The Informational Feedback Effect of Stock Prices on Corporate Disclosure

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ABSTRACT

This paper studies whether managers use investor information they learn from the stock market when making forward-looking disclosures. Using annual management earnings 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, the effect of investor information on the revision-return relation remains after controlling for various sources of managerial and public information, and 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 but a weaker market reaction to the subsequent forecast announcement. My study highlights the two-way information flows between firms and capital markets and has implications for the real effects of financial markets.

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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 investor information they learn from the stock market when making forward-looking disclosures. Despite the large literature on the capital market consequences of corporate disclosure (see Beyer, Cohen, Lys and Walther (2010) for a review), few studies examine whether and how capital markets affect disclosure. I examine the informational feedback effect of stock prices on corporate disclosure.

I focus on one form of forward-looking disclosures, management earnings forecasts, 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 Chen, Goldstein and Jiang (2007) and use a modified version of the probability of privately informed trading net of all insider transactions. This measure starts with the probability of informed trading (*PIN*), estimated following Easley, Hvidkjaer and O'Hara (2002), and is adjusted for insider trading based on the strongest assumption (to my least favor) that all insider trades are informed. It is derived from a structural market microstructure model, in which trades come from either noise traders or informed traders. It directly measures the probability of informed trading by outsiders, and thus captures the amount of investor information reflected in stock prices.[1]

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 more informed trading. In the regression, I control for managers' private information about future earnings using earnings surprises for earnings announced concurrently with revised forecasts, and control for public information about future earnings using prevailing consensus analyst forecast revisions. In terms of economic significance, an increase in the extent of informed trading from the bottom to the top decile doubles the revision-return sensitivity. This result suggests that in revising earnings forecasts, managers respond more strongly to stock price changes when there is more informed trading, consistent with managers learning from investor information reflected in stock prices.

One potential concern is that privately informed traders dig out information already known by managers, and more informed trading leads to more managerial information impounded into stock prices. So the results that I document actually reflect the effect of managerial information, instead of investors' private information unknown to managers. However, it is important to note that the effect of managerial information on the revision-return relation should be driven by the *total* amount of managerial information impounded into stock prices, which depends on not only the extent of informed trading, but also a firm's nature and its

[1] All results remain largely unchanged when I use unadjusted *PIN* or several alternative measures of investor information, including the adverse selection component of the bid-ask spread, price impact, and price nonsynchronicity.

disclosure policies. To control for the *total* amount of managerial information impounded into stock prices, I use two proxies, a firm's growth opportunities and the degree of its financial reporting transparency. The *total* amount of managerial information impounded into stock prices should be less for firms with a larger investment opportunity set and more opaque financial reporting. In addition, I control for the amount of private information held by managers using forecast horizon (i.e., the number of days between the forecast date and the estimate period end). Managers are expected to have more private information about earnings in the short term than about earnings in the long term. If the extent of informed trading only captures the amount of information already known by managers, and if a firm's growth opportunities, the degree of its financial reporting transparency, and forecast horizon reflect managerial information, then the effect of informed trading on the revision-return relation should become weaker or even disappear after I put in those controls. To the contrary, the economic magnitude and statistical significance remain largely unchanged after I control for those variables. I also perform a battery of additional tests to control for other alternative interpretations of my main result. I show that the positive effect of investor information on the revision-return relation persists after I control for the effects of "prices leading earnings," investor sentiment, analyst coverage, and firm size.

To strengthen my inference, I conduct one cross-sectional test to examine whether the positive effect of investor information on the revision-return relation is more pronounced when the information is more relevant to predicted earnings. I predict that investor 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. Consistent with these arguments, I find that the effect of investor information on the revision-return relation is stronger when managers make long-horizon earnings forecasts. 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. 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 investor information contained in prior stock price changes affects the extent of improvement in management forecast accuracy. If stock prices contain outside investors' information that is new to managers and helps them improve their predictions of future earnings, there will be a positive association between the amount of investor information contained in stock prices and the extent of improvement in forecast accuracy. We should not expect such relation if informed traders only dig out information already known by managers. Moreover, investors should react less strongly to management forecasts when those forecasts contain more information that has already been reflected in stock prices. I find evidence consistent with these predictions, lending further support to the managerial learning hypothesis.

My study contributes to the literature in several ways. First, it highlights the two-way information flows between firms and capital markets in the context of corporate disclosure. An implicit assumption in most of the prior empirical accounting research is that managerial information completely subsumes that of outside investors.[2] If this is the case, we should expect

[2] 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.

no managerial learning from capital markets. Dye and Sridhar (2002) note that the current disclosure 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 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 shows that the stock market provides a significant amount of information that affects firms' own forward-looking disclosures.

Second, my findings of the two-way information flows between firms and capital markets suggest a potential cost of corporate disclosure. In the feedback literature, private 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' ex-ante incentives for acquiring private information that may be new to managers (Gao and Liang 2013). This argument is in line 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. 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.

Third, my study contributes to the growing literature on the informational content of market prices and the real effects of financial markets (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 improves managers' assessment of their firms' future prospects, which is one means through which investor information affects corporate investment decisions.

Finally, 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.

The remainder of the paper is organized as follows. I discuss related literature and develop the hypothesis in Section 2. Section 3 describes empirical models. In Section 4, I describe my sample and 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 some 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.[3] 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.

