Price Informativeness and Investment Sensitivity to Stock Price

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The article shows that two measures of the amount of private information in stock price—price nonsynchronicity and probability of informed trading (*PIN*)—have a strong positive effect on the sensitivity of corporate investment to stock price. Moreover, the effect is robust to the inclusion of controls for managerial information and for other information-related variables. The results suggest that firm managers learn from the private information in stock price about their own firms' fundamentals and incorporate this information in the corporate investment decisions. We relate our findings to an alternative explanation for the investment-to-price sensitivity, namely that it is generated by capital constraints, and show that both the learning channel and the alternative channel contribute to this sensitivity. (*JEL* G14, G31)

One of the main roles of financial markets is the production and aggregation of information. This occurs via the trading process that transmits information produced by traders for their own speculative trading into market prices [e.g., Grossman and Stiglitz (1980), Glosten and Milgrom (1985), and Kyle (1985)]. The markets' remarkable ability to produce information that generates precise predictions about real variables has been demonstrated empirically in several contexts. Roll (1984) showed that private information of citrus futures traders regarding weather conditions gets impounded into citrus futures' prices, so that prices improve even public predictions of the weather. Relatedly, the literature on prediction markets has shown that

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markets provide better predictions than polls and other devices [see Wolfers and Zitzewitz (2004)].

The theoretical literature in corporate finance has argued that managers can learn from the information in stock price about the prospects of their own firms. Two prominent examples of this theory are Dow and Gorton (1997) and Subrahmanyam and Titman (1999).[1] The idea behind the theory is that stock prices aggregate information from many different participants who do not have channels for communication with the firm outside the trading process. Thus, stock prices may contain some information that managers do not have.[2] This information, in turn, can guide managers in making corporate decisions, such as the decision on corporate investments. This theory has far-reaching implications for the role of financial markets as it implies that financial markets affect the real economy and are not just a sideshow [see Morck, Shleifer, and Vishny (1990), Stein (2003)].

In this article, we empirically assess the hypothesis that managers learn from the private information in stock price when they make corporate investment decisions. We do so by examining the relation between measures of the amount of private information in stock price and the sensitivity of corporate investment to price. The learning hypothesis predicts a positive relation based on the following reasoning. It is commonly believed that stock prices reflect public information and private information about firms' fundamentals. The private information gets into the price via speculators' trading activities. If, at a given point in time, managers decide on the level of investment attempting to maximize the expected value of the firm, they will use all information available to them at that point. This includes both the information in the stock price and other information that managers have and that has not found its way to the price yet. In this environment, investment will be more sensitive to stock price when the price provides more information that is new to managers. Information that managers already had will move the price but not affect the investment decision (as it already affected past investments) and thus will decrease the sensitivity of investment to price. Based on this reasoning, an empirical finding of a positive relation between the investment sensitivity to stock price and the amount of private information incorporated into the price by speculators would imply that the private information in price is new to managers and that managers look at the price to learn this information and use it in their investment decisions.

Key to our empirical analysis is determining when stock prices contain more private information. In equilibrium, different stocks may have different amounts of private information in their prices due, for example,

[1] See also Dye and Sridhar (2002), Dow and Rahi (2003), and Goldstein and Guembel (2005).

[2] This information is more likely to be about the demand for the firm's products or about strategic issues, such as competition with other firms. It is less likely to be about the technology used by the firm, because the manager is expected to have an informational advantage about technological factors.

to different costs of private information production [see Grossman and Stiglitz (1980)]. While such costs are difficult to measure directly, two strands of the finance literature have come up with measures to assess the equilibrium level of private information in price based on the resulting price and trading behaviors. We use two such measures for our empirical analysis.

The first measure is price nonsynchronicity. This measure was first proposed by Roll (1988) and recently developed by Morck, Yeung, and Yu (2000), Durnev et al. (2003), and Durnev, Morck, and Yeung (2004). It is computed on the basis of the correlation between the stock's return and the return of the corresponding industry and of the market. The idea is that if a firm's stock return is strongly correlated with the market and industry returns, then the firm's stock price is less likely to convey firm-specific information, which is useful for managerial investment decisions. Thus, the measure will be higher when the return on the stock is less correlated with the market and industry returns. There is a large body of empirical work demonstrating the information content captured by this measure (a detailed review is provided in Section 1). Moreover, the seminal paper by Roll (1988) showed unambiguously that this measure has very little correlation with public news, and thus, it seems to capture private information. In Roll's own words, he suggests that, based on his results, it seems that "the financial press misses a great deal of relevant information generated privately."

The second measure, probability of informed trading (*PIN*), utilizes information from the trading process. The measure was developed in Easley, Kiefer, and O'Hara (1996 1997a,b) and used in many other articles (a detailed review is provided in Section 1). Based on a structural market microstructure model, this measure directly captures the probability of informed trading in a stock. Thus, the composition of information for stocks with high *PIN* is coming more from private sources than from public sources. This idea is consistent with the finding of Easley, Hvidkjaer, and O'Hara (2002) that stocks with high *PIN* earn higher returns that compensate investors for the high risk of private information.

We find that both measures are strongly positively correlated with the sensitivity of investment to price, consistent with the hypothesis that stock prices with large content of private information provide managers with more new information, which, in turn, affects managers' investment decisions. Two clarifications about this conclusion are in order. First, we do not wish to imply that only the private information in stock price is new to managers. Clearly, some public information—such as the realization of GDP or the success or the failure of a patent application—get reflected in stock price at the same time when it is revealed to managers via public sources and thus is new to managers. Our results only suggest that, on average, the private information of speculators increases the amount of information in price that is new to managers and thus the extent to which managers rely on the price when they make their investment decisions. Second, our results do not imply that stock prices with large content of private information are closer to fundamental value. The distance of a price from fundamental value depends on the total amount of information in the price, not just the amount of private information. In fact, as the incorporation of private information into price is a process that takes time, it might be that stock prices with more private and less public information are farther away from fundamentals. Still, our results suggest that the private information in price makes price more informative to managers, in the sense that it is new to managers and thus affects their investment decisions.

We perform more tests to assess the validity of this conclusion. First, our conclusion implies that price nonsynchronicity and *PIN* measure the private information in price that is not otherwise available to managers. We assess this more directly by controlling for the amount of managerial information with two different proxies. The first proxy is firms' insider trading activities. The idea is that on average, managers with more private information are more likely to trade and thus greater activity represents more managerial information. The second proxy is earnings surprises, measured as the absolute abnormal return around earnings announcement dates. As managers know the earnings before they are released to the public, this variable captures information that managers have before it is reflected in the price. We find that both insider trading and earnings surprises are negatively correlated with the sensitivity of investment to price, consistent with the idea that managers are expected to rely less strongly on the price in their investment decision when they have more private information on their own. More importantly, we find that the effects of price nonsynchronicity and *PIN* on the investment-to-price sensitivity remain equally strong in the presence of the proxies for managerial information. Thus, to the extent that insider trading and earnings surprises are good proxies for managerial private information, this result suggests that our measures of private information in price reflect some information that is not already known to managers and thus lends more support to the idea that managers learn from prices. Second, we examine the relation between the amount of private information in price and firms' future operating performance. A positive relation is expected if the private information in price helps managers make better investment decisions. We find that our measures of private information in price have significantly positive relations to firms' ex post performance as measured by return on assets *(ROA)*, sales growth and assets turnover rate.

Another result that we find is related to the role of financial analysts. We show that the sensitivity of investment to price decreases in the amount of analyst coverage a firm gets. This implies that the information released by analysts and impounded in the stock price does not have much effect on managers' investment decisions. This result is consistent with empirical evidence suggesting that a large fraction of the information analysts have come from firm managers, especially for our sample period which was before Regulation Fair Disclosure (Reg FD) took effect [see, e.g., Bailey et al. (2003), Agrawal, Chadha, and Chen (2006), Hutton (2005), and others]. Thus, analyst information is expected to move price and improve the overall information content of price. However, as managers already know the information produced by analysts, they do not adjust their investments to it when it gets reflected in the price, and this results in a lower sensitivity of investment to price. On top of that, as argued by Easley, O'Hara, and Paperman (1998), the presence of analysts can attract more noise trading to the stock. This reduces the content of private information in the stock price and thus decreases the sensitivity of investment to price even further.

We relate our findings to the literature in economics and finance that documents a strong positive correlation between stock prices and corporate investments. While many articles document this correlation [see Barro (1990), Morck, Shleifer, and Vishny (1990), Blanchard, Rhee, and Summers (1993)], the reasons behind it are still under debate. Our findings suggest that an important factor contributing to the correlation between stock price and corporate investment is that managers incorporate what they learn from the private information in price in their investment decisions. Baker, Stein, and Wurgler (2003) have shown that the sensitivity of investment to price increases in the level of capital constraints faced by the firm. The idea is that financing constraints prevent firms from pursuing their optimal investment plans and that an increase in stock price may ease these constraints and thus enable firms to increase investments. To relate our results to those reported by Baker, Stein, and Wurgler (2003), we conduct our analysis on five quintile subsamples sorted by the degree of capital constraints. We show that both the capital constraints and the amount of private information in price have a role in generating the investment-to-price sensitivity and that each factor affects different firms to a different degree.

