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Which Firms Follow the Market?
An Analysis of Corporate Investment Decisions

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September 19, 2006

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We would like to thank Morris Davis, Alexander Ljungqvist, Antonio Mello, Stavros Panageas, Paul Povel, Michael Roberts, Missaka Warusawitharana, and seminar participants at the University of Wisconsin and the Minnesota-Wisconsin Corporate Finance Conference for helpful suggestions.

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Abstract

This paper examines whether firms extract information from their own stock price when making investment decisions. To answer this question, we use an econometric errors-in-variables remedy, which is appropriate because movements in the stock price in which the manager takes little interest can be treated econometrically as measurement error. We find that firm investment does not respond to measures of stock-market mispricing. We also find that only some firms respond to market signals when investing: those whose stock prices are not mispriced and those that rely on outside equity financing. Interestingly, these firms' behavior changed only little during the late 1990's.

Does the stock market affect corporate investment? Put differently, does a firm manager make real investment decisions based solely on fundamentals—the intrinsic present value of cash flows attributable to these investments? On the other hand, does he in part base investment decisions on external signals sent by the stock market? In a world of symmetric information, efficient capital markets, and no regulatory distortions, this question is uninteresting, because movements in asset prices reflect changes in underlying economic fundamentals, and the fundamental value of investment *is* the market value. However, the question has been of interest at least since Keynes' (1936) idea that "animal spirits" influence the real economy, precisely because many accept the notion that capital markets are not entirely efficient; that is, that non-fundamental factors do affect a firm's stock price. The question is also relevant for monetary policy, because a link between the stock market and real economic activity opens the door for policy makers to target the stock market.

No single answer to the question has emerged. History has provided clear associations between the stock-market and investment, such as during the late 1990's in the U.S. technology sector. However, history has also provided episodes in which investment has moved independently of the stock market, such as the 1987 stock market crash, which had no effect on real investment. Similarly, the numerous papers that tackle this question find conflicting evidence, some, such as Baker, Stein, and Wurgler (2003), finding a role for the stock market and others, such as Chirinko and Schaller (1996), finding no role. Given this background of scattered anecdotal and formal evidence, this paper takes a step back, identifies the difficulties to overcome in ascertaining whether the stock market influences investment, and then develops and applies a methodology that can tackle these difficulties.

Developing a convincing empirical approach requires an elaboration of the basic question. On one hand, Morck, Shleifer and Vishny (1990) argue that managers are better informed about the investment opportunities of the firm than outside investors. Because investors may have smaller information sets than managers, no new knowledge is gained by observing market signals, and therefore stock market movements can be safely ignored. In addition, managers may be reluctant to issue equity to exploit overvaluation of the company's shares.

This reluctance stems from the role of equity issuance as a signal that, in the spirit of Myers and Majluf (1984), can deflate equity values.

Two alternatives exist to this point of view. First, in Dow and Gorton (1997) and Subrahmanyam and Titman (1999) managers can improve their investment decisions by observing stock-price movements, because the stock price contains information that is aggregated from investors who do not communicate directly with the firm.[1] Second, investment may respond to irrational stock-price fluctuations. For example, in the model in Panageas (2005a) investors have heterogeneous beliefs and short sales are restricted. He shows that mispricing is embedded in marginal q and that it is optimal for firms to respond to this mispricing. In a slightly different vein, Bosworth (1975) and Merton and Fisher (1984) argue that if a company's stock is overvalued, the manager can benefit existing shareholders by issuing equity. What the manager does with the proceeds is an open question. On one hand, the manager might view his firm's equity as over-valued, but nevertheless fail to perceive a change in the cost of capital. In this case, the manager can use the proceeds to increase the firm's cash stock or pay dividends. However, if the manager perceives equity overvaluation as lowering the cost of capital, it may be optimal for the firm to invest the proceeds of the issue. It is this equity-financing channel in which we are interested.

This discussion of whether and how the stock market affects investment reveals three obstacles to overcome in understanding the issue. The first problem arises because stock prices can reflect fundamental investment opportunities. It is therefore important to separate stock-price movements that reflect these fundamentals from those that do not. The second problem is ascertaining whether any such deviations affect managers' investment decisions, and the third is determining how managers use nonfundamental information in the stock price. These three problems are difficult to solve because they are couched in terms of unobservable quantities, such as fundamentals and information. Although a few studies, such as Chirinko and Schaller (1996, 2001), have addressed the first two problems, to our knowledge none has addressed all three.

[1] In a similar vein, Chang and Yu (2004) show theoretically that it can be optimal for firms to incorporate stock-price information in their capital structure decisions.

The methodology we develop does, and our empirical approach makes a difference for understanding the economic mechanisms that influence the feedback of the stock market to investment. We use our technique to identify characteristics of firms that use external information in stock prices, as well as those that exploit stock-market mispricing. Briefly, we find that only some firms glean information from stock prices when making investment decisions: those that depend on equity finance and those with little stock-market mispricing. We do not, however, find that firms exploit over-valuation to obtain cheap equity financing for projects. This evidence holds up even during the bubble of the late 1990's.

Our method for separating the effects on investment of the stock market from those of fundamentals uses a model in which investment is determined primarily, though not solely, by Tobin's q: the market value of the capital stock divided by its replacement value. Because variation in Tobin's q (hereafter referred to simply as q) stems primarily from variation in equity, if a manager making an investment decision pays attention to stock-price movements unrelated to fundamentals, an econometric signal-extraction procedure on q should produce little noise and a great deal of signal. In other words, the manager interprets stock-price movements unrelated to fundamentals as an informative signal. Conversely, suppose the manager disregards the stock market and only follows cues from his own valuation of investment projects, perhaps because he believes that the market has inferior information. In this case a signal extraction exercise should uncover a great deal of noise in q because the manager treats stock-price movements unrelated to fundamentals as noise.

To isolate the effect of non-fundamental information on q, we turn to the errors-in-variables remedy in Erickson and Whited (2000, 2002). Although stock-market noise is not literally measurement error, it can be modeled econometrically as such. We pick this technique for three reasons. First, as explained in Erickson and Whited (2000), other, more traditional remedies require implausible assumptions. Second, Erickson and Whited (2000) demonstrate that this technique has good finite-sample properties in the case of cross-sectional investment regressions. Most importantly, the technique provides an estimate of the ratio of signal to the sum of signal and noise for q, a quantity we refer to hereafter as τ^2.

Figure 1 fleshes out the intuition behind how we use τ^2 to examine whether the market matters for investment. The distance between points a and d represents the variance of an observed measure of Tobin's q. This variance can be decomposed in a variety of ways: The distance between points a and b represents the component that is due to fundamental investment opportunities, the distance between points b and d represents the component that is not due to fundamentals, and the distance between points b and c represents the portion of the non-fundamental component to which the manager reacts. It is this last "managerial-attention" component in which we are interested. An estimate of τ^2 measures the ratio of the distance between points a and c to the distance between points a and d; that is, the fundamental component plus the part of the nonfundamental component to which the manager responds, all expressed as a fraction of the total variance of observed Tobin's q.

To examine the size of the managerial-attention component of q, we filter out of observed q variation in proxies for the amount of information embedded in the stock price and for mispricing, as either factor can induce variation in the stock price unrelated to fundamentals. If the managerial-attention component of q is small, filtering removes variation in observable q of little interest to the manager, thereby raising the estimate of τ^2 over an estimate obtained with an unfiltered version of q. In Figure 1, filtering removes all or part of the distance from points c to d, which raises τ^2. Conversely, if the managerial-attention component of q is large, then filtering removes relevant variation from q, and the estimate of τ^2 falls. Figure 1 illustrates this case as removal of all or part of the distance between points b and c, which lowers τ^2. Our tests compare the estimates of τ^2 from filtered and unfiltered versions of q, and we structure the tests so that noise in the proxies does not affect test consistency.

To put this method in perspective, we examine the rest of the literature, which can be divided into two strands: one that does not attempt to distinguish fundamental movements in the stock price from nonfundamental movements, and one that does. The first strand is dominated by papers that examine the sensitivity of investment to observed q. Panageas (2005b) shows that investment closely followed q during a natural experiment with short-sales constraints during the 1920's. Baker, Stein, and Wurgler (2003) find a high sensitivity of investment to q for equity-dependent firms, interpreting this finding as evidence that stock market mispricing leads these firms to issue equity and to use the proceeds for investment. Chen, Goldstein, and Jiang (2006) examine the connection between the sensitivity of investment to q and measures of external information embedded in the stock price. They find a positive relation, interpreting it as evidence that managers glean information from stock prices when they make investment decisions. Using a slightly different approach, Luo (2005) finds that merger announcement returns predict deal completions, interpreting this result as evidence that merging firms extract information from stock prices. Other papers in this strand include Gilchrist, Himmelberg, and Huberman (2005) and Polk and Sapienza (2006), both of which include proxies for mispricing in an investment-q regression.

The second strand is dominated by papers that employ proxies for fundamental investment opportunities. Along this line, Morck, Shleifer and Vishny (1990) find that although returns can predict investment, this predictive power disappears once they control for fundamentals. Also, consistent with the irrelevance of stock markets for investment, Blanchard, Rhee, and Summers (1993) find evidence that although the stock market does not change investment, it can change the composition of external finance. In contrast, Chirinko and Schaller (2005) do find an independent role for the stock market conditional on their proxy for fundamentals. Chirinko and Schaller (1996, 2001) take a slightly different approach by comparing the empirical performance of an investment-q regression to that of an investment Euler equation, explaining that failure of both approaches indicates an independent role for the stock market. They find such a role in Japanese data, but not in U.S. data.

