# The Informational Feedback Effect of Stock Prices on Corporate Disclosure[*]

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January 2013

## Abstract

This paper studies whether managers use information contained in stock prices when making forward-looking disclosures. Using annual management forecasts from 1996 to 2010, I find that the association between forecast revisions and stock price changes over the revision periods is stronger when there is more informed trading. Further, I find that the positive effect of investors' information on the revision-return relation is more pronounced when the information is more relevant to predicted earnings. In addition, more investor information contained in stock prices leads to a greater improvement in forecast accuracy. My study highlights the two-way information flows between firms and capital markets.

**JEL Classification**: G14, G30, M41

**Keywords**: Informational Feedback Effect, Informed Trading, Information Asymmetry, Management Forecast

# 1. Introduction

A growing literature in financial economics suggests that managers can learn from outside investors' information contained in stock prices and incorporate that information into their corporate investment decisions (e.g., Chen, Goldstein and Jiang 2007). The idea that market prices are a useful source of information goes back to Hayek (1945). In essence, stock prices aggregate diverse pieces of information from different traders who have no other means of communicating with managers outside the trading process. As a result, the stock market can have an effect on the real economy due to this transmission of information (see Bond, Edmans and Goldstein (2012) for a review). In this paper, I build on this literature and study whether managers use the information contained in stock prices when making forward-looking disclosures. Despite the large literature on the capital market consequences of corporate disclosure (e.g., Beyer et al. 2010), few studies examine whether and how capital markets affect disclosure. I examine the informational feedback effect of stock prices on corporate disclosure.

I use annual management forecasts as a proxy for forward-looking disclosures, and test the hypothesis that managers learn from outside investors' information in stock prices when forecasting future earnings. Specifically, I examine whether the amount of outside investors' information in stock prices has a positive effect on the association between management forecast revisions and prior stock price changes. Investor information includes both investors' private information and their interpretations of public information. To measure the extent of informed trading and thus the amount of investor information contained in stock prices, I follow prior research and use the level of information asymmetry between informed and uninformed investors in the equity market (e.g., Chen, Goldstein and Jiang 2007). I use four market-based measures of information asymmetry between informed and uninformed investors: the adverse selection

component of the bid-ask spread, the probability of informed trading, price impact, and a combination of these three.

The sample consists of 16,471 management forecast revisions from 1996 to 2010. I first show that the association between management forecast revisions and stock price changes over the revision periods is stronger when there is higher information asymmetry. In terms of economic significance, an increase in information asymmetry from the bottom decile to the top doubles the revision-return sensitivity. This result suggests that firms with more informed trading have a stronger revision-return relation, consistent with managers learning from investors' information in stock prices.

To strengthen this inference, I conduct two cross-sectional tests to examine whether the positive effect of investors' information on the revision-return relation is more pronounced when the information is more relevant to predicted earnings. First, I predict that investors' information contained in stock prices is more relevant to forecasts of earnings that are further in the future. For imminent earnings realizations, managerial information is likely to dominate investors' information. Second, I predict that negative information contained in stock prices is more likely to be reflected in forecast earnings (of the current or next fiscal year), consistent with accounting conservatism. Consistent with these arguments, I find that the effect of investors' information on the revision-return relation is stronger when managers make long-horizon earnings forecasts and when stock returns contain negative information.

I perform a battery of tests to control for alternative interpretations of my main result. I show that the positive effect of investors' information on the revision-return relation persists after I control for the effect of "prices leading earnings," the amount of managerial information, analyst coverage, and firm size. I also conduct a test using mutual fund redemptions as an

exogenous shock to the level of stock prices (following Edmans, Goldstein and Jiang 2012). I find that the revision-return relation is weaker when price changes are caused by price pressure that is not driven by investor information, supporting the managerial learning hypothesis. In addition, since my sample only includes firms that issue and revise management forecasts, I employ a Heckman (1979) two-step estimation model to address potential sample selection issues. My conclusions continue to hold under this approach.

In addition, I investigate whether the amount of investors' information contained in stock prices affects the improvement in management forecast accuracy. If stock prices contain outside investor information that is new to managers and helps them improve their predictions of future earnings, I predict a positive association between the amount of investor information contained in stock prices and the improvement in forecast accuracy. I find evidence consistent with this prediction, lending further support to the managerial learning hypothesis.

My study contributes to the literature in several ways. First, it shows that the stock market provides a significant amount of information that affects firms' own forward-looking disclosures. An implicit assumption in most of the prior empirical accounting research is that managerial information completely subsumes that of outside investors.[1] If this is the case, we should expect no managerial learning from capital markets. Dye and Sridhar (2002) note that the current literature fails to recognize that information flows between capital markets and firms need not be just from firms to capital markets (as recognized in the extant literature), but also be from capital markets to firms. Hence, corporate disclosure both affects and is affected by capital

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[1] Two papers are notable exceptions: McNichols (1989) and Hutton, Lee and Shu (2012). McNichols (1989) uses a sample of management forecasts from 1979 to 1983 and concludes that stock prices reflect information beyond that in management earnings forecasts because investors have access to some information that managers do not. Hutton, Lee and Shu (2012) find that managers do not always know better than analysts. Specifically, they find that analysts have a macroeconomic-level information advantage, while managers' information advantage resides at the firm level. However, neither paper examines managers' learning behavior.

markets. My study provides evidence in support of information flows from capital markets to firms.

Two prior studies document evidence that the stock market affects managers' incentives to issue forecasts: Bergman and Roychowdhury (2008) and Sletten (2012). While these studies provide evidence that the stock market affects managers' decisions to issue forecasts, they assume that managers have complete information about future earnings (as do most empirical studies on corporate disclosure). Thus, these studies do not consider the informational feedback effect of stock prices, only the one-way effect of disclosure on market characteristics. In contrast, my study highlights two-way information flows between firms and capital markets.

Second, my study contributes to the growing literature on the informational content of market prices (e.g., Bond, Edmans and Goldstein 2012). I show that the information contained in stock prices enlarges managers' information sets and affects their forecasts of future earnings. To the extent that managers' information sets affect their corporate disclosures as well as other corporate decisions such as operational, investment, and financing decisions, the results documented in my paper have implications for other dimensions of managerial decision making. Extant research in financial economics finds that managers use the information contained in stock prices when making investment decisions (e.g., Luo 2005; Chen, Goldstein and Jiang 2007). My study corroborates this research by providing evidence that investor information contained in stock prices affects managers' assessment of their firms' future prospects.

My findings also relate to prior empirical evidence that analysts extract useful information from the stock market (e.g., Clement, Hales and Xue 2011). Those studies document that outsiders can learn new information from outsiders. My study finds that even managers (i.e., insiders), arguably the most well-informed individuals about the fundamentals of their own firms,

glean from the stock market useful information generated by investors. Taken together, the evidence supports the notion that stock prices are a useful source of information.

Finally, my findings suggest a potential cost of corporate disclosure. In the feedback literature, information acquisition by investors is vital. Information asymmetry allows investors to profit from their information advantage and thus induces them to acquire more information (which is costly). When this information is impounded into stock prices, prices become more informative to managers. To the extent that corporate disclosure reduces information asymmetry between informed and uninformed investors, it also reduces the informational feedback effect by dampening investors' incentives for acquiring private information that may be new to managers (Gao and Liang 2012). Consistent with this theoretical argument, Maffett (2012) documents that more opaque firms experience more privately informed trading by institutional investors. My study suggests that firms benefit from this informed trading by extracting relevant information that cannot otherwise be accessed by managers.

The remainder of the paper is organized as follows. I discuss related literature and develop the hypothesis in Section 2. Section 3 describes my sample and empirical models. In Section 4, I present empirical results. Finally, I conclude in Section 5.

## 2. Hypothesis Development

Financial markets produce and aggregate information via the trading process – investors trade on their information about firm value and as a result, their information is incorporated into prices. Several theoretical papers suggest that managers learn about their own firms' prospects from the information in stock prices (e.g., Dow and Gorton 1997; Subrahmanyam and Titman 1999). The assumption in these models is not that managers are less informed overall than investors are, but simply that investors collectively possess information that managers do not

have. This information more likely concerns macroeconomic conditions, industry competition or consumer demand; investors are less likely to have firm-specific information about technology (where managers would have an information advantage). In addition, corporate bureaucracy can hinder the collection of some information that exists within a firm's scope, if the information is difficult to standardize or to interpret or incentive incompatible with the information possessors.[2] Moreover, investors may collectively have superior processing abilities with respect to public information, such as macroeconomic news. Trading in the stock market elicits this information from profit-driven traders.