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 public information, 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. In other words, investors' information and

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

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

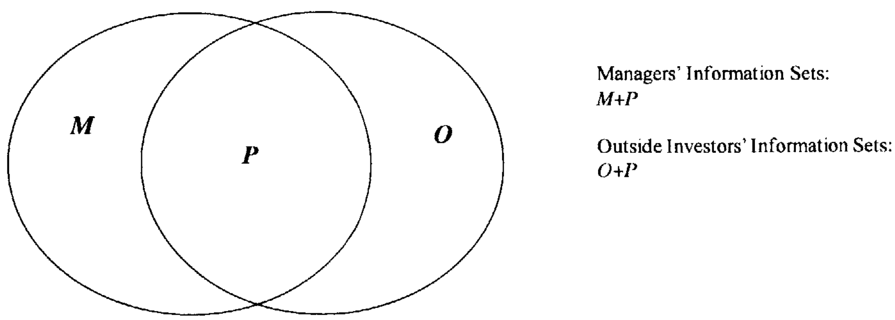

Figure 1: The Information Sets of Managers and Outside Investors

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). Fergus MacLeod, an award winning sell-side analyst, was appointed the head of BP Investor Relations for his ability "to speak the market's language and translate its views back to the company" (Miller, Beyersdorfer and Sjoman 2006, p.3). 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.[4] In this paper, I focus on management earnings forecasts, a key voluntary disclosure mechanism.[5] 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 investor information they learn from the stock market 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

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[4] Three theory papers are exceptions: Dye and Sridhar (2002), Langberg and Sivaramakrishnan (2010), and Gao and Liang (2013). However, these papers do not consider whether managers use investor information they learn from the stock market 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.

[5] 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 whether the amount of investor information contained in stock prices affects the quality of managers' forward-looking disclosures.

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). In addition, managers may not be willing or able to decipher investor information contained in stock prices and incorporate that into their internal decisions. 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.

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.[6] 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; Stocken 2000; Lee, Matsunaga and Park 2012). Consistent with these theoretical and empirical studies, empirical evidence suggests that management forecasts have credibility comparable to audited financial information (Healy and Palepu 2001).

[6] The possibility that some managers have incentives to distort their forecasts likely works against my predictions. Under that scenario, managers learn from investor information contained in stock prices but do not use it when issuing their forecasts. In addition, if managers wish to withhold some information, they can choose not to disclose (instead of disclosing untrue information and suffering potential penalties). Sletten (2012) finds evidence that managers withhold bad news and that exogenous stock price declines can induce its *disclosure*.

3. Research Design

3.1 Intuition

The essence of my main empirical test is a regression of management 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 investor information (*INFO*):

$$Forecast\_Revision = \alpha + \beta_1 Return \times INFO + \beta_2 Return + \beta_3 INFO + \Gamma \text{Controls} + \varepsilon. \tag{1}$$

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 $Forecast_{i,t-1}$.[7] 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 systematic component instead of market-adjusted or industry-adjusted returns because both market and industry returns affect future earnings predictions. *INFO* is the probability of privately informed trading net of all insider transactions (defined below) measured prior to $Forecast_{i,t-1}$.[8] 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 ΔM is the change in managers' private information, ΔP is the change in public information, and

[7] All results are similar when I define *Forecast_Revision* as $100\times(Forecast_{i,t} - Forecast_{i,t-1})/|Forecast_{i,t-1}|$, where $|Forecast_{i,t-1}|$ is the absolute value of $Forecast_{i,t-1}$.

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

ΔO is the change in outside investors' information. To concentrate on the intuition, I use ΔM to denote managerial information that has not found its way to the price yet, and use ΔO to denote investor information that has been incorporated into prices through trading.[9] Then:

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

where ε is noise. For the learning hypothesis to hold, the condition is not that the market is always right or there is no noise trading (i.e., $\varepsilon = 0$). It only needs to be the case that the market is not always wrong. Assuming that managers use their private information in their forecasts:

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

where λ is between zero and one and denotes the fraction of outside investors' information that managers are willing and able to incorporate into their forecast revision. The coefficient of a regression of forecast revisions on returns is:

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

Different stocks may have different amounts of investor information in their prices due to different benefits and costs of information production. Consider the following simplified example in which outside investor information is either high or low. If the outside information is high ($\text{var}(\Delta O_H) = \text{var}(\Delta O) > 0$), 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 ($\text{var}(\Delta O_L) = 0$), then this coefficient is: $\theta_{Low} = \text{var}(\Delta P_L)/\text{var}(Return_L)$. The difference is:

[9] 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.

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

If I empirically observe that this difference (i.e., $\theta_{High\text{-}Low}$) 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., $\text{var}(Return_H) \geq \text{var}(Return_L)$.[10] Thus, a positive $\theta_{High\text{-}Low}$ 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.[11] Thus, a positive $\theta_{High\text{-}Low}$ 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. Note that 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 managers.[12] My prediction will hold as long as, on average, investor

[10] In the sample, the extent of informed trading (*INFO*) and stock return volatility (*RetVol*) is positively correlated (ρ = 0.27).

[11] Consistent with this view, Maffett (2012) documents that more opaque firms experience more privately informed trading by institutional investors. In addition, Barth, Konchitchki and Landsman (2013) document a negative link between earnings transparency and information asymmetry.