Our results stand out from those in all of these papers. In essence, they are not as "black and white." Instead of finding no support for an effect of the stock market on investment, we do find some. Instead of finding broad-based support for the idea that market-mispricing or information in the stock price affects investment, we find no role for the former and only a limited role for the latter—for firms whose equity is correctly valued and who depend on external equity to finance projects. Our results also stand out in that we examine the late 1990's separately, finding almost no differences in our basic conclusions. Because our results are different, we examine why. We find that they stem from more accurate identification of firms that depend on equity, from the use of a better measure of q, and most importantly, from our methodology, which we demonstrate is more informative than those used in previous attempts to understand whether firms follow market signals.

The rest of the paper is organized as follows. Section 1 reviews the Erickson and Whited estimators, discusses their use in the current context, and explains the value added from our econometric approach. Section 2 summarizes the data, Section 3 presents the results and compares them to those in the literature, and Section 4 concludes. The Appendix describes the estimators and presents a Monte Carlo experiment designed to evaluate their performance.

1. Methodology

This section describes our methodology. First, we outline our econometric model. Second we discuss its applicability. Finally, we explain our testing procedure and its advantages over previously used approaches.

1.1. Econometric Model

Our testing strategy is based on the estimators in Erickson and Whited (2000, 2002). These estimators employ the structure of the classical errors-in-variables model. Applied to a single cross section, this model can be written as

$$y_i = z_i\alpha + q_i\beta + u_i, \tag{1}$$

$$x_i = \gamma + q_i + \varepsilon_i, \tag{2}$$

in which q_i is the true q of firm i, x_i is an estimate of its true q, and z_i is a row vector of perfectly measured regressors, whose first entry is 1. The regression error, u_i, and the measurement error, ε_i, are assumed independent of each other and of (z_i, q_i), and the observations within a cross section are assumed $i.i.d.$ Note that the intercept in (2) allows for bias in the measurement of true q. Using the third and higher order moments of (x_i, y_i), the Erickson and Whited estimators provide consistent estimates of the slope coefficients, α and β, as well as the variances of the unobservable variables $(q_i, u_i, \varepsilon_i)$. These estimators are only identified if $\beta \neq 0$ and q_i is nonnormally distributed. Erickson and Whited (2002) develop a test of the null hypothesis that $\beta = 0$ and q_i is nonnormally distributed—a test we refer to hereafter as an "identification test." See the Appendix and Erickson and Whited (2000, 2002) for details concerning estimation and testing.

Because these estimators can only be applied to samples that are arguably *i.i.d.*, we obtain these estimates in two steps. First, we estimate τ^2 for each cross section of our unbalanced panel. Second, we pool these estimates via the procedure in Fama and MacBeth (1973). We do not include firm fixed effects in our regressions for two reasons. First, the resulting model almost never passes the identification test. Second, our OLS results are little changed by the inclusion of fixed effects, suggesting that the within-firm variation in investment and q mirrors the cross sectional variation.[2] This result makes sense inasmuch as investment is a flow variable and therefore has already been first-differenced to remove any potential fixed effects.

Recently, Petersen (2005) has re-emphasized that Fama-Macbeth standard errors are often inappropriate in panel data. We deal with this issue by using the bootstrap in Hall and Horowitz (1996) to calculate the finite sample distribution of the t-statistics produced with these standard errors. The unit of observation for resampling is the firm. Interestingly, we find that many of these finite-sample critical values are close to their asymptotic critical values, though in several instances we do find critical values for a nominal 5% two-sized t-test as high as 6, especially in the case of the GMM estimates of the coefficient on q.

1.2. Applicability of the Model

The interpretation of ε_i is important and worth further discussion, because if factors other than market noise or the manager's interpretation of market noise influence ε_i, our results

[2] Because there may nonetheless be some cross-sectional dependence among the firms in the same industry, we also try to include two-digit industry fixed effects. The results are quite similar, though we find a higher incidence of unidentified models and consequently higher standard errors.

might be due to these other factors, rather than the divergence of fundamentals from market signals. To organize our discussion, we start with a precise definition of "fundamentals" as marginal q—the intrinsic value of the future marginal product of capital. Classical q-theory predicts that investment should be a function of marginal q alone. Although marginal q is inherently unobservable, a series of links relates it to an observable proxy.

The first is the relation between marginal q and average q, which is the intrinsic value of the capital stock divided by its replacement value. If the firm is perfectly competitive and has linearly homogeneous technology, then marginal q equals average q. Clearly, if these assumptions are violated, then it is difficult to interpret ε_i as the difference between fundamental and market value. However, several recent papers have shown theoretically and empirically that when marginal q does not equal average q, investment is a function of average q plus other variables. For example, Abel and Eberly (2001) and Cooper and Ejarque (2003) show that the presence of market power implies that investment is a function of average q and cash flow. Similarly, Hennessy (2004) shows that when a firm has outstanding debt, investment is a function of average q and a debt-overhang correction. Therefore, to deal with the difficulty in interpreting ε_i that arises from the inequality of marginal and average q, we include cash flow and Hennessy's debt-overhang correction in our regressions. We also do not interpret the coefficient on cash flow as an indicator of external finance constraints because of the well-known ambiguities in the meaning of this coefficient. See Erickson and Whited (2000), Gomes (2001), and Moyen (2004).

At this point we can define average q as fundamental investment opportunities, as long as we include other appropriate regressors. This definition is bolstered by recent papers that have questioned the plausibility of convex capital-adjustment costs, one of the assumptions which yield marginal q as a sufficient statistic for investment incentives. Caballero and Leahy (1996) and Caballero (1999) show that if there is a fixed cost of changing the capital stock, then one can obtain a scalar measure of investment incentives; interestingly, the scalar measure so produced is average q. Also, Gomes (2001) develops a general equilibrium model with financial frictions in which average q is the more appropriate explanatory variable.

The next link between fundamental investment opportunities and an observable proxy is the equality between average q and Tobin's q, which is the financial markets' valuation of average q. A discrepancy between these two quantities can arise if stock market inefficiencies cause the manager's valuation of capital to differ from the market valuation. This is the interpretation on which we will focus.

However, many problems arise in estimating Tobin's q from accounting data that do not adequately capture the relevant economic concepts of market and replacement values. These problems admit a further interpretation of ε_i as literal measurement error. Nonetheless, we view this interpretation as unimportant, in light of the evidence in Erickson and Whited (2006) that none of the available algorithms for estimating Tobin's q improve measurement quality beyond the estimates produced directly from accounting data. This result arises because the cross-sectional variation in the estimated components of Tobin's q dwarfs any variation arising from imprecise measurement. Thus, although literal measurement difficulties may exist, they are unlikely to be sufficiently important to alter our basic inferences.

Complicating the interpretation of our results is the existence of two different ways to calculate q. The first is the market-to-book ratio, which is the market value of assets divided by their book value, and the second is what we call macro q: the sum of the market values of debt and equity less the value of current assets, all divided by the value of the capital stock.

Two separate issues arise with using the market-to-book ratio or macro q. First, the market-to-book ratio is the correct explanatory variable for investment only if the firm's only asset is the capital stock. Second, the numerator of macro q only approximates the market value of the capital stock. The market values of debt and equity equal the market value of the firm. If current assets and capital are the firm's only assets, the market value of the capital stock is correctly obtained by subtracting current assets from the value of the firm. However, if the firm holds nonphysical assets such as human capital, intangibles, and goodwill, this measure of the market value of the capital stock is biased upward. We deal with this issue below. Macro q is our primary proxy for true investment opportunities because the estimates of τ^2 corresponding to the market-to-book ratio are tiny.

In sum, although a series of links joins an observable measure of q to the concept of fundamental investment opportunities, we have argued that the link most likely to be broken is that between the stock market valuation of the firm and its intrinsic value. Therefore, the factor most likely to drive variation in ε_i is the divergence of fundamental and market values, and our testing strategy based on a signal extraction exercise is indeed appropriate for studying this divergence.

1.3. Testing Strategy

Our parameter of interest is the population R^2 of equation (2), which we denote τ^2, and which under our assumptions can be written

$$\tau^2 = \frac{\text{var}\,(q_i)}{\text{var}\,(q_i) + \text{var}\,(\varepsilon_i)}. \tag{3}$$

In the context of a pure errors-in-variables model, a value of τ^2 close to unity implies that the proxy is quite informative about intrinsic investment opportunities. Conversely, a value close to zero implies the proxy is nearly worthless. In the context of trying to understand the relationship between investment and the stock market, the interpretation of τ^2 becomes more complex. The difficulty lies in two separate factors that can affect $\text{var}\,(\varepsilon_i)$, which we illustrate in Figure 1. One can think of the distance between points a and d as $\text{var}\,(q_i) + \text{var}\,(\varepsilon_i)$, and the distance between points c and d as $\text{var}\,(\varepsilon_i)$. In this diagram an increase in the deviation of the market value of the firm from its fundamental value is represented, ceteris paribus, by a leftward shift in point b, and an increase in the manager's tendency to disregard market signals is represented, ceteris paribus, by a leftward shift in point c. Clearly, both of these factors can affect $\text{var}\,(\varepsilon_i)$ and τ^2.