We consider several other robustness issues in the article. The most important one concerns the effect of firm size. Both our measures of private information in price are negatively correlated with firm size. Firm size, in turn, may affect the sensitivity of investment to price for reasons unrelated to the amount of private information reflected in the price. Thus, to ensure that our results are not driven by firm size, we conduct our analysis on five quintile subsamples sorted by firm size. We also control for size directly in our main regressions by including it as an additional variable. In both these tests, we find that private information in price remains important after size is controlled for. We also control for other factors such as diversification and institutional holding as well as examine different empirical specifications. Our results remain intact in all these tests.

Another issue we address in this article is the effect of the private information in price on the sensitivity of investment to cash flow. The finance literature has thoroughly discussed the investment-to-cash flow sensitivity and found that investments are strongly correlated with cash flows.[3] We find that the investment-to-cash flow sensitivity is lower when prices contain more private information. A possible interpretation of this result originates from the recent work of Gomes (2001) and Alti (2003). They argue that investments may be correlated with cash because cash provides information on the profitability of firms' investments beyond stock prices. According to this hypothesis, when prices become more informative to managers, managers will rely less on cash and more on prices to obtain information about investment profitability.

Several recent articles have studied hypotheses related to our article. Giammarino et al. (2004) analyzed a sample of seasoned equity offerings and found that managers seem to learn from prices as prices affect managers' decisions to withdraw the offering but do not have any causal relationship with their trading. Luo (2005) found that the positive correlation between announcement date return and the completion of mergers can be attributed to insiders' learning from outsiders after controlling for common information. Gilchrist, Himmelberg, and Huberman (2004) analyzed how real investment reacts to the "bubble" component in prices as measured by analysts' forecast dispersion.

A more closely related article is Durnev, Morck, and Yeung (2004). They find that firms with high level of price nonsynchronicity make more efficient investment decisions in that their marginal Tobin's Q is closer to one. Our article is different from Durnev, Morck, and Yeung (2004) in two important dimensions. First, we analyze directly the effect of price nonsynchronicity on the sensitivity of investment to price. This effect may be a mechanism that generates their result that price nonsynchronicity enhances efficiency. Second, we examine the effect of private information more directly by using the *PIN* measure. To the best of our knowledge, our article is the first one to relate the *PIN* to real investment, and one of the first empirical articles to use a market-microstructure measure in a corporate finance context.[4]

Finally, we acknowledge that the interpretation of the results in the article depends on our measures of private information in the price. We rely on prior literature establishing price nonsynchronicity and *PIN* as measures of private information. However, one can still view our analysis

[3] For example, see Fazzari, Hubbard, and Petersen (1988) and, more recently, Stein (2003).

[4] For a theoretical article that relates the *PIN* measure to corporate finance issues, see Easley and O'Hara (2004).

as testing the joint hypotheses (i) that price nonsynchronicity and *PIN* are measures of private information in the price and (ii) that managers learn the private information from the price and use it in their investment decisions. Clearly, the strength of interpreting our results as consistent with managers learning from stock price depends on the extent to which our measures actually capture private information in the price. Admittedly, it is also possible that our measures are correlated with other factors that make firms' viability unusually dependent on stock market valuation and that drive the sensitivity of investment to stock price. We believe that our extensive robustness tests mitigate this concern to a large extent. But, it remains possible that something else is behind our results.

The remainder of the article is organized as follows: Section 1 presents the measures of private information used in this article. In Section 2, we describe the data and the construction of the main variables. Section 3 presents the main empirical results on the relation between the private information in price and the sensitivity of investment to price. Section 4 extends the basic tests to control for managerial information and analyst coverage, relates our results to the effects of capital constraints and size, and examines the effect of private information in price on firm performance. Section 5 presents several robustness checks. Section 6 concludes.

1. Measures of Private Information

1.1 Price nonsynchronicity

The variation of a stock return can be decomposed into three different components: a market-related variation, an industry-related variation, and a firm-specific variation. The first two components measure systematic variations. The last one captures firm-specific variation or price nonsynchronicity. This is the first measure we use in the article. It can be estimated by $1 - R^2$, where R^2 is the R-square from the following regression:

$$r_{i,j,t} = \beta_{i,0} + \beta_{i,m} \cdot r_{m,t} + \beta_{i,j} \cdot r_{j,t} + \varepsilon_{i,t}. \tag{1}$$

Here, $r_{i,j,t}$ 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 is based on a large body of literature, both empirical and theoretical. Roll (1988) was the first one to suggest that price nonsynchronicity (or firm-specific return variation) is correlated with private information. His argument goes as follows: prices move upon new information, which is capitalized into prices in two ways. The first is through a general revaluation of stock values following the release of public information, such as unemployment statistics or quarterly earnings. The second is through the trading activity of speculators who gather and possess private information. As Roll (1988) found that firm-specific stock price movements are generally not associated with identifiable news release, he argued that private information is especially important in the capitalization of firm specific information. However, he acknowledged two possible explanations of his findings: the existence of either private information or else occasional frenzy.

The relative importance of these two possibilities is an empirical question. Empirical evidence documented since then provides strong support to the hypothesis that price nonsynchronicity reflects more private information than noise. For example, Durnev et al. (2003) found that stock price nonsynchronicity is highly correlated with stock prices' ability to predict firms' future earnings, supporting the argument that price nonsynchronicity reflects more private information than noise.

Other articles in this literature provide consistent evidence. Morck, Yeung, and Yu (2000) showed that firm-specific return variation is high in countries with well-developed financial systems and low in emerging markets. They argued that in countries with well-developed financial markets, traders are more motivated to gather information on individual firms, and thus, prices reflect more firm-specific information. Durnev, Morck, and Yeung (2004) showed that industries with higher firm-specific return variation allocate capital more efficiently in the sense that their marginal Tobin's Qs are closer to 1. They argued that the private information in price, as measured by price nonsynchronicity, enhances investment efficiency. Wurgler (2000) obtained a similar result in a cross-country analysis. Defond and Hung (2004) showed that the association between lagged stock returns and subsequent Chief Executive Officer (CEO) turnover is stronger in countries with low stock return synchronicity. In their framework, stocks with high nonsynchronicity contain more private information about firm performance and hence generate an effect of price on CEO turnover decisions. Finally, Bris, Goetzmann, and Zhu (2004) used price nonsynchronicity to measure the effects of short sales on the amount of private information being impounded in price.

On the theoretical level, stock price co-movements can reflect phenomena such as lack of transparency [Li and Myers (2005)], contagion [Kodres and Pritsker (2002), Kyle and Xiong (2001)], style investing [Barberis and Shleifer (2003)], and investors' sentiment [Barberis, Shleifer, and Wurgler (2005)], all of which are associated with less information on fundamentals being impounded into the stock price. As such, prices are less likely to reflect refined firm-specific information, which is important for managerial investment decisions. This mechanism is formally analyzed in Veldkamp (2006), who developed a model in which high fixed costs of producing information on individual firms cause investors to focus on signals that are common to many firms. When this happens, prices will exhibit greater co-movement and will reflect less private information on each firm's fundamentals. Thus, her model predicts a negative correlation between the price synchronicity and the amount of private information investors produce about a firm, which is the basis of our first empirical measure.

1.2 Probability of informed trading

Our second measure, the *PIN* measure, has strong theoretical foundations as a measure of the amount of private information in stock price. The measure was developed and used in a series of articles by Easley et al. (1996), Easley, Kiefer, and O'Hara (1996, 1997a,b), Easley, O'Hara, and Paperman (1998), Easley, O'Hara, and Srinivas (1998), and Easley, Hvidkjaer, and O'Hara (2002). It is based on a structural market microstructure model in which trades can come from noise traders or from informed traders. It measures the probability of informed trading in a stock. By definition, informed traders will trade on their information only if they think it is not yet publicly known. As *PIN* directly estimates the probability of informed trading, it is conceptually a sound measure for the private information reflected in stock price.