Managers' Information Sets:
*M+P*

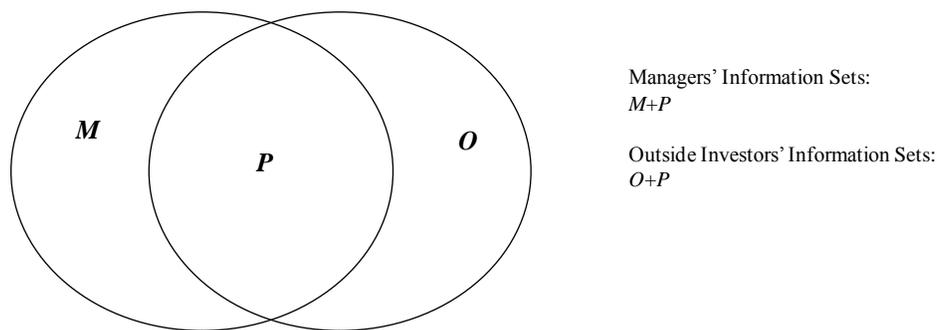Outside Investors' Information Sets:
*O+P*

Figure 1: The Information Sets of Managers and Outside Investors

Figure 1 provides an illustration: managers' information sets contain their private information, *M*, and public information, *P*, while outside investors' information sets include their private information, *O*, and *P*. It could be the case that *M* is much larger than *O*, i.e., that managers have a significant information advantage over investors. However, as long as *O* is nonempty, managers can learn something from stock prices if, through trading, investors' information *O* is incorporated into stock prices. This paper suggests that investors' information

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[2] Consistent with this view, Allen (1993) argues that the usefulness of market information has increased as production processes have become more complex.

and managers' information complement each other. Not only is there information overlap between managers and outsiders, each group also has information that the other lacks.

Anecdotal evidence also suggests that managers generally view market information as valuable. David Allen, Managing Director and Chief of Staff of British Petroleum (BP), stated: "I have deep faith in markets and a huge respect for them. Within the company you have, at least in theory, access to all the information, but there is only you. Outside you have imperfect information but a lot of brains. If you accept these two different realities and use that creatively, you can learn a lot" (Miller, Beyersdorfer and Sjoman 2006, p.5). The Investor Relations Group at BP actively tracks the market's general view of industry and company fundamentals, deciphers the information contained in prices, and provides this information to top management.

To see specifically how managers can learn from the stock market, consider, as an example, that Apple is launching a new product. Even though the firm's top executives are arguably the most well-informed individuals about the new device's specific functions, its value depends crucially on many other factors, such as the functionality of similar new devices produced by competitors (e.g., Samsung), customers' tastes, and compatibility with other new products (software or hardware). It is possible that among those who trade in the stock market, some have information that is unknown to Apple's managers. This information gets impounded into the stock price through trading and affects Apple's assessment of the new device's future profitability. Similar arguments can be made about macroeconomic news (e.g., an oil price spike) or other social/political news.

However, extant accounting research has paid little attention to the informational feedback effect of stock prices on corporate disclosure.[3] In this paper, I focus on management

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[3] Three theory papers are exceptions: Dye and Sridhar (2002), Langberg and Sivaramakrishnan (2010), and Gao and Liang (2012). However, these papers do not consider whether managers use information contained in stock prices

earnings forecasts, a key voluntary disclosure mechanism (see Beyer et al. (2010) for a review).[4]

I hypothesize that investors have useful information that is new to managers and thus impacts their forecasts of future earnings. My hypothesis, stated in an alternate form, is as follows:

**H:** Managers use outside investors' information contained in stock prices when making forward-looking disclosures.

The reasoning is as follows: in forecasting future earnings, managers assess the expected future cash flows to be generated by existing investments and potential future investments. Stock prices reflect both public and private information about firms' future cash flows. Investors' information gets impounded into stock prices via the trading process. When managers forecast future earnings, they use all the information available to them, including information reflected in stock prices and their private information (not yet reflected in prices).

Nevertheless, anecdotal evidence suggests that although some executives agree that knowing the broad market view helps with internal planning, others argue the market's data could not offer much insight as it is less complete than a firm's internal information, particularly about detailed operations or short term plans (Miller, Beyersdorfer, and Sjoman 2006). Roll (1986) argues that managers view their proprietary information as superior to the aggregate public information set (including investor information reflected in stock prices) when bidding to acquire other firms. Thus, it remains an empirical question as to whether investor information contained in stock prices helps managers forecast future earnings.

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when making forward-looking disclosures. Instead, they focus on a firm's decision about whether or not to disclose and how that affects the amount of information contained in stock prices that would be useful to subsequent corporate investment decisions.

[4] I focus on management forecasts rather than alternative forms of forward-looking disclosures for the following three reasons: (1) management forecasts can be precisely measured for a large sample of firms, (2) the timing of the disclosures is typically known, and (3) their accuracy can be easily verified by comparing forecasts to actual earnings. The last attribute allows me to examine how the amount of investor information contained in stock prices affects the quality of managers' forward-looking disclosures.

The maintained assumption in this analysis is that conditional on issuing management forecasts, most managers provide the best forecasts, given their ability and the available information.[5] Earnings forecast errors can impose severe legal costs on managers (Kasznik 1999), and inaccurate forecasts can also result in a loss of reputation, thereby lowering managerial compensation and stock prices (Trueman 1986). Consistent with these theoretical and empirical studies, empirical evidence suggests that management forecasts have credibility comparable to audited financial information (Healy and Palepu 2001).

## 3. Research Design

The essence of my main empirical test is a regression of forecast revisions (*Forecast_Revision*) on stock returns over the revision periods (*Return*) in which I compare the revision-return relation between firms with different amounts of outside information (*INFO*).

$$Forecast\_Revision = \alpha + \beta_1 Return \times INFO + \beta_2 Return + \beta_3 INFO + \Gamma Controls + \varepsilon. \qquad (1)$$

*Forecast_Revision* is $100 \times (Forecast_{i,t} - Forecast_{i,t-1})/Price_{i,t-1}$, where $Forecast_{i,t}$ is the earnings forecast released by firm $i$ at time $t$; $Forecast_{i,t-1}$ is the most recent earnings forecast pertaining to the same forecast period released by firm $i$ prior to $Forecast_{i,t}$; and $Price_{i,t-1}$ is the stock price two days before the issuance of $Forecast_{i,t-1}$.[6] I require the time interval between $Forecast_{i,t}$ and $Forecast_{i,t-1}$ to be more than 10 days and less than a year to exclude potential outliers. *Return* is the buy-and-hold return of firm $i$ over the period from the day of the issuance of $Forecast_{i,t-1}$ to one day before the issuance of $Forecast_{i,t}$. I use raw returns including the

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systematic component instead of market-adjusted or industry-adjusted returns because both market and industry returns affect future earnings predictions. *INFO* is a proxy for information asymmetry (defined below) measured prior to *Forecast$_{i,t-1}$*.[7] The variable of interest is *Return×INFO*.

The intuition of this regression is as follows. From Figure 1, the new information between the initial forecast and the revised forecast can be expressed as $\Delta M + \Delta P + \Delta O$, where $\Delta M$ is the change in managers' private information, $\Delta P$ is the change in public information, and $\Delta O$ is the change in outside investors' information. To concentrate on the intuition, I assume that the change in managerial information ($\Delta M$) remains private to managers until they make their forecasts, and that all of the outside investors' information ($\Delta O$) is incorporated into prices through trading.[8] Then:

$$Return = \Delta P + \Delta O + \varepsilon, \tag{2}$$

where $\varepsilon$ is noise. Assuming that managers use their private information in their forecasts:

$$Forecast\_Revision = \Delta M + \Delta P + \lambda \Delta O, \tag{3}$$

where $\lambda$ is the fraction of outside investors' information that managers are willing and able to incorporate into their forecast revisions. The coefficient of a regression of forecast revisions on returns is:

$$\theta = \text{cov}(Return, Forecast\_Revision)/\text{var}(Return). \tag{4}$$

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[7] I use lagged *INFO* to alleviate potential endogeneity concerns. The results are essentially unchanged when I use contemporaneous *INFO*.

[8] More realistically, some of managers' private information can be incorporated into prices through corporate disclosure or manager trading, and trading costs likely prevent all outside information from getting into prices. Incorporating this does not change the conclusion of the example, but complicates the analysis.

Consider the following simplified example in which outside information is either high or low. If the outside information is high ($\Delta O_H = \Delta O > 0$), then this coefficient is: $\theta_{High} = [\text{var}(\Delta P_H) + \lambda \text{var}(\Delta O)]/\text{var}(Return_H)$. If the outside information is low ($\Delta O_L = 0$), then this coefficient is: $\theta_{Low} = \text{var}(\Delta P_L)/\text{var}(Return_L)$. The difference is:

$$\theta_{High-Low} = \frac{\text{var}(\Delta P_H) + \lambda \text{var}(\Delta O)}{\text{var}(Return_H)} - \frac{\text{var}(\Delta P_L)}{\text{var}(Return_L)}. \tag{5}$$

If I empirically observe that this difference (i.e., $\theta_{High-Low}$) is positive, I infer managerial learning (i.e., $\lambda \text{var}(\Delta O) > 0$). This conclusion follows from two considerations. First, firms with more informed trading likely have more volatile stock returns, i.e., $\text{var}(Return_H) \geq \text{var}(Return_L)$. Thus, a positive $\theta_{High-Low}$ implies that $[\text{var}(\Delta P_H) + \lambda \text{var}(\Delta O) - \text{var}(\Delta P_L)]$ is positive. Second, $[\text{var}(\Delta P_H) - \text{var}(\Delta P_L)]$ is likely to be negative. In other words, firms with more informed trading likely have less common information between managers and investors (Maffett 2012). Thus, a positive $\theta_{High-Low}$ is unlikely to be driven by the differential amount of public information between firms with high and low outside information. Hence, if I empirically observe that the revision-return relation is stronger for firms with a higher amount of outside information, it suggests that $\lambda \text{var}(\Delta O)$ is positive, i.e., investors possess some information that managers lack and managers are willing and able to incorporate that information.

