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Abstract

Stock prices and real investments are highly correlated. Previous literature has offered two main explanations for this high correlation. The first explanation relies on price being informative about investment opportunities, the second one is based on financing constraints. In this paper we empirically examine the effect of price informativeness on the sensitivity of investment to stock price. Using price non-synchronicity and PIN as measures of price informativeness, we find that the degree of informativeness is positively correlated with the sensitivity of investment to stock price. Since, according to previous literature, these measures reflect private information, the result suggests that prices perform an active role, i.e., that managers learn from stock price when making investment decisions. This result is robust to the inclusion of various control variables (such as controls for managerial information) and to changes in specification.

1 Introduction

Stock prices and real investments are strongly correlated. Two main explanations of this correlation have been offered in the literature. The first explanation relies on the hypothesis that stock prices reflect information about firms' fundamentals. Since information on firms' fundamentals affects real investment decisions made by firms' managers, we should expect to observe positive correlation between stock prices and real investments when prices reflect such information. The second explanation is based on the hypothesis that firms face financing constraints that prevent them from pursuing their optimal investment plans. Under this hypothesis, an increase in stock price will make financing constraints less binding by making equity financing (or external financing in general) less costly, and will thus enable firms to increase investments.

Many empirical papers study the correlation between stock prices (as measured by Q) and investments (see, for example, Barro (1990), Morck, Shleifer, and Vishny (1990), and Blanchard, Rhee, and Summers (1993)). However, as Baker, Stein, and Wurgler (2003) recently note, there is very little direct analysis on the relative merits of the possible explanations offered in the literature for this correlation. Baker, Stein, and Wurgler (2003) conduct a cross-sectional analysis and analyze the role of the second channel discussed above - financing constraints - in generating the correlation between prices and investments. They show that firms that are more equity dependent have a stronger sensitivity of investment to price.

In this paper we focus on the first channel mentioned above, and test whether price informativeness has an important role in generating the correlation between stock prices and real investments. Our empirical analysis is based on the premise that there are some firms whose stock prices reflect more aspects of fundamental value than others. Hence, they provide a more accurate depiction of fundamental value. We consider the stock prices of those firms to be more informative. Based on this definition of informativeness, our hypothesis is that investments are sensitive to information about fundamental value. Thus, if the price is more informative – i.e., if it reflects more accurate information on fundamental value – then investment will be more sensitive to price. Using measures of price informatveness, we test this hypothesis empirically.

It is important to note that the correlation between price informativeness and investment sensitivity to stock price can reflect two different mechanisms, depending on whether the price is informative relative to the information set of the firm's manager. If the price is informative relative to the manager's information set – i.e., if it reflects more information than what is known to the manager – then the sensitivity of investment to price may result from an *active* role of price: the manager could learn the information from the price and make the investment decision accordingly. On the other hand, if the price is generally informative, but not relative to the manager's information set, then investment could still be correlated with price, as the underlying information affects both of them. However, in this case, the correlation reflects a *passive* role of price, as the manager does not learn from the price.

While it is interesting to document each of these two mechanisms, in this paper we are more interested in situations where investment is sensitive to price because managers learn from the price. The possibility of this active role was studied theoretically in several models; most prominently in Dow and Gorton (1997) and in Subrahmanyam and Titman (1999). The idea is that stock prices aggregate information from multiple sources and so may contain information managers do not have.[1] Empirically, identifying an active role of price requires that we find a measure of price informativeness that captures information not already known to managers. We use two measures of informativeness in the paper – price non-synchronicity and probability of informed trading (PIN). We believe both of them qualify for the purpose of detecting an active role of price, since, based on previous literature, they seem to capture private information incorporated into the price by traders and not public information.

Our first measure, price non-synchronicity, was first proposed by Roll (1988) and recently developed by Morck, Yeung, and Yu (2000), Durnev, Morck, Yeung, and Zarowin (2003) and Durnev, Morck, and Yeung (2004). This measure is computed on the basis of the correlation between a 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

[1] Note that our approach assumes that managers wish to maximize the expected value of their firm given the information available to them. We thus abstract from any agency problem between shareholders and managers.

decisions. Thus, the measure will be higher when the return on the stock is less correlated with the market and industry returns. This measure was supported as a measure of price informativeness in many different papers (a detailed review is provided in the next section). 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".

Our second measure, PIN, goes even farther than non-synchronicity. The measure was developed in Easley, Kiefer, and O'Hara (1996), Easley, Kiefer, and O'Hara (1997a), and Easley, Kiefer, and O'Hara (1997b) and used in many other papers (a detailed review is provided in the next section). 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, and this is why these stocks may provide more information to managers. 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.

Our results show that both measures are significantly positively correlated with investment-to-price sensitivity. As both measures seem to reflect private information incorporated into the price by traders, the results indicate that managers may indeed be learning from prices in making their investment decisions. This implies that financial markets affect the real economy, and thus are not just a sideshow.[2]

Of course, it may still be the case that managers have the same private information that is held by traders, and thus that they do not really learn from prices. To further strengthen our tests of the existence of an active role, we control for managerial information using two proxies. The first proxy is the firm's insider trading activity. The idea is that, on average, managers with more private information are more likely to trade, and thus greater activity represents more managerial

[2] We borrow this terminology from Morck, Shleifer, and Vishny (1990). For a recent review on the question of whether stock markets are only a sideshow, see Stein (2003).

information. The second proxy is earnings surprises, measured as the absolute abnormal return around earnings announcement dates. Since managers know the earnings before they are released to the public, this variable captures private information that managers have. We repeat our tests while controling for these variables, and find that the effects of price non-synchronicity and PIN on the investment-to-price sensitivity remain equally strong. Thus, to the extent that insider trading and earnings surprises are good proxies for managerial private information, this result suggests that our measures of informativeness reflect some information that is not known to managers, and thus lends more support to the conclusion that prices play an active role. Another result, documented in our paper, that strengthens this conclusion is that ex-ante price informativeness is positively correlated with ex-post firm performance. This result is expected if managers use the information in price to make better investment decisions.

Our paper considers a number of robustness issues. To relate our results to those reported by Baker, Stein, and Wurgler (2003), we modify our analysis and conduct it on five quintile subsamples sorted by the degree of capital constraints. We show that both capital constraints and price informativeness have a role in generating the investment-to-price sensitivity, and that each one of them affects different firms to a different degree. We conduct similar analysis with respect to size, and find that price informativeness remains important after this variable is controlled for. We control for other parameters such as analyst coverage, diversification, and institutional holding. We also examine different empirical specifications. Our results remain intact in all these tests.