Let us briefly describe the basic idea behind the measure. Suppose the daily arrival rates of noise traders that submit buy and sell orders are ε_b and ε_s, respectively. The probability that an information event occurs is α, in which case the probability of bad news is δ and the probability of good news is $(1-\delta)$. If an information event occurs, the arrival rate of informed traders is μ. Informed traders submit a sell order if they get bad news and a buy order if they get good news. Thus, on a day with no information event [which happens with probability $(1-\alpha)$], the arrival rate of a buy order will be ε_b and the arrival rate of a sell order will be ε_s. On a day with a bad information event (which happens with probability $\alpha\delta$), the arrival rate of a buy order will be ε_b and the arrival rate of a sell order will be $\varepsilon_s + \mu$. On a day with a good information event [which happens with probability $\alpha(1-\delta)$], the arrival rate of a buy order will be $\varepsilon_b + \mu$ and the arrival rate of a sell order will be ε_s. Let $\theta = \{\varepsilon_b, \varepsilon_s, \alpha, \delta, \mu\}$. The likelihood function for a single trading day is given by

$$L(\theta|B,S) = (1-\alpha)e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!} + \alpha\delta e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}e^{-(\varepsilon_s+\mu)}\frac{(\varepsilon_s+\mu)^S}{S!} + \alpha(1-\delta)e^{-\varepsilon_b+\mu}\frac{(\varepsilon_b+\mu)^B}{B!}e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!}. \quad (2)$$

Here, B is the number of buy orders and S is the number of sell orders in a single trading day. Using trading information over J days and assuming cross-trading-day independence, one can estimate the parameters of the model (ε_b, ε_s, α, δ, and μ) by maximizing the following likelihood function:

$$V = L(\theta|B,S) = \prod_{j=1}^{j=J} L\left(\theta|B_j,S_j\right). \tag{3}$$

Then, the probability of informed trading in a given stock for a given period, which determines the *PIN* measure, will be:

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_s + \varepsilon_b}. \tag{4}$$

Intuitively, *PIN* is low for stocks with less fluctuations of daily buy and sell orders. If a stock receives roughly balanced buy and sell orders from day to day, these orders are more likely to arise from investors' independent liquidity needs or noise trading. The law of large numbers smooths out these orders, and accordingly, the probability of information events is small (small α). Following the same line of reasoning, the measure will be high for stocks that exhibit frequent large deviations from their "normal" order flows.

In the articles mentioned above, the *PIN* measure has been used to study various important issues. These include the differences in information across exchanges, informed trading in options versus stocks, and information and liquidity in the trading of less-frequently-traded stocks. Recently, Easley, Hvidkjaer, and O'Hara (2002) related the *PIN* measure to the asset pricing literature and found that the risk of private information as captured by this measure is priced, so that high *PIN* stocks earn higher expected returns. These articles also directly test the validity of the *PIN* measure by comparing the predictions of the information-based model with other alternative models. The overall results from these tests strongly support *PIN* as a measure of the probability of informed trading. More recently, Vega (2005) found further evidence supporting *PIN* as a measure of private information in price. She showed that stocks with higher *PIN* values have smaller post-earnings-announcement drifts, suggesting high *PIN* stocks adjust to fundamentals quicker. As she found that this quicker adjustment is not because of media coverage or other public news releases, her results suggest that stocks with high *PIN* values likely contain more private information by speculators.

2. Sample Selection, Specification, and Variable Construction

We collect our data from six databases. We obtain firms' stock price and return information from Center for Research in Security Prices (CRSP) investment and other financial data from Compustat, intraday transaction data from Trade And Quote (TAQ), insider trading information from the Thomson Financial's TFN database, analysts' coverage data from Zacks Investment Research database, and institutional holding data from Spectrum. Our sample consists of an unbalanced panel of Compustat firms from 1981 to 2001, excluding firms in the financial industries (SIC code 6000–6999) and utility industries (SIC code 4200). We exclude firm-year observations with less than \$10 million book value of equity or with less than 30 days of trading activities in a year. Our final sample consists of 68,277 firm-year observations with 7268 firms. Analyses using intraday transaction data (*PIN*) have fewer observations (19,208 firm-year observations) because TAQ's coverage starts from 1993.

Our baseline equation for testing the hypothesis is as follows:

$$\begin{aligned} I_{it} = \alpha_t + \eta_i + \beta_1 \cdot Q_{it-1} + \beta_2 \cdot INFO_{it-1} \cdot Q_{it-1} \\ + \gamma \cdot CONTROL + \varepsilon_{it}, \end{aligned} \tag{5}$$

where I_{it} is firm i's investment in year t, and α_t and η_i represent year and firm-fixed effects. We use three different investment measures for the dependent variable $(I_{i,t})$: $CAPXRND_{it}$, measured as the sum of capital expenditure and R&D expenses (Compustat Annual Item 128 + Item46), scaled by beginning-of-year book assets (A_{it-1}, Item 6); $CAPX_{it}$, capital expenditures scaled by A_{it-1}; and $CHGASSET_{it}$, measured as the percentage change in book assets. All three variables are expressed in percentage points. Both $CAPXRND_{it}$ and $CAPX_{it}$ are direct measures of firms' ongoing investment and R&D activities, whereas $CHGASSETS_{it}$ includes firms' acquisition and divestiture activities.

Q_{it-1} is the (normalized) price in our analysis and is measured by firm i's Q. It is calculated as the market value of equity (price times shares outstanding from CRSP) plus book value of assets minus the book value of equity (Item 6–Item 60), scaled by book assets, all measured at the end of year $t-1$. We expect $\beta_1 > 0$, that is, I_{it} be positively correlated with Q_{it-1}, as has been observed in the literature many times. The focus of this article, however, is β_2, the coefficient for $INFO_{it-1} \cdot Q_{it-1}$, which measures the effect of private information in price on the sensitivity of investment to price.

$INFO_{it-1}$ is a measure of the private information in stock price. As discussed in Section 1, we have two such measures. The first is $(1-R2)$, where $R2$ is the R^2 from a regression of firm i's daily stock returns in year $t-1$ on a constant, the CRSP value-weighted market return, and the return of the three-digit SIC industry portfolio. We set a firm-year's $(1-R2)$ to be missing if it is estimated with less than 30 daily observations. The second measure is the *PIN*. Following the procedure prescribed in Easley, Hvidkjaer, and O'Hara (2002), for each trading day in year $t-1$, we classify all trades between 9:30 A.M. and 4:00 P.M. as either a buyer-initiated trade or a seller-initiated trade using the Lee and Ready (1991) algorithm.[5] We eliminate large size trades (trade size greater than 10,000 shares) and trades coded by TAQ as trading with special conditions. We then estimate a firm-year *PIN* based on the number of buys and sells in each trading day of the year. For reliability, we set a firm's *PIN* to be missing if it is estimated with less than 30 trading days.

Based on prior studies on investment, our basic regressions include the following set of control variables $(CONTROL): 1/ASSETS_{i,t-1}$, $CF_{i,t}$, $INFO_{it-1} \cdot CF_{i,t}$, $RET_{i,t+3}$, and $INFO_{it-1}$. We include $1/ASSETS_{i,t-1}$ because both the dependent variable (I_{it}) and the regressor $Q_{i,t-1}$ are scaled by last-year book assets $(ASSETS_{i,t-1})$, which could introduce spurious correlation. Therefore, $1/ASSETS_{i,t-1}$ is included to isolate the correlation between I_{it} and Q_{it-1} induced by the common scaling variable. Cash flow $(CF_{i,t})$ is included both separately and in interaction with $INFO_{it-1}$ to accommodate the well-documented effect of cash flow on investment [e.g., Fazzari, Hubbard, and Petersen (1988)]. We measure CF_{it} as the sum of net income before extraordinary items (Item 18), depreciation and amortization expenses (Item 14), and R&D expenses (Item 46), scaled by beginning-of-year book assets.[6] We include future returns $(RET_{i,t+3})$ because Loughran and Ritter (1995), Baker and Wurgler (2002), and Baker, Stein, and Wurgler (2003) argued that firms invest more when their stocks are overvalued (i.e., when expected future returns are lower). Thus, we include firms' future returns $(RET_{i,t+3})$ to control for managers' market timing of investment. $RET_{i,t+3}$ is measured as the value-weighted market adjusted three-year cumulative return, starting from the end of the investment year.[7] Finally, $INFO_{it-1}$ is included separately to control for its direct effect on investment and to make sure that this direct effect does not drive the result on β_2.

Except for *PIN*, Table 1 summarizes the summary statistics for all variables for the whole sample of 68,277 observations. The summary statistics for the subsample of observations where *PIN* is available are very similar to those shown in Table 1 and hence not reported. The mean (standard deviation) of $1-R2$ is 0.83 (0.23), indicating that, on average,

[5] Specifically, we compare trade prices with the midpoint of the bid-ask spread five seconds before the trades. We classify trades above the midpoint as buys and classify trades below the midpoint as sells. For trades at the midpoint, we compare their prices with the preceding trade price and classify those executed at a higher price than the preceding trades as buys and those at a lower price as sells.

[6] We add back R&D expenses because US GAAP require expensing R&D expenditure in the income statement.

[7] For observations in the last two years of our sampling period, two-year or one-year future returns are used.