Our interest lies in measuring or approximating the distance between points b and c; that is, the "managerial attention" component of the non-fundamental part of q. To isolate this component we use a simple strategy based on the residuals from projecting observed q on our measures of price informativeness and market mispricing.

First we consider our proxy for mispricing: dispersion of investor opinion. Suppose, as in Panageas (2005a), this dispersion is capitalized into q and that this over-priced q influences managerial investment decisions. In that case regressing observed q on a mispricing proxy removes information from observed q that is useful for investment decisions. In terms of Figure 1, this regression removes much of the variation associated with the distance between b and c. The residual from this regression therefore produces a lower τ^2 when used in place of observed q in (1) than observed q itself. Conversely, if the manager does not pay much attention to mispricing, then regressing observed q on a mispricing proxy removes inconsequential information from observed q. The residual from this regression therefore produces a higher τ^2 when used in place of observed q in (1) than observed q itself. We denote the estimate of τ^2 corresponding to the residual of the regression of observed q on a mispricing proxy as τ_m^2.

Next, we consider measures of the information embedded in the stock price. As above, we estimate τ^2 with versions of observed q in which the effects of these proxies have been regressed out, denoting the resulting estimates as τ_p^2. The intuition behind using this proxy is similar to that behind using a mispricing proxy, except along one line. Ideally, we would like to find a measure of the type of information embedded in the stock price, rather than the amount. For example, good information clearly has a positive effect on the stock price, but the amount has an ambiguous effect. In contrast, the mispricing proxy has definite positive effect on q because increased dispersion of investor opinion leads to overpricing. Therefore, the price informativeness proxies are likely to be of poorer quality than the mispricing proxy.

To describe the testing strategy more formally, let ω_i be a proxy for either price informativeness or mispricing, and let $\hat{\delta}\omega_i$ be the fitted value from regressing x_i on ω_i. Next, rewrite (2) as

$$x_i - \hat{\delta}\omega_i = q_i^* + v_i \tag{4}$$

$$x_i = q_i^* + \hat{\delta}\omega_i + v_i, \tag{5}$$

in which q_i^* and v_i are defined in terms of the null and alternative hypotheses below. In this framework, the null hypothesis that ω_i has no effect on observed q, x_i, can be written as $H_0 : \hat{\delta} = 0$. With reference to the original measurement equation, (2), if $\hat{\delta} = 0$, then $q_i^* = q_i$

and $v_i = \varepsilon_i$; and, therefore, $\tau_p^2 = \tau^2$ and $\tau_m^2 = \tau^2$. The first alternative joint hypothesis is that ω_i affects x_i and that the manager pays attention to ω_i. This hypothesis can be written as $H_1 : \hat{\delta} \neq 0$, $q_i = q_i^* + \hat{\delta}\omega_i$, and $\varepsilon_i = v_i$. Under this first alternative we will find that $\tau_p^2 < \tau^2$ or $\tau_m^2 < \tau^2$. The second alternative joint hypothesis that ω_i affects x_i and that the manager ignores ω_i can be written as $H_2 : \hat{\delta} \neq 0$, $q_i = q_i^*$, and $\varepsilon_i = v_i + \hat{\delta}\omega_i$. Under this second alternative we will find that $\tau_p^2 > \tau^2$ or $\tau_m^2 > \tau^2$.

To test whether τ_m^2 and τ_p^2 are greater or less than τ^2, we create the two ratios, τ_m^2/τ^2 and τ_p^2/τ^2 and then test whether these ratios are significantly different from one. In this framework, our null hypothesis is either $\tau_m^2/\tau^2 = 1$ or $\tau_p^2/\tau^2 = 1$. Our first alternative hypothesis can be expressed as $\tau_m^2/\tau^2 < 1$ or $\tau_p^2/\tau^2 < 1$. Such findings imply that firms react to mispricing or to information in the stock price, respectively. Our second alternative hypothesis can be expressed as $\tau_m^2/\tau^2 > 1$ or $\tau_p^2/\tau^2 > 1$. Such findings imply that firms ignore mispricing or information in the stock price, respectively.

We conclude this section by discussing intermediate cases in which we cannot reject our null hypothesis. A scenario that leads to a test statistic near one occurs when the manager only pays attention to part of the information in proxies for price informativeness or mispricing. A second complicating factor that can produce a ratio near one is the possibility that our measures of price informativeness or mispricing are imperfect proxies for the underlying concepts of price informativeness or mispricing. As shown in a Monte Carlo simulation in the Appendix, however, the presence of measurement error in these proxies only lowers the power of our tests relative to a situation in which we use (hypothetical) perfect measures. Further, our tests have good power to detect the alternative hypotheses that τ_m^2/τ^2 and τ_p^2/τ^2 are either greater than or less than one, even when we measure price informativeness and mispricing indirectly.

1.4. Advantages

We next explain the advantages of this testing strategy. First, we model explicitly the deviation of market signals from fundamentals, a feature shared by some of the empirical papers in this area. Omitting this feature is especially serious in the context of tests based on investment-q sensitivity, which may be influenced by many factors other than stock market signals. For example, classical q-theory implies that this sensitivity is due to the magnitude of physical adjustment costs, and Gomes (2001) shows that it can also be due to financial frictions. Therefore, it is impossible to isolate the effects of stock market signals unless one controls for adjustment costs and financial frictions, both of which are hard to observe. In contrast, our method is robust to these concerns because it is applicable in cases in which non-convex adjustment costs or financial frictions are important. Because our method is based on investment-q regressions, it is appropriate in the presence of financial frictions inasmuch as they are capitalized into q, as in Gomes (2001), or inasmuch as they are reflected in a debt-overhang correction, as in Hennessy (2004). It is also appropriate in the presence of alternative forms of adjustment costs, as in Abel and Eberly (2001), Caballero and Leahy (1996), and Caballero (1999). These frictions affect the coefficient on q, but as long as the basic regression is appropriately specified, they do not affect our tests.

A more serious difficulty with investment-q sensitivity lies in its dependence on both the amount of non-fundamental information present in the stock price and the extent to which the manager finds this non-fundamental information to be useful. In the context of the classical errors-in-variables model, the presence of less non-fundamental information raises investment-q sensitivity, but the manager paying attention to this non-fundamental information also raises investment-q sensitivity. Estimates of the slope-coefficient on q in an investment regression do not contain sufficient information to distinguish these two possibilities. Our methodology, in contrast, does.

Our method is also more informative than tests based on including mispricing proxies in an investment-q regression. These types of tests are difficult to interpret because they include more than one mismeasured regressor: both observable q and the mispricing proxy. As shown in Klepper and Leamer (1984), it is rarely possible to sign coefficient bias in regressions with multiple mismeasured regressors. In contrast, the Appendix shows that our use of proxies for price informativeness and mispricing only lowers the power of our tests.

Several of the papers that distinguish market signals from fundamentals rely on the untestable accuracy of a proxy for fundamentals. In contrast, we use the structure of an econometric model to identify fundamentals, and the specification can be tested via the usual GMM test of overidentifying restrictions. A different approach is in Chirinko and Schaller (1996, 2001), who identify the difference between market signals and fundamentals via estimation of a structural model. Although clever, this strategy relies on estimating an investment Euler equation derived under the assumption of quadratic adjustment costs and perfect markets for external finance. A large amount of evidence has accumulated that these Euler equations are only correctly specified for a small subset of firms. See, for example, Whited (1992) and Love (2003). Therefore, as above, attempts to identify mispricing may pick up the effects of financial or real frictions. Our method shares with these papers an explicit modeling of the discrepancy between the stock market and fundamentals. However, we go one step further with our use of proxies for price informativeness and mispricing to determine whether and how the manager pays attention to market signals.

2. Data and Summary Statistics

This section describes our data sources. It then explains how we construct measures of price informativeness and equity-dependence. It concludes by presenting summary statistics.

2.1. Data and Variable Construction

The data come from three sources. The first is the combined annual, research, and full coverage 2005 Standard and Poor's COMPUSTAT industrial files. We select the sample by first deleting any firm-year observations with missing data. Next, we delete any observations for which total assets, the gross capital stock, or sales are either zero or negative. Then for each firm we select the longest consecutive times series of data and exclude firms with only one observation. Finally, we omit all firms whose primary SIC classification is between 4900 and 4999, between 6000 and 6999, or greater than 9000, because our model is inappropriate for regulated, financial, or quasi-public firms.

Data variables from Compustat are defined as follows: book assets is Item 6; the gross capital stock is Item 7; investment is Item 128; cash flow is the sum of Items 18 and 14; net equity issuance is Item 108 minus Item 115; total long-term debt is Item 9 plus Item 34; total dividends is Item 19 plus Item 21; cash is Item 1; research and development costs are Item 46; inventories is Item 3; and sales is Item 12. The debt overhang correction represents the current value of lenders' rights to recoveries in default and is computed following Hennessy (2004). We use two proxies for true, unobservable q. The first is the market-to-book ratio, whose numerator is the sum of the market value of equity (Item 199 times Item 25) and total book assets minus the book value of equity (Item 60+Item 74), and whose denominator is book assets. We also define a "macro q," as in Erickson and Whited (2000, 2006). The numerator is the market value of equity plus total long-term debt less inventories, and the denominator is the gross capital stock.