A related issue we address in this paper is the effect of price informativeness on the sensitivity of investments to cash flows. 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 are more informative. There are two possible interpretations for this negative correlation. First, if the investment-to-cash sensitivity results from frictions in external financing that cause firms to forego profitable investments, a higher degree of price informativeness can ease such inefficiencies to some extent by mitigating the information asymmetry between providers of capital and those who use it. This will enable

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

firms whose prices are believed to be informative to raise capital more easily and rely less on cash. Second, in a recent paper, Alti (2003) argues that investments can be highly 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, firms can rely less on cash and more on prices to obtain information about investment profitability. Both explanations provide support for our hypothesis that information in stock prices is an important factor in determining investments.

Several recent papers have studied hypotheses related to our paper. Giammarino, Heinkel, Hollifield, and Li (2004) analyze a sample of seasoned equity offerings and find 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 (2004) finds that the positive correlation between announcement date return and the completion of mergers can be attributed to insiders' learning from outsiders after controling for common information. Sunder (2001) finds that firms with high analyst coverage and bid-ask spread pay lower interest rates on their bank loans. She interprets this result as evidence that lenders learn from stock prices, and thus can charge a lower interest rate when the price is more informative. Liu and Qi (2002) show that firms with more analyst coverage have a higher sensitivity of investment to cash. Gilchrist, Himmelberg, and Huberman (2004) analyze how real investment reacts to the "bubble" component in prices as measured by analysts' forecast dispersion.

A more closely related paper is Durnev, Morck, and Yeung (2004). Using price non-synchronicity as a measure for price informativeness, they show that firms with more informative prices make more efficient investment decisions in that their marginal Tobin's Q is closer to one. Our paper is different from Durnev, Morck, and Yeung (2004) in two important dimensions. First, we analyze directly the effect of price informativeness on the sensitivity of investment to price. This effect may be a mechanism that generates the result that informativeness enhances efficiency. Second, we look more directly at the effect of private information by using the PIN measure. To the best of our knowledge, our paper is the first one to relate the probability of informed trading to real investment, and one of the first papers to use a market-microstructure measure in a corporate finance context.[4]

Finally, we acknowledge that the interpretation of the results in the paper depends on the measures of informativeness that we use. Clearly, measuring price informativeness is a non-trivial task, and there is no one definite way to do it. The two measures used in this paper were recently developed in the literature and represent the current state of the art on empirical measures of the informativeness concept. Thus, our empirical analysis sheds light on the relation between price informativeness, as it is currently captured in the literature, and the sensitivity of investment to price.

The remainder of the paper is organized as follows: Section 2 presents the basic hypothesis and the measures of informativeness used in this paper. In Section 3, we describe the data and the construction of the main variables. Section 4 presents the main empirical results on the relation between price informativeness and the sensitivity of investment to price. In Section 5, we extend the basic tests to control for managerial information, to relate our results to the effect of capital constraints and size, and to examin the effect of price informativeness on firm performance. Section 6 presents several robustness checks. Section 7 concludes.

2 Basic Hypothesis and Measures of Informativeness

Our goal in this paper is to test whether the informativeness of stock prices has an important role in generating positive correlation between stock prices and real investments. Our analysis is based on two different measures of informativeness: price non-synchronicity and the probability of informed trading (PIN). Both measures focus on private information incorporated into the stock price. We now turn to describe these measures in more details.

2.1 Price non-synchronicity

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

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

non-synchronicity. This is our first measure of informativeness. 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 non-synchronicity (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 risk arbitrageurs who gather and posses private information. Since Roll (1988) finds that firm-specific stock price movements are generally not associated with identifiable news release, he argues that the latter channel is especially important in the capitalization of firm specific information. However, he acknowledges that two explanations of his findings are actually possible: 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 non-synchronicity reflects more private information than noise. The most convincing piece of evidence, in our view, is provided by Durnev, Morck, Yeung, and Zarowin (2003). They find that stock price non-synchronicity is highly correlated with stock prices' ability to predict firms' future earnings, supporting the argument that price non-synchronicity reflects more private information than noise.

Other papers in this literature provide consistent evidence. Morck, Yeung, and Yu (2000) show that firm-specific return variation is high in countries with well-developed financial systems and low in emerging markets. They argue 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) show that industries with higher firm-specific return variation allocate capital more efficiently in the sense that their marginal Tobin's Q's are closer to one. They argue that price informativeness enhances investment efficiency. Wurgler (2000) obtains a similar result in a cross-country analysis. DeFond and Hung (2004) show that the association between lagged stock returns and subsequent CEO turnover is stronger in countries with low stock return synchronicity. In their framework, non-synchronicity enhances informativeness, which generates an effect of price on CEO turnover decisions. Finally, price non-synchronicity is being used in other recent papers as a measure for the efficiency of market prices. One prominent example is the recent paper by Bris, Goetzmann, and Zhu (2004) on the effects of short sales on market efficiency.

On the theoretical level, when stock prices move together, they are less likely to reflect refined firm-specific information, which is important for managerial investment decisions. Such co-movement can reflect phenomena such as contagion (Kodres and Pritsker (2002), and 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. Closest to our notion of informativeness is a recent paper by Veldkamp (2004). She develops a model, where 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 information on each firm's fundamentals. Thus, her model predicts a negative correlation between price synchronicity and informativeness, which is the basis of our first empirical measure.

2.2 Probability of informed trading (*PIN*)

Our second measure, the *PIN* measure, has strong theoretical foundations. The measure was developed and used in a series of papers by Easley, Kiefer, O'Hara, and Paperman (1996), Easley, Kiefer, and O'Hara (1996, 1997a, 1997b), 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:

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

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:

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

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 papers 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 vs. 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 showed that the risk of private information captured by this measure is priced, so that high PIN stocks earn higher returns. The results from all these papers are highly consistent with the idea that *PIN* indeed measures the probability of informed trading. These papers also directly test the validity of the *PIN* measure by comparing the predictions of the information-based model with other alternative models. In all these tests, the results support the *PIN* as a measure of the probability of informed trading. More recently, Vega (2004) provided further evidence supporting the *PIN* as a measure of informativeness. She shows that stocks with higher *PIN* values have smaller post-earnings-announcement drift and thus seem to have more informative pre-earnings-announcement prices.

3 Sample Selection, Specification, and Variable Construction

We collect our data from six databases. We obtain firms' stock price and return information from CRSP, investment and other financial data from Compustat, intra-day 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 7,268 firms. Analyses using intra-day transaction data (*PIN*) have fewer observations (19,208 firm-year observations) because TAQ's coverage starts from 1993.