Table 1
Variable definitions and summary statistics

Variable	Definition
	Panel A: Definitions
CAPXRND	Capital expenditure plus R&D scaled by beginning-of-year assets (%)
CAPX	Capital expenditure scaled by beginning-of-year assets (%)
CHGASSET	Change in assets scaled by beginning-of-year assets (%)
Q	Market value of equity plus book value of assets minus book value of equity, scaled by book value of assets
1 – R2	One minus R^2 from regressing daily return on market and industry index over year t
PIN	PIN measure per Easley et al. (1996)
CF	Net income before extraordinary item + depreciation and amortization expenses + R&D expenses, scaled by lagged assets
RET	Value-weighted market return adjusted firm return for next three years
ASSET	Total book value of assets in $billions
INV_AST	Inverse of *ASSET*
INSIDER	Number of transactions by insiders scaled by total number of transactions recorded in TAQ
KZ4	Four-variable KZ score (excluding Q) per Kaplan and Zingales (1997)
ERC	Average of the absolute stock returns over the four quarterly earnings announcement periods (day –1 to day 1) (in %)
SIZE	Market capitalization ($million)
SALES	Total sales revenues ($million)
HERFINDAHL	Herfindahl index of sales based on firms segment reports
ANALYST	Number of analysts issuing forecasts or recommendations for the firm
INSTITUTION	Percentage of shares held by institutional investors
ROA	Operating earnings (i.e., earnings before interest, taxes, depreciation, and amortization) as a percentage of market value of assets, which is the sum of market value of equity and book value of debt (in %)
Sales growth	Annual growth rate in sales revenues (%)
Asset turnover	Sales revenue divided by total asset values (%)

Variable	Number of observations	MEAN	SD	5%	25%	50%	75%	95%
				Panel B: Summary statistics				
CAPXRND	68277	14.81	17.53	1.22	4.78	9.61	17.85	45.88
CAPX	68277	9.82	11.76	0.82	3.29	6.28	11.48	31.18
CHGASSET	68274	29.22	79.08	–18.77	–0.52	9.51	26.59	137.98
Q	64783	1.81	1.48	0.75	1.00	1.31	1.98	4.67
1 – R2	68277	0.83	0.23	0.27	0.79	0.92	0.98	1.00
PIN	19208	0.21	0.08	0.09	0.16	0.21	0.26	0.34
CF	68276	0.13	0.16	–0.09	0.06	0.12	0.19	0.39
RET	68277	0.02	0.81	–0.88	–0.50	–0.12	0.28	1.51
ASSET	68277	1.30	3.90	0.02	0.06	0.16	0.62	6.08
INSIDER	25412	2.78	7.72	0.00	0.00	0.34	1.78	13.18
KZ4	68176	0.01	1.65	–2.44	–0.60	0.18	1.02	2.02
ERC	56029	5.13	3.58	1.24	2.61	4.20	6.61	12.40
SIZE	68277	1650.95	9726.13	12.36	44.27	137.58	576.76	5625.30
SALES	68277	1263.97	3550.92	12.75	59.20	179.71	681.90	6296.45
HERFINDAHL	53501	0.94	0.16	0.51	1.00	1.00	1.00	1.00
ANALYST	58618	5.29	6.53	0.00	1.00	3.00	7.00	19.00
INSTITUTION	32037	37.6	21.9	5.16	19.5	35.9	54.5	75.0
ROA	64708	13.76	10.00	–3.29	8.42	13.77	19.19	30.18
Sales growth	59965	16.34	40.51	–26.55	–1.44	9.04	23.21	80.21
Asset turnover	68277	149.23	104.41	25.59	82.68	129.68	186.36	347.94

the market and industry returns account for about 17% of firms' return variations. This number is similar to that reported in Roll (1988), who argued that a large amount of stock price movements are driven by firm-specific information. The average sample property of our *PIN* estimate is comparable to that reported in Easley, Hvidkjaer, and O'Hara (2002). Specifically, the mean (median) *PIN* in our sample is 0.211 (0.209) with standard deviation of 0.077. Furthermore, similar to Easley, Hvidkjaer, and O'Hara (2002), we also find that our *PIN* estimates are fairly firm-specific and relatively stable across years. It is also positively correlated with $(1-R2)$ with Pearson (Spearman) correlation coefficients of 0.27 (0.34), consistent with the idea that both $(1-R2)$ and *PIN* capture private firm-specific information impounded in stock price.

The correlation between our private information measures and other variables is also of interest. We find that both measures are negatively correlated with size, positively correlated with the Kaplan–Zingales measure of financial constraints, and negatively correlated with analyst coverage. All these correlations are significant. The two measures show significant negative correlations with institutional holdings. Price non-synchronicity is significantly negatively correlated with firm diversification, whereas the relation between *PIN* and diversification is not significant. These results motivate some of the robustness checks discussed later in the article.

Lastly, ε_{it} in Equation (5) is the disturbance term that is uncorrelated with the regressors but is allowed to be serially correlated for the same firm. In the estimation, all standard errors are adjusted for arbitrary heteroskadasticity and for error correlations clustered by firm. Following the standard procedure in the literature, we winsorize all unbounded variables at 1 and 99% to mitigate the influences of outliers. All multiplicative variables in front of Q and CF are subtracted of their respective median values, so that the coefficient before $Q(CF)$ can be interpreted as the investment sensitivity to $Q(CF)$ for a firm with median characteristics. Unless otherwise noted, we use less than the 5% level in a two-tailed test as the criterion for statistical significance.

3. The Basic Tests

In this section, we test whether the sensitivity of investment to price is increasing in our measures of private information in price. Table 2 summarizes the results from estimating Equation (5). Columns 1, 4, and 7 estimate the baseline regression for the different investment measures with $(1-R2)$ as an information measure and no control variables (except the direct effect of the information measure). Columns 2, 5, and 8 repeat the same analysis with *PIN* instead of $(1-R2)$ as an information measure. Finally, Columns 3, 6, and 9 include both information measures

Table 2
Relation between investment-price sensitivity and private information measures

Dependent variable	CAPXRND			CAPX			CHGASSET		
	1	2	3	4	5	6	7	8	9
Q	**3.52****	**2.18****	**1.95****	**2.20****	**1.37****	**1.08****	**20.26****	**15.47****	**10.56****
	0.08	0.10	0.12	0.06	0.06	0.06	0.53	0.69	0.71
(1–R2)*Q	**3.13****	–	**1.80****	**1.42****	–	**0.45****	**14.79****	–	**2.70**
	0.28	–	0.42	0.20	–	0.25	1.72	–	2.65
PIN*Q	–	**4.21****	**3.37****	–	**1.92****	**1.70*****	–	**19.83****	**20.33****
	–	1.04	1.11	–	0.67	0.67	–	6.36	6.28
CF	–	–	**17.68****	–	–	**7.67****	–	–	**135.88****
	–	–	1.33	–	–	0.67	–	–	6.78
(1–R2)*CF	–	–	**–29.09****	–	–	**–17.43****	–	–	**–181.35****
	–	–	6.33	–	–	3.93	–	–	38.39
PIN*CF	–	–	**14.89**	–	–	**10.01**	–	–	**–32.11**
	–	–	14.37	–	–	7.07	–	–	74.97
RET	–	–	**–0.21******	–	–	**–0.44****	–	–	**–3.58****
	–	–	0.11	–	–	0.07	–	–	0.62
INV_AST	–	–	**–0.05**	–	–	**–0.08****	–	–	**–2.33****
	–	–	0.03	–	–	0.01	–	–	0.15
1–R2	**–7.20****	–	**2.78****	**–5.62****	–	**1.02**	**–23.09****	–	**37.22****
	0.56	–	1.04	0.46	–	0.77	3.23	–	6.64
PIN	–	**–3.31******	**–5.31*****	–	**–1.09**	**–2.49**	–	**–9.28**	**–11.68**
	–	1.98	2.21	–	0.76	1.57	–	11.58	11.96
Adjusted R^2	0.54	0.54	0.57	0.44	0.44	0.46	0.20	0.00	0.17
Within R^2	0.10	0.08	0.14	0.07	0.06	0.10	0.12	0.13	0.28

Definitions of all variables are listed in Table 1 Panel A. Dependent variables (*CAPXRND*, *CAPX*, and *CHGASSET*) are expressed as percentage points of book assets at the beginning of the year. Both firm- and year-fixed effects are included. Coefficient estimates are shown in bold and their standard errors are displayed right below. Standard errors adjust for both heteroskedasticity and within correlation clustered by firm. Number of observations is 64,782 for Columns 1, 4, and 7 and 19,208 for other columns.
*, **, and *** indicate a two-tailed test significance level of less than 1%, 5%, and 10%, respectively.

and other control variables—cash flows, future returns, and inverse book assets—in the regression. All the three investment measures show similar results. Thus, we illustrate the main message here with *CAPXRND*, our default investment measure (Columns 1, 2, and 3).

Column 1 shows that $CAPXRND_{it}$ is positively correlated with Q_{it-1}, with the coefficient for Q_{it-1} estimated at 3.52, significant at less than the 1% level. This result supports the observation in the literature that investments are positively correlated with prices. We focus on the coefficient for $(1-R2) \cdot Q$. As Column 1 shows, this coefficient is estimated at 3.13 with *t*-statistic of 11.2. This shows that the investment-to-price sensitivity is higher for firms whose stock prices have greater firm-specific return variations. Given that the 25th percentile value of $(1-R2)$ is 0.79 and median value is 0.92 (Table 1), these estimates indicate that the investment-to-price sensitivity for a firm with a 25th percentile value of $(1-R2)$ is 3.11 [= 3.52 – (0.92 – 0.79)3.13]. The investment-to-price sensitivity will increase by 0.60 (or 19%), if a firm's $(1-R2)$ increases from a 25th percentile value to a 75th percentile value of 0.98.