[12] An effect driven by public information (i.e., ΔP) should result in a positive association between management forecast revisions and stock returns (i.e., a positive θ), 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 $\theta_{High\text{-}Low}$). In addition, I

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.

3.2 Measure of Investor Information

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 extent of informed trading in the stock market is positively associated with the amount of this information. Following this logic, I use a modified version of the probability of privately informed trading net of all insider transactions to proxy for the amount of investor information contained in prices. I construct this measure (*INFO*) in two steps. First, I estimate the probability of informed trading (*PIN*) following Easley, Hvidkjaer and O'Hara (2002). Second, I adjust for insider trading.

The *PIN* 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 investor information reflected in stock prices. The trading process is modeled in the following way. The daily arrival rates of noise traders that submit buy and sell orders are ε_b and ε_s, respectively. The probability that some traders acquire new (private) information about the fundamental value of the firm is α. Given an information event occurs, the arrival rate of informed traders is μ. Then, the probability of informed trading in a given stock for a given period will be: $PIN = \alpha\mu / (\alpha\mu + \varepsilon_s + \varepsilon_b)$. *PIN* should be low for stocks with little fluctuation in their daily buy and sell orders, which are more likely to arise from liquidity or noise trading. Likewise, *PIN* should be high for stocks that display frequent large deviations from their normal order flows. Easley, Hvidkjaer and O'Hara (2002) find that stocks

control for public information revealed to managers during the management forecast revision period by including the prevailing consensus analyst forecast revision in the regressions.

with high *PIN* earn higher returns that compensate investors for the high risk of private information. To adjust for insider trading, I make the strongest assumption (to my least favor) that all insider trades are informed, and calculate *INFO* for the outside informed traders as $PIN \times (1 - Insider)$, where *Insider* is the percentage of insider transactions to the total number of all transactions over the period in which *PIN* is calculated. I use *INFO* as my main proxy for the amount of investor information contained in stock prices.[13] In the robustness check, I use three alternative measures of investor information, including the adverse selection component of the bid-ask spread, price impact, and price nonsynchronicity.

3.3 Empirical Specification

To assess the managerial learning hypothesis, I augment (1) as follows:

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

I control for managers' private information about future earnings (i.e., ΔM) 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,[14] 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

[13] All results remain virtually unchanged when I use unadjusted *PIN*. I acknowledge that the measure of investor information is imperfect. *PIN* might capture some illiquidity effects not related to investor information. However, it is important to note that there is no reason to believe that measurement error in *PIN* can explain my findings. If anything, it makes it harder to detect any underlying relation between the latent variables.

[14] Following Rogers and Van Buskirk (2013), 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.

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., ΔP) 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 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 $Forecast_{i,t-1}$.[15]

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

[15] 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 investor 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.

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.

4. Sample and Empirical Results

4.1 Sample Selection and Summary Statistics

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.[16] 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.[17] 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), analysts' forecasts and actual earnings per share data from I/B/E/S, and insider trading data from Thomson Reuters. The final sample contains 16,471 management forecast revisions (with non-missing variables) from 1996 to 2010.[18]

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

[16] Chuk, Matsumoto and Miller (2013) 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 investor information contained in stock prices into their earnings forecasts once their decisions to issue forecasts have been made.
[17] As elaborated in Section 4.7, I use forecast reiterations as a control group under the Heckman (1979) framework.
[18] 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.

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).[19] 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.[20]

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. 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.

[19] The results are essentially unchanged when I restrict my sample to the period post Reg FD.

[20] 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 investor 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.

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.

4.2 Main Results

Table 3 presents the results of the main test. 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 all positive and significant at the 1% level, as expected. More importantly, the coefficient on the interaction term between *Return* and *INFO* (*Return×INFO*) is positive and significant at the 1% level, 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 to the top decile doubles the revision-return sensitivity. The Variance Inflation Factor (*VIF*) on *Return×INFO* equals 5.42, suggesting that multicollinearity is not high. In sum, the result in Table 3 suggests that managers learn from investor information contained in stock prices, supporting my 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 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.

4.3 Controlling for the Effect of Managerial Information

The positive coefficient on *Return×INFO* documented in Table 3 is consistent with the idea that managers learn from stock prices when forecasting future earnings. However, one potential concern is that more informed trading leads to more managerial information impounded into stock prices. In other words, the information that informed traders gather is not new to managers. So the effect that I document, i.e., the positive effect of investor information on the revision-return relation is contaminated by the effect of managerial information. However, it is important to note that the effect of managerial information on the revision-return relation should be driven by the *total* amount of managerial information impounded into stock prices, which depends on not only the extent of informed trading, but also a firm's nature and its disclosure policies. In Table 4, I use several variables to control for the effect of managerial information.