Our baseline equation for testing the hypotheses is as follows:

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

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 + Item 46), 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' on-going investment and R&D activities, while $CHGASSETS_{it}$ 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 paper, however, is β_2, the coefficient for $INFO_{it-1} \cdot Q_{it-1}$, which measures the effect of price informativeness on the sensitivity of investment to price.

$INFO_{it-1}$ is a measure of stock price informativeness. As discussed in Section 2, we have two such measures. The first measure we use 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 3-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 we use is the probability of informed trading (i.e., 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 am and 4:00 PM 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 ten thousand shares) and trades coded by

[5]Specifically, we compare trade prices with the midpoint of the bid-ask spread five seconds before the trades.

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 $INFO_{it-1}$. The reason we include $1/ASSETS_{i,t-1}$ is that the dependent variable (I_{it}) and our key regressor $Q_{i,t-1}$ are both 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 seperately 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) argue that firms invest more when their stocks are over-valued (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 seperately 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 reports the summary statistics for the main 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, the market and industry returns account for about 17% of firms' return variations. This number is similar to that reported

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.

in Roll (1988), who argues 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. Further, 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 informativeness measures and other general data 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 insignificant correlation with institutional holdings. Price non-synchronicity is significantly negatively correlated with firm diversification, whereas the relation between PIN and this variable is not significant. These results motivate some of the robustness checks discussed later in the paper.

Lastly, ε_{it} in (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.

4 Testing the Basic Hypothesis

In this section, we test our basic hypothesis that price informativeness affects investment-to-price sensitivity. We start with the first measure of informativeness: price non-synchronicity.

Table 2 reports the results from estimating (5) using the three different investment measures and the information measure $(1-R2)$. For each investment measure, we estimate the baseline regression with only the direct effect of informativeness as a control variable (odd-numbered columns), and with the other control variables – cash flows, future returns, and inverse book assets – included as well (even-numbered columns). All three measures show similar results, thus we illustrate the main message here with $CAPXRND$, our default investment measure.

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 in this paper 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 provides support to the hypothesis 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 (see 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-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 adds the control variables to the baseline regression. In addition to firms' contemporaneous cash flow (CF_{it}) and future return (RET_{it+3}), we also allow the investment-to-cash flow sensitivity to vary with $(1-R2)$ (by including $(1-R2) \cdot CF$). As shown in the table, including the control variables does not affect the sign or significance of $(1-R2) \cdot Q$ (e.g., with $CAPXRND$, $\widehat{\beta}_2 = 3.84$ and $t = 12.4$). The coefficient estimate for CF is positive and significant (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 (at less than the 1% level), suggesting that firms invest more when their stocks are over-priced. Finally, a novel result from our analysis is that the coefficient for $(1-R2) \cdot CF$ is negative and significant (at less than the 1% level). This suggests that firms with more informative stock prices have lower sensitivity of investment to cash. As we discussed earlier, this can happen if price informativeness enables firms to raise capital more easily for new investment projects or if it enables them to rely less on cash as a source of information on investment profitability. Both explanations re-enforce justifying $1 - R^2$ as an informativeness measure.

In summary, if higher firm-specific return variations (higher $(1 - R2)$) imply more firm-specific information being impounded in stock prices, the results in Table 2 are consistent with the hypothesis that firms with more informative stock prices have a higher sensitivity of investment to price.

We now incorporate our second measure: probability of informed trading (*PIN*). Table 3 reports the results using this measure. We first re-estimate equation (5), replacing $(1 - R2)_{it-1}$ with PIN_{it-1}. Columns 1, 3, and 5 show that across all investment measures, investment-to-price sensitivity is higher for firms with higher probability of informed trading. For example, for $CAPXRND$ (Column 1), the coefficient for $PIN \cdot Q$ is 4.21 (significant at less than 1%). 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-price sensitivity of a firm with a 25 percentile value of *PIN* is 1.97 $(= 2.18 - (0.21 - 0.16) * 4.21)$, and that for a firm with 75 percentile value of *PIN* is higher by more than 21% at 2.39.

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 $(1 - R2)$. Columns 2, 4 and 6 show that this is not the case. These columns include in the regression $(1 - R2) \cdot Q$, $PIN \cdot Q$ and the other control variables, and find that the coefficient for $PIN \cdot Q$ remains significantly positive. The coefficient estimate for $(1 - R2) \cdot Q$ also remains significantly positive in two of the three regressions, although the significance level is overall lower than in Table 2 where *PIN* is not included. However, since the sample size is much smaller than in Table 2, this lower significance level is expected.

As indicated above, we believe that both $(1 - R2)$ and *PIN* capture private information impounded in stock price. The fact that both are significant in explaining investment-to-price sensitivity suggests that they may capture different aspects of informativeness. This may be the case as PIN captures the source of information reflected in price, i.e., the trading activities of informed traders, while $(1 - R2)$ captures the result of this information, i.e., its effect on the price. Overall, these results indicate that private information contained in stock prices affects managers' investment decisions.

5 Extending the Basic Tests

5.1 Controlling for managerial information

The positive coefficients on $(1-R2)\cdot Q$ and $PIN\cdot Q$ documented above are consistent with the idea of an active role of stock prices, i.e., with the idea that managers learn from stock prices. However, one cannot rule out that $(1-R2)$ and PIN simply correlate with managers' information set, or that the private information revealed by speculators' trading activity is already known by the managers, in which case managers do not learn from prices. In this subsection, we perform tests to assess the plausibility of this alternative explanation. The results appear in Table 4. Our tests rely on measures that proxy for the private information held by managers (these measures are denoted as $MANAGER$ in Table 4).

The first measure that we use 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. For example, see: Seyhun (1992), Meulbroek (1992), Damodoran and Liu (1993), Seyhun (1998), Ke, Huddart, and Petroni (2002), and Piotroski and Roulstone (2005).

We collect firms' insider trading information from the Thomson Financial's TFN database and measure the intensity of a firm's insider trading activities in a given year as the percentage of insider transactions to the total number of all transactions for a given firm-year as recorded in TAQ. This intensity serves as a measure for managers' information.

Columns 1 and 2 in Table 4 report the effect of the intensity of insider trading. Column 1 shows a negative coefficient estimate (-6.91) for $INSIDER\cdot Q$, indicating a negative correlation between insider trading and investment-to-price sensitivity. The negative correlation is expected since 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.