Column 2 repeats the same analysis with *PIN*. We can see that the coefficient for $PIN \cdot Q$ is 4.21 (significant at less than 1%). This demonstrates that the investment sensitivity to price is higher for firms with a higher *PIN*. Given that the 25th, 50th, and 75th percentile values for *PIN* are 0.16, 0.21, and 0.26, respectively, this estimate implies that the investment-to-price sensitivity of a firm with a 25th percentile value of *PIN* is 1.97 [= 2.18 – (0.21 – 0.16)4.21] and that for a firm with 75th percentile value of *PIN* is higher by more than 21% at 2.39.

Column 3 puts both measures of private information, together with the control variables, in the regression. Because $(1-R2)$ is positively correlated with *PIN* (with a correlation coefficient of 0.27), it is possible that *PIN* captures the same effect as $(1-R2)$. The results in Column 3 indicate that this is not the case, as the coefficients for $(1-R2) \cdot Q$ and $PIN \cdot Q$ remain significantly positive. The significance level is lower than that in Columns 1 and 2, as expected. The fact that both measures are significant in explaining investment-to-price sensitivity suggests that they may capture different aspects of private information. This may be the case as *PIN* captures the source of information reflected in price, that is, the trading activities of informed traders, whereas $(1-R2)$ captures the result of this information, that is, its effect on the price. Overall, these results are consistent with the hypothesis that private information contained in stock prices, as captured by $(1-R2)$ and *PIN*, affects managers' investment decisions.

As to the control variables, all columns in Table 2 show that the coefficient estimate for *CF* is significantly positive (at less than the 1% level), confirming the result in the prior literature that investments depend positively on cash. Consistent with the market mispricing argument, the coefficient for RET_{it+3} is negative and significant, suggesting that firms invest more when their stocks are overpriced. Finally, we find that the coefficient for $(1-R2) \cdot CF$ is negative and significant (at less than the 1% level). This suggests that firms with more private information in stock price have lower sensitivity of investment to cash. As discussed earlier, this can happen if the private information in stock price enables firms to rely less on cash as a source of information on investment profitability. We do not get a similar result for $PIN \cdot CF$ in Table 2, although we will see that such result emerges under a different specification in Table 6.

4. Extending the Basic Tests

4.1 Controlling for managerial information

The positive coefficients on $(1-R2) \cdot Q$ and $PIN \cdot Q$ documented above are consistent with the idea that managers learn from stock prices. In this subsection, we attempt to strengthen this interpretation by controlling directly for managerial information and thus establishing more firmly that the private information captured by $(1-R2)$ and PIN is new to managers. The results appear in the first three columns of Table 3. Our tests rely on measures that proxy for the private information held by managers (these measures are denoted as $MANAGER$ in Table 3).

Our first measure for managerial information is based on insider trading activities. Although managers do not always trade on their private information, the premise underlying our test is that, on average, managers with greater private information will trade more. Prior research has shown that insider trade indeed reveals private, firm-specific information not impounded in price.[8] We measure managers' information with the intensity of a firm's insider trading activities in a given year, calculated as the percentage of insider transactions to the total number of all transactions for a given firm-year as recorded in TAQ.

Column 1 in Table 3 reports the effect of the intensity of insider trading. It shows a negative coefficient estimate (−6.57) for $INSIDER \cdot Q$, indicating a negative correlation between insider trading and investment-to-price sensitivity. The negative correlation is expected because more insider trading activities indicate that managers possess more private information and thus rely less on the information in stock price for their investment decisions. The coefficient, however, is not statistically significant at conventional levels.

More important for us is the effect of including $INSIDER \cdot Q$ on the estimated coefficients for $(1-R2) \cdot Q$ and $PIN \cdot Q$. If PIN and $(1-R2)$

[8] See, for example, Seyhun (1992, 1998), Meulbroek (1992), Damodoran and Liu (1993), Ke, Huddart, and Petroni (2002), and Piotroski and Roulstone (2005).

Table 3
Controlling for managerial information and analyst coverage

	1	2	3	4
	INSIDER	PIN*	ERC	ANALYST
Q	**1.98***	**1.97***	**2.04***	**1.98***
	0.12	0.12	0.12	0.12
MANAGER*Q	**–6.57**	–	**–2.53****	–
	6.73	–	1.02	–
ANALYST*Q	–	–	–	**–0.57***
	–	–	–	0.08
(1 – R2)*Q	**1.84***	**1.84***	**1.79***	**0.87***
	0.42	0.42	0.41	0.33
PIN*Q	**3.16***	**3.22***	**3.30***	**1.40****
	1.08	1.06	1.13	0.70
Number of observations	19130	19130	18722	19208
Adjusted R^2	0.58	0.58	0.58	0.58
Within R^2	0.14	0.14	0.15	0.15

Definitions of all variables are listed in Table 1 Panel A. The dependent variable is *CAPXRND*. The variable *MANAGER* represents the manager's relative information advantage over the market, which is proxied, from Columns 1–3, by *INSIDER* (the percentage of insider transactions to total number of transactions), *PIN** (the PIN measure adjusted to exclude insider trading from informed trading, and *ERC* (the average of the absolute market-model abnormal stock returns around the two-day windows of the four quarterly earnings announcement dates in the previous year). *ANALYST* is the number of Zacks analysts covering the firm during the previous year, in logarithms. Both firm- and year-fixed effects are included. Shown are coefficient estimates for *Q, MANAGER*Q, (1–R2)*Q,* and *PIN*Q* (in bold print) and their standard errors (displayed right below). Standard errors adjust for both heteroskedasticity and within correlation clustered by firm.
*, **, and *** indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

reflect information already known by insiders and if *INSIDER* captures insiders' information, then we should expect the coefficients on $(1-R2) \cdot Q$ and $PIN \cdot Q$ to become insignificant once $INSIDER \cdot Q$ is present. This does not appear to be the case. Column 1 shows that both the coefficient for $PIN \cdot Q$ and the coefficient for $(1-R2) \cdot Q$ remain positive and highly significant in the presence of $INSIDER \cdot Q$.

In sensitivity checks (results not tabulated), we first re-estimate Column 1 using the percentage of insider buys and the percentage of insider sells instead of the percentage of all insider transactions. The idea is that insider purchases may convey different information than insider sales. We find that both numbers of buys and sells are negatively related to investment-to-price sensitivity and that the coefficients of $(1-R2) \cdot Q$ and $PIN \cdot Q$ remain significantly positive after adding these alternative insider trading controls. We also obtain qualitatively similar results when we re-estimate Column 1 using the unscaled number of insider transactions in the firm-year to capture the insider trading activity.

In Column 2 of Table 3, we adjust for insider trading differently. We use a modified version of the probability of privately informed trading (PIN^*) net of all insider transactions. Specifically, we make the strongest assumption (to our least favor) that all insider trades are informed, and calculate PIN^* for the outside informed traders as $(PIN{*}\#trans - \#insider)/\#trans$, where *#trans* is the total number of transactions in the firm-year recorded on TAQ and *#insider* is the total number of insider transactions in the same firm-year. This modified PIN^* measure thus gets us closer to the goal of testing whether managers learn from price. Column 2 finds that using this alternative measure of *PIN* has little effect on the coefficients of $(1-R2) \cdot Q$ and $PIN \cdot Q$.

Our second proxy for managerial private information is based on earnings surprise. We measure earnings surprise as the abnormal stock return around the earnings announcement dates. Specifically, for each firm-year, we compute the abnormal (relative to a market model-adjusted benchmark) stock returns in the three-day period centering on each of the four quarterly earnings announcement dates. We then use the average of the absolute abnormal returns as a proxy for the earnings surprise. The idea is that if the average absolute abnormal return is high, there is information in earnings that was not known to investors and was not impounded in price. Because managers have access to internal accounting data and thus know the earnings before they are released to the public, earnings surprise is a measure for managers' private information. This measure has been used in the literature as a measure of managers' information advantage. For example, Gomes and Phillips (2004) showed that firms with lower earnings surprises are able to issue more information sensitive public securities; and Gomes, Gorton, and Madureira (2004) used earnings surprise to test whether Reg FD improves information transmission from the firm to the market.

As Column 3 shows, earnings surprise (*ERC*) has a negative effect on the sensitivity of investment to stock price. Similar to the result obtained with measures of insider trading, this suggests that when managers have a greater informational advantage, they rely less on the price in their investment decisions. Moreover, Column 3 shows that when earnings surprise is included as a measure of managerial information, both the coefficient for $PIN \cdot Q$ and the coefficient for $(1-R2) \cdot Q$ remain positive and highly significant. This suggests that $(1-R2)$ and *PIN* reflect some information that is not known to managers.

In summary, to the extent that insider trading activities and earnings surprises are reasonable proxies for managers' private information, the results in Table 3 lend support to the interpretation that $(1-R2)$ and *PIN* capture some private information in price that is new to managers.

4.2 Controlling for analyst coverage

Column 4 in Table 3 adds the effect of analyst coverage to the empirical analysis. Our goal is twofold. First, we want to verify that the coefficients for $(1-R2) \cdot Q$ and $PIN \cdot Q$ remain positive and statistically significant after controlling for analyst coverage. Second, we wish to explore the effect of analyst coverage, which constitutes an important source of information in financial markets, on the investment-to-price sensitivity and deepen our understanding of the main factors affecting this sensitivity. We measure analyst coverage as the logarithm of the number of analysts that have issued either an earnings forecast or a stock recommendation for the firm in year $t-1$.