Our monthly and daily return data are from the 2005 CRSP tapes, and our data on analysts' earnings forecasts are from I/B/E/S. After merging these three data sources, and after deleting the top and bottom 1% of our regression variables, we are left with an unbalanced panel of firms with between 1683 and 2428 observations per year, with a sample period that runs from 1991 to 2004. We restrict our samples to these years, because only in these years that we have enough data for our econometric model to pass our identification tests.

2.2. Measures of Price Informativeness

We construct two measures of stock-price informativeness. Our first, from Roll (1988), measures the idiosyncratic variation in the firm's stock price. As explained and demonstrated in Durnev, Morck, and Yeung (2004), if a firm's stock return is weakly correlated with the market and industry returns, then the stock price likely reflects firm-specific information. They measure idiosyncratic return variation as $\Psi \equiv \ln\left((1 - R_i^2)/\, R_i^2\right)$, in which R_i^2 is R^2 from the regression of firm-specific weekly returns on value-weighted market and value-weighted industry indices. The industry is defined at the three-digit SIC-code level. We hereafter refer to Ψ as price non-synchronicity. As surveyed in Chen, Goldstein, and Jiang

(2006) and Jin and Myers (2006), a large empirical literature has shown that this measure tends to reflect corporate transparency. Clearly, more transparent companies are likely to have more informative stock prices. Similarly, Chen, Goldstein, and Jiang (2006) survey several papers that argue and show that stock-price co-movement is related to stock-price *un*informativeness.

Our second measure is the probability of informed trading, or PIN. Developed by Easley, Kiefer, and O'Hara (1996), this measure is based on estimation of a structural market microstructure model in which trades can come from noise traders or from informed traders. Because PIN directly quantifies the probability of informed trading in a stock, and because informed traders trade on their information only if it is not yet publicly known, PIN is a theoretically appealing measure of the private information reflected in the stock price. Further, Vega (2006) finds that the values of high-PIN stocks are close to their fundamental values in that they have low post-earnings-announcement drift. Our PIN data are from Easley, Hvidkjaer, and O'Hara (2002). Their sample is considerably smaller than ours, allowing model identification only in the years 1994 to 1999, in which the sample size ranges from 1198 to 1238. We therefore use PIN only as a robustness check.

We employ one measure of market mispricing, denoted $SDEV$. A measure of belief heterogeneity, this proxy is defined as the standard deviation of analysts' earnings-per-share forecasts from the Summary History file from I/B/E/S. As argued in Panageas (2005a), Diether, Malloy, and Scherbina (2002), and Gilchrist, Himmelberg and Huberman (2005), dispersion of investor opinion combined with short-sale constraints can lead to equity overvaluation. The Summary History file is potentially less accurate than the Detail History file due to the presence of stale forecasts and coding errors. However, Diether, Malloy, and Scherbina (2002) report that both the Summary and Detail history files give very similar results, and consequently only report their results using the Summary data. In addition, we follow Diether, Malloy, and Scherbina (2002) by collecting yearly rather than quarterly earnings forecasts, as this choice results in a larger sample. Because I/B/E/S forecasts are reported monthly, and because the standard deviation of these forecasts grows as the forecast period lengthens, to construct an average standard deviation, we first scale each forecast by the square root of the number of months between the estimate and the earnings announcement date. We then average the scaled forecasts. Finally, we re-scale the standard deviation as a fraction of the capital stock instead of as a fraction of total shares. Our intent is to scale all of our variables by firm size, and the number of shares outstanding is an arbitrary number that does not necessarily measure the size of the firm.

We reject several candidate measures of mispricing and price informativeness. For example, Polk and Sapienza (2006) use R&D intensity and accruals as measures of possible stock-market mispricing. However, these variables are chosen endogenously with investment. We also discard the direct measure of the stock-price informativeness from Damodaran (1993) and Brisley and Theobald (1996), which measures the speed of adjustment of stock prices to information. The cross-sectional variation in this measure in our sample is quite low. Finally, several authors have used share turnover as a proxy for mispricing. As argued in Stein (1996) and Panageas (2005a), stock market mispricing is most likely to affect firms whose investors have short-term horizons, a phenomenon that should manifest itself in high share turnover. However, the interpretation of share turnover is ambiguous, given the simple observation that the prices of liquid stocks are likely to be more informative than the prices of illiquid stocks.

2.3. Measures of Equity Dependence

Our preferred measure of equity dependence is firm size, as small firms tend to be young, and young firms tend to rely more heavily on outside equity finance than older firms. The most important advantage of this measure is that it can be considered exogenous, because firm size is not a choice variable for the manager in the short run and is unlikely to depend on investment over the short time period covered by our panel. Size is measured as the book value of total assets.[3]

We also use a previously formulated index of equity dependence, the KZ index, primarily

[3]Using total sales as a measure of firm size produces almost identical results.

to compare our results with those in the rest of the literature. This index comes from Kaplan and Zingales (1997), who examine the annual reports of the 49 firms in Fazzari, Hubbard, and Petersen's (1988) "constrained" sample, using this information to rate the firms on a financial constraints scale. The index is then the fitted value of an ordered logit of this scale on observable firm characteristics. Several authors have used these logit coefficients on data from a broad sample of firms to construct a "synthetic KZ index" to measure finance constraints. As argued in Baker, Stein, and Wurgler (2003) and as found in Hennessy and Whited (2006), financially constrained firms issue more equity than their unconstrained counterparts. Therefore, an index of finance constraints can be interpreted as an index of equity dependence. However, the KZ index is unlikely to be as exogenous to the investment decision as size because it is a function of variables such as cash flow and dividend payout.

The KZ index is constructed as

$$-1.001909CF + 3.139193TLTD - 39.36780TDIV - 1.314759CASH + 0.2826389Q,$$

in which CF is the ratio of cash flow to book assets, $TLTD$ is the ratio of total long-term debt to book assets, $TDIV$ is the ratio of total dividends to book assets, $CASH$ is the ratio of the stock of cash to book assets, and Q is the market-to-book ratio. By construction, the index isolates firms with low cash, low cash flow, and high debt burdens, all of which are characteristics one would associate with firms facing costly external finance. Following Baker, Stein, and Wurgler (2003), we exclude the Q term when computing the synthetic KZ index for each firm.

2.4. Summary Statistics

Summary statistics for the sample stratified into quartiles by size and the KZ index are in Table 1. The first panel contains the sort on size, which confirms the intuition that small firms issue equity much more often and in greater quantities than large firms. Further, small firms carry little debt on their balance sheets, few of the small firms have bond ratings, and the incidence of bond ratings increases monotonically with size. Finally, the small firms have better investment opportunities, as captured by Tobin's q and the market-to-book ratio, and they invest more than large firms, despite much lower cash flow. These patterns reinforce the idea that firm size is a good indicator of a tendency to depend on outside equity financing.

The next panel contains the results for the KZ index. High-KZ firms use much more debt than low-KZ firms, they issue equity slightly less often than low-KZ firms, and the size of issuance as a percent of total assets is nearly identical across the different KZ groups. Further, the distribution of bond ratings across the four KZ quartiles is quite even, and no discernible pattern appears in the distribution of total assets. The KZ index clearly does not capture the notion of equity dependence, nor does it capture the notion of financial constraints. For example, as also found in Whited and Wu (2006), high-KZ firms invest at the same rate as their unconstrained counterparts, despite substantially lower values of Tobin's q. Because of these difficulties, in what follows we primarily rely on size, only using the KZ index to place our results in the literature.

Summary statistics for the sample stratified into quartiles by our price informativeness and mispricing proxies are in Table 2. The top panel presents the summary statistics for the sample sorted on price non-synchronicity (Ψ). The first interesting pattern is the positive relation between Ψ and the levels of investment and Tobin's q. This finding is reassuring in that the strong cross-sectional association between Ψ and observable q implies that our strategy of projecting q on Ψ is likely to be fruitful. The positive relation also assuages the concern that Ψ measures the amount rather than the type of information imbedded in the stock price. If Ψ embodies both positive and negative information, then we ought to have observed no relation between Ψ and q. The second interesting pattern is the decrease in firm size, decrease in bond-rating incidence and increase in equity issuance as Ψ rises. This pattern brings up the importance of disentangling price-informativeness effects from size or equity-dependence effects on investment—an issue we address below.

The second panel examines subsamples sorted by PIN. The figures are calculated using the subsample of firms for which PIN is available. The results are similar to those for Ψ, except along two dimensions. The relation between PIN and observable q is, if anything, slightly negative, and equity issuance appears to be largely unrelated to PIN. This second pattern is useful for sorting out the effects of equity dependence and price informativeness on investment.

The third panel presents the results for $SDEV$. It is interesting that Tobin's q and investment both increase with this proxy for overvaluation. It is impossible to attribute any causation to this relation, however, as high $SDEV$ firms also are small, with a low incidence of bond ratings, high sales growth, and a strong tendency to rely on equity finance. As in the case of Ψ separating the effects of $SDEV$ from size is clearly an issue.