Column 2 includes both $(1-R2)\cdot Q$ and $PIN\cdot Q$ with $INSIDER\cdot Q$. The idea is that if PIN and $(1-R2)$ 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 2 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 (not reported), we re-estimate Columns 1 and 2 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. Our results indicate that both numbers of buys and sells are negatively related to investment-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. In another sensitivity check (also not reported), we re-estimate Columns 1 and 2 using the unscaled number of insider transactions in the firm-year to capture the insider trading activity. We obtain qualitatively similar results regarding $(1-R2)\cdot Q$ and $PIN \cdot Q$: both coefficients remain significantly positive.

In Column 3 of Table 4, 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 $\frac{PIN * \#trans - \#insider}{\#trans}$, 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 3 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 days 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. Since this information was known to firms' insiders, who have access to internal accounting data and thus know the earnings before they are released to the public, earnings surprise is a measure for private information that managers have, which is not known to the market. This measure has been used often as a measure of managers' information advantage. Two recent papers that use this measure are Gomes and Phillips (2004) who show that firms with lower earnings surprises are able to issue more information sensitive public securities; and Gomes, Gorton, and Madureira (2004) who use earnings surprise to test whether Reg FD improves information transmission from the firm to the market.

As Column 4 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 5 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 again 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 4 do not support the interpretation that $(1 - R2)$ and PIN only capture information that managers already know. Thus, the results provide further support to the conclusion that private information in price, captured by $(1 - R2)$ and PIN, affects investment-to-price sensitivity since managers learn from prices when making their investment decisions.

5.2 Sorting by capital constraints and size

Thus far, our results indicate that price informativeness is a significant and important variable in explaining the sensitivity of investment to stock price. In a recent article, Baker, Stein, and Wurgler (2003) show that capital constraints are also important in driving this sensitivity. Based on parameter estimates from Kaplan and Zingales (1997), Baker, Stein, and Wurgler (2003) construct a KZ score as a proxy for firms' degree of equity dependence. In particular, they use the four-variable version of the Kaplan-Zingales measure, $KZ4$, which is 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)):

$$KZ4 = -1.002 CF_{it}/A_{it-1} - 39.368 DIV_{it}/A_{it-1} - 1.315 C_{it}/A_{it-1} + 3.139 LEV_{it}. \tag{6}$$

Higher values of $KZ4$ indicate that firms are more constrained to equity financing. Baker, Stein, and Wurgler (2003) find 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.

Given the findings of Baker, Stein, and Wurgler (2003), we now check whether our results on the relation between price informativeness and investment-to-price sensitivity hold after we control for capital constraints. Thus, we construct $KZ4$ along the same lines described above and incorporate it into the 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.

Table 5 (Panel A) reports the estimation results for each KZ quintile portfolio. We notice 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, due to the limited availability of data required for the PIN measure). More important for us are the estimates for the β_2 coefficients, i.e., the coefficients for $(1 - R2) \cdot Q$ and $PIN \cdot Q$. We find that they stay positive across all KZ quintiles. Moreover, $(1 - R2) \cdot Q$ is significantly positive in $KZ4$ quintiles 1 to 4, and $PIN \cdot Q$ is significant in quintiles 1 and 3. These results indicate that price informativeness remains an important factor even when capital constraints are considered. The lowered significance is expected because of the smaller sample size in each quintile than the full sample. Thus, we conclude that both price informativeness 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.

An interesting observation is that the effect of price informativeness 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. It should be noted, however, that the point estimates on β_2 are not monotonic across quintiles, which goes against this intuition.

Another variable of interest is size. Larger firms are less likely, on average, to exhibit strong sensitivity of investment to stock price. This is because, for large firms, changes in stock price are less likely to affect their ability to finance investment. Since size is negatively correlated with both our measures of informativeness, we need to verify that our results on the relation between price informativeness and investment sensitivity to stock price are not driven merely by size. To check this point, we construct portfolios by size quintiles (size is measured by market equity), and estimate equation (5) for each quintile.

Panel B of Table 5 reports the estimation results for each size quintile portfolio. As expected, we find that investment-to-price sensitivity is mostly decreasing in size. Importantly, we find that the coefficients for $(1-R2)\cdot Q$ and $PIN\cdot Q$ stay positive across all size quintiles. Moreover, $(1-R2)\cdot Q$ is significantly positive in size quintiles 3 to 5, and $PIN \cdot Q$ is significant in quintile 5. Given that the significance is expected to decrease relative to the basic regressions due to reduced sample size in quintiles, these results indicate that price informativeness remains an important factor even when size is considered. The results may also indicate that the effect of price informativeness on investment-to-price sensitivity is more significant for bigger firms. Our interpretation is that bigger firms can respond more easily to information in prices when they make their investment plans, since they are less affected by capital constraints.

In further checks (not reported), we repeated the size analysis, using NYSE quintiles instead of the size quintiles in our sample. As is expected, the results are more spread out, in the sense that statistical significance is not concentrated among large firms. Importantly, the coefficients for $(1 - R\hat{}2) \cdot Q$ and for $PIN \cdot Q$ are always positive and mostly significant in this robustness check (significance in this robustness check is overall higher than in the size quintile analysis reported in Panel B of Table 5). Another robustness test we performed (not reported), is to include $SIZE \cdot Q$ and $KZ \cdot Q$ as control variables in the pooled regression. Our intention is to see if the results still hold when these variables are directly controlled for the full range rather than through a quintile-type analysis. Again, our main results hold: The coefficient estimates for $(1 - R2) \cdot Q$ and $PIN \cdot Q$ as well as their significance levels remain almost intact. Finally, going back to the quintile analysis, we performed double sorting by capital constraints and size (not reported), and found the same qualitative results.

5.3 Informativeness and ex-post performance

If prices play an active role by revealing information that is not known to managers and guiding them in their investment decisions, prices should contribute to firms' efficiency. This effect should be stronger when prices are more informative. Thus, we should expect that price informativeness will generate stronger performance. In this subsection, we test this aspect of the theory.

We construct three measures of ex-post performance. The first measure is the return on assets (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 non-performance-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 price informativeness 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 3. We regress the performance measures on the scores, controlling for other variables that can potentially affect performance, such as size, capital constraints, and diversification. Importantly, we add firm and year fixed effects to the regressions. As a result, our regressions look at the relation between above-firm-average price informativeness and above-firm-average future performance. Thus, they capture the within-firm effect of price informativeness on future performance, which is the effect of interest here.

The results are reported in Table 6. Columns 1, 3 and 5 of the table report results based on $(1 - R2)$ as a measure of informativeness, and columns 2, 4 and 6 report results that are based on both $(1 - R2)$ and PIN as measures of informativeness. The results show a significant positive correlation between price informativeness and future performance. These results are obtained across all measures of performance and all measures of informativeness. For example, when $(1 - R2)$ increases from the 25th to the 75th percentile, return on assets increase by 0.76 percentage points, sales growth increases by 2.98 percentage points, and total asset turnover increases by 5.69 percentage points.