High analyst coverage could have two opposite effects on the investment-to-price sensitivity. If the information produced by analysts and impounded in the stock price is new to managers, we should expect a positive relation between analyst coverage and investment-to-price sensitivity. A more commonly held view, however, is that a large fraction of the information analysts produce came from firm managers, especially for our sample period (i.e., before Reg FD). Bailey et al. (2003), Agrawal, Chadha, and Chen (2006), and Hutton (2005), among others, provide empirical support for this view. If analysts mainly transfer information from managers to the markets, information released by analysts will move the stock price (closer to firms' fundamental values because it helps stock prices impound managerial information) but will unlikely affect managers' investment decisions (because managers had already incorporated such information in their past investments). This would suggest a negative relation between analyst coverage and investment-to-price sensitivity. Which effect dominates is an empirical question that we address here.

The results show that after the inclusion of analyst coverage, the coefficient estimates of $(1-R2)\cdot Q$ and $PIN\cdot Q$ remain significantly positive. We also find that analyst coverage has a significantly negative effect on the investment-to-price sensitivity, suggesting that the negative effect discussed above is the dominant effect. Another possible effect that also contributes to a negative relation in our setting is offered by Easley, O'Hara, and Paperman (1998), who argued that the presence of analysts may attract more noise trading to the stock. This reduces the content of private information in the stock price and thus further decreases the sensitivity of investment to price.

4.3 Sorting by capital constraints and size

Thus far, our results indicate that the private information in price is a significant and important variable in explaining the sensitivity of investment to stock price. In a recent article, Baker, Stein, and Wurgler (2003) showed that capital constraints are also important in driving this sensitivity. On the basis of parameter estimates from Kaplan and Zingales (1997), Baker, Stein, and Wurgler (2003) constructed a four-variable version of the Kaplan–Zingales measure, $KZ4$, as a proxy for firms' degree of equity dependence. In particular, $KZ4$ is calculated as a weighted sum of cash flow (CF_{it}), cash dividends (DIV_{it}, Item 19+Item 21), and cash balances (C_{it}, Item 1), all scaled by lagged assets (Item 6), as well as leverage ratio [LEV, (Item 9 + Item 34)/(Item 9 + Item 34 + Item 216)]:

$$KZ4 = -\frac{1.002CF_{it}}{A_{it-1}} - \frac{39.368DIV_{it}}{A_{it-1}} - \frac{1.315C_{it}}{A_{it-1}} + 3.139LEV_{it}. \quad (6)$$

Higher values of $KZ4$ indicate that firms are more constrained to equity financing. Baker, Stein, and Wurgler (2003) found that the coefficient for Q is higher in portfolios of higher KZ values, consistent with their hypothesis that more equity-financing constrained firms have higher investment-to-price sensitivity.

To assess the sensitivity of our results to firms' capital constraints, we construct $KZ4$ along the same lines described above and incorporate it into our analysis. We find that $KZ4$ is positively correlated with both $(1-R2)$ and PIN. We follow Baker, Stein, and Wurgler (2003) and assign firm-year observations to quintiles based on their $KZ4$ score. We estimate equation (5) for each quintile and report the results in Table 4, Panel A.

Table 4
Effects of financial constraints and size

	Q1	Q2	Q3	Q4	Q5
Panel A: Quintiles formed by KZ					
KZ4 Quintiles					
Q	**0.42***	**0.44***	**1.06***	**1.94***	**3.17***
	0.14	0.17	0.25	0.37	0.46
(1 –R2)*Q	**2.49***	**1.97***	**1.99****	**3.82***	**1.71**
	0.52	0.57	0.97	1.17	1.05
PIN*Q	**2.63*****	**2.10**	**3.80****	**4.80**	**1.80**
	1.52	1.41	1.55	3.86	3.19
Number of observations	3391	4324	4146	3968	3358
Adjusted R^2	0.28	0.28	0.23	0.18	0.15
Within R^2	0.13	0.07	0.08	0.08	0.06
Panel B: Quintiles formed by market size					
SIZE Quintiles					
Q	**4.22***	**5.47***	**4.08***	**2.31***	**1.59***
	0.55	0.42	0.28	0.21	0.29
(1 –R2)*Q	**0.60**	**0.59**	**1.49*****	**1.97****	**1.44***
	1.65	0.93	0.88	0.75	0.57
PIN*Q	**0.62**	**1.58**	**0.73**	**0.54**	**4.98***
	3.29	3.14	1.65	1.90	1.74
Number of observations	2989	3557	3863	4056	4743
Adjusted R^2	0.49	0.67	0.66	0.69	0.71
Within R^2	0.07	0.16	0.20	0.19	0.29

Definitions of all variables are listed in Table 1 Panel A. All observations are sorted into five subsamples depending on the quintile in which a firm's *KZ4* score (Panel A) or market size (Panel B) falls during the previous year. *KZ4* is used to proxy for a firm's financing constraints. Regressions of *CAPXRND* on *Q, (1–R2)*Q, PIN*Q,* and the same control variables as in Table 3 are estimated in each quintile. We estimate the five-quintile equations simultaneously with both year- and firm-fixed effects. Shown are the coefficient estimates for *Q*,,*(1 – R2)*Q* and *PIN*Q* (in bold font) and their standard errors (displayed right below). Standard errors adjust for both heteroskedasticity and within correlation clustered by firm. *, **, and *** indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

We find that investment-to-price sensitivity (i.e., the estimate for β_1) stays relatively flat from quintile 1 to quintile 2, and increases monotonically from quintile 2 to quintile 5. This confirms that the Baker, Stein, and Wurgler (2003) result exists in our dataset (which is smaller than their dataset because of the limited availability of data required for the *PIN* measure). More important for us are the coefficient estimates for $(1-R2)\cdot Q$ and $PIN\cdot Q$. We find that they stay positive across all *KZ* quintiles, with $(1-R2)\cdot Q$ significantly positive in *KZ*4 quintiles 1–4, and $PIN\cdot Q$ significant in quintiles 1 and 3. The lowered significance is expected because of the smaller sample size in each quintile than the full sample. These results indicate that both private information in price and capital constraints play important roles in generating the variation in the sensitivity of investment to price, with different firms affected by each factor to a different degree. Panel A also shows that the effect of private information in price on investment-to-price sensitivity is more statistically significant for firms that are less financially constrained. This result may be generated by the intuition that firms can respond to information in market prices more easily (in adjusting their investment levels) when they are less constrained in financing their investment.

We also assess the sensitivity of our results to firm size. Larger firms are less likely, on average, to exhibit strong sensitivity of investment to stock price, possibly because changes in their stock prices are less likely to affect their ability to finance investment. As size is negatively correlated with both price nonsynchronicity and *PIN*, we need to verify that our main results are not driven merely by size. To check this point, we construct portfolios by size quintiles (where size is measured by firms' market equity) and estimate Equation (5) for each quintile.

Panel B of Table 4 reports the estimation results for each size quintile portfolio. As expected, we find that investment-to-price sensitivity decreases in size. Importantly, we find that the coefficients for $(1-R2)\cdot Q$ and $PIN\cdot Q$ stay positive across all size quintiles, with $(1-R2)\cdot Q$ significantly positive in size quintiles 3–5, and $PIN\cdot Q$ significant in quintile 5. Given that the significance is expected to decrease relative to the basic regressions because of reduced sample size in quintiles, these results indicate that the private information in price, as captured by $(1-R2)$ and *PIN*, remains an important factor even when size is considered. They also indicate that the effect of information in price on investment-to-price sensitivity is more significant for bigger firms. This is consistent with the idea that bigger firms may be less affected by capital constraints and therefore can respond more easily to information in prices when they make their investment plans.

We perform a series of robustness checks and obtain similar results (not tabulated). These tests include using NYSE quintiles instead of the size quintiles in our sample, forming quintiles using double sorting by capital constraints and size, as well as including $SIZE \cdot Q$ and $KZ \cdot Q$ directly as control variables in the pooled regression. In all these tests, the coefficient estimates for $(1-R2) \cdot Q$ and $PIN \cdot Q$ remain positive, whereas their significance levels either remain intact or improve.

4.4 Private information in stock price and firms' future operating performance

If price contains private information that is new to managers and hence helps managers make better investment decisions, we should expect that the amount of private information in price will have a positive effect on firms' future operating performance. In this subsection, we test this aspect of the theory.

We construct three measures of operating performance. The first measure is the *ROA*, calculated as the percentage of earnings before interest, taxes, depreciation, and amortization (i.e., EBITDA) to firms' market value of assets, where the market value of assets is calculated as the sum of market value of equity and the book value of liabilities. (As Healy, Palepu, and Ruback (1992) note, this measure overcomes the nonperformance-related differences caused by the different accounting methods used by firms.) The second measure is sales growth. The third measure is asset turnover, calculated as the ratio of sales revenues to total assets. We then construct a "score" variable, representing the degree of private information in price for a given firm, and test whether firms with higher score also exhibit stronger ex post performance. We construct two scores: one based on $1 - R2$ value and one based on both $1 - R2$ and *PIN*. For the score based on $1 - R2$, we take the score to be the percentage ranking of the observation's $1 - R2$ in the sample. For the score based on both $1 - R2$ and *PIN*, we take the score to be the percentage ranking of a weighted average of these two values, with the weights as the coefficient estimates on $1 - R2$ and *PIN* from regressions in Table 2. We regress the performance measures on the scores, controlling for other variables that can potentially affect performance, such as size, capital constraints, and diversification. We include firm and year-fixed effects in the regressions to capture the within-firm effect of private information in price on future performance, which is the effect of interest here.