3. Results

This section is divided into four parts. The first part examines firm heterogeneity along the lines of equity dependence and price informativeness. All sample splits are done on the basis of once-lagged variables to mitigate endogeneity concerns. The second part examines the bubble period of the late 1990's. The third conducts robustness checks, and the fourth compares our results to those in the rest of the literature.

3.1. Equity dependence, price informativeness, and mispricing

Table 3 examines the relation between equity dependence and the response of investment to the stock market. The table presents results from estimating (1) via OLS and from estimating (1) and (2) via the fourth-order estimator in Erickson and Whited (2000) on subsamples sorted by size. This particular estimator performs best for estimating τ^2 in a Monte Carlo simulation in the Appendix. We present estimates of the slope coefficients on observed q, cash flow and the overhang corrections, estimates of τ^2, τ_m^2/τ^2, and τ_p^2/τ^2, and also an estimate of the coefficient of determination of (1), which we denote as ρ^2.

Both the OLS and GMM estimates of the slope coefficient on q vary little with firm size. At the very least this result indicates the fragility of previous findings in the literature of a positive relation between investment-q sensitivity and equity dependence or finance constraints. This evidence also shows that investment-q sensitivity is likely to be affected by many factors other than equity dependence, such as technology and the cost of external finance. Otherwise, some relation would have been evident. All of the OLS estimates of the cash-flow coefficient and all but one of the estimates of the overhang-correction coefficient are significantly different from zero. In contrast, all but one of the GMM estimates of the cash-flow coefficient are insignificantly different from zero, whereas the overhang-correction coefficients remain significant.

The interesting part of this table is the estimates of τ^2, τ_p^2/τ^2, and τ_m^2/τ^2. First, in contrast to the results on investment-q sensitivity, τ^2 increases sharply with size.[4] In other words, the non-fundamental component of the variation in observable q is larger for small firms than for large firms. This result could stem from small firms having a larger non-fundamental component in stock prices or from the manager paying less attention to the nonfundamental component. To disentangle these rival explanations we examine the ratios τ_p^2/τ^2 and τ_m^2/τ^2. We find that both ratios decrease monotonically as size falls. Further, τ_p^2/τ^2 is significantly smaller than one for the smallest firms. This result means that removing the amount of private information in observable q actually removes cross-sectional variation in q that managers consider important for investment. The point estimate of 0.779 implies via straightforward algebra that variation in Ψ accounts for approximately 36% of the variation in q_i. In contrast, the estimate of τ_m^2/τ^2 is significantly larger than one for the largest firms. This second result implies the component of q due to mispricing is not relevant for the investment of large firms. This point estimate similarly implies that approximately 23% of the variation in ε_i is due to variation in $SDEV$.[5] One reason large firms ignore market mispricing is their tendency to self-finance combined with the existence of underwriting costs for seasoned equity issues. Even if equity values are too high, they must be high enough to overcome these costs. Further, although the manager may issue equity when he perceives the stock price as too high, it is optimal for the manager to use the proceeds for investment only if he perceives a change in the cost of capital.

[4]This result is different from that in Erickson and Whited (2000), which finds that τ^2 is approximately the same across size classes. We attribute this difference to our much larger sample size.

[5]The result in Table 3 that the ratios τ_m^2/τ^2 and τ_p^2/τ^2 both increase with size can lead one to think that our measure of mispricing and our measure of price informativeness are proxying for the same underlying concept. However, this interpretation is likely false because the correlation coefficient between two measures is 0.047.

We next examine the relationship between the level of informativeness of the stock price and the extent to which managers use information in the stock price to make investment decisions. Accordingly, we split the sample into quartiles based on Ψ and $SDEV$. The results are in Table 4. First, we find that our estimates of τ^2 are monotonically increasing in Ψ and monotonically decreasing in $SDEV$. These results make sense inasmuch as Ψ measures the amount of information in the stock price and $SDEV$ measures the amount of mispricing. One therefore expects $\text{var}(\varepsilon_i)$ to decrease with Ψ and increase with $SDEV$. Interestingly, we find that the estimates of the ratios τ_p^2/τ^2 and τ_m^2/τ^2 increase monotonically with $SDEV$, the estimate of τ_m^2/τ^2 lying significantly greater than one for the highest $SDEV$ quartile. This result indicates that firms facing a great deal of potential mispricing have a greater tendency to ignore that mispricing. We also find that the estimate of τ_p^2/τ^2 is significantly less than one for the lowest $SDEV$ quartile. Similarly, we find that, with one exception, the estimates of the ratios τ_p^2/τ^2 and τ_m^2/τ^2 decrease monotonically with Ψ, and the estimate of τ_m^2/τ^2 is significantly greater than one for the lowest Ψ quartile. However, we find no estimates of either τ_p^2/τ^2 or τ_m^2/τ^2 that are significantly less than one.

This result stands in contrast to those in Chen, Goldstein, and Jiang (2006), who find that high-Ψ firms respond to information in the stock price. Instead, we find that only firms with minimal mispricing respond to such information. This evidence is also inconsistent with a story in which managers tend to exploit market mispricing to invest via cheap equity finance, because in that case we should have found that the estimates of τ_m^2/τ^2 decreased with $SDEV$. Although this evidence suggests that firms with informative stock prices pay more attention to market signals than firms with uninformative prices, we do not find any estimates of these ratios that are significantly less than one. This result may be a result of heterogeneity within the high-Ψ and low-$SDEV$ firms.

We next investigate this possibility by double-sorting our sample by size and by each of Ψ and $SDEV$. In particular, we remove the middle fifth of the distribution of each of Ψ and $SDEV$ and then split each subsample in half at the median of the size distribution. We remove the middle fifth of the distributions of our price-informativeness and mispricing measures because the observations near the center of these distributions exhibit very little variation. In Table 5 we find estimates of τ_m^2/τ^2 significantly greater than one in the high-$SDEV$/large group but not in the low-$SDEV$/large group; i.e., only the large firms with a great deal of mispricing actively ignore its effects when making investment decisions. We also find estimates of τ_p^2/τ^2 and τ_m^2/τ^2 greater than one in the low-Ψ/large group but not in the high-Ψ/large group, thus confirming the general notion that variation in price informativeness or mispricing across firms does not matter for firms with uninformative prices. In other words, the relation between price informativeness and investment is nonlinear. Finally, we also find an estimate of τ_p^2/τ^2 significantly less than one for the high-Ψ/small group, which indicates that equity dependent firms incorporate information from the stock price when making investment decisions, but only those whose stock prices are informative. This evidence is also consistent with the notion that firms glean information about the cost of capital from the stock price. In contrast, we never find an estimate of τ_m^2/τ^2 significantly less than one for any group of firms. In other words, for no group of firms do we find evidence that investment responds to mispricing.

3.2. The Bubble

Table 6 is structured as Table 5, but it examines the "bubble" years 1997 to 2000. Interestingly, our results are quite similar to those for the full sample. The low-$SDEV$/small and the high-Ψ/small groups produce estimates of τ_p^2/τ^2 significantly less than one. The estimate of τ_m^2/τ^2 is significantly less than one for the high-Ψ/small group. This result is not evident in the full sample period and suggests a limited response of investment to market mispricing. However, because we do not find an estimate of τ_m^2/τ^2 significantly less than one for either large or small firms with a great deal of mispricing, the result does not support the notion that firms with highly overpriced equity responded to this mispricing by investing more.

This limited evidence of a response of investment to market mispricing is at first puzzling in light of the sharp increase in aggregate investment that accompanied the stock market bubble. During these years gross private investment increased by 8.4 percent per year, which is extraordinarily high in comparison to the post-war average of 1.8 percent per year.

Part of the explanation clearly lies in the stock market capturing the improved real investment opportunities that accompanied many of the technological innovations in the late 1990's. A second explanation is a rational response by firms to these innovations, as in DeMarzo, Kaniel, and Kremer (2006), who present a model in which endogenous relative wealth concerns lead firms to over-invest in new technologies for fear of being left behind. A final explanation is more firms using equity finance, even though the behavior of equity-dependent firms changed little. Evidence in our sample gives some support to this explanation. For instance, the incidence of firms issuing equity is 11 percent higher in the bubble years than in the full sample. Also the average size of an equity issue (as a fraction of total assets) is 37 percent higher in those years. High stock prices afforded cheap financing, which in turn caused many otherwise unprofitable projects to be undertaken. The drift of more firms into the equity dependent category does, nonetheless, indicate some market timing. Investment opportunities clearly improved, but the boom should have also improved the availability of internal funds as well. Therefore, the migration of firms into the equity-dependent category during the boom does hint at a strong reaction to the boom.

We conclude with one final result that is important for all of the results in Tables 3 through 7. We rarely reject the overidentifying restrictions from yearly estimates underlying the averages presented in these tables. This result is important because possible model misspecification, such as model nonlinearity, heteroskedasticity, or an error-regressor correlation, could lead to biased estimates of τ^2. However, the lack of rejections indicates that these possibilities are not likely, especially in light of the evidence in Erickson and Whited (2000) that the test of overidentifying restrictions has good finite-sample power to detect even small amounts of misspecification. In other words, even though the classical errors-in-variables model is not a perfect representation of the relationship between investment and q, our specification testing indicates that it is a useful approximation.