In column (1) of Table 4, I control for the *total* amount of managerial information impounded into stock prices using a firm's growth opportunities. The *total* amount of managerial information impounded into stock prices should be less for firms with larger investment opportunity sets. Managers of growth firms hold a strong information advantage over outside investors and should respond less strongly to stock price changes over the forecast revision period. I put *Tobin's_Q* as a direct control and use the following model:

$$\begin{aligned} Forecast\_Revision = \alpha &+ \beta_1 Return{\times}INFO + \beta_2 Return{\times}Tobin's\_Q \\ &+ \beta_3 Return + \beta_4 INFO + \beta_5 Tobin's\_Q \\ &+ \beta_6 UE{\times}INFO + \beta_7 UE{\times}Tobin's\_Q + \beta_8 UE \\ &+ \beta_9 Analyst\_Revision{\times}INFO + \beta_{10} Analyst\_Revision{\times}Tobin's\_Q \\ &+ \beta_{11} Analyst\_Revision + \Gamma\text{Controls} + \text{Industry FE} + \text{Year FE} + \varepsilon. \end{aligned} \tag{7}$$

The coefficient on *Return×Tobin's_Q* is negative (with *t*-statistic equal to -3.76). The negative coefficient is expected because managers in firms with more growth opportunities possess more private information and thus rely less on the information in stock prices for forecasting future earnings. More importantly, the coefficient on *Return×INFO* remains positive and significant at the 1% level.

In column (2), I control for the amount of managerial information disclosed to the stock market by using the *Fog* index in Li (2008). The idea is that more managerial information is impounded into stock prices when firms have better disclosure quality. As the *Fog* index is negatively correlated with disclosure quality, it should have a negative effect on the revision-return relation. To test this, I replace *Tobin's_Q* in equation (7) with *Fog*. As expected, the coefficient on *Return×Fog* is negative and significant at the 5% level, and the coefficient on *Return×INFO* remains positive and significant at the 1% level.

In column (3), I control for the amount of private information managers hold. I use *Horizon* as a measure of the amount of managerial information. Managers are expected to have more private information about earnings in the short term than about earnings in the long term, so *Horizon* is inversely related to the amount of private information held by managers. To test this, I replace *Tobin's_Q* in equation (7) with *Horizon*. The coefficient on *Return×Horizon* is positive and significant, indicating that managers rely more on information in stock prices when they possess less private information themselves. The coefficient on *Return×INFO* remains positive and significant at the 1% level.

In column (4), I put the three measures of managerial information into the regression. If *INFO* only captures information already known by managers and if *Tobin's_Q*, *Fog*, and *Horizon* reflects managerial information, then the coefficient on *Return×INFO* should become insignificant after I put in those controls. This does not appear to be the case. The coefficient on *Return×INFO* remains positive and highly significant in the presence of those control variables.

4.4 Controlling for Other Confounding Factors

4.4.1 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 investor 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:

$$\begin{aligned} Forecast\_Revision = {} & \alpha + \beta_1 Return\times INFO + \beta_2 Return\times FINC + \beta_3 Return + \beta_4 INFO + \beta_5 FINC \\ & + \beta_6 UE\times INFO + \beta_7 UE\times FINC + \beta_8 UE \\ & + \beta_9 Analyst\_Revision\times INFO + \beta_{10} Analyst\_Revision\times FINC \\ & + \beta_{11} Analyst\_Revision + \Gamma\text{Controls} + \text{Industry FE} + \text{Year FE} + \varepsilon, \end{aligned} \tag{8}$$

where *FINC* is the future earnings incremental explanatory power measure from Durnev, Morck, Yeung and Zarowin (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 ΔE_{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 investor 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 investor 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; Barth, Konchitchki and Landsman 2013; Gao and Liang 2013). In my sample, I find a negative and statistically significant correlation between *FINC* and *INFO* (-0.05).

Column (1) of Table 5 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."

4.4.2 Controlling for Investor Sentiment

Even in the absence of managerial learning, management forecast revisions can be sensitive to prior stock price changes due to managerial catering to investor sentiment. If that is the case, management forecast revisions should be more sensitive to stock returns when investor sentiment is strong. To measure investor sentiment, I use the absolute value of the investor sentiment index developed in Baker and Wurgler (2006, 2007). In column (2) of Table 5, I replace *FINC* in equation (8) with *|Sentiment|*. The coefficient on *Return×INFO* remains positive and significant at the 1% level, while the coefficient on *Return×|Sentiment|* is insignificant.

4.4.3 Controlling for Analyst Coverage

In column (3) of Table 5, I control for analyst coverage by replacing *FINC* in equation (8) 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 that analysts merely piggyback on recent news and their outputs are largely information-free (Altinkilic and Hansen 2009), and that the presence of analysts can attract more noise trading to the stock (Easley, O'Hara and Paperman 1998).

4.4.4 Controlling for Firm Size

Since *Size* has a strong negative correlation with measures of investor information (-0.47), I directly control for it to ensure that firm size does not drive my results on the effect of investor information on the revision-return relation. To test this, in equation (8) I replace *FINC* with *Size*. The results are tabulated in column (4) of Table 5. 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 5, 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 5 suggest that my results are unlikely to be driven by confounding factors that are potentially associated with the extent of informed trading.

4.5 Cross-Sectional Test on the Relevance of Investor Information

The positive effect of investor information on the revision-return relation should be more pronounced when this information is more relevant to predicted earnings. 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.