Hence, I expect the coefficient on *Return×INFO* to be positive, suggesting that managers rely more strongly on stock returns to forecast future earnings when stock prices contain more investor information that is new to them.

I do not argue that only investors' information in stock prices is new to managers. It could be the case that some public information, such as the realization of GDP or the unemployment rate, gets impounded into stock prices at the same time it is revealed to

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managers.[9] My prediction will hold as long as, on average, investor information increases the amount of information present in prices that is new to managers and thus increases the extent to which they rely on stock prices when revising their earnings forecasts.

## 3.1 Sample Selection

I use the "Company Issued Guidance" (CIG) database maintained by Thomson First Call to obtain all annual management earnings forecasts issued between January 1996 and December 2010.[10] I only include point and range forecasts, and exclude one-sided directional forecasts and qualitative forecasts that are not specific enough to determine numerical values as well as earnings pre-announcements. To determine a numeric value for each forecast, I use the value of the point forecasts and midpoint of the range forecasts. I identify forecast revisions when a firm issues more than one forecast for a given fiscal year and the new forecast is not simply a reiteration of the old one.[11] For each forecast revision identified above, I obtain related stock price and return data from the Center for Research in Security Prices (CRSP), financial statement data from Compustat, intraday transaction data from Trade and Quote (TAQ), and analysts' forecasts and actual earnings per share data from I/B/E/S. The final sample contains 16,471 management forecast revisions (with non-missing variables) from 1996 to 2010.[12]

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[9] An effect driven by public information (i.e., $\Delta P$) should result in a positive association between management forecast revisions and stock returns (i.e., a positive $\theta$), but it is unlikely to explain why the revision-return relation is stronger when there is more investor information contained in stock prices (i.e., a positive $\theta_{High-Low}$). In addition, I control for the amount of public information revealed to managers during the management forecast revision period by including the prevailing consensus analyst forecast revision in the regressions.

[10] Chuk, Matsumoto and Miller (2012) compare a sample of management forecasts in First Call to a hand-collected sample of forecasts contained in company press releases. They document that the CIG database is incomplete and caution against using it to examine the association between certain firm characteristics and the probability of disclosure. The incompleteness of the CIG database is of less concern to my study since I examine whether managers incorporate information contained in stock prices into their earnings forecasts once their decisions to issue forecasts have been made.

[11] As elaborated in Section 4.3, I use forecast reiterations as a control group under the Heckman (1979) framework.

[12] Quarterly forecast revisions happen much less often. Following the same procedure, I identify 2,982 quarterly forecast revisions between 1996 and 2010. All results are similar when I include this set of revisions in the tests.

Table 1 presents the number of management forecast revisions by year and by industry. As Panel A shows, the number of management forecast revisions varies substantially from year to year, ranging from 33 forecast revisions in 1996 to 2,065 revisions in 2006. There are few observations in the earlier years (1996 and 1997) because First Call began compiling management forecast data more systematically in 1998 (Anilowski, Feng and Skinner 2007). The large increase in the number of management forecast revisions in 2001 is due to the passage of Regulation Fair Disclosure (Reg FD).[13] Panel B of Table 1 shows that firms in the Retail industry revise earnings forecasts most often, accounting for 10.11 percent of my sample, followed by Business Services (9.08 percent) and Computer Software (7.98 percent).

A caveat is needed about the sample selection. By construction, I only include firms that issue management forecasts and subsequently revise the initial forecasts. While this restriction may affect the generalizability of my results, it is unlikely to bias them, since I rely on variation within my sample to draw conclusions about how managers use information in stock prices when revising their earnings forecasts. In additional analysis, I employ a Heckman two-step selection model (using forecast reiterations as the control group) to further bolster confidence that the sample selection does not bias my results.[14]

## 3.2 Measures of Information Asymmetry

While it is difficult to directly measure the amount of investor information contained in stock prices that is new to managers, prior studies (e.g., Chen, Goldstein and Jiang 2007) suggest that the level of information asymmetry between informed and uninformed investors in the stock

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[13] The results are essentially unchanged when I restrict my sample to the period post Reg FD.
[14] I do not consider the joint effects of materiality thresholds and voluntary disclosure incentives on firms' disclosure decisions (Heitzman, Wasley and Zimmerman 2010; Li, Wasley and Zimmerman 2012) because the focus of my study is on whether managers use the information contained in stock prices when making forward-looking disclosures. It is not that important whether these forward-looking disclosures are voluntary or mandatory because of materiality concerns.

market is positively associated with the amount of this information. The intuition is as follows: information asymmetry allows investors to profit from their information advantage and thus induces them to acquire more information. Their information is impounded into prices through trading. This argument is consistent with the fundamental theory that the information that guides market participants' trading decisions is the root cause of adverse selection and illiquidity in the stock market. Maffett (2012) uses cross-country data on trading by international mutual funds and finds that opaque firms experience more privately informed trading by institutional investors. Following this logic, I use the level of information asymmetry between informed and uninformed investors in the stock market to proxy for the amount of investor information contained in prices.

I follow the prior literature and employ multiple measures of information asymmetry (*INFO*). My first measure, *ASC_Spread*, is the adverse selection component of the bid-ask spread, estimated following Madhavan, Richardson, and Roomans (1997). *ASC_Spread* measures the extent to which unexpected order flows affect prices and is increasing in information asymmetry. My second measure, *PIN*, is the probability of informed trading and is estimated following Easley, Hvidkjaer and O'Hara (2002). This measure is based on a structural market microstructure model, in which trades come from either noise traders or informed traders. It directly measures the probability of informed trading and thus captures the amount of investors' information reflected in stock prices. *Amihud* is my third measure of information asymmetry; it is estimated following Amihud (2002). The magnitude of the price impact as measured by *Amihud* should be positively related to the perceived amount of informed trading on a stock (Kyle 1985). Finally, for parsimony, I extract the first principal component of the above three measures as my fourth measure of information asymmetry (*INFO*).[15]

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[15] The first principal component accounts for 71% of the variability in my data. The second and third principal components account for 19% and 10% of the variability, respectively.

### 3.3 Empirical Specification

#### 3.3.1 Test 1: The Effect of Investors' Information on the Revision-Return Relation

To assess the managerial learning hypothesis, I conduct three empirical tests. For my main test, I augment (1) as follows:

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\begin{aligned}
Forecast\_Revision = {} & \alpha + \beta_1 Return \times INFO + \beta_2 Return + \beta_3 INFO \\
& + \beta_4 UE \times INFO + \beta_5 UE \\
& + \beta_6 Analyst\_Revision \times INFO + \beta_7 Analyst\_Revision \\
& + \Gamma Controls + Industry\ FE + Year\ FE + \varepsilon.
\end{aligned} \tag{6}
$$

I control for managers' private information about future earnings (i.e., $\Delta M$) using earnings surprises for earnings announced at the same time as revised forecasts ($UE$). $UE$ is the unexpected quarterly earnings of firm $i$ on the issuance day of $Forecast_{i,t}$ for bundled forecasts,[16] defined as $100 \times (Actual\ Earnings_{i,t} - Consensus\ Analyst\ Forecast_{i,t})/Price_{i,t}$, where *Consensus Analyst Forecast*$_{i,t}$ is the prevailing consensus analyst forecast one day before the quarterly earnings announcement, and $Price_{i,t}$ is the stock price two days before the quarterly earnings announcement. For forecasts not issued concurrently with quarterly earnings announcements, I code $UE$ as zero. To the extent that earnings innovations have positive persistence (Kormendi and Lipe 1987), there will be a positive association between unexpected earnings and forecast revisions.

I control for public information about future earnings (i.e., $\Delta P$) using prevailing consensus analyst forecast revisions. *Analyst_Revision* is defined as $100 \times (Analyst\_Forecast_{i,t} -$ *Analyst_Forecast*$_{i,t-1})/Price_{i,t-1}$, where *Analyst_Forecast*$_{i,t}$ is the prevailing consensus analyst

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[16] Following Rogers and Van Buskirk (2012), I define bundled forecasts as those that fall within two days of the earnings announcement date and non-bundled forecasts as those issued outside the earnings announcement period. They show that bundled forecasts have evolved to become the most common type of management forecasts. In my sample, 80% of revised forecasts are bundled forecasts.

forecast immediately prior to firm *i* releasing *Forecast*$_{i,t}$; *Analyst_Forecast*$_{i,t-1}$ is the prevailing

consensus analyst forecast at the time when firm *i* releases *Forecast*$_{i,t-1}$; and *Price*$_{i,t-1}$ is the stock

price two days before the issuance of *Forecast*$_{i,t-1}$.[17]

Other control variables include: (1) *Size*, the book value of total assets measured at the

end of the most recent fiscal year prior to the issuance of *Forecast*$_{i,t-1}$; (2) *Tobin's_Q*, the market

value divided by the book value of the firm's assets, both measured at the end of the most recent

fiscal year prior to the issuance of *Forecast*$_{i,t-1}$; (3) *Coverage*, the number of analysts covering

the firm immediately before the issuance of *Forecast*$_{i,t-1}$; (4) *Horizon*, the number of days

between the *Forecast*$_{i,t}$ date and the estimate period end date; and (5) *Gap*, the number of days

between *Forecast*$_{i,t-1}$ and *Forecast*$_{i,t}$. I include *Size* and *Coverage* to control for the general

information environment of the firm. I include *Tobin's_Q* and *Horizon* to control for the

difficulty in forecasting earnings. I use the natural logarithm of *Size*, *Coverage*, *Horizon* and *Gap*.