3.3. Robustness and Extensions

We now consider a number of alternative explanations for our results. First, one could argue that observable q diverges from true investment opportunities more for small firms than for large firms because small firms have more intangible capital that is not on the books. This problem inflates the macro version of observable q because intangibles cannot be subtracted from the numerator, and this problem inflates the market-to-book ratio because intangibles are not counted in the denominator. In either case, groups of firms with more intangible capital ought to have lower estimates of τ^2. One feature of our econometric model that mitigates this concern is the intercept in the measurement equation (2). To the extent that the intercept captures the effects of intangible capital, this source of bias does not affect our estimates of τ^2. To examine this possibility in an extreme case, we isolate three industries in which we expect human capital to constitute a large component of total assets: electronic equipment (SIC 35), instruments (SIC 36), and business services (SIC 73). We also isolate three industries in which we expect human capital to be inconsequential: stone, glass, clay, and concrete products (SIC 32), lumber and wood products (SIC 24), and agriculture (SIC's 01, 02, and 07). The estimate of τ^2 for the human-capital intensive industries is 0.449, whereas the estimate of τ^2 for the human-capital unintensive industries is 0.493. Both estimates are significantly different from zero, and they are not significantly different from one another. This similarity means that it is unlikely that our results are an artifact of the presence of intangible capital.

Another concern for the interpretation of our results is the strong correlations between Ψ and size and between $SDEV$ and size. These correlations bring up the possibility that the results in Table 5 are merely the product of a size effect. To alleviate this concern, we recompute the results in Table 5, throwing away the middle third of the size distribution. The intent is to examine differences in Ψ and $SDEV$ in subsamples that are fairly homogenous along the size dimension. Although not reported for brevity, the results are almost identical to those in Table 5, except that the standard errors are higher as a result of the smaller sample size. As a second check we also compute the correlations between Ψ and size and between $SDEV$ and size, both in the full sample and in the large and small thirds of the sample. We find that these correlations are much smaller in these two subsamples than in the full sample. We conclude that our original double-sorts are not picking up a size effect.

Because we are interested in firms' dependence on equity rather than on size, per se, as a further robustness check we examine a different measure private information, PIN, which is not correlated with equity issuance. Table 7 presents double-sorted regressions based on size and PIN. These results are quite similar to those using Ψ, except that we only obtain one estimate of either τ_p^2/τ^2 or τ_m^2/τ^2 significantly less than one because of the small sample size. Nonetheless, the point estimates of τ^2 are higher for the high-PIN groups than for the low-PIN groups, and the estimates of τ_p^2/τ^2 and τ_m^2/τ^2 are less than one in the high-PIN/small group and greater than one in the low-PIN/large group. These results support the general conclusions obtained using price-nonsynchronicity, Ψ.

Next, it is possible that the manager pays attention to information not captured by the stock price when making investment decisions. This scenario can manifest itself in two ways in our econometric model. First, it can imply that the regression equation (1) ought to contain omitted variables. The J-tests, however, almost never produce rejections of the overidentifying restrictions, and the evidence in Erickson and Whited (2000) indicates that these tests are sensitive to generic error-regressor correlations, which can be induced by omitted variables. Second, this scenario can simply imply that the variance of u_i is large and that our econometric model is valid.

The result that price-nonsynchronicity matters more than the standard deviation of earning estimates might simply a mechanical result of the former having more explanatory power for observed q than the latter. As discussed above, however, price-nonsynchronicity gives no information about the direction of the effect of information on the stock price, whereas the standard deviation of earning estimates does. From a theoretical point of view, therefore, this alternative mechanical explanation for our results appears unlikely. Further, the R^2 from regressing observed q on Ψ is 0.13, and the R^2 from regressing observed q on $SDEV$ is 0.17. This evidence renders it unlikely that our results are purely mechanical in nature.

One final concern is the possibility that Ψ captures information that is in both the manager's and investors' information sets. In this case, our results cannot be interpreted as evidence that managers use information in the stock price when making investment decisions. To deal with this concern, we filter out of observed q information that is clearly in both the investors' and the manager's information sets: once-lagged cash flow. Because the value of the firm is the expected present value of future cash flows, and because cash flows are highly positively serially correlated, extracting variation in cash flow from observed q is likely to remove a large portion of the fundamental component of q. We then re-run our tests that use Ψ, comparing the τ^2 estimates obtained from versions of q in which we filter out cash flow and in which we filter out both Ψ and cash flow. Not surprisingly, the estimates of τ^2 for the version of q in which cash-flow variation is absent are from 25 to 30 percent smaller than those from an unfiltered version. We still find, nonetheless, a point estimate of τ_p^2/τ^2 significantly less than one for the high-Ψ/small group. Because it is impossible to construct a perfect proxy for fundamentals, this evidence does not completely eliminate the possibility that Ψ captures both managerial and investor information, but it does make this possibility unlikely.

3.4. Comparisons with the Literature

This section compares our results to those in Baker, Stein, and Wurgler (2003) and Chen, Goldstein, and Jiang (2006). The intent is to clarify the meaning of the results in those papers and to distinguish our results from theirs.

How do our results compare to those in Baker, Stein, and Wurgler (2003)? In light of their evidence that the sensitivity of investment to the market-to-book ratio is highest for firms with high KZ indices, they conclude that equity-dependent firms respond to market mispricing. As pointed out in the Table 1, however, high-KZ firms are more likely to use debt than equity. Nonetheless, even if one takes their results at face value, our results are different inasmuch as we find that mispricing does not matter for any firms. This difference is a result of our using both a proxy for true underlying investment opportunities with a much higher average τ^2 and a metric for gauging whether firms follow the market that explicitly identifies managerial attention to the nonfundamental component of the market. Figure 2 plots the OLS and GMM estimates of investment-q sensitivity and τ^2 for four KZ quartiles. All estimates are calculated using both the market-to-book ratio and macro q. Using the market-to-book ratio, however, results in models that are only sometimes identified. This problem manifests itself in unstable estimates over time and in large standard errors, and we therefore do not emphasize these GMM results for the market-to-book ratio.

As seen in the first panel, we replicate the Baker, Stein, and Wurgler result that the sensitivity of investment to the market-to-book ratio rises sharply with the KZ index. However, the sensitivity of investment to macro q does not. As seen in the second panel, this same pattern is evident in the GMM estimates of the slope coefficient on q. At the very least, one can conclude that the results concerning investment-q sensitivity are an artifact of type of q proxy used. The third panel shows that the τ^2 estimates corresponding to the market-to-book ratio are much lower than those corresponding to macro q, neither varying with the KZ index. Although not plotted for brevity, the ratios τ_p^2/τ^2 and τ_m^2/τ^2 have no clear relationship to the KZ index. We conclude that the market-to-book ratio is a particularly unreliable proxy for investment opportunities and that investment-q sensitivity is a poor metric for gauging whether firms follow the market.

We next compare our results to those in Chen, Goldstein, and Jiang. They find that firms with high price informativeness have higher sensitivities of investment to the market-to-book ratio, thereby concluding that these have a greater tendency to follow market signals. In contrast, our results indicate that only small firms with low levels of mispricing incorporate market signals in their investment decisions. Once again, this difference can be explained by their use of the market-to-book ratio. Figure 3 plots the OLS and GMM estimates of investment-q sensitivity and τ^2 for four Ψ quartiles. Only the OLS estimates of the slope coefficient on the market-to-book ratio increase with Ψ. This increase is likely a result of the sharp increase in the estimates of τ^2 corresponding to the market-to-book ratio with Ψ. Whereas these estimates of τ^2 more than double, the estimates corresponding to macro

q only increase by less than 50%. In other words, more informative prices lead to higher estimates of τ^2, which in turn lead to less attenuation bias on the OLS slope coefficient on the mismeasured regressor.[6]

4. Conclusion

This paper has attempted to see if firms follow the market; that is, if they look to their own stock price when making investment decisions. This question is of particular importance in light of recent debate among policy makers over whether central banks should try to target stock markets. This sort of targeting only makes sense if the stock market affects real economic activity, in particular, investment. Our innovation in examining this old question is using an errors-in-variables remedy to identify legitimate information about the firm embedded in the stock price. The intuition behind this idea is simple. If firms follow the market then stock-price movements unrelated to fundamentals are more likely to be used as a signal by the manager. In contrast, if the firm ignores the market, the manager is more likely to view these stock-price movements as irrelevant. Consequently, to examine the relationship between the stock market and investment, we use the measurement-error-consistent estimators from Erickson and Whited (2000), which can distinguish the noise from the signal embedded in q.

This method is quite different from those that have been used previously; and, accordingly, the results are also different. In contrast to much of the recent literature that finds strong support for the idea that market mispricing influences investment, we find that only small firms with low levels of market mispricing are more likely to use information contained in the stock price. This result is driven in particular by firms that depend on outside equity for finance, which are more likely than their non-equity-dependent counterparts to use market signals in making investment decisions. In contrast, large firms with less informative stock prices are less likely to follow the market. We do not find, however, that firms

[6] The attenuation bias is given by $\text{plim}\left(\hat{\beta}_{OLS}\right) = \beta\tau_x^2$, in which $\tau_x^2 \equiv \left[\left(\tau^2 - R_x^2\right)/\left(1 - R_x^2\right)\right]$, with R_x^2 being the probability limit of the sample coefficient of determination from the OLS regression of x_i on z_i.

incorporate market mispricing of their stock into their investment decisions. This evidence is inconsistent with the hypothesis of market timing, which predicts that firms with more mispricing should be more likely to exploit that mispricing. Finally, we examine the bubble period of the late 1990s. Interestingly, even during this period only firms with low levels of mispricing and with informative prices use market signals, although we do uncover some evidence that these firms also time the market.