We believe these results provide additional support to the hypothesis that prices play an active role in guiding managers in their investment decisions. The results also reinforce the interpretation of $(1 - R2)$ and PIN as measures of informativeness. This is because if these measures were capturing noise or mispricing, we should not have expected that they would be correlated with future performance.

6 Robustness Checks

6.1 Portfolio regressions

One possible concern is that the positive coefficient estimates for $(1 - R2) \cdot Q$ and $PIN \cdot Q$ are driven only by observations at both ends of the measures and do not represent a general stable relation. One way to address this concern is to 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 $\widehat{\beta}_1$ increasing from low $(1-R2)$ or PIN quintiles to high quintiles will confirm that our main results represent stable relations across the sample.

Table 7 presents the results from estimating (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 $\widehat{\beta}_1 = 1.70$ and that for the highest quintile (column 5) is the largest at $\widehat{\beta}_1 = 3.92$, 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 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.

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 price informativeness and investment-to-price sensitivity represents a general relation.

Another interesting result that comes out of Table 7 is that the sensitivity of investment to cash flow is mostly decreasing in both measures of informativeness. This is consistent with the result reported in Section 4. The difference here is that the result is obtained not only for $(1-R2)$, but also for PIN. In fact, as is apparent from the table, the result is even stronger for PIN here.

6.2 Cross-firm vs. within-firm effect

In this paper 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 informative prices have higher sensitivities of investment to price; and whether overtime, firms are more responsive to stock prices when their stock prices are more informative. 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 reestimate our main specification using the Fama-MacBeth approach. Specifically, each year, we estimate (5) with all firms in that 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 due to correlation of disturbances among same-firm observations.[8]

The results from the Fama-MacBeth approach (reported in Table 8) are qualitatively similar to those reported in Tables 2 and 3. 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.

Thus, while our pooled regressions identify both within-firm and between-firm effects, the analysis we conduct in Table 8 shows that the cross-sectional effect is robust. This is consistent with prior literature on the effect of the measures of informativeness. For example, Easley, Hvidkjaer, and O'Hara (2002) incorporate 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 non-synchronicity (see the review above) also shows that this measure explains cross-sectional regularities.

6.3 The effects of diversification, analyst coverage, and institutional investors

In this section, we examine three firm characteristics that may be related to our measures of informativeness and may affect the investment-to-price sensitivity: diversification structure, analyst coverage, and percentage of shares held by institutional investors. 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 these variables. Second, we wish to explore the effect of these variables on the investment-to-price sensitivity and deepen our understanding of the main factors affecting this sensitivity.

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. We retrieve analyst information from Zacks Investment Research

[8] 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.

Database and 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 $t-1$. We use the average percentage of shares held by institutional investors as reported on Spectrum to capture the dominance of such investors.

Table 9 reports the results after including the interactive terms of $HERFINDAHL$, $ANALYST$, and $INSTITUTION$ with both Q and CF. The most important finding for our study is that across all specifications, the coefficients for $(1-R2)\cdot Q$ and $PIN \cdot Q$ remain positive and statistically significant. Thus, the positive correlations between $(1-R2)$ and PIN and investment-to-price sensitivity are robust to the inclusion of the effects of diversification, analyst coverage, or institutional holdings.

As for the effect of the control variables on the investment-to-price sensitivity: Column 1 shows that investments in more diversified firms are less responsive to stock prices. This result is intuitive since 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.

Column 2 shows that analyst coverage negatively affects investment-to-price sensitivity. This result seems puzzling at first. However, further research reveals that it is highly consistent with existing findings in the literature, and with the overall economic story behind our analysis. Below, we review the findings in the literature that are consistent with this finding, and then relate it to the economic story in our paper. This discussion is very important for understanding the main effects in the paper.

In the literature on the PIN measure, Easley, O'Hara, and Paperman (1998) find that the probability of information-based trade is lower for stocks with more analysts. While they show that stocks with more analysts do have more informed trade, they demonstrate that these stocks tend to attract even greater rates of uninformed trades, which lead to a lower probability of informed trade. Their result is consistent with the analysis of Brennan and Subrahmanyam (1995), who identify a negative correlation between bid-ask spreads and analyst coverage. This finding suggests that while analysts' clients may be trading on information, analyst coverage attracts even more uninformed trading on a stock, and it is this greater depth that reduces the overall risk of information-based trading. Another result that is consistent with this conclusion is provided by Vega (2004), who shows that the drift is higher for firms covered by a larger number of analysts. This is also consistent with Merton (1987)'s analysis in which traders transact only in stocks with which they are familiar, and it supports the view that analysts serve to increase trading volume by showcasing stocks to uninformed traders.

Easley, O'Hara, and Paperman (1998) go on to show that financial analysts do not appear to create new private information: the probability of private information events is the same across stocks with many and few analysts, as are the probabilities of good and bad information events. This is consistent with Womack (1996) finding that only 24 of 694 added-to-buy-list recommendations discussed facts deemed private or new. Their results thus confirm the view that analysts' recommendations are generally based on public, rather than private, information.

In the literature that builds on price non-synchronicity, Piotroski and Roulstone (2004) provide results on analysts that are also consistent with the above view. They find that price-non-synchronicity is negatively associated with analyst activity, consistent with the idea that analysts focus their efforts on obtaining and mapping industry and market-level information into prices, rather than obtaining firm-specific information. They note that their results are consistent with evidence suggesting that industry-level preferences exist among analysts. For example, Ramnath (2002) shows that analysts revise their earning forecasts in response to the earning announcements of other firms in the same industry.

Overall, the above evidence seems to suggest that analysts do not create new private information; that they do not focus much on firm-specific information; and even more important, that, while they do attract some informed traders, they attract even more noise traders, such that they reduce the informativeness of the price. As a result, it is not surprising that analyst coverage is negatively correlated with the investment-to-price sensitivity.

Since analysts increase a firm's visibility, the discussion on analyst coverage is also related to the effect that firms' visibility has on stocks' liquidity and informativeness. Grullon, Kanatas, and Weston (2004) show that firms that are more visible (where visibility is measured by advertising costs) attract many noise traders that ultimately reduce the bid-ask spreads of their stocks as well as their price-to-order-flow sensitivity. Vega (2004) shows that stocks with high media coverage tend to exhibit a greater post-earnings-announcement drift, suggesting that the prices of those stocks are less informative. Again, these results are consistent with ours. Indeed, in our sample, the most visible firms tend to have a low level of informativeness and a low sensitivity of investment to price.