The results are summarized in Table 5, with columns 1, 3, and 5 using $(1-R2)$ as a measure of private information in the price, and columns 2, 4, and 6 report results that are based on both $(1-R2)$ and *PIN* as measures of private information in the price. The results show a significant positive correlation between the amount of private information in price, as captured by $(1-R2)$ and *PIN*, and future performance. These results are obtained across all measures of performance and all measures of information. For example, when $(1-R2)$ increases from the 25th to the 75th percentile, *ROA* increases by 0.76 percentage points, sales

Table 5
Regression of future performance on investment-price sensitivity scores

	1	2	3	4	5	6
Dependent variable	ROA	ROA	Sales Growth	Sales Growth	Asset Turnover	Asset Turnover
SCORE based on	*1–R2*	*1–R2&PIN*	*1–R2*	*1 –R2&PIN*	*1–R2*	*1–R2&PIN*
SCORE	**1.51****	**0.42******	**5.96****	**9.59****	**11.38****	**5.11****
	0.17	0.23	0.78	1.29	1.03	1.27
SALES	**–0.83****	**–0.95****	**–3.09****	**–3.09****	**–7.79****	**–17.15****
	0.06	0.14	0.22	0.22	0.45	1.08
KZ4	**0.07******	**0.43****	**–2.65****	**–2.20****	**–2.32****	**0.28**
	0.04	0.06	0.22	0.49	0.24	0.33
HERFINDAHL	**2.02****	**1.03****	**7.72****	**11.60****	**19.48****	**11.14****
	0.24	0.32	1.08	1.88	1.65	2.19
Q	**–0.56****	**–0.20****	**–0.44*****	**–1.96****	**–1.49****	**–2.20****
	0.03	0.04	0.22	0.36	0.19	0.25
Number of observations	46304	11315	46393	11351	46409	11354
Adjusted R^2	0.68	0.78	0.34	0.29	0.86	0.91
Within R^2	0.03	0.03	0.02	0.03	0.04	0.15

Definitions of all variables are listed in Table 1 Panel A. The dependent variable is *ROA* in columns 1 and 2, *Sales Growth* in columns 3 and 4, and *Asset Turnover* in columns 5 and 6. *ROA* is calculated as the percentage of operating earnings to firms' total market value of assets (sum of market value of equity and book value of liabilities). *Sales Growth* is the annual growth rate in sales revenues. *Asset Turnover* is the percentage ratio of sales revenue to total assets. All dependent variables are averages over the three-year periods after year *t*. *SCORE* is a variable between 0 and 1, representing the percentile of the "learning score" in the sample. The score based on *1 – R2* is the percentage ranking of the observation's *1–R2* in the sample. The score based on both *1–R2* and *PIN* is calculated as the percentage ranking of a weighted average of these two values, with the weights being the coefficient estimates on *1–R2* and *PIN* from regressions in Table 3. *SALES* is the sales revenue in year *t* – 1. Both firm- and year-fixed effects are included. Coefficient estimates are printed in bold and their standard errors are displayed right below. Standard errors adjust for both heteroskedasticity and within correlation clustered by firm.
*, **, and *** indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

growth increases by 2.98 percentage points, and total asset turnover increases by 5.69 percentage points.

Overall, these results provide additional support to the hypothesis that prices contain private information new to managers and hence help managers in their investment decisions. They also reinforce the interpretation of $(1-R2)$ and PIN as measures of private information and not measures of noise. This is because if these measures capture noise or mispricing, we should not expect them to be positively correlated with future performance.

5. Robustness Checks

5.1 Portfolio regressions

To address the concern that the positive coefficient estimates for $(1-R2)\cdot Q$ and $PIN\cdot Q$ are driven only by extreme observations of the information measures, we sort firm-year observations into quintiles based on their $(1-R2)$ or *PIN* values and estimate the following regression for each quintile:

$$I_{it} = \alpha_t + \beta_1 Q_{it-1} + \gamma CONTROL + \varepsilon_{i,t}. \tag{7}$$

A finding of $\hat{\beta}_1$ increasing from low $(1-R2)$ or *PIN* quintiles to high quintiles will confirm that our main results represent stable relations across the whole sample.

Table 6 summarizes the results from estimating Equation (7) for both the quintiles sorted by $(1-R2)$ (Panel A) and the quintiles sorted by *PIN* (Panel B). In Panel A, we see that the average investment-to-price sensitivity for the lowest $(1-R2)$ quintile (Column 1) is also the smallest at $\hat{\beta}_1 = 1.70$ and that for the highest quintile (Column 5) is the largest at $\hat{\beta}_1 = 3.92$, with the difference significant at less than the 1% level. The increase is approximately monotonic except that quintile 4 has an investment-to-price sensitivity slightly lower than that for quintile 3.

Panel B reports similar results for quintiles formed on *PIN* values. Column 1 shows that the investment-to-price sensitivity is the lowest for

Table 6
Sensitivity to alternative specification: the portfolio approach

	Q1	Q2	Q3	Q4	Q5
Panel A: Quintiles formed by 1 – R2					
Q	**1.70***	**2.63***	**3.35***	**3.24***	**3.92***
	0.19	0.19	0.24	0.23	0.36
CF	**31.64***	**26.88***	**24.11***	**25.80***	**25.87***
	2.24	2.05	2.06	2.01	2.23
RET	**–0.41*****	**–0.11**	**0.11**	**–0.13**	**–0.08**
	0.23	0.20	0.22	0.15	0.18
INV_AST	**0.25***	**0.17***	**0.12***	**0.07***	**0.04***
	0.04	0.02	0.01	0.01	0.01
Number of observations	9602	9610	9613	9610	9598
Adjusted R^2	0.28	0.24	0.21	0.20	0.20
Panel B: Quintiles formed by PIN					
Q	**1.55***	**2.69***	**3.33***	**3.67***	**5.26***
	0.22	0.23	0.34	0.33	0.50
CF	**29.32***	**24.34***	**22.23***	**19.44***	**18.79***
	3.13	3.05	3.41	2.73	3.64
RET	**0.45**	**0.64****	**0.78*****	**0.31**	**0.72****
	0.30	0.32	0.41	0.29	0.35
INV_AST	**0.49***	**0.32***	**0.22***	**0.12***	**0.07***
	0.09	0.04	0.03	0.02	0.02
Number of observations	3581	3310	3160	2951	2721
Adjusted R^2	0.30	0.28	0.22	0.23	0.26

Definitions of all variables are listed in Table 1 Panel A. Each firm-year observation is assigned into quintiles by its *1–R2* value in Panel A and by its *PIN* value in Panel B, with the lowest value in quintile 1 and the highest value in quintile 5. The dependent variable is *CAPXRND*. Shown below are coefficient estimates for each quintile, with standard errors shown below. Year-fixed effects are included. Standard errors adjust for both heteroskedasticity and within correlation clustered by firm.
*, **, and *** indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

quintile 1 at 1.55. The sensitivity increases monotonically from quintile 1 to quintile 5 with the sensitivity estimate in quintile 5 at 5.26. The difference is significant at less than the 1% level.

Also notable from Table 6 is that the sensitivity of investment to cash flow is mostly decreasing in both measures of private information in price. This is consistent with the result reported in Section 3. The difference here is that the result is obtained not only for $(1-R2)$ but also for PIN.

Overall, the portfolio approach indicates that our results are not driven only by observations with extreme values of $(1-R2)$ or PIN: that the positive correlation between private information in the price and investment-to-price sensitivity represents a general relation.

5.2 Cross-firm versus within-firm effect

In this article, we are interested in both a cross-firm effect and a within-firm effect. That is, we wish to test whether, cross-sectionally, firms with more private information in the price have higher sensitivities of investment to price and whether, overtime, firms are more responsive to stock prices when their stock prices contain more private information. Results from pooled regressions on unbalanced panel data (our main regressions) can be driven by both within- and cross-firm effects. To identify the cross-firm effect, we re-estimate our main specification using the Fama–MacBeth approach. Specifically, we estimate Equation (5) with all firms each year and report the simple averages of yearly estimated coefficients. The standard errors are obtained through cluster-controlled bootstrap to adjust for the correlation among estimates from different years because of correlation of disturbances among same-firm observations.[9]

The results from the Fama–MacBeth approach (reported in Table 7) are qualitatively similar to those reported in Table 2. Specifically, with the exception of the regression where the dependent variable is $CAPX$, the coefficient estimate for $(1-R2)\cdot Q$ is significantly positive. The coefficient estimate for $PIN \cdot Q$ remains positive and significant across all specifications. While the results of the pooled regressions identify both within-firm and between-firm effects, the results in Table 7 indicate that the cross-sectional effect is robust. Overall, these results are consistent with prior literature on the effect of our measures. For example, Easley, Hvidkjaer, and O'Hara (2002) incorporated their estimates into a Fama and French (1992) asset-pricing framework and show that PIN affects cross-sectional asset returns. The empirical literature on price

[9] The bootstraping approach amounts to grouped re-sampling with replacement, that is, when a firm-year observation gets sampled, all observations belonging to the same firm get sampled automatically. For details, see Hardin and Hilbe (2001), Chapter 17.

