY	Indicator variable set to 1 if the firm-year is in the top quintile of *INVENTORY* and 0 otherwise.
ABNORMAL INVENTORY (ABI)	Normalized deviation from the industry days inventory measured as (DI_{it} – Industry mean DI_t) /Industry standard deviation of DI_t where DI = inventory (invt) * 365) / cost of goods sold (cogs). This measure is based on Chen et al. (2005) and Kesavan and Mani (2010). Industry classification is based on Fama and French (1997).

APPENDIX 1 (CONTINUED)

Variable definitions (Compustat data items in parentheses):

HORIZON	Number of days between the date of the management forecast and the end of the fiscal year.
SIZE = LN(ASSETS)	Natural logarithm of total assets (at), measured at the end of the prior fiscal year.
MB	Market value of equity (prcc_f*csho) divided by book value of equity (ceq), measured at the end of the prior fiscal year.
LEVERAGE	Total assets (at) divided by book value of equity (ceq) measured at the end of the prior fiscal year.
ANALYST FOLLOWING = LN(ANALYST)	Natural logarithm of the number of analyst forecasts issued thirty days before the management forecast.
DISPERSION	Standard deviation of the consensus analyst forecasts scaled by the mean consensus analyst forecast, both measured in the month prior to the management forecast.
FOG INDEX	Measure of the readability of the firm's prior period's 10-K filings based on Li (2008).
HERFINDAHL	Herfindahl Index is a measure of industry concentration and is defined as $\sum_{i=1}^{N} MKTSHARE_i^2$ where *MKTSHARE* is the market share for each firm in the industry. Market share for firm i is measured as the revenue for firm i divided by total revenue for all firms in the industry. Industry classification is based on Fama and French (1997).
POINT	Indicator variable set to 1 if management forecast is a point estimate and 0 otherwise.
GOOD NEWS	Indicator variable set to 1 if management forecast is strictly greater than analyst forecast and 0 otherwise.
DEMAND SHOCK	Demand unanticipated by analysts defined as (Actual Revenue – Analyst Consensus Revenue Forecast)/Actual Revenue. Analyst consensus revenue forecast is measured in the month prior to the management forecast.
NEGATIVE DEMAND SHOCK	Indicator variable set to 1 if (Actual Revenue – Analyst Consensus Revenue Forecast) <0 and 0 otherwise. Analyst consensus revenue forecast is measured in the month prior to the management forecast.