Finally, Column 3 shows that institutional holdings have a negative effect on investment-to-price sensitivity. Since institutional holdings are highly correlated with size and with analyst coverage, this result is expected given the results we have discussed thus far.

6.4 Robustness of price non-synchronicity

Price non-synchronicity is a measure that looks at firm-specific return variation. Thus, when we use it as a measure of informativeness, we concentrate on firm-specific information, instead of industry- or market-related information. In principle, however, one could imagine that managers may learn from those other types of information as well.

Overall, we believe it is more reasonable that firm-specific return variation captures the part of information managers would want to learn from. This is because of the following reasons. First, as we described above, phenomena like contagion, style investing, and investors sentiment, which do not reflect information about fundamentals, are likely to be captured by the industry-related variation, and by the market-related variation. Second, information about the industry and the market is more likely to be public information, and thus there is no need for managers to learn it from the price. Third, in those cases where an industry- or market-related event has unusual implications for a particular firm, this will be captured by the firm-specific return variation. Finally, the extensive literature (reviewed earlier) on price non-synchronicity suggests that this measure is a good proxy for informativeness.

However, despite these reasons, we acknowledge that there is a possibility that managers will learn from industry- or market-related information. We believe that whether this happens is, after all, an empirical question. We thus address it empirically. To check the effect of industry-related information (which seems more relevant to managers than market-related information), we conduct a robustness test, where our measure of informativeness includes both industry-related return variation and firm-specific return variation (i.e., it is the $1 - R^2$ from the regression of a firm return on the market return). The results (not reported) show that adding industry-related return variation reduces the explanatory power of our informativeness measure. This is an empirical indication that industry-related information is not important in driving investment-to-price sensitivity. As for the effect of market-related information on investment-to-price sensitivity: such an effect would require a significant negative coefficient for $(1 - R^2) * Q$ in our regressions. Since this is never obtained, it seems that market-related return variation also does not play a role in determining investment-to-price sensitivity.

Another issue we check is whether the residual standard deviation (i.e., the standard deviation of the residuals from the firms' daily return regression on market and industry returns) can serve as a better measure of informativeness than the normalized R-squared currently used in the paper. The results (not reported) indicate that this alternative variable has a weaker effect than the measure used in the paper both in economic and in statistical significance. This indicates that the measure used in the paper is overall a better measure for informativeness. It could be due to the fact that return standard deviation also captures the risk in a firm's business while the R-squared measure is normalized by the total variation.

Finally, 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 baseline results established in Table 2.

6.5 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 the same 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.

7 Conclusion

This paper studies the empirical relation between price informativeness and the sensitivity of investment to stock price. Using two different measures of informativeness - price non-synchronicity and probability of informed trading (PIN) - we find strong positive correlation between price informativeness and the investment-to-price sensitivity. Since, based on previous literature, both measures seem to capture private information incorporated into the price by traders, our results suggest that price informativeness plays more than just a passive role. That is, in some cases, prices reflect information that is not known to managers, and provide guidance for managers' investment decisions. This conclusion is strengthened after we control for managerial information and find the same effect of price informativeness on investment-to-price sensitivity. Our paper considers many other robustness issues and shows that the main result remains intact.

The possibility that prices guide managers in their investment decisions is intriguing as it means that financial markets affect the real economy. This observation has important implications. On the one hand, as Subrahmanyam and Titman (1999) argue, financial markets may enhance investment efficiency since they provide valuable information to managers. On the other hand, as Goldstein and Guembel (2003) show, 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.

References

Alti, Aydogan, 2003, How sensitive is investment to cash flow when financing is frictionless, *Journal of Finance* 58, 707–722.

Baker, Malcolm, Jeremy Stein, and Jeffrey Wurgler, 2003, When does the market matter? stock prices and the investment of equity-dependent firms, *Quarterly Journal of Economics* 118, 969–1006.

Baker, Malcolm, and Jeffrey Wurgler, 2002, Market timing and capital structure, *Journal of Finance* 57, 1–32.

Barberis, Nicholas, and Andrei Shleifer, 2003, Style investing, *Journal of Financial Economics* 68, 161–199.

———, and Jeffrey Wurgler, 2005, Comovement, *Journal of Financial Economics* 75, 283–317.

Barro, Robert, 1990, The stock market and investment, *Review of Financial Studies* 3, 115–131.

Blanchard, Olivier, Changyong Rhee, and Lawrence Summers, 1993, The stock market, profit, and investment, *Quarterly Journal of Economics* 108, 115–136.

Brennan, M., and A. Subrahmanyam, 1995, Investment analysis and price formation in securities markets, *Journal of Financial Economics* 38, 361–381.

Bris, Arturo, William N. Goetzmann, and Ning Zhu, 2004, Efficiency and the bear: Short sales and markets around the world, Working Paper, Yale School of Management.

Damodoran, A., and C. H. Liu, 1993, Insider trading as a signal of private information, *Review of Financial Studies* 6, 79–119.

DeFond, M., and M. Hung, 2004, Investor protection and corporate governance: Evidence from worldwide ceo turnover, *Journal of Accounting Research* 42, 269–312.

Dow, James, and Gary Gorton, 1997, Stock market efficiency and economic efficiency: Is there a connection?, *Journal of Finance* 52, 1087–1129.

Durnev, Art, Randall Morck, and Bernard Yeung, 2004, Value enhancing capital budgeting and firm-specific stock return variation, *Journal of Finance* 59, 65–105.

——— , and Paul Zarowin, 2003, Does greater firm-specific return variation mean more or less informed stock pricing, *Journal of Accounting Research* 41, 797–836.

Easley, David, Soeren Hvidkjaer, and Maureen O'Hara, 2002, Is information risk a determinant of asset returns?, *Journal of Finance* 57, 2185–2221.

Easley, David, Nicholas Kiefer, and Maureen O'Hara, 1996, Cream-skimming or profit-sharing? the curious role of purchased order flow, *Journal of Finance* 51, 811–833.

——— , 1997a, The information content of the trading process, *Journal of Empirical Finance* 4, 159–186.

——— , 1997b, One day in the life of a very common stock, *Review of Financial Studies* 10, 805–835.

——— , and Joseph Paperman, 1996, Liquidity, information, and less-frequently traded stocks, *Journal of Finance* 51, 1405–1436.

Easley, David, and Maureen O'Hara, 2004, Information and the cost of capital, *Journal of Finance* 59, 1553 – 1583.

——— , and Joseph Paperman, 1998, Financial analysts and information-based trade, *Journal of Financial Markets* 1, 175–201.