In short we do find limited evidence that prices guide the managers of some firms in their investment decisions, thereby uncovering a direct channel by which the stock market affects real decisions. Further, we find that this feedback primarily operates through an information-gathering mechanism rather than a market-exploitation mechanism. Because we find that this effect is only found in firms that depend on outside equity finance, it is likely that firms use the stock price as a signal concerning the cost of capital. In terms of policy these findings imply that attempts to regulate the stock market should be those that enhance its production of information. Given our findings of a link between the stock market and investment, further research into possible links between the stock market and other corporate decisions, such as employment and capital structure, should be fruitful.

Appendix

For reference we reproduce (1) and (2) from the text

$$y_i = z_i\alpha + q_i\beta + u_i \tag{6}$$

$$x_i = \gamma_0 + q_i + \varepsilon_i. \tag{7}$$

ε_i is a mean-zero error independent of (u_i, z_i, q_i), and u_i is independent of (q_i, z_i). The intercept γ_0 allows for the non-zero means of some sources of measurement error. The EW estimators also require the assumption that $(\varepsilon_i, u_i, z_i, q_i)$, $i = 1, \ldots, n$, are *i.i.d.*, that the residual from the projection of q_i on z_i has a skewed distribution, and that $\beta \neq 0$. The last two assumptions are required for estimator identification and are testable. The one questionable assumption here is the independence of u_i and (q_i, z_i). Clearly, investment, q, and cash flow are determined simultaneously. However, as delineated in Erickson and Whited (2000), plausible economic assumptions do exist under which the independence assumption holds. Further, because the EW estimators are based on GMM, the J-test can be used to detect assumption violations.

Let $(\dot{y}_i, \dot{x}_i, \dot{q}_i)$ be the residuals from the linear projection of (y_i, x_i, q_i) on z_i. Then (6) and (7) can be written as

$$\dot{y}_i = \beta\dot{q}_i + u_i \tag{8}$$

$$\dot{x}_i = \dot{q}_i + \varepsilon_i. \tag{9}$$

If we square (8), multiply the result by (9), and take unconditional expectations of both sides, we obtain

$$E\left(\dot{y}_i^2\dot{x}_i\right) = \beta^2 E\left(\dot{q}_i^3\right). \tag{10}$$

Analogously, if we square (9), multiply the result by (8), and take unconditional expectations of both sides, we obtain

$$E\left(\dot{y}_i\dot{x}_i^2\right) = \beta E\left(\dot{q}_i^3\right). \tag{11}$$

As shown in Geary (1942), if $\beta \neq 0$ and $E\left(\dot{q}_i^3\right) \neq 0$, dividing (10) by (11) produces a consistent estimator for $\beta \equiv \beta^2 E\left(\dot{q}_i^3\right) / \beta E\left(\dot{q}_i^3\right)$. The innovation in Erickson and Whited

(2002) consists of combining the information in moment equations of order two up through seven via GMM to obtain a more efficient estimator for β. Note that α_1 can be recovered by the identity

$$\alpha_1 = \mu_y - \beta\mu_x,$$

in which (μ_y, μ_x) are the slope coefficients in the projection of (y_i, x_i) on z_i.

The coefficients of determination (R^2's) for (6) and (7) are calculated as

$$\rho^2 = \frac{\mu_y' \operatorname{var}(z_i)\mu_y + E(\dot{q}_i^2)\,\beta^2}{\mu_y' \operatorname{var}(z_i)\mu_y + E(\dot{q}_i^2)\,\beta^2 + E(u_i^2)} \tag{12}$$

$$\tau^2 = \frac{\mu_x' \operatorname{var}(z_i)\mu_x + E(\dot{q}_i^2)}{\mu_x' \operatorname{var}(z_i)\mu_x + E(\dot{q}_i^2) + E(\varepsilon_i^2)}. \tag{13}$$

Equation (13) is exactly equivalent to equation (3) in the text.

In order to allay skepticism of empirical results that have been produced by unusual estimators on fairly small samples, we report a Monte Carlo simulation using artificial data similar to our real data, both in terms of sample size and observable moments. The specific purpose of these simulations is threefold. First, we wish to determine which of the Erickson and Whited GMM estimators is best for τ^2. Second, we wish to estimate the finite-sample two-sided 5% critical values for the t-statistics produced with the Fama-MacBeth standard errors. Third, we wish to ascertain whether our tests have power to detect mispricing and price informativeness if our measures of these two phenomena are noisy.

For the first two goals we generate 10,000 simulated panels with a cross-sectional sample size equal to 336, the size of the smallest cross section in any of our estimations. We set the length of the panel equal to the length of our actual panel. We set the parameters β, ρ^2 and τ^2 approximately equal to the averages of the corresponding GMM estimates from Table 3. For brevity, we omit perfectly measured regressors, though this embellishment changes the Monte Carlo results little. Each observation is of the form (y_i, x_i), where we generate (y_i, x_i) according to (1)-(2) so that y_i and x_i have, on average over the simulation samples, first and second moments equal to, serial correlation comparable to, and higher-order moments comparable to, the corresponding average sample moments from our real data.

For the third-, fourth-, and fifth-order GMM estimators, Table 12 reports the mean value of an estimator, its mean absolute deviation (MAD) and the probability an estimate is within 20% of its true value. Table 12 shows that the fourth-order GMM estimator (GMM4) gives the best estimates of all parameters in terms of bias, MAD, and probability concentrations.

Our next set of simulations examines the effects on our tests of poor proxies for mispricing. We consider two alternative scenarios. In the first we allow q_i (true unobserved q) to be a linear function of a "mispricing" or "price informativeness" variable, m_i, according to

$$q_i = m_i + \eta_i, \tag{14}$$

in which η_i is an i.i.d random variable. This scenario describes a situation in which mispricing matters for true investment opportunities. In the second we allow ε_i (the discrepancy between true and observable q) to be a function of m_i according to

$$\varepsilon_i = m_i + \eta_i. \tag{15}$$

In other words m_i is a component of ε_i and therefore affects observable q but not true investment opportunities. We set the coefficients of determination of (14) and (15) equal to 0.25. Our actual observed variable $\hat{m}_i$ is then a function of m_i, according to

$$\hat{m}_i = m_i + \hat{\eta}_i. \tag{16}$$

We allow the coefficient of determination of (16) to range from 0.2 to 1, corresponding to situations in which $\hat{m}_i$ is a poor proxy to situations in which $\hat{m}_i$ is a good proxy for m_i.

For each scenario we generate 10,000 simulated panels and calculate the ratio τ_m^2/τ^2, and we then count the number of times this t-test associated with τ_m^2/τ^2 exceeds the nominal two-sided 5% critical value for the null that $\tau_m^2/\tau^2 = 1$. In the first scenario depicting managerial attention to mispricing, we find that the t-test produces rejections 33 to 90 percent of the time as the coefficient of determination of (16) ranges from 0.2 to 0.8. In the second scenario depiction managerial inattention to mispricing we find that the t-test produces rejections 31 to 92 percent of the time as the coefficient of determination of (16) ranges from 0.2 to 1. We conclude that having noisy proxies for mispricing or price informativeness only lowers the power of our tests. It does not appear to cause a tendency to reject the null.

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Table 1: Summary Statistics: Firms Sorted by Equity Dependence

Calculations are based on a sample of unregulated and non-financial firms from the annual 2005 COMPUSTAT industrial files. The sample period is 1990 to 2004. The denominator of Tobin's q is the gross capital stock. The numerator is the sum of the market value of common equity and the book value of debt less the book value of inventories. The denominator of the market-to-book ratio is the book value of total assets. The numerator is the book value of total assets minus the book value of equity minus balance-sheet deferred taxes plus the market value of equity. Equity Issuance is the size of the equity issue as a fraction of total book assets, conditional on actually issuing. Issuance Incidence is the fraction of observations with positive equity issuance. Net Equity Issuance is issuance less share repurchases. Bond Rating is an indicator that takes the value of one if the firm has a bond rating. The total assets figures are in millions of 1997 dollars. Leverage is defined as the ratio of total long term debt to total assets. The KZ index is an index of financial constraints Kaplan and Zingales (1997), in which higher numbers indicate a greater likelihood facing external finance constraints. Tobin's q has been removed from the KZ index.