Table 6 presents the results for both long-horizon and short-horizon forecasts, where long-horizon forecasts are defined as those forecasts issued more than 90 days before the estimate period end date (Bergman and Roychowdhury 2008). My sample includes 10,885 long-horizon forecasts and 5,586 short-horizon ones. Column (1) shows that the coefficient on *Return×INFO* is 0.84 (with *t*-statistic equal to 7.00) for long-horizon forecasts, while column (2) shows that the coefficient on *Return×INFO* is 0.33 (with *t*-statistic equal to 2.23) for short-horizon forecasts. The difference between these two coefficients is 0.51 and statistically significant at the 5% level, indicating that the effect of investor information on the association between forecast revisions and stock returns is stronger for long-horizon forecasts. Consistent with my prediction, 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.

4.6 Using Mutual Fund Redemptions to Proxy for Investor Information

In the main tests, I use the extent of informed trading 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.[21] 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 effects of managerial information, "prices leading earnings," investor sentiment, analyst coverage, and firm size.

4.7 The Heckman Selection Model

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:

$$\begin{aligned} D\_Revision = {} & \alpha + \beta_1 RetVol + \beta_2 Return \times INFO + \beta_3 Return + \beta_4 INFO \\ & + \beta_5 UE \times INFO + \beta_6 UE \\ & + \beta_7 Analyst\_Revision \times INFO + \beta_8 Analyst\_Revision \\ & + \Gamma \text{Controls} + \text{Industry FE} + \text{Year FE} + \varepsilon. \end{aligned} \tag{9}$$

[21] 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.

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.[22] I include in the first step all other variables used in the second step.

The second-step model is as follows:

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

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.

[22] In untabulated results, when I replace *FINC* with *RetVol* as a control variable in model (8), the coefficients on *RetVol* and *Return×RetVol* are both statistically insignificant from zero (consistent with my justifications for the exclusion restriction).

4.8 Additional Analyses

4.8.1 The Effect of Investor 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 investor 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:

$$\Delta Accuracy = \alpha + \beta_1 INFO + \Gamma\text{Controls} + \text{Industry FE} + \text{Year FE} + \varepsilon. \quad (11)$$

$\Delta Accuracy$ 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 investor information contained in stock prices improves management forecast accuracy.

Table 9 presents the results. It shows that the coefficient on *INFO* is positive and statistically significant at the 1% level, indicating a positive association between the amount of investor information contained in stock prices and changes in forecast accuracy ($\Delta Accuracy$). Consistent with my prediction, the results suggest that investor information contained in stock prices helps managers improve their forecasts of future earnings.

4.8.2 The Effect of Prior Investor Information on Subsequent Market Reaction

If managers' revised forecasts contain more investor information already reflected in stock prices, investors will react less strongly to those forecasts. To test this, I use the following regression equation:

$$Market\_Reaction = \alpha + \beta_1 INFO + \beta_2 Earn\_Surp + \Gamma \text{Controls} + \text{Industry FE} + \text{Year FE} + \varepsilon. \qquad (12)$$

Following Hilary and Hsu (2011), I calculate *Market_Reaction* as the ratio of the two-day (0,1) market-adjusted stock return around the forecast announcement to forecast news, where forecast news is proxied by the difference between the management forecast and the prevailing consensus analyst forecast (scaled by the price two days before the issuance of the management forecast).[23] To control for potential confounding effects of concurrent earnings announcements, I include *Earn_Surp*, the unexpected earnings of firm i at the issuance of $Forecast_{i,t}$ (scaled by forecast news). For earnings forecasts not issued concurrently with earnings announcements, I code *Earn_Surp* as zero. The variable of interest is *INFO*. I expect the coefficient on *INFO* to be negative, suggesting that investors react less strongly to management forecasts if those forecasts contain more information that has already been reflected in stock prices.

Table 10 shows that the coefficient on *INFO* is negative and statistically significant at the 5% level, indicating a negative association between the amount of investor information reflected in stock prices and the market reaction to the subsequent forecast announcement. Consistent with my prediction, the result suggests that investors react less strongly to forecast news when more information has already been reflected in stock prices through informed trading.

[23] Forecast news measured in this way includes both managers' private information and investors' information revealed to managers through stock prices. The implicit assumption in this calculation is that analysts do not fully incorporate investors' information into their earnings forecasts. Otherwise, forecast news will only include managers' private information and there should be no relation between *INFO* and *Market_Reaction*.

4.9 Alternative Measures of Investor Information

I use three alternative measures of investor information, including the adverse selection component of the bid-ask spread, price impact, and price nonsynchronicity. All measures are estimated over the year prior to $Forecast_{i,t-1}$ to alleviate potential endogeneity concerns. My first alternative measure, the adverse selection component of the bid-ask spread (*ASC_Spread*), is estimated following Madhavan, Richardson, and Roomans (1997). To estimate *ASC_Spread*, I gather trade-by-trade and quote data from the TAQ database. I match trades and quotes using the Lee and Ready (1991) algorithm with a five-second lag to determine the direction of the trade (i.e., buy or sell). I clean trades and quotes using the algorithm described in Ng, Rusticus and Verdi (2011). Once trades are classified as either buyer-initiated or seller-initiated, I estimate the following firm-specific regression:

$$\frac{\Delta p_t}{p_{t-1}} = \Psi \Delta D_t + \lambda\left(D_t - \rho D_{t-1}\right) + u_t, \tag{13}$$

where p_t is the transaction price, D_t is the sign of trade (+1 if buy and -1 if sell), and ρ is the AR(1) coefficient for D_t. The fitted λ in the above is *ASC_Spread*. *ASC_Spread* measures the extent to which unexpected order flows affect prices and is increasing in information asymmetry. Prior studies (e.g., Gao and Liang 2013) suggest that the level of information asymmetry between informed and uninformed investors in the stock market is positively associated with the amount of investor information contained in stock prices.