Easley, David, Maureen O'Hara, and P. S. Srinivas, 1998, Option volume and stock prices: evidence on where informed traders trade, *Journal of Finance* 53, 431–465.

Fama, Eugene F., and Kenneth R. French, 1992, The cross section of expected stock returns, *Journal of Finance* 47, 427–465.

Fazzari, Steven, R. Glenn Hubbard, and Bruce C. Petersen, 1988, Finance constraints and corporate investment, *Brookings Papers on Economic Activity* pp. 141–195.

Giammarino, Ronald, Robert Heinkel, Burton Hollifield, and Kai Li, 2004, Corporate decisions, information and prices: Do manages move prices or do prices move managers?, *Economic Notes by Banca Monte dei Paschi di Siena SpA* pp. 1–28.

Gilchrist, Simon, Charles Himmelberg, and Gur Huberman, 2004, Do stock price bubbles influence corporate investment?, *Journal of Monetary Economics* forthcoming.

Goldstein, Itay, and Alexander Guembel, 2003, Manipulation, the allocational role of prices and production externalities, Working Paper, University of Pennsylvania and Oxford University.

Gomes, A., G. Gorton, and L. Madureira, 2004, Sec regulation fair disclosure, information, and the cost of capital, Working Paper, University of Pennsylvania Wharton School.

Gomes, A., and G. Phillips, 2004, Why do public firms issue public and private equity, debt, and convertibles?, Working Paper, University of Pennsylvania Wharton School.

Grullon, Gustavo, George Kanatas, and James Weston, 2004, Advertising, breadth of ownership, and liquidity, *Review of Financial Studies* 17, 439–461.

Hardin, James, and Joseph Hilbe, 2001, *Generalized Linear Models and Extensions* (Stata Press: Texas).

Healy, Paul M., Krishna G. Palepu, and Richard S. Ruback, 1992, Does corporate performance improve after mergers?, *Journal of Financial Economics* 31, 135–175.

Kaplan, Steven, and Luigi Zingales, 1997, Do investment-cash flow sensitivities provide useful measures of financing constraints, *Quarterly Journal of Economics* 112, 169–215.

Ke, B., S. Huddart, and K. Petroni, 2002, What insiders know about future earnings and how they use it: Evidence from insider trades, *Journal of Accounting and Economics* 35, 315–346.

Kodres, Laura, and Matthew Pritsker, 2002, A rational expectations model of financial contagion, *Journal of Finance* 57, 769–799.

Kyle, Albert, and Wei Xiong, 2001, Contagion as a wealth effect, *Journal of Finance* 56, 1401–1439.

Lee, Charles, and Mark Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733–746.

Liu, Qiao, and Rong Qi, 2002, Information production, cash flow and corporate investment, Working Paper, University of Hong Kong and Columbia Business School.

Loughran, Tim, and Jay Ritter, 1995, The new issues puzzle, *Journal of Finance* 50, 23–51.

Luo, Yuanzhi, 2004, Do insiders learn from outsiders? evidence from mergers and acquisitions, Journal of Finance forthcoming.

Merton, Robert, 1987, A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42, 483–510.

Meulbroek, Lisa K., 1992, An empirical analysis of illegal insider trading, *Journal of Finance* 47, 1661–1699.

Morck, Randall, Andrei Shleifer, and Robert Vishny, 1990, The stock market and investment: is the market a side-show?, *Brookings Papers on Economic Activity* 2, 157–215.

Morck, Randall, Bernard Yeung, and Wayne Yu, 2000, The information content of stock markets: why do emerging markets have synchronous stock price movements?, *Journal of Financial Economics* 59, 215–260.

Piotroski, Joseph, and Darren Roulstone, 2004, The influence of analysts, institutional investors and insiders on the incorporation of market, industry and firm-specific information into stock prices, *The Accounting Review* 79, 1119–1152.

———, 2005, Do insider trades reflect both contrarian beliefs and superior knowledge about future cash-flow realizations?, *Journal of Accounting and Economics* 39 forthcoming.

Ramnath, S., 2002, Investor and analyst reactions to earnings announcements of related firms: An empirical analysis, *Journal of Accounting Research* 40, 1351–1376.

Roll, Richard, 1988, R2, *Journal of Finance* 43, 541–566.

Seyhun, H. Nejat, 1992, Why does aggregate insider trading predict future stock returns?, *Quarterly Journal of Economics* 107, 1303–1331.

——— , 1998, *Investment Intelligence From Insider Trading* (MIT Press: Cambridge).

Stein, Jeremy, 2003, Agency, information and corporate investment, in George Constantinides, Milton Harris, and Rene Stultz, ed.: *Handbook of the Economics of Finance* (Elsecier Science: USA).

Subrahmanyam, A., and S. Titman, 1999, The going-public decision and the development of financial markets, *Journal of Finance* 54, 1045–1082.

Sunder, Jayanthi, 2001, Information spillovers and capital structure: Theory and evidence, Working paper, Northwestern University.

Vega, Clara, 2004, Are investors overconfident?, Working paper, University of Rochester.

Veldkamp, Laura, 2004, Information markets and the comovement of asset prices, Working paper, New York University.

Womack, K. L., 1996, Do brokerage analysts recommendations have investment value?, *Journal of Finance* 51, 137–167.

Wurgler, Jeffrey, 2000, Financial markets and the allocation of capital, *Journal of Financial Economics* 58, 187–214.

Table 1: Variable Definitions and Summary Statistics

Panel A: Definitions

Variable	Definition
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 assts
1-R2	One minus R-squared 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	Raw unadjusted firm return for next 3 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 (%)

Panel B: Summary statistics

	#OBS	MEAN	STDEV	5%	25%	50%	75%	95%
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

Table 2: Relation between Investment-Price Sensitivity and Firm-specific Return Variations

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.

Dependent variable	*CAPXRND*		*CAPX*		*CHGASSET*	
	1	2	3	4	5	6
Q	**3.52***	**2.89***	**2.20***	**1.76***	**20.26***	**16.49***
	0.08	0.09	0.06	0.06	0.53	0.60
(1-R2)*Q	**3.13***	**3.84***	**1.42***	**1.95***	**14.79***	**17.53***
	0.28	0.31	0.20	0.22	1.72	1.94
CF	**--**	**20.17***	**--**	**12.68***	**--**	**128.70***
	--	0.82	--	0.51	--	5.09
(1-R2)*CF	**--**	**-24.94***	**--**	**-18.09***	**--**	**-82.80***
	--	3.29	--	2.49	--	21.56
RET	**--**	**-0.48***	**--**	**-0.62***	**--**	**-1.94***
	--	0.06	--	0.04	--	0.33
INV_AST	**--**	**0.00**	**--**	**0.00**	**--**	**-0.78***
	--	0.01	--	0.01	--	0.04
1-R2	**-7.20***	**-3.58***	**-5.62***	**-2.86***	**-23.09***	**-4.54**
	0.56	0.55	0.46	0.45	3.23	3.32
adj. R-sqr	0.54	0.56	0.44	0.46	0.20	0.28
within R-sqr	0.10	0.15	0.07	0.11	0.12	0.20

*, **, and *** indicate a two-tailed test significance level of less than 1%, 5%, and 10%, respectively.