APPENDIX 2
Descriptive Statistics by Industry

Panel A: Mean and Median Cyclicality, Energy and Spread by Industry

INDUSTRY	CYCLICALITY		ENERGY		SPREAD	
	Mean	Median	Mean	Median	Mean	Median
Aircraft	**0.431**	0.365	**0.296**	0.196	**0.302**	0.271
Agriculture	0.219	0.154	0.199	0.132	0.136	0.100
Automobiles and Trucks	0.233	0.111	0.176	0.082	0.182	0.101
Banking	**0.441**	0.442	**0.287**	0.178	**0.357**	0.328
Alcoholic Beverages	0.153	0.075	0.086	0.081	0.109	0.074
Construction Materials	0.253	0.157	0.223	0.097	0.207	0.156
Printing and Publishing	0.188	0.107	0.123	0.084	0.132	0.075
Shipping Containers	0.173	0.103	0.164	0.077	0.182	0.115
Business Services	0.316	0.250	0.238	0.143	0.229	0.144
Chemicals	0.240	0.147	0.156	0.066	0.191	0.106
Electronic Equipment	**0.424**	0.355	**0.334**	0.289	**0.278**	0.160
Apparel	0.238	0.181	0.199	0.125	0.184	0.111
Construction	**0.458**	0.527	**0.299**	0.190	**0.304**	0.293
Coal	0.371	0.360	0.234	0.108	0.450	0.431
Computers	0.314	0.249	0.257	0.159	0.212	0.126
Pharmaceutical Products	0.255	0.134	0.205	0.121	0.183	0.101
Electrical Equipment	**0.469**	0.499	**0.352**	0.328	**0.340**	0.369
Petroleum and Natural Gas	0.336	0.208	**0.277**	0.183	**0.258**	0.177
Fabricated Products	**0.371**	0.381	0.274	0.180	0.343	0.362
Trading	0.328	0.247	0.250	0.154	0.225	0.160
Food Products	0.168	0.112	0.136	0.059	0.111	0.060
Entertainment	0.206	0.169	0.162	0.077	0.171	0.153
Precious Metals	0.224	0.224	0.137	0.137	0.248	0.248
Defense	**0.382**	0.273	0.182	0.124	0.257	0.122
Healthcare	**0.406**	0.394	0.261	0.201	0.281	0.242
Consumer Goods	0.251	0.201	0.190	0.117	0.172	0.103
Insurance	0.327	0.271	0.215	0.143	0.201	0.112
Lab Equipment	0.313	0.224	0.258	0.185	0.211	0.149
Machinery	0.347	0.213	**0.299**	0.231	**0.292**	0.215
Restaurants, Hotel, Motel	0.278	0.246	0.220	0.165	0.204	0.167
Medical Equipment	0.324	0.230	0.252	0.177	0.240	0.148
Nonmetallic Mining	0.150	0.088	0.117	0.056	0.124	0.049
Miscellaneous	0.000	0.000	0.000	0.000	0.000	0.000
Business Supplies	0.227	0.187	0.209	0.169	0.217	0.194
Personal Services	0.318	0.209	0.183	0.112	0.203	0.138
Retail	0.212	0.135	0.160	0.086	0.160	0.104
Real Estate	0.256	0.248	**0.324**	0.157	**0.217**	0.119
Rubber and Plastic Products	0.140	0.121	0.103	0.064	0.190	0.159
Shipbuilding, Railroad	**0.803**	0.882	**0.567**	0.708	**0.537**	0.646
Tobacco Products	0.140	0.087	0.169	0.117	0.102	0.106
Candy and Soda	0.081	0.037	0.069	0.039	0.068	0.021
Steel Works	**0.414**	0.382	**0.385**	0.345	**0.247**	0.169
Telecommunications	0.233	0.135	0.227	0.193	0.183	0.068
Recreational Products	0.240	0.165	0.248	0.156	0.167	0.126
Transportation	0.363	0.303	0.272	0.166	0.267	0.158
Textiles	0.127	0.106	0.222	0.240	0.059	0.014
Utilities	0.134	0.057	0.118	0.058	0.113	0.045
Wholesale	0.361	0.310	0.256	0.124	0.241	0.154

Notes to Appendix 2 Panel A:
The industry classification is based on Fama and French (1997). The top ten industries with the highest mean for each measure (*CYCLICALITY, ENERGY* and *SPREAD*) are in bold.

APPENDIX 2 (CONTINUED)
Descriptive Statistics by Industry

Panel B: Mean and Median Industry *Revenue Synchronicity* by Industry

INDUSTRY	REVENUE SYNCHRONICITY	
	Mean	Median
Aircraft	**0.338**	0.385
Agriculture	0.099	0.064
Automobiles and Trucks	0.094	0.040
Banking	0.183	0.104
Alcoholic Beverages	0.115	0.055
Construction Materials	0.140	0.070
Printing and Publishing	0.124	0.078
Shipping Containers	0.138	0.086
Business Services	0.234	0.155
Chemicals	0.224	0.157
Electronic Equipment	**0.274**	0.184
Apparel	0.158	0.101
Construction	0.193	0.107
Coal	0.184	0.123
Computers	0.130	0.070
Pharmaceutical Products	0.109	0.062
Electrical Equipment	0.097	0.070
Petroleum and Natural Gas	0.233	0.189
Fabricated Products	0.111	0.051
Trading	**0.242**	0.157
Food Products	0.119	0.047
Entertainment	0.138	0.048
Precious Metals	0.134	0.134
Defense	0.160	0.038
Healthcare	0.129	0.043
Consumer Goods	0.093	0.034
Insurance	0.085	0.043
Lab Equipment	**0.240**	0.210
Machinery	**0.261**	0.160
Restaurants, Hotel, Motel	0.109	0.079
Medical Equipment	0.122	0.067
Nonmetallic Mining	0.088	0.052
Miscellaneous	0.000	0.000
Business Supplies	**0.292**	0.170
Personal Services	0.146	0.095
Retail	0.170	0.117
Real Estate	**0.242**	0.097
Rubber and Plastic Products	**0.270**	0.177
Shipbuilding, Railroad	0.193	0.065
Tobacco Products	0.177	0.197
Candy and Soda	0.152	0.158
Steel Works	**0.274**	0.239
Telecommunications	0.110	0.093
Recreational Products	0.086	0.030
Transportation	0.154	0.147
Textiles	0.225	0.149
Utilities	**0.262**	0.166
Wholesale	0.077	0.041

Notes to Appendix 2 Panel B:
The industry classification is based on Fama and French (1997). The top ten industries with the highest *Revenue Synchronicity* are in bold.