Amihud is my second alternative measure of investor information; it is estimated following Amihud (2002). This measure is defined as the annual average of the daily ratio between a stock's absolute return and its dollar volume (multiplied by 10^6):

$$Amihud = \frac{1}{D_i} \sum_{t=1}^{D_i} \frac{|r_{it}|}{VOLD_{it}}, \tag{14}$$

where D_i is the annual number of valid observation days for stock i, r_{it} is the return of stock i in day t, and $VOLD_{it}$ is the dollar volume of stock i on day t. This ratio gives the absolute (percentage) price change per dollar of daily trading volume and proxies for the price impact of order flow. 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).

The extant literature also uses price nonsynchronicity (*Nonsync*) 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. Specifically, it is estimated by $1 - R^2$, where R^2 is the R-squared from the following regression:

$$r_{i,j,t} = \beta_{i,0} + \beta_{i,m} \cdot r_{m,t} + \beta_{i,j} \cdot r_{j,t} + \varepsilon_{i,t}, \tag{15}$$

where $r_{i,j,t}$ is the return of firm i in industry j at time t, $r_{m,t}$ is the market return at time t, and $r_{j,t}$ is the return of industry j at time t. 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 correlations among the four measures of investor information (i.e., *INFO*, *ASC_Spread*, *Amihud*, and *Nonsync*) are high (ranging from 0.23 to 0.71). Table 11 reports the results for the main regression with these alternative measures of investor information. All results are quite similar (in terms of magnitude and statistical significance) to those reported in Table 3 when I use any one of the three alternative measures of investor information.

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 investor information they learn from the stock market when making forward-looking disclosures. I use the extent of informed trading in the stock market 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 contained in stock prices is higher. The results are robust after I control for the effects of managerial information, "prices leading earnings," investor sentiment, analyst coverage, and firm size. Further, I find the positive effect of investor information on the revision-return relation to be stronger when investor information is more relevant to predicted earnings. 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 investor information contained in stock prices to improve their forecasts and that investors react less strongly to subsequent forecast announcements when more information has already been incorporated into stock prices through informed trading.

This study provides empirical evidence that investor 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 and has implications for the real effects of financial markets. One interesting implication of my study is that to the extent that privately informed trading provides managers with valuable information, corporate disclosure that reduces information asymmetry between informed and uninformed investors also dampens the potential informational feedback effect by weakening investors' ex-ante incentives for acquiring private information that may be new to managers.

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Appendix: Variable Definitions

Forecast_Revision	$Forecast\_Revision_{i,t}$ = 100×($Forecast_{i,t}$ – $Forecast_{i,t-1}$)/$Price_{i,t-1}$, 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 $Forecast_{i,t}$.
INFO	Probability of informed trading net of all insider transactions, calculated as *PIN*×(1 – *Insider*) and measured over the year prior to $Forecast_{i,t-1}$, where *PIN* is the probability of informed trading, estimated following Easley, Hvidkjaer and O'Hara (2002), and *Insider* is the percentage of insider transactions to the total number of all transactions as recorded in TAQ.
UE	Unexpected quarterly earnings of firm *i* on the issuance day of $Forecast_{i,t}$: *UE* = 100×($Actual\ Earnings_{i,t}$ – $Consensus\ Analyst\ Forecast_{i,t}$)/$Price_{i,t}$, 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×($Analyst\_Forecast_{i,t}$ – $Analyst\_Forecast_{i,t-1}$)/$Price_{i,t-1}$, 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 $Forecast_{i,t}$.
Fog	*Fog* index from Li (2008), measured over the year prior to $Forecast_{i,t-1}$.
FINC	Future earnings incremental explanatory power measure from Durnev, Morck, Yeung and Zarowin (2003), measured over the year prior to $Forecast_{i,t-1}$.
Sentiment	The investor sentiment score from Baker and Wurgler (2006, 2007), measured over the year prior to $Forecast_{i,t-1}$.
|*Sentiment*|	Absolute value of *Sentiment*.
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 $Forecast_{i,t-1}$.
IMR	Inverse Mills' ratio, calculated by using the Heckman model.
ΔAccuracy	-100×(|$Forecast_{i,t}$ – *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 $Forecast_{i,t-1}$.
Market_Reaction	The ratio of the two-day (0,1) market-adjusted stock return around the revised forecast announcement to forecast news, measured following Hilary and Hsu (2011).
Earn_Surp	Unexpected quarterly earnings of firm *i* at the issuance of $Forecast_{i,t}$ (scaled by forecast news).
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 $Forecast_{i,t-1}$.
Amihud	Price impact, estimated following Amihud (2002) and measured over the year prior to $Forecast_{i,t-1}$.
Nonsync	Price nonsynchronicity, estimated as the portion of a firm's stock return variation unexplained by market and industry returns, and measured over the year prior to $Forecast_{i,t-1}$.