I use the decile rankings of *INFO* (rescaled to range from zero to one) to facilitate the

interpretation of the coefficients. I include both industry and year fixed effects in the regressions,

where industry fixed effects are based on the Fama-French 49 industries, and year fixed effects

are based on the year the forecasts (*Forecast*$_{i,t}$) are issued.[18]

### 3.3.2 Test 2: Cross-Sectional Predictions on the Relevance of Investor Information

I predict that the positive effect of investor information on the revision-return relation

will be more pronounced when this information is more relevant to predicted earnings. To test

this, I use the following regression equation:

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[17] Since analysts also incorporate some information from stock returns when forecasting earnings (e.g., Clement, Hales and Xue 2011), the effect of stock returns on management forecast revisions after controlling for consensus analyst forecast revisions provides a lower bound estimate of the amount of information in stock prices that is useful to managers (in the sense that it is not fully incorporated into analyst forecast revisions). All results are quite similar if I do not include analyst forecast revisions in the regressions.

[18] Over the sample period, there is a negative time trend for the measures of information asymmetry. All results in the paper are quite similar when I use de-trended information asymmetry measures.

$Forecast\_Revision = \alpha + \beta_1 Return \times INFO \times Relevance + \beta_2 Return \times INFO$

$\qquad + \beta_3 Return + \beta_4 INFO + \beta_5 Relevance$

$\qquad + \beta_6 UE \times INFO \times Relevance + \beta_7 UE \times INFO + \beta_8 UE$

$\qquad + \beta_9 Analyst\_Revision \times INFO \times Relevance + \beta_{10} Analyst\_Revision \times INFO$

$\qquad + \beta_{11} Analyst\_Revision + \Gamma Controls + Industry\ FE + Year\ FE + \varepsilon. \qquad (7)$

I make two cross-sectional predictions. First, I predict that investor information contained in stock prices is more relevant to earnings realizations further in the future. Consider an extreme case in which managers forecast earnings that will be realized tomorrow. In such a case, managers have almost perfect information about the predicted earnings and the information contained in stock prices has a much more limited effect on managers' predictions. Second, because of accounting conservatism (Watts 2003a, 2003b), negative information contained in stock prices is more likely to be incorporated into earnings in the near future and is hence more relevant to forecast earnings (of the current or next fiscal year). Moreover, given litigation concerns, i.e., managers' greater likelihood of being sued when they overestimate future earnings (by under-reacting to negative or overreacting to positive information) than when they underestimate them, managers are more likely to incorporate negative information in their forecasts in a timely manner.

*Relevance* refers to one of the following two variables: (1) *Long_Horizon*, a dummy variable that equals one for any management forecast issued more than 90 days before the estimate period end date (Bergman and Roychowdhury 2008); and (2) *Neg_Return*, a dummy variable that equals one if the stock return measured over the forecast revision period (*Return*) is negative. The variable of interest is *Return×INFO×Relevance*. I expect the coefficients on *Return×INFO×Long_Horizon* and *Return×INFO×Neg_Return* to be positive, suggesting that the positive effect of investors' information on the revision-return relation is stronger when

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managers forecast earnings further in the future or the prior stock price changes contain negative information.

### 3.3.3 Test 3: The Effect of Investors' Information on Changes in Forecast Accuracy

I argue that investors' information as reflected in stock prices supplements managers' information concerning future earnings. Given that managers have strong incentives to issue accurate forecasts due to litigation and reputation concerns, managers will use the investors' information contained in stock prices to improve their forecasts. Thus, I predict that more investor information contained in stock prices leads to a greater improvement in forecast accuracy. To test this prediction, I use the following regression equation:

$$\Delta Accuracy = \alpha + \beta_1 INFO + \Gamma Controls + \text{Industry FE} + \text{Year FE} + \varepsilon. \tag{8}$$

$\Delta Accuracy$ is defined as $-100 \times (|Forecast_{i,t} - Actual\ Earnings| - |Forecast_{i,t-1} - Actual\ Earnings|)/Price_{i,t-1}$, where $Forecast_{i,t}$ is the earnings forecast released by firm $i$ at time $t$; $Forecast_{i,t-1}$ is the most recent earnings forecast pertaining to the same forecast period released by firm $i$ prior to $Forecast_{i,t}$; and $Price_{i,t-1}$ is the stock price two days before the issuance of $Forecast_{i,t-1}$. The variable of interest is $INFO$. I expect the coefficient on $INFO$ to be positive, suggesting that the investor information contained in stock prices improves management forecast accuracy.

### 3.3.4 Summary of Empirical Predictions

My hypothesis is that managers use the outside investor information contained in stock prices when making forward-looking disclosures. Based on this hypothesis, I make three empirical predictions, which I have discussed in detail above:

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**P1:** The association between management forecast revisions and stock returns is stronger when stock prices contain more investor information.

**P2a:** The effect of investor information on the association between forecast revisions and stock returns is stronger for long-horizon forecasts.

**P2b:** The effect of investor information on the association between forecast revisions and stock returns is stronger for negative stock returns.

**P3:** More investor information leads to a greater improvement in forecast accuracy.

## 4. Empirical Results

### 4.1 Summary Statistics

Table 2, Panel A presents the descriptive statistics for the variables. All continuous variables are winsorized at the top and bottom 1% levels to mitigate the influence of extreme values. There is a large variation in *Forecast_Revision* in the sample, with a mean value of -0.14, a median value of 0.06, and a standard deviation of 0.92. My sample contains 66% long-horizon forecasts (*Long_Horizon*); 42% of the observations have negative stock returns over the forecast revision periods (*Neg_Return*). The average (median) number of days between the revised forecast date and the estimate period end date (*Horizon*) is 165 (156) days. The average (median) number of days between the initial forecast and the revised forecast (*Gap*) is 88 (90) days. Δ*Accuracy* also exhibits a large variation, with a mean value of 0.45, a median value of 0.18, and a standard deviation of 0.91.

The Pearson correlation matrix is tabulated in Panel B of Table 2. The correlation between *Forecast_Revision* and *Return* is positive (0.32) and statistically significant at the 1% level; *UE* and *Analyst_Revision* also have positive and statistically significant correlations with both *Forecast_Revision* and *Return*, suggesting that controlling for *UE* and *Analyst_Revision* is

important in my empirical tests. The correlations among *ASC_Spread*, *PIN*, *Amihud* and *INFO* are high (ranging from 0.44 to 0.87), consistent with them capturing the same underlying construct – the amount of investor information contained in stock prices.

## 4.2 Main Results

### 4.2.1 Test 1: The Effect of Investors' Information on the Revision-Return Relation

Table 3 presents the results of the main test (P1). In this and all subsequent regressions, I report *t*-statistics corrected for heteroskedasticity and cross-sectional and time-series correlations using a two-way cluster at the firm and year levels (Petersen 2009). The coefficients on *Return*, *UE*, and *Analyst_Revision* are positive and significant at the 1% level in all columns, as expected. More importantly, the coefficients on the interaction term between *Return* and *INFO* (*Return×INFO*) are positive and significant at the 1% level across all four measures of information asymmetry, suggesting that managers respond more strongly to stock returns when stock prices contain more investor information that is new to them. The effect is also economically large. An increase in *INFO* from the bottom decile to the top doubles the revision-return sensitivity. The Variance Inflation Factor (*VIF*) on *Return×INFO* ranges from 5.42 to 7.10 across the four columns, suggesting that multicollinearity is not high. In sum, these results in Table 3 suggest that managers learn from investors' information contained in stock prices, supporting my first prediction.

I also find that management forecast revisions are positively associated with growth opportunities (*Tobin's_Q*) and analyst coverage (*Coverage*), and negatively associated with the time lag between the initial forecast and the revised forecast (*Gap*). These results can be interpreted as follows: growth firms revise earnings forecasts upward when certain growth opportunities materialize. Firms with more analyst coverage face less pressure to walk down

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analyst forecasts because the possibility that some analysts understand the true situation of such firms is higher and these analysts will independently revise their earnings forecasts downward. Managers act more quickly for upward than for downward revisions.

### 4.2.2 Test 2: Cross-Sectional Predictions on the Relevance of Investors' Information

Table 4 presents the results of my second empirical prediction (P2). For parsimony, in this and all subsequent regressions, I only report the results when I use the first principal component of *ASC_Spread*, *PIN*, and *Amihud* as the measure of information asymmetry. The results are quite similar when I use the individual measures of information asymmetry. Column (1) shows that the coefficient on *Return×INFO×Long_Horizon* is positive and statistically significant at the 1% level, indicating that the effect of investors' information on the association between forecast revisions and stock returns is stronger for long-horizon forecasts. Consistent with P2a, the results suggest that the information provided by capital markets is more relevant to earnings realizations further in the future, less so for imminent earnings realizations.

Column (2) shows that the coefficient on *Return×INFO×Neg_Return* is positive and statistically significant at the 5% level, indicating that the effect of investors' information on the association between forecast revisions and stock returns is stronger when stock returns are negative. Consistent with P2b, the results suggest that due to conservative accounting and potential litigation concerns, negative information is incorporated into earnings forecasts in a more timely manner than is positive information.