Table 7
Sensitivity to cross-sectional correlations: the Fama–Macbeth approach

	1	2	3	4	5	6
Dependent variable	*CAPXRND*	*CAPX*	*CHGASSET*	*CAPXRND*	*CAPX*	*CHGASSET*
Q	**3.55****	**1.55****	**12.95****	**2.74****	**0.37*****	**7.44****
	0.22	0.14	0.72	0.23	0.16	0.48
(1–R2)*Q	**3.91***	**0.33**	**10.76***	**4.16***	**0.33**	**–1.62**
	0.68	0.49	1.50	0.69	0.46	2.33
PIN*Q	–	–	–	**3.93****	**3.01****	**34.42***
	–	–	–	1.90	1.42	6.43
CF	**29.91***	**16.17***	**65.63***	**24.86***	**10.67***	**68.55***
	1.38	1.03	4.89	1.76	1.23	5.64
(1–R2)*CF	**–17.83***	**–0.23**	**25.65**	**–30.95***	**–12.83****	**23.82**
	5.09	4.37	18.71	9.03	6.48	28.98
PIN*CF	–	–	–	**–3.97**	**4.49**	**46.65**
	–	–	–	19.21	14.41	66.52
RET	**–0.90***	**–0.99***	**–3.06***	**0.03**	**–0.62**	**–1.67***
	0.10	0.09	0.34	0.17	0.12	0.52
INV_AST	**0.04***	**–0.04***	**–0.20***	**0.12***	**–0.06***	**–0.57***
	0.01	0.00	0.02	0.01	0.01	0.03
1 – R2	**–2.10***	**–0.38**	**–9.32***	**–2.09**	**0.11**	**7.18****
	0.77	0.72	2.23	1.26	0.84	3.83
PIN	–	–	–	**–1.46**	**2.86**	**–6.78**
	–	–	–	3.12	2.49	11.64

Definitions of all variables are listed in Table 1 Panel A. Regressions are estimated for each year. Reported coefficient estimates are the averages of yearly estimates. Standard errors are estimated with clustered controlled bootstrapping. Number of observations is 64,782 in Columns 1–3 and 19,208 in Columns 4–6.
*, **, and *** indicate a two-tailed test significance level of less than 1%, 5%, and 10%, respectively.

non-synchronicity (as reviewed in Section 1) also shows that price non-synchronicity explains cross-sectional regularities.

5.3 The effects of institutional investors and diversification

In this section, we examine two firm characteristics that may be related to our measures of private information and may affect the investment-to-price sensitivity: percentage of shares held by institutional investors and diversification structure.

We use the average percentage of shares held by institutional investors as reported on Spectrum to capture the dominance of such investors. We use Herfindahl index based on firms' sales in different business segments (as disclosed in firms' segment disclosure) to proxy for firms' degree of diversification. More focused firms have higher Herfindahl index values.

Columns 1 and 2 in Table 8 report the results after including the interactive terms of *INSTITUTION* and *HERFINDAHL* with both Q and CF. We note that the coefficients for $(1-R2)\cdot Q$ and $PIN\cdot Q$ remain positive and statistically significant. As for the effect of the control variables on the investment-to-price sensitivity, Column 1 shows that institutional holdings have a negative effect on the investment-to-price sensitivity. As institutional holdings are highly correlated

Table 8
Sensitivity to other factors affecting investment-price sensitivity

	1	2	3
CONTROL	*INSTITUTION*	*HERFINDAHL*	*PURE PLAY*
Q	**2.02***	**2.06***	**2.03***
	0.13	0.14	0.15
(1–R2)*Q	**1.14***	**2.15***	**1.80***
	0.36	0.47	0.53
PIN*Q	**1.49****	**3.41***	**4.49***
	0.76	1.23	1.38
CONTROL*Q	**–2.72***	**0.57*****	–
	0.37	0.30	–
Number of observations	15,635	15,213	11,518
Adjusted R^2	0.60	0.51	0.49
Within R^2	0.17	0.15	0.14

Definitions of all variables are listed in Table 1 Panel A. The dependent variable is *CAPXRND*. In Columns 1 and 2, the dependent variables are those in Table 3 plus the additional *CONTROL* variable: *INSTITUTION* (measured as the average percentage of shares held by institutional investors in year $t-1$) and *HERFINDAHL* (the Herfindahl index of firms' reported business segments based on previous-year sales). In Column 3, the same regression (without the extra *CONTROL* variable) is performed on "pure play" firms (i.e., firms that have only one reported business segment). Both firm- and year-fixed effects are included. Coefficient estimates for *Q, (1 – R2)*Q, PIN*Q* and *CONTROL*Q* are printed in bold and their standard errors are displayed right below. Standard errors adjust for both heteroskedasticity and within correlation clustered by firm.
*, **, and *** indicate a two-tailed test significance level of less than 1, 5, and 10%, respectively.

with size and with analyst coverage, this result is expected given the results we have discussed thus far. Column 2 shows that investments in more diversified firms are less responsive to stock prices. This result is intuitive because stock prices may not be as informative about the internal operations of diversified firms as they are for focused firms. Lower sensitivity for a more diversified firm may also result from the cross-subsidizations of investments within the firm.

Finally, Column 3 considers another specification to control for the effect of diversification. One may argue that our measures of information, especially $(1-R2)$, are mechanically affected by diversification structure and that, as a robustness check, we should focus on pure-play firms, that is, firms with only one reported business segment. We thus run our basic regression using only pure-play firms. Column 3 shows that the effects of $(1-R2)$ and *PIN* on the investment to price sensitivity remain intact.

5.4 Robustness of price non-synchronicity

Price nonsynchronicity measures firm-specific return variation and is supported by prior literature as a measure for the amount of private information in price. We perform several robustness checks with respect to this measure (results not tabulated). First, we add lagged market and industry returns (one day or two days lagged) to the regression estimating $(1 - R^2)$ to control for the possibility that some market or industry information may take longer than a day to be reflected in firms' returns. The resulting $1 - R2$ measure is highly correlated with our baseline measure and does not affect our main results established in Table 2. We also examine whether industry- or market-related return variation affect investment-to-price sensitivity similarly as the firm-specific return variation does. For the effect of industry-related return variation, we use the $1 - R^2$ from regressing a firm return on the market return alone (thus, it is a measure of both industry-related return variation and firm-specific return variation). We find that adding industry-related return variation reduces the explanatory power of the $1 - R^2$ measure, consistent with the idea that industry-related return variation is most likely from information managers already knew and hence would reduce investment-to-price sensitivity. As to the effect of market-related return variation (which can be captured by R^2), the fact that we find significantly positive coefficient for $(1 - R^2)*Q$ in our regressions implies that market-related return variation would likely have a negative effect on investment-to-price sensitivity, suggesting that market-related return variation does not play a role in determining managers' investment decisions.

5.5 Other specifications

Our main parameter of interest is the coefficient estimate (β_2) for the interactive term $INFO_{it-1} \cdot Q_{it-1}$. To ensure that β_2 is not capturing any nonlinear relation between I_{it} and Q_{it-1}, we perform a cubic-spline regression diagnosis and find that the relation between I_{it} and Q_{it-1} is approximately linear. Such a linear relation is also documented in Baker, Stein, and Wurgler (2003). In addition, we obtain qualitatively similar results (hence not reported) regarding the coefficient estimate for $INFO_{it-1} \cdot Q_{it-1}$ after we include a squared-term of Q_{it-1} in the estimation. Finally, results are not qualitatively affected if we include lagged investment ($I_{i,t-1}$) to control for the autocorrelation in firms' investments.

6. Conclusion

This article studies the empirical relation between the amount of private information in stock price and the sensitivity of investment to stock price. Using two different measures of the amount of private information in price—price nonsynchronicity and *PIN*—we find strong positive correlation between the amount of private information in price and the investment-to-price sensitivity. This relation is robust to the inclusion of controls for managerial information, analyst coverage, capital constraint, and firm size, as well as to a variety of different specifications. Overall, our results are consistent with the hypothesis that some private information in price is new to managers and that managers learn it from the price and incorporate it in their investment decisions.

The possibility that prices guide managers in their investment decisions implies that financial markets affect the real economy. This observation has important implications. On the one hand, as Subrahmanyam and Titman (1999) argued, financial markets may enhance investment efficiency because they provide valuable information to managers. On the other hand, as Goldstein and Guembel (2005) showed, the feedback effect from prices to the real economy may make price manipulation possible, which can cause inefficiencies in the real economy. These effects have important implications for regulations aimed at increasing market transparency and encouraging information acquisition.

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