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
INFO	16,471	0.12	0.11	0.06
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
Fog	13,794	19.7	19.5	2.1
FINC	13,636	0.14	0.08	0.17
|*Sentiment*|	16,471	0.34	0.17	0.44
MFFlow	12,121	0.30	0.14	0.47
RetVol	16,471	0.03	0.02	0.02
Δ*Accuracy*	15,876	0.45	0.18	0.91
Market_Reaction	14,755	0.17	0.08	0.67
Earn_Surp	16,471	0.39	0.00	1.85
ASC_Spread	16,471	0.04	0.02	0.06
Amihud	16,471	0.04	0.00	0.16
Nonsync	16,471	0.62	0.68	0.27

Panel B: Pearson Correlation Coefficients

	Forecast_Revision	*Return*	*INFO*	*UE*	*Analyst_Revision*	*Size*	*Tobin's_Q*	*Coverage*	*Horizon*
Return	0.32								
INFO	-0.05	0.08							
UE	0.52	0.21	-0.04						
Analyst_Revision	0.51	0.27	-0.01	0.59					
Size	0.04	-0.06	-0.47	0.04	0.01				
Tobin's_Q	0.06	-0.05	-0.07	0.05	0.05	-0.27			
Coverage	0.06	-0.07	-0.46	0.04	0.02	0.54	0.19		
Horizon	0.02	0.05	-0.02	0.00	-0.01	0.01	0.04	0.04	
Gap	-0.06	0.06	0.07	-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. Correlations greater than 0.02 and 0.04 in absolute values are significant at the 5% and 1% levels, respectively. All variables are defined in the appendix.

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

	Dependent Variable: *Forecast_Revision*
Return×INFO	**0.67***** **(4.77)**
Return	0.43*** (4.01)
INFO	-0.05* (-1.86)
UE×INFO	-0.10 (-1.40)
UE	0.47*** (7.92)
Analyst_Revision×INFO	-0.08 (-1.06)
Analyst_Revision	0.33*** (5.72)
Size	0.01 (0.77)
Tobin's_Q	0.03*** (2.99)
Coverage	0.06*** (2.72)
Horizon	0.00 (0.40)
Gap	-0.05*** (-3.08)
Constant	-0.18** (-2.24)
Industry FE	Yes
Year FE	Yes
Observations	16,471
Adjusted R^2	37.6%

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 4: Controlling for the Effect of Managerial Information

	Dependent Variable: *Forecast_Revision*			
	(1)	(2)	(3)	(4)
Return×INFO	**0.61*** **	**0.53*** **	**0.66*** **	**0.40** **
	(4.47)	**(2.92)**	**(4.58)**	**(2.14)**
Return×Tobin's_Q	-0.57***			-0.72***
	(-3.76)			(-3.60)
Return×Fog		-0.26**		-0.31***
		(-2.51)		(-3.17)
Return×Horizon			0.44***	0.45***
			(3.27)	(3.14)
Return	0.78***	0.64***	0.23*	0.89***
	(4.98)	(4.14)	(1.79)	(3.82)
INFO	-0.04	-0.04	-0.05*	-0.02
	(-1.31)	(-1.21)	(-1.80)	(-0.63)
Tobin's_Q	0.17***			0.19***
	(3.25)			(3.27)
Fog		-0.01		-0.00
		(-0.42)		(-0.21)
Horizon			-0.02	-0.03
			(-0.50)	(-0.82)
UE & Interactions	Included	Included	Included	Included
Analyst_Revision & Interactions	Included	Included	Included	Included
Controls	Included	Included	Included	Included
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	16,471	13,794	16,471	13,794
Adjusted R^2	38.0%	37.8%	37.7%	38.4%

I use the decile rankings of *INFO*, *Tobin's_Q*, *Fog* and *Horizon* (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: Controlling for Other Confounding Factors

	Dependent Variable: *Forecast_Revision*				
	(1)	(2)	(3)	(4)	(5)
Return×INFO	**0.84*** **	**0.65*** **	**0.50*** **	**0.65*** **	**0.68*** **
	(5.58)	**(4.52)**	**(2.98)**	**(3.44)**	**(4.05)**
Return×FINC	0.39**				0.37*
	(2.08)				(1.94)
Return×|Sentiment|		0.05			0.10
		(0.40)			(0.73)
Return×Coverage			-0.32*		-0.36**
			(-1.67)		(-2.20)
Return×Size				-0.04	0.16
				(-0.20)	(0.87)
Return	0.16	0.42***	0.67***	0.47***	0.32
	(0.92)	(3.86)	(3.91)	(2.69)	(1.34)
INFO	-0.04	-0.05*	-0.05*	-0.03	-0.03
	(-1.37)	(-1.86)	(-1.76)	(-1.19)	(-0.91)
FINC	0.00				0.00
	(0.08)				(0.04)
|Sentiment|		0.08			0.10*
		(1.05)			(1.66)
Coverage			0.10**		0.09**
			(2.20)		(2.40)
Size				0.06	0.11***
				(1.38)	(3.33)
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	36.7%	37.8%	37.6%	38.0%	37.2%

I use the decile rankings of *INFO, FINC*, *|Sentiment|*, *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 6: Cross-Sectional Test on the Relevance of Investor Information