### 4.2.3 Test 3: The Effect of Investors' Information on Changes in Forecast Accuracy

Table 5 presents the results of my third empirical prediction (P3). Column (1) shows that the coefficient on *INFO* is positive and statistically significant at the 1% level, indicating a positive association between the amount of investors' information and changes in forecast

accuracy (Δ*Accuracy*). Consistent with P3, the results suggest that investor information contained in stock prices helps managers improve their forecasts of future earnings.

## 4.3 Robustness Checks

### 4.3.1 Controlling for Confounding Factors

#### 4.3.1.1 Controlling for the Effect of "Prices Leading Earnings"

Extant accounting research suggests that prices lead earnings, i.e., information first gets impounded into stock prices before it is reflected in earnings (Kothari and Sloan 1992). One concern is that a stock price with a larger amount of investor information better captures future earnings, and as a result, the positive effect of investors' information on the revision-return relation simply reflects this mechanical relation of prices and earnings. To control for the effect of "prices leading earnings," I use the following model:

$$
\begin{aligned}
Forecast\_Revision = {}& \alpha + \beta_1 Return \times INFO + \beta_2 Return \times FINC + \beta_3 Return + \beta_4 INFO + \beta_5 FINC \\
& + \beta_6 UE \times INFO + \beta_7 UE \times FINC + \beta_8 UE \\
& + \beta_9 Analyst\_Revision \times INFO + \beta_{10} Analyst\_Revision \times FINC \\
& + \beta_{11} Analyst\_Revision + \Gamma Controls + \text{Industry FE} + \text{Year FE} + \varepsilon,
\end{aligned} \tag{9}
$$

where *FINC* is the future earnings incremental explanatory power measure from Durnev et al. (2003), measured over the year prior to *Forecast*$_{i,t-1}$. *FINC* is defined as the increase in the coefficient of determination ($R^2$) of the annual regression on each two-digit SIC industry with at least 10 firms: $r_{it} = b_0^b + b_1^b \Delta E_{it} + \sum_{\tau=1}^{3} b_{2,\tau}^b \Delta E_{i,t+\tau} + \sum_{\tau=1}^{3} b_{3,\tau}^b r_{i,t+\tau} + \varepsilon_{it}^b$, relative to the base regression,

$r_{it} = b_0^c + b_1^c \Delta E_{it} + \varepsilon_{it}^c$, where $r_{it}$ is annual stock return calculated from the fiscal year-end share price plus dividends adjusted by stock splits and distributions, and $\Delta E_{it}$ is the annual change in

earnings before interest, taxes, depreciation, and amortization scaled by the previous fiscal year-end market capitalization.

By definition, *FINC* will be higher for firms whose returns better predict future earnings. However, it is not necessarily the case that a larger amount of investors' information leads to a higher *FINC*. *FINC* depends on the total amount of information in stock prices, not just the amount of investor information. As incorporation of investors' information into stock prices takes time, it might be that stock prices with more investor information and less public information are further away from fundamentals (Chen, Goldstein and Jiang 2007). Intuitively, *FINC* is likely to be higher for transparent firms than for opaque firms, but opaque firms attract more informed trading (Maffett 2012; Gao and Liang 2012). In my sample, I find a negative and statistically significant correlation between *FINC* and *INFO* (-0.06).

Column (1) of Table 6 presents the result after I control for the effect of "prices leading earnings." As expected, I find a positive and significant coefficient on *Return×FINC*. More importantly, the coefficient on *Return×INFO* remains positive and statistically significant at the 1% level. Hence, my results are unlikely to be driven by the mechanical effect of "prices leading earnings."

**4.3.1.2 Controlling for the Amount of Managerial Information**

I use the level of information asymmetry between informed and uninformed investors in the stock market to capture the amount of investor information contained in stock prices. To better capture the amount of investors' information that is new to managers, I control for the amount of private information managers hold. I use the inverse of *Horizon* as a measure of the amount of managerial information (*Manager*). Managers are expected to have more private information about earnings in the short term than in the long term. To test this, I replace *FINC* in

equation (9) with *Manager*. The result is tabulated in column (2) of Table 6. The coefficient on *Return×Manager* is negative and significant, indicating that managers rely less on information in stock prices when they possess more private information themselves. The coefficient on *Return×INFO* remains positive and significant at the 1% level.

**4.3.1.3 Controlling for Analyst Coverage**

In column (3) of Table 6, I control for analyst coverage by replacing *FINC* in equation (9) with *Coverage*. The coefficient on *Return×INFO* remains positive and significant. The negative coefficient on *Return×Coverage* suggests that analysts are mainly information intermediaries (instead of information producers). They get information from managers that moves stock prices but that, to managers, represents old information; as a result, managers rely less strongly on stock returns when stock prices contain more analyst information. This result is consistent with the findings in Altinkilic and Hansen (2009) that analysts merely piggyback on recent news and that their outputs are largely information-free.

**4.3.1.4 Controlling for Firm Size**

Since *Size* has a strong negative correlation with measures of information asymmetry (ranging from -0.31 to -0.57), I directly control for it to ensure that firm size does not drive my results on the effect of investors' information on the revision-return relation. To test this, in equation (9) I replace *FINC* with *Size*. The results are tabulated in column (4) of Table 6. The coefficient on *Return×Size* is insignificant, but the coefficient on *Return×INFO* remains positive and statistically significant at the 1% level.

In column (5) of Table 6, the coefficient on *Return×INFO* remains positive and statistically significant at the 1% level after I put all controls in one regression. In sum, the

results in Table 6 suggest that my results are unlikely to be driven by confounding factors that are potentially associated with information asymmetry.

### 4.3.2 Using Mutual Fund Redemptions to Proxy for Investor Information

In the main tests, I use the level of information asymmetry between informed and uninformed investors in the stock market to proxy for the amount of investor information contained in stock prices. Here, I conduct a test using exogenous price shifts to further support the managerial learning hypothesis. Edmans, Goldstein and Jiang (2012) use mutual fund redemptions as a shock to price changes that is exogenous to cash flow news. They create a measure, *MFFlow*, the price pressure created by mutual fund trading that is not induced by information but by investor flows.[19] I calculate *MFFlow* over the management forecast revision period and predict that the revision-return relation is weaker when *MFFlow* is higher because, in such a case, the price changes are caused by investor flows rather than information. Table 7 presents the results. Consistent with my prediction, *MFFlow* negatively affects the revision-return relation, suggesting that managers glean less useful information from the stock market when price changes are caused by investor flows rather than information. In untabulated results, I find that the negative effect of price pressure generated by mutual fund redemptions on the revision-return relation persists after I control for the effect of "prices leading earnings," the amount of managerial information, analyst coverage, and firm size.

### 4.3.3 The Heckman Selection Model

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[19] An important feature of the *MFFlow* measure is that it is constructed not using mutual funds' actual purchases and sales, but instead using hypothetical orders projected from their previously disclosed portfolios. Therefore, *MFFlow* does not reflect mutual funds' discretionary trades that may be based on information. Rather, this measure captures an expansion or contraction of a fund's existing positions that is mechanically induced by investor flows to and from the fund. Those flows are in turn unlikely to be driven by investors' views on an individual firm held by the fund, since such views would be expressed through direct trading of that firm's stock rather than a mutual fund share. I thank Alex Edmans for providing me with the data on mutual fund redemptions. For this test, I only include observations from 1996 to 2007 for which I have this data.

Because revisions of management forecasts are voluntary, it is possible that my results are affected by potential sample selection bias. To address this issue, I employ a Heckman two-step estimation procedure. In the first step, I estimate the following probit model of the choice to revise earnings forecasts:

$$D\_Revision = \alpha + \beta_1 RetVol + \beta_2 Return \times INFO + \beta_3 Return + \beta_4 INFO$$
$$+ \beta_5 UE \times INFO + \beta_6 UE$$
$$+ \beta_7 Analyst\_Revision \times INFO + \beta_8 Analyst\_Revision$$
$$+ \Gamma Controls + Industry\ FE + Year\ FE + \varepsilon. \tag{10}$$

*D_Revision* is a dummy variable that equals one for forecast revisions, zero otherwise. I use forecast reiterations (i.e., the new forecast being a reiteration of the old one) as the benchmark group. *RetVol* is included in the model to satisfy the exclusion restriction (Lennox, Francis and Wang 2012). I predict that firms operating in a more volatile environment are more likely to revise earnings forecasts (rather than to simply restate their initial forecasts). However, *RetVol* is unlikely to be directly related to the value of the forecast revision (i.e., the dependent variable in the second step). Firms with high *RetVol* could have both a big upward revision and a similarly large downward one.[20] I include in the first step all other variables used in the second step.

The second-step model is as follows:

$$Forecast\_Revision = \alpha + \beta_1 IMR + \beta_2 Return \times INFO + \beta_3 Return + \beta_4 INFO$$
$$+ \beta_5 UE \times INFO + \beta_6 UE$$
$$+ \beta_7 Analyst\_Revision \times INFO + \beta_8 Analyst\_Revision$$
$$+ \Gamma Controls + Industry\ FE + Year\ FE + \varepsilon. \tag{11}$$

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[20] In untabulated results, when I include *RetVol* as a control variable in model (1), the coefficient on *RetVol* is statistically insignificant from zero (consistent with my justifications for the exclusion restriction).