Table 3: Relation between Investment-Price Sensitivity and the Probability of Informed Trading

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 19,208.

Dependent variable	*CAPXRND*		*CAPX*		*CHGASSET*	
	1	2	3	4	5	6
Q	**2.18***	**1.95***	**1.37***	**1.08***	**15.47***	**10.56***
	0.10	0.12	0.06	0.06	0.69	0.71
(1-R2)*Q	--	**1.80***	--	**0.45*****	--	**2.70**
	--	0.42	--	0.25	--	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	--	**2.78***	--	**1.02**	--	**37.22***
	--	1.04	--	0.77	--	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
adj. R-sqr	0.54	0.57	0.44	0.46	0.00	0.17
within R-sqr	0.08	0.14	0.06	0.10	0.13	0.28

*, **, and *** indicate a two-tailed test significance level of less than 1%, 5%, and 10%, respectively.

Table 4: Controlling for Managers' Information Using Insider Trading and Stock Response to Earnings Announcement

Definitions of all variables are listed in Table 1 Panel A. The dependent variable is *CAPXRND*. For the variable *MANAGER*, Columns 1 and 2 use *INSIDER*, the percentage of insider transactions to total number of transactions. Columns 4 and 5 use *ERC*, the average of the absolute abnormal stock returns around the four quarterly earnings announcement dates in the previous year to proxy for managers' information. The abnormal stock return is the market-model adjusted cumulative abnormal return from one day before to one day after each earnings announcement date. In Column 3, the *PIN* measure is adjusted to exclude insider trading from informed trading. 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.

	1	2	3	4	5
MANAGER	*INSIDER*	*INSIDER*	*PIN**	*ERC*	*ERC*
Q	**1.77***	**1.98***	**1.97***	**1.82***	**2.04***
	0.11	0.12	0.12	0.11	0.12
MANAGER*Q	**-6.91**	**-6.57**	--	**-2.20****	**-2.53****
	6.18	6.73	--	1.04	1.02
(1-R2)*Q	--	**1.84***	**1.84***	--	**1.79***
	--	0.42	0.42	--	0.41
PIN*Q	--	**3.16***	**3.22***	--	**3.30***
	--	1.08	1.06	--	1.13
No. obs.	19130	19130	19130	18722	18722
adj. R-sqr	0.57	0.58	0.58	0.57	0.58
within R-sqr	0.13	0.14	0.14	0.14	0.15

*, **, and *** indicate a two-tailed test significance level of less than 1%, 5%, and 10%, respectively.

Table 5: Effects of Financial Constraints and Size

Definitions of all variables are listed in Table 1 Panel A. All observations are sorted into five sub-samples 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 quintiles. We estimate the five quintile equations simultaneously with both the year and the 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.

Panel A: Quintiles formed by KZ

KZ4 Quintiles	Q1	Q2	Q3	Q4	Q5
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
nobs	3391	4324	4146	3968	3358
adj R-sqr	0.28	0.28	0.23	0.18	0.15
within R-sqr	0.13	0.07	0.08	0.08	0.06

Panel B: Quintiles formed by Market Size

SIZE Quintiles	Q1	Q2	Q3	Q4	Q5
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
nobs	2989	3557	3863	4056	4743
adj R-sqr	0.49	0.67	0.66	0.69	0.71
within R-sqr	0.07	0.16	0.20	0.19	0.29

*, **, and *** indicate a two-tailed test significance level of less than 1%, 5%, and 10%, respectively.

Table 6: Regression of Future Performance on Investment-Price Sensitivity Scores

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. 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 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.

	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
Nob	46304	11315	46393	11351	46409	11354
adj. R-sqr	0.68	0.78	0.34	0.29	0.86	0.91
within R-sqr	0.03	0.03	0.02	0.03	0.04	0.15

*, **, and *** indicate a two-tailed test significance level of less than 1%, 5%, and 10%, respectively.

Table 7: Sensitivity to Alternative Specification:
The Portfolio Approach

Definitions of all variables are listed in Table 1 Panel A. Each firm-year observation is sorted 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. 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.

Panel A: Quintiles formed by 1-R2

	Q1	Q2	Q3	Q4	Q5
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
Nob	9602	9610	9613	9610	9598
adj R-sqr	0.28	0.24	0.21	0.20	0.20

Panel B: Quintiles formed by PIN

	Q1	Q2	Q3	Q4	Q5
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
nob	3581	3310	3160	2951	2721
adj R-sqr	0.30	0.28	0.22	0.23	0.26

*, **, and *** indicate a two-tailed test significance level of less than 1%, 5%, and 10%, respectively.

Table 8: Sensitivity to Cross-sectional Correlations:
The Fama-MacBeth Approach

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 to 3 and 19,208 in Columns 4-6.

	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

*, **, and *** indicate a two-tailed test significance level of less than 1%, 5%, and 10%, respectively.

Table 9: Sensitivity to Other Variables Affecting Investment-Price Sensitivity

Definitions of all variables are listed in Table 1 Panel A. The dependent variable is *CAPXRND*. The dependent variables are those in Table 3 plus the additional *CONTROL* variable: *HERFINDAHL* in Column 1, *ANALYST* (the logarithm of number of analysts following the firm in year t-1) in Column 2, and *INSTITUTION* (measured as the average percentage of shares held by institutional investors in year t-1) in Column 3. 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.

	1	2	3
CONTROL	*HERFINDAHL*	*ANALYST*	*INSTITUTION*
Q	**2.06***	**1.98***	**2.02***
	0.14	0.12	0.13
(1-R2)*Q	**2.15***	**0.87***	**1.14***
	0.47	0.33	0.36
PIN*Q	**3.41***	**1.40****	**1.49****
	1.23	0.70	0.76
CONTROL*Q	**0.57*****	**-0.57***	**-2.72***
	0.30	0.08	0.37
nob	15213	19208	15635
adj R-sqr	0.51	0.58	0.60
within R-sqr	0.15	0.15	0.17

*, **, and *** indicate a two-tailed test significance level of less than 1%, 5%, and 10%, respectively.

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