	Dependent Variable: *Forecast_Revision*	
	(1) Long-Horizon Forecasts	(2) Short-Horizon Forecasts
Return×INFO	**0.84*****	**0.33****
	(7.00)	**(2.23)**
Return	0.47***	0.36***
	(5.48)	(3.48)
INFO	-0.07**	0.00
	(-2.37)	(0.04)
UE×INFO	-0.10**	-0.11**
	(-2.43)	(-2.12)
UE	0.46***	0.50***
	(16.45)	(14.21)
Analyst_Revision×INFO	-0.12***	0.05
	(-3.97)	(1.21)
Analyst_Revision	0.37***	0.23***
	(16.30)	(7.60)
Size	0.01	-0.00
	(1.47)	(-0.05)
Tobin's_Q	0.03***	0.02***
	(4.29)	(2.75)
Coverage	0.04***	0.09***
	(2.68)	(4.94)
Horizon	0.10***	0.09***
	(4.66)	(3.86)
Gap	-0.04***	-0.07***
	(-2.96)	(-3.87)
Constant	-0.76***	-0.25
	(-2.67)	(-0.68)
Difference in Coefficients on *Return×INFO*	0.51**	
Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	10,885	5,586
Adjusted R^2	36.8%	41.3%

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 7: Using Mutual Fund Redemptions to Proxy for Investor Information

	Dependent Variable: *Forecast_Revision*
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 Dependent Variable: *D_Revision* (1)	Second Step Dependent Variable: *Forecast_Revision* (2)
RetVol	**0.05****	
	(2.02)	
IMR		0.04
		(0.28)
Return×INFO	0.26*	**0.68*****
	(1.86)	**(7.18)**
Return	-0.30***	0.43***
	(-3.03)	(6.33)
INFO	-0.03	-0.05**
	(-0.84)	(-2.01)
UE×INFO	-0.07	-0.10***
	(-1.41)	(-3.02)
UE	0.10***	0.47***
	(3.00)	(20.44)
Analyst_Revision×INFO	0.12***	-0.07***
	(3.20)	(-2.75)
Analyst_Revision	-0.07***	0.33***
	(-2.60)	(17.60)
Size	-0.02***	0.01
	(-2.72)	(0.98)
Tobin's_Q	0.02***	0.03***
	(2.67)	(5.11)
Coverage	0.07***	0.06***
	(4.20)	(4.77)
Horizon	-0.26***	0.00
	(-22.59)	(0.02)
Gap	0.72***	-0.04
	(49.62)	(-0.75)
Constant	-0.15	-0.22
	(-0.36)	(-0.83)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	27,810	16,471
Pseudo/Adjusted R^2	12.2%	37.9%

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.

Table 9: The Effect of Investor Information on Changes in Forecast Accuracy

	Dependent Variable: $\Delta Accuracy$
INFO	**0.67*****
	(6.21)
Size	-0.03***
	(-3.21)
Tobin's_Q	-0.08***
	(-8.02)
Coverage	-0.13***
	(-4.04)
Horizon	0.03
	(1.43)
Gap	0.17***
	(6.11)
Constant	-0.14
	(-0.68)
Industry FE	Yes
Year FE	Yes
Observations	15,876
Adjusted R^2	9.1%

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 10: The Effect of Prior Investor Information on Subsequent Market Reaction

	Dependent Variable: *Market_Reaction*
INFO	**-0.26****
	(-2.03)
Size	-0.02***
	(-5.70)
Tobin's_Q	0.02***
	(4.73)
Coverage	0.08***
	(6.12)
Horizon	-0.02**
	(-2.09)
Gap	0.00
	(0.32)
Earn_Surp	-0.01
	(-0.90)
Constant	0.33**
	(2.11)
Industry FE	Yes
Year FE	Yes
Observations	14,755
Adjusted R^2	1.6%

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 11: Alternative Measures of Investor Information

	Dependent Variable: *Forecast_Revision*		
	(1)	(2)	(3)
INFO =	*ASC_Spread*	*Amihud*	*Nonsync*
Return×INFO	**0.49*** **	**0.60*** **	**0.41*** **
	(5.18)	**(4.49)**	**(3.43)**
Return	0.51***	0.46***	0.60***
	(6.14)	(4.34)	(6.37)
INFO	0.01	-0.01	-0.07**
	(0.20)	(-0.13)	(-2.25)
UE×INFO	-0.13	-0.02	0.01
	(-1.22)	(-0.21)	(0.13)
UE	0.50***	0.41***	0.40***
	(6.53)	(5.80)	(6.74)
Analyst_Revision×INFO	-0.01	-0.14*	-0.16***
	(-0.15)	(-1.93)	(-3.24)
Analyst_Revision	0.29***	0.38***	0.38***
	(4.38)	(5.68)	(9.27)
Size	0.01	0.01	0.00
	(1.20)	(0.76)	(0.47)
Tobin's_Q	0.03***	0.03***	0.03***
	(3.24)	(3.22)	(3.18)
Coverage	0.06***	0.06***	0.05**
	(2.87)	(2.92)	(2.57)
Horizon	0.00	0.01	0.01
	(0.33)	(0.44)	(0.53)
Gap	-0.05***	-0.05***	-0.05***
	(-3.13)	(-3.13)	(-3.13)
Constant	-0.24**	-0.22	-0.16*
	(-2.06)	(-1.21)	(-1.91)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	16,471	16,471	16,471
Adjusted R^2	37.5%	37.6%	37.6%

I use the decile rankings of *ASC_Spread*, *Amihud* and *Nonsync* (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.