I include the inverse Mills' ratio (*IMR*) calculated based on the estimation results from the first step as a control in the second step. The two steps are jointly estimated.

The results are tabulated in Table 8. Column (1) presents the first-step results. The coefficient on *RetVol* is positive and statistically significant at the 5% level, suggesting that firms with more volatile stock returns are more likely to revise earnings forecasts. Column (2) presents the second-step results. Both the magnitude and the statistical significance of the coefficient on *Return×INFO* are quite similar to those reported in Table 3. The *VIF* on *Return×INFO* is 6.14, suggesting that multicollinearity is not high.

### 4.3.4 Using Price Nonsynchronicity to Proxy for Investors' Information

The extant literature also uses price nonsynchronicity as a measure of the amount of investor information contained in stock prices that is new to managers (e.g., Chen, Goldstein and Jiang 2007). It is measured as the portion of a firm's stock return variation unexplained by market and industry returns. This measure was first proposed by Roll (1988). Roll (1988) argues that information about firm fundamentals is capitalized into stock prices in two ways: through the release of public information such as GDP statistics or earnings and through the impounding of investors' information into stock prices via the trading process. He further shows that price nonsynchronicity has very little correlation with identifiable public news releases, and thus it seems to capture investor information. In Roll's (1988, p.564) own words, the results suggest that "the financial press misses a great deal of relevant information generated privately." However, several recent studies cast doubt on the validity of this measure (e.g., Dasgupta, Gan and Gao 2010). Given those concerns, I do not use price nonsynchronicity as my main measure of the amount of investor information contained in stock prices. In the sample, the correlation between price nonsynchronicity and *INFO* is high (0.44). All results (untabulated) are quite

similar (in terms of magnitude and statistical significance) to those reported when price nonsynchronicity is used as the measure.

## 5. Conclusion

While numerous studies have documented the capital market consequences of corporate disclosure, relatively little is known about the role stock prices play in shaping a firm's disclosure. In this paper, I examine whether managers use information contained in stock prices when making forward-looking disclosures. I use the level of information asymmetry between informed and uninformed investors as an empirical proxy for the amount of investor information contained in stock prices. I find that managers rely more strongly on stock returns in revising their earnings forecasts when the amount of investor information in stock prices is higher. Further, I find the positive effect of investors' information on the revision-return relation to be stronger when managers make long-horizon earnings forecasts and when stock returns contain negative information. The results are robust after I control for the effect of "prices leading earnings," the amount of managerial information, analyst coverage, and firm size. Using mutual fund redemptions as an instrument for exogenous price shifts, I find a weaker revision-return relation when the price pressure driven by investor flows is higher, consistent with the managerial learning hypothesis. In addition, I find evidence that managers use investors' information contained in stock prices to improve their forecasts.

This study provides empirical evidence that the information contained in stock prices enlarges managers' information sets and affects their forward-looking disclosures. My study provides empirical evidence supporting the notion that market prices are a useful source of information. My research also highlights the two-way information flows between firms and capital markets.

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## Appendix: Variable Definitions

| | |
|---|---|
| *Forecast_Revision* | $Forecast\_Revision_{i,t} = 100 \times (Forecast_{i,t} - Forecast_{i,t-1})/Price_{i,t-1}$, where $Forecast_{i,t}$ is the earnings forecast released by firm $i$ at time $t$; $Forecast_{i,t-1}$ is the most recent earnings forecast pertaining to the same forecast period released by firm $i$ prior to $Forecast_{i,t}$; and $Price_{i,t-1}$ is the stock price two days before the issuance of $Forecast_{i,t-1}$. |
| *Return* | The buy-and-hold return of firm $i$ over the period from the day of the issuance of $Forecast_{i,t-1}$ to one day before the issuance of $Forecast_{i,t}$. |
| *ASC_Spread* | The adverse selection component of the bid-ask spread, estimated following Madhavan, Richardson and Roomans (1997) and measured over the year prior to $Forecast_{i,t-1}$. |
| *PIN* | Probability of informed trading, estimated following Easley, Hvidkjaer and O'Hara (2002) and measured over the year prior to $Forecast_{i,t-1}$. |
| *Amihud* | Price impact, estimated following Amihud (2002) and measured over the year prior to $Forecast_{i,t-1}$. |
| *INFO* | The first principal component of *ASC_Spread*, *PIN*, and *Amihud*, measured over the year prior to $Forecast_{i,t-1}$. |
| *UE* | Unexpected quarterly earnings of firm $i$ on the issuance day of $Forecast_{i,t}$: $UE = 100 \times (Actual\ Earnings_{i,t} - Consensus\ Analyst\ Forecast_{i,t})/Price_{i,t}$, where $Consensus\ Analyst\ Forecast_{i,t}$ is the prevailing consensus analyst forecast one day before the quarterly earnings announcement and $Price_{i,t}$ is the stock price two days before the quarterly earnings announcement. |
| *Analyst_Revision* | $Analyst\_Revision_{i,t} = 100 \times (Analyst\_Forecast_{i,t} - Analyst\_Forecast_{i,t-1})/Price_{i,t-1}$; where $Analyst\_Forecast_{i,t}$ is the consensus analyst forecast right before firm $i$ releases $Forecast_{i,t}$; $Analyst\_Forecast_{i,t-1}$ is the consensus analyst forecast at the time when firm $i$ releases $Forecast_{i,t-1}$; and $Price_{i,t-1}$ is the stock price two days before the issuance of $Forecast_{i,t-1}$. |
| *Size* | Total assets measured at the end of the most recent fiscal year prior to $Forecast_{i,t-1}$. |
| *Tobin's_Q* | The market value divided by the book value of the firm's assets, both measured at the end of the most recent fiscal year prior to the issuance of $Forecast_{i,t-1}$. |
| *Coverage* | Number of analysts covering the firm immediately prior to the issuance of $Forecast_{i,t-1}$. |
| *Horizon* | The number of days between the $Forecast_{i,t}$ date and the estimate period end date. |
| *Gap* | The number of days between $Forecast_{i,t-1}$ and $Forecast_{i,t}$. |
| *Long_Horizon* | A dummy variable that equals one for any management forecast issued more than 90 days before the estimate period end date (Bergman and Roychowdhury 2008). |
| *Neg_Return* | A dummy variable that equals one if the stock return measured over the forecast revision period (*Return*) is negative. |
| *ΔAccuracy* | $-100 \times (|Forecast_{i,t} - Actual\ Earnings| - |Forecast_{i,t-1} - Actual\ Earnings|)/Price_{i,t-1}$, where $Forecast_{i,t}$ is the earnings forecast released by firm $i$ at time $t$; $Forecast_{i,t-1}$ is the most recent earnings forecast pertaining to the same forecast period released by firm $i$ prior to $Forecast_{i,t}$; and $Price_{i,t-1}$ is the stock price two days before the issuance of $Forecast_{i,t-1}$. |
| *FINC* | Future earnings incremental explanatory power measure from Durnev et al. (2003), measured over the year prior to $Forecast_{i,t-1}$. |
| *Manager* | Managerial information, as proxied by the inverse of *Horizon*, the number of days between the $Forecast_{i,t}$ date and the end of the forecast period. |
| *MFFlow* | The price pressure created by mutual fund trading over the revision period, estimated following Edmans, Goldstein and Jiang (2012) . |
| *D_Revision* | A dummy variable that equals one for forecast revisions, zero otherwise. |
| *RetVol* | The standard deviation of the daily stock return measured over the year prior to the issuance of $Forecast_{i,t-1}$. |
| *IMR* | Inverse Mills' ratio, calculated by using the Heckman model. |

Table 1: Sample Distribution

Panel A: Number of Management Forecast Revisions by Year

| Year | Freq. | Percent |
| --- | --- | --- |
| 1996 | 33 | 0.20 |
| 1997 | 56 | 0.34 |
| 1998 | 118 | 0.72 |
| 1999 | 182 | 1.10 |
| 2000 | 236 | 1.43 |
| 2001 | 907 | 5.51 |
| 2002 | 1,319 | 8.01 |
| 2003 | 1,458 | 8.85 |
| 2004 | 1,976 | 12.00 |
| 2005 | 1,988 | 12.07 |
| 2006 | 2,065 | 12.54 |
| 2007 | 1,783 | 10.83 |
| 2008 | 1,614 | 9.80 |
| 2009 | 1,294 | 7.86 |
| 2010 | 1,442 | 8.75 |
| Total | 16,471 | 100 |

Panel B: Number of Management Forecast Revisions by Fama-French Industry

| Industry_Number | Industry_Description | Freq. | Percent |
|---|---|---|---|
| 43 | Retail | 1,666 | 10.11 |
| 34 | Business Services | 1,495 | 9.08 |
| 36 | Computer Software | 1,314 | 7.98 |
| 31 | Utilities | 939 | 5.70 |
| 12 | Medical Equipment | 801 | 4.86 |
| 13 | Pharmaceutical Products | 711 | 4.32 |
| 21 | Machinery | 694 | 4.21 |
| 42 | Wholesale | 628 | 3.81 |
| 44 | Restaurants, Hotels, Motels | 601 | 3.65 |
| 46 | Insurance | 572 | 3.47 |
| 48 | Trading | 515 | 3.13 |
| 11 | Healthcare | 509 | 3.09 |
| 37 | Electronic Equipment | 499 | 3.03 |
| 10 | Apparel | 411 | 2.50 |
| 9 | Consumer Goods | 392 | 2.38 |
| 2 | Food Products | 349 | 2.12 |
| 38 | Measuring and Control Equipment | 344 | 2.09 |
| 33 | Personal Services | 313 | 1.90 |
| 18 | Construction | 270 | 1.64 |
| 41 | Transportation | 237 | 1.44 |
| 14 | Chemicals | 233 | 1.41 |
| 45 | Banking | 233 | 1.41 |
| 35 | Computers | 216 | 1.31 |
| 23 | Automobiles and Trucks | 212 | 1.29 |
| 30 | Petroleum and Natural Gas | 202 | 1.23 |
| 32 | Communication | 201 | 1.22 |
| 7 | Entertainment | 191 | 1.16 |
| 22 | Electrical Equipment | 185 | 1.12 |
| 24 | Aircraft | 184 | 1.12 |
| 17 | Construction Materials | 177 | 1.07 |
| 8 | Printing and Publishing | 170 | 1.03 |
| 39 | Business Supplies | 155 | 0.94 |
| 26 | Defense | 116 | 0.70 |
| 20 | Fabricated Products | 83 | 0.50 |
| 6 | Recreation | 80 | 0.49 |
| 3 | Candy & Soda | 79 | 0.48 |
| 47 | Real Estate | 73 | 0.44 |
| 15 | Rubber and Plastic Products | 68 | 0.41 |
| 5 | Tobacco Products | 56 | 0.34 |
| 49 | Almost Nothing | 50 | 0.30 |
| 4 | Beer & Liquor | 49 | 0.30 |
| 29 | Coal | 42 | 0.25 |
| 25 | Shipbuilding, Railroad Equipment | 39 | 0.24 |
| 19 | Steel Works, Etc. | 36 | 0.22 |
| 16 | Textiles | 25 | 0.15 |
| 1 | Agriculture | 24 | 0.15 |
| 28 | Non-Metallic and Industrial Metal Mining | 17 | 0.10 |
| 40 | Shipping Containers | 13 | 0.08 |
| 27 | Precious Metals | 2 | 0.01 |
| Total | | 16,471 | 100 |

Table 2: Summary Statistics

Panel A: Descriptive Statistics

|  | Observations | Mean | Median | SD |
|---|---|---|---|---|
| *Forecast_Revision* | 16,471 | -0.14 | 0.06 | 0.92 |
| *Return* | 16,471 | 0.03 | 0.03 | 0.20 |
| *ASC_Spread* | 16,471 | 0.04 | 0.02 | 0.06 |
| *PIN* | 16,471 | 0.12 | 0.11 | 0.06 |
| *Amihud* | 16,471 | 0.04 | 0.00 | 0.16 |
| *INFO* | 16,471 | -0.07 | -0.35 | 0.94 |
| *UE* | 16,471 | -0.08 | 0.00 | 0.68 |
| *Analyst_Revision* | 16,471 | -0.11 | 0.00 | 0.85 |
| *Size* | 16,471 | 6,131 | 1,227 | 14,959 |
| *Tobin's_Q* | 16,471 | 2.06 | 1.63 | 1.30 |
| *Coverage* | 16,471 | 10 | 8 | 7 |
| *Horizon* | 16,471 | 165 | 156 | 100 |
| *Gap* | 16,471 | 88 | 90 | 43 |
| *Long_Horizon* | 16,471 | 0.66 | 1 | 0.47 |
| *Neg_Return* | 16,471 | 0.42 | 0 | 0.49 |
| *ΔAccuracy* | 15,876 | 0.45 | 0.18 | 0.91 |
| *FINC* | 13,636 | 0.14 | 0.08 | 0.17 |
| *MFFlow* | 12,121 | 0.30 | 0.14 | 0.47 |
| *RetVol* | 16,471 | 0.03 | 0.02 | 0.02 |

Panel B: Pearson Correlation Coefficients

| | Forecast_Revision | Return | ASC_Spread | PIN | Amihud | INFO | UE | Analyst_Revision | Size | Tobin's_Q | Coverage | Horizon |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Return* | 0.32*** | | | | | | | | | | | |
| *ASC_Spread* | -0.07*** | 0.09*** | | | | | | | | | | |
| *PIN* | -0.05*** | 0.08*** | 0.54*** | | | | | | | | | |
| *Amihud* | -0.03*** | 0.09*** | 0.71*** | 0.44*** | | | | | | | | |
| *INFO* | -0.07*** | 0.09*** | 0.80*** | 0.87*** | 0.61*** | | | | | | | |
| *UE* | 0.52*** | 0.21*** | -0.05*** | -0.04*** | -0.01 | -0.06*** | | | | | | |
| *Analyst_Revision* | 0.51*** | 0.27*** | -0.03*** | -0.01* | 0.01 | -0.03*** | 0.59*** | | | | | |
| *Size* | 0.04*** | -0.06*** | -0.46*** | -0.47*** | -0.31*** | -0.57*** | 0.04*** | 0.01 | | | | |
| *Tobin's_Q* | 0.06*** | -0.05*** | -0.10*** | -0.07*** | -0.10*** | -0.10*** | 0.05*** | 0.05*** | -0.27*** | | | |
| *Coverage* | 0.06*** | -0.07*** | -0.45*** | -0.46*** | -0.39*** | -0.55*** | 0.04*** | 0.02** | 0.54*** | 0.19*** | | |
| *Horizon* | 0.02** | 0.05*** | -0.01** | -0.02*** | -0.02** | -0.02** | 0.00 | -0.01 | 0.01 | 0.04*** | 0.04*** | |
| *Gap* | -0.06*** | 0.06*** | 0.09*** | 0.07*** | 0.05*** | 0.09*** | -0.06*** | -0.04*** | -0.08*** | 0.01 | -0.08*** | -0.10*** |

*ASC_Spread* is multiplied by 100. All continuous variables are winsorized at the top and bottom 1% levels to mitigate the influence of extreme values. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in the appendix.

Table 3: The Effect of Investors' Information on the Revision-Return Relation

| | Dependent Variable: *Forecast_Revision* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| INFO = | ASC_Spread | PIN | Amihud | INFO |
| **Return×INFO** | **0.49*** | **0.67*** | **0.60*** | **0.62*** |
| | **(5.18)** | **(4.69)** | **(4.49)** | **(4.97)** |
| Return | 0.51*** | 0.44*** | 0.46*** | 0.44*** |
| | (6.14) | (4.00) | (4.34) | (4.25) |
| INFO | 0.01 | -0.05* | -0.01 | -0.03 |
| | (0.20) | (-1.85) | (-0.13) | (-1.31) |
| UE×INFO | -0.13 | -0.10 | -0.02 | -0.10 |
| | (-1.22) | (-1.42) | (-0.21) | (-1.20) |
| UE | 0.50*** | 0.47*** | 0.41*** | 0.47*** |
| | (6.53) | (7.90) | (5.80) | (6.96) |
| Analyst_Revision×INFO | -0.01 | -0.08 | -0.14* | -0.06 |
| | (-0.15) | (-1.07) | (-1.93) | (-0.76) |
| Analyst_Revision | 0.29*** | 0.33*** | 0.38*** | 0.33*** |
| | (4.38) | (5.72) | (5.68) | (4.67) |
| Size | 0.01 | 0.01 | 0.01 | 0.01 |
| | (1.20) | (0.78) | (0.76) | (0.98) |
| Tobin's_Q | 0.03*** | 0.03*** | 0.03*** | 0.03*** |
| | (3.24) | (2.99) | (3.21) | (3.03) |
| Coverage | 0.06*** | 0.06*** | 0.06*** | 0.06*** |
| | (2.87) | (2.72) | (2.92) | (2.81) |
| Horizon | 0.00 | 0.00 | 0.01 | 0.00 |
| | (0.33) | (0.40) | (0.44) | (0.39) |
| Gap | -0.05*** | -0.05*** | -0.05*** | -0.05*** |
| | (-3.13) | (-3.09) | (-3.13) | (-3.07) |
| Constant | -0.24** | -0.18** | -0.22 | -0.20** |
| | (-2.06) | (-2.24) | (-1.21) | (-2.42) |
| | | | | |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Observations | 16,471 | 16,471 | 16,471 | 16,471 |
| Adjusted R$^2$ | 37.5% | 37.6% | 37.6% | 37.6% |

I use the decile rankings of *ASC_Spread*, *PIN*, *Amihud* and *INFO* (rescaled to range from zero to one) to facilitate interpretation of the coefficients. The *t*-statistics, presented in parentheses below the coefficients, are corrected for heteroskedasticity and cross-sectional and time-series correlations using a two-way cluster at the firm and year levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels for two-tailed tests, respectively. All variables are defined in the appendix.

Table 4: Cross-Sectional Tests on the Relevance of Investors' Information

| | Dependent Variable: *Forecast_Revision* | |
|---|---|---|
| | (1) | (2) |
| *Relevance =* | *Long_Horizon* | *Neg_Return* |
| ***Return×INFO×Relevance*** | **0.51*** ** | **0.58** ** |
| | **(4.29)** | **(2.33)** |
| ***Return×INFO*** | **0.27** ** | **0.51*** ** |
| | **(2.24)** | **(2.66)** |
| *Return* | 0.46*** | 0.40*** |
| | (4.02) | (2.79) |
| *INFO* | -0.03 | -0.00 |
| | (-1.28) | (-0.03) |
| *Relevance* | -0.04 | -0.01 |
| | (-1.45) | (-0.27) |
| *UE×INFO×Relevance* | -0.01 | -0.13** |
| | (-0.22) | (-2.55) |
| *UE×INFO* | -0.09 | -0.02 |
| | (-0.96) | (-0.21) |
| *UE* | 0.47*** | 0.47*** |
| | (6.99) | (6.96) |
| *Analyst_Revision×INFO×Relevance* | 0.00 | -0.07 |
| | (0.07) | (-1.54) |
| *Analyst_Revision×INFO* | -0.06 | -0.03 |
| | (-0.66) | (-0.40) |
| *Analyst_Revision* | 0.32*** | 0.33*** |
| | (4.61) | (4.72) |
| *Size* | 0.01 | 0.01 |
| | (1.01) | (0.85) |
| *Tobin's_Q* | 0.03*** | 0.03*** |
| | (3.08) | (3.19) |
| *Coverage* | 0.06*** | 0.06*** |
| | (2.84) | (2.68) |
| *Horizon* | | 0.01 |
| | | (0.49) |
| *Gap* | -0.06*** | -0.05*** |
| | (-3.19) | (-2.58) |
| Constant | -0.11 | -0.24*** |
| | (-1.64) | (-2.62) |
| Industry FE | Yes | Yes |
| Year FE | Yes | Yes |
| Observations | 16,471 | 16,471 |
| Adjusted $R^2$ | 37.7% | 37.8% |

I use the decile rankings of *INFO* (rescaled to range from zero to one) to facilitate interpretation of the coefficients. The *t*-statistics, presented in parentheses below the coefficients, are corrected for heteroskedasticity and cross-sectional and time-series correlations using a two-way cluster at the firm and year levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels for two-tailed tests, respectively. All variables are defined in the appendix.

Table 5: The Effect of Investors' Information on Changes in Forecast Accuracy

| | Dependent Variable: $\Delta Accuracy$ |
|---|---|
| | (1) |
| **INFO** | **0.10*** |
| | **(10.46)** |
| *Size* | -0.02 |
| | (-1.44) |
| *Tobin's_Q* | -0.07*** |
| | (-7.38) |
| *Coverage* | -0.10*** |
| | (-3.27) |
| *Horizon* | 0.02 |
| | (1.41) |
| *Gap* | 0.17*** |
| | (6.11) |
| Constant | -0.29 |
| | (-1.30) |
| | |
| Industry FE | Yes |
| Year FE | Yes |
| Observations | 15,876 |
| Adjusted $R^2$ | 9.5% |

The *t*-statistics, presented in parentheses below the coefficients, are corrected for heteroskedasticity and cross-sectional and time-series correlations using a two-way cluster at the firm and year levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels for two-tailed tests, respectively. All variables are defined in the appendix.

Table 6: Controlling for Confounding Factors

| | Dependent Variable: *Forecast_Revision* | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ***Return×INFO*** | **0.75\*\*\*** | **0.61\*\*\*** | **0.43\*\*\*** | **0.63\*\*\*** | **0.55\*\*\*** |
| | **(5.28)** | **(4.76)** | **(3.37)** | **(4.02)** | **(4.31)** |
| *Return×FINC* | 0.38\*\* | | | | 0.35\* |
| | (2.06) | | | | (1.86) |
| *Return×Manager* | | -0.41\*\*\* | | | -0.44\*\*\* |
| | | (-3.17) | | | (-3.11) |
| *Return×Coverage* | | | -0.33\* | | -0.46\*\* |
| | | | (-1.86) | | (-2.54) |
| *Return×Size* | | | | 0.02 | 0.21 |
| | | | | (0.12) | (1.06) |
| *Return* | 0.21 | 0.68\*\*\* | 0.70\*\*\* | 0.44\*\*\* | 0.72\*\*\* |
| | (1.21) | (4.76) | (5.15) | (3.00) | (3.20) |
| *INFO* | -0.03 | -0.03 | -0.03 | -0.01 | -0.02 |
| | (-1.24) | (-1.32) | (-1.39) | (-0.47) | (-0.75) |
| *FINC* | 0.00 | | | | 0.00 |
| | (0.04) | | | | (0.03) |
| *Manager* | | 0.01 | | | -0.00 |
| | | (0.34) | | | (-0.15) |
| *Coverage* | | | 0.11\*\* | | 0.09\*\* |
| | | | (2.26) | | (2.46) |
| *Size* | | | | 0.07\* | 0.12\*\*\* |
| | | | | (1.80) | (3.21) |
| | | | | | |
| *UE* & Interactions | Included | Included | Included | Included | Included |
| *Analyst_Revision* & Interactions | Included | Included | Included | Included | Included |
| Controls | Included | Included | Included | Included | Included |
| Industry FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 13,636 | 16,471 | 16,471 | 16,471 | 13,636 |
| Adjusted $R^2$ | 36.6% | 37.6% | 37.6% | 37.9% | 37.1% |

I use the decile rankings of *INFO*, *FINC*, *Manager*, *Coverage*, and *Size* (rescaled to range from zero to one) to facilitate interpretation of the coefficients. The *t*-statistics, presented in parentheses below the coefficients, are corrected for heteroskedasticity and cross-sectional and time-series correlations using a two-way cluster at the firm and year levels. \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels for two-tailed tests, respectively. All variables are defined in the appendix.

Table 7: Using Mutual Fund Redemptions to Proxy for Investors' Information

|  | Dependent Variable: *Forecast_Revision* |
| --- | --- |
|  | (1) |
| ***Return×MFFlow*** | **-0.67**** |
|  | **(-2.06)** |
| *Return* | 1.33*** |
|  | (7.14) |
| *MFFlow* | 0.10 |
|  | (1.57) |
| *UE×MFFlow* | 0.04 |
|  | (0.33) |
| *UE* | 0.42*** |
|  | (5.79) |
| *Analyst_Revision×MFFlow* | 0.10 |
|  | (1.07) |
| *Analyst_Revision* | 0.36*** |
|  | (6.90) |
| *Size* | 0.01 |
|  | (1.23) |
| *Tobin's_Q* | 0.04*** |
|  | (3.14) |
| *Coverage* | 0.05** |
|  | (2.27) |
| *Horizon* | 0.00 |
|  | (0.16) |
| *Gap* | -0.08** |
|  | (-2.49) |
| Constant | -0.05 |
|  | (-0.59) |
|  |  |
| Industry FE | Yes |
| Year FE | Yes |
| Observations | 12,121 |
| Adjusted $R^2$ | 32.4% |

I use the decile rankings of *MFFlow* (rescaled to range from zero to one) to facilitate interpretation of the coefficients. The *t*-statistics, presented in parentheses below the coefficients, are corrected for heteroskedasticity and cross-sectional and time-series correlations using a two-way cluster at the firm and year levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels for two-tailed tests, respectively. All variables are defined in the appendix.

Table 8: The Heckman Model

| | First Step | Second Step |
| --- | --- | --- |
| | Dependent Variable: *D_Revision* | Dependent Variable: *Forecast_Revision* |
| | (1) | (2) |
| ***RetVol*** | **0.05**\*\* | |
| | **(2.17)** | |
| *IMR* | | 0.05 |
| | | (0.37) |
| ***Return×INFO*** | 0.15 | **0.63**\*\*\* |
| | (1.04) | **(6.56)** |
| *Return* | -0.23\*\* | 0.44\*\*\* |
| | (-2.19) | (6.18) |
| *INFO* | -0.07\* | -0.03 |
| | (-1.85) | (-1.05) |
| *UE×INFO* | -0.10\*\* | -0.10\*\*\* |
| | (-2.01) | (-2.94) |
| *UE* | 0.12\*\*\* | 0.47\*\*\* |
| | (3.48) | (19.15) |
| *Analyst_Revision×INFO* | 0.15\*\*\* | -0.06\*\* |
| | (3.85) | (-2.14) |
| *Analyst_Revision* | -0.09\*\*\* | 0.32\*\*\* |
| | (-3.27) | (15.72) |
| *Size* | -0.03\*\*\* | 0.01 |
| | (-3.21) | (1.07) |
| *Tobin's_Q* | 0.02\*\* | 0.03\*\*\* |
| | (2.41) | (5.22) |
| *Coverage* | 0.06\*\*\* | 0.06\*\*\* |
| | (3.92) | (4.93) |
| *Horizon* | -0.26\*\*\* | -0.00 |
| | (-22.62) | (-0.07) |
| *Gap* | 0.72\*\*\* | -0.03 |
| | (49.63) | (-0.67) |
| Constant | -0.04 | -0.25 |
| | (-0.10) | (-0.96) |
| | | |
| Industry FE | Yes | Yes |
| Year FE | Yes | Yes |
| Observations | 27,810 | 16,471 |
| Pseudo/Adjusted $R^2$ | 12.2% | 37.8% |

I use the decile rankings of *INFO* (rescaled to range from zero to one) to facilitate interpretation of the coefficients. The *t*-statistics, presented in parentheses below the coefficients, are based on the two-step variance estimator derived by Heckman (1979). \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels for two-tailed tests, respectively. All variables are defined in the appendix.