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Firms Sorted by Size				
Investment/Capital	0.177	0.178	0.160	0.130
Tobin's q	4.238	3.453	3.304	2.984
Market-to-Book	2.045	1.728	1.700	1.696
Cash Flow/Capital	0.078	0.191	0.202	0.194
Total Assets	41.621	154.944	507.378	6687.158
Sales Growth	0.146	0.122	0.109	0.080
Leverage	0.126	0.173	0.221	0.226
Bond Rating	0.028	0.112	0.309	0.711
Equity Issuance	0.060	0.032	0.022	0.012
Net Equity Issuance	0.052	0.013	0.001	-0.008
Issuance Incidence	0.257	0.167	0.130	0.087
Firms Sorted by Kaplan-Zingales Index				
Investment/Capital	0.146	0.200	0.156	0.142
Tobin's q	3.544	4.719	3.070	2.644
Market-to-Book	2.094	1.998	1.614	1.462
Cash Flow/Capital	0.269	0.252	0.085	0.059
Total Assets	2600.803	1365.438	2242.282	1223.728
Sales Growth	0.082	0.125	0.123	0.127
Leverage	0.101	0.070	0.175	0.400
Bond Rating	0.383	0.193	0.282	0.302
Equity Issuance	0.020	0.040	0.038	0.030
Net Equity Issuance	-0.008	0.010	0.027	0.028
Issuance Incidence	0.077	0.192	0.186	0.184

Table 2: Summary Statistics: Firms Sorted by Measures of Price Informativeness and Mispricing

Calculations are based on a sample of unregulated and non-financial firms from the annual 2005 COMPUSTAT industrial files. The sample period is 1990 to 2004. The denominator of Tobin's q is the gross capital stock. The numerator is the sum of the market value of common equity and the book value of debt less the book value of inventories. The denominator of the market-to-book ratio is the book value of total assets. The numerator is the book value of total assets minus the book value of equity minus balance-sheet deferred taxes plus the market value of equity. Equity Issuance is the size of the equity issue as a fraction of total book assets, conditional on actually issuing. Issuance Incidence is the fraction of observations with positive equity issuance. Net Equity Issuance is issuance less share repurchases. Bond Rating is an indicator that takes the value of one if the firm has a bond rating. The total assets figures are in millions of 1997 dollars. Leverage is defined as the ratio of total long term debt to total assets. $SDEV$ is the standard deviation of analysts' earning estimates, rescaled as a fraction of the capital stock. Ψ is a measure of idiosyncratic volatility from Durnev, Morck, and Yeung (2004). PIN is a measure of the probability of informed trading from Easley, Kiefer, and O'Hara (1996).

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Firms Sorted by Ψ				
Investment/Capital	0.129	0.159	0.177	0.179
Tobin's q	2.575	2.685	3.568	5.150
Market-to-Book	1.708	1.601	1.750	2.111
Cash Flow/Capital	0.221	0.218	0.191	0.036
Total Assets	4511.857	1861.335	700.040	359.229
Sales Growth	0.081	0.107	0.130	0.139
Leverage	0.188	0.205	0.193	0.160
Bond Rating	0.524	0.312	0.208	0.116
Equity Issuance	0.010	0.016	0.031	0.068
Net Equity Issuance	-0.011	0.001	0.015	0.053
Issuance Incidence	0.061	0.102	0.175	0.302
Firms Sorted by PIN				
Investment/Capital	0.142	0.163	0.156	0.155
Tobin's q	3.570	3.882	3.628	3.190
Market-to-Book	1.811	1.682	1.515	1.345
Cash Flow/Capital	0.225	0.152	0.126	0.106
Total Assets	5691.942	1228.408	575.263	270.953
Sales Growth	0.080	0.099	0.092	0.089
Leverage	0.210	0.220	0.226	0.217
Bond Rating	0.618	0.363	0.235	0.098
Equity Issuance	0.014	0.025	0.025	0.021
Net Equity Issuance	-0.009	0.007	0.009	0.009
Issuance Incidence	0.073	0.120	0.119	0.099
Firms Sorted by $SDEV$				
Investment/Capital	0.141	0.146	0.168	0.189
Tobin's q	2.387	2.212	3.261	6.117
Market-to-Book	1.593	1.605	1.778	2.193
Cash Flow/Capital	0.121	0.186	0.237	0.122
Total Assets	1811.615	3134.954	1731.790	753.805
Sales Growth	0.107	0.107	0.112	0.131
Leverage	0.223	0.219	0.174	0.129
Bond Rating	0.265	0.444	0.309	0.142
Equity Issuance	0.028	0.016	0.024	0.057
Net Equity Issuance	0.017	0.000	0.004	0.037
Issuance Incidence	0.138	0.106	0.139	0.256

Table 3: Size-Sorted Investment Regressions

Calculations are based on a sample of unregulated and non-financial firms from the annual 2005 COMPUSTAT industrial files. The sample period is 1990 to 2004. The first quartile contains the smallest firms. Overhang is the debt-overhang correction term from Hennessy (2004). ρ^2 is a measurement error consistent estimate of the regression coefficient of determination; τ^2 is the ratio of signal to the sum of signal and noise for the observable q-proxy, τ_p^2 is a version of τ^2 in which Ψ been filtered out of the observable q-proxy; and τ_m^2 is a version of τ^2 in which $SDEV$ has been filtered out of the observable q-proxy. $SDEV$ is the standard deviation of analysts' earning estimates, rescaled as a fraction of the capital stock. Ψ is a measure of idiosyncratic volatility from Durnev, Morck, and Yeung (2004). Fama-MacBeth (1973) standard errors are in parentheses under the parameter estimates. An asterisk indicates that the t-statistic associated with the standard error exceeds its 5% bootstrapped critical value. A dagger indicates that over half of the t-statistics corresponding to the yearly estimates exceed their 5% bootstrapped critical values.

	OLS Estimates				GMM Estimates						
	q	Cash Flow	Overhang	R^2	q	Cash Flow	Overhang	ρ^2	τ^2	τ_p^2/τ^2	τ_m^2/τ^2
Quartile 1	$0.008^{*\dagger}$	$0.055^{*\dagger}$	$-0.731^{*\dagger}$	0.150	$0.022^{*\dagger}$	0.057^{*}	-0.849^{*}	$0.283^{*\dagger}$	$0.402^{*\dagger}$	$0.779^{*\dagger}$	1.004
	(0.000)	(0.005)	(0.276)		(0.003)	(0.006)	(0.343)	(0.033)	(0.040)	(0.050)	(0.008)
Quartile 2	$0.009^{*\dagger}$	$0.064^{*\dagger}$	-0.231^{*}	0.174	$0.029^{*\dagger}$	0.011	$-0.662^{*\dagger}$	$0.324^{*\dagger}$	$0.401^{*\dagger}$	1.012	1.015
	(0.001)	(0.009)	(0.079)		(0.003)	(0.015)	(0.221)	(0.016)	(0.046)	(0.014)	(0.028)
Quartile 3	$0.008^{*\dagger}$	$0.057^{*\dagger}$	$-0.272^{*\dagger}$	0.176	$0.028^{*\dagger}$	-0.080^{*}	$-0.754^{*\dagger}$	$0.319^{*\dagger}$	$0.531^{*\dagger}$	1.006	1.031
	(0.001)	(0.009)	(0.070)		(0.003)	(0.019)	(0.208)	(0.027)	(0.042)	(0.024)	(0.034)
Quartile 4	$0.007^{*\dagger}$	$0.087^{*\dagger}$	0.077	0.219	$0.020^{*\dagger}$	-0.034	-0.222	$0.296^{*\dagger}$	$0.648^{*\dagger}$	1.108	$1.130^{*\dagger}$
	(0.001)	(0.015)	(0.093)		(0.003)	(0.024)	(0.149)	(0.018)	(0.028)	(0.077)	(0.044)

Table 4: Investment Regressions Sorted by Price Informativeness and Mispricing

Calculations are based on a sample of unregulated and non-financial firms from the annual 2005 COMPUSTAT industrial files. The sample period is 1990 to 2004. *SDEV* is the standard deviation of analysts' earning estimates, rescaled as a fraction of the capital stock. Ψ is a measure of idiosyncratic volatility from Durnev, Morck, and Yeung (2004). Overhang is the debt-overhang correction term from Hennessy (2004). ρ^2 is a measurement error consistent estimate of the regression coefficient of determination; τ^2 is the ratio of signal to the sum of signal and noise for the observable q-proxy, τ_p^2 is a version of τ^2 in which Ψ has been filtered out of the observable q-proxy; and τ_m^2 is a version of τ^2 in which *SDEV* has been filtered out of the observable q-proxy. Fama-MacBeth (1973) standard errors are in parentheses under the parameter estimates. An asterisk indicates that the t-statistic associated with the standard error exceeds its 5% bootstrapped critical value. A dagger indicates that over half of the t-statistics corresponding to the yearly estimates exceed their 5% bootstrapped critical values.

	OLS Estimates				GMM Estimates						
	q	Cash Flow	Overhang	R^2	q	Cash Flow	Overhang	ρ^2	τ^2	τ_p^2/τ^2	τ_m^2/τ^2
SDEV											
Quartile 1	0.010*†	0.074*†	-0.341*†	0.185	0.020*†	-0.120	-0.483*†	0.315*†	0.522*†	0.902*†	0.990
	(0.001)	(0.012)	(0.089)		(0.007)	(0.053)	(0.149)	(0.029)	(0.033)	(0.016)	(0.006)
Quartile 2	0.009*†	0.131*†	-0.273	0.151	0.028*†	-0.198	-0.847*†	0.280*†	0.482*†	0.915†	1.018
	(0.001)	(0.014)	(0.139)		(0.006)	(0.102)	(0.324)	(0.032)	(0.043)	(0.023)	(0.025)
Quartile 3	0.008*†	0.057*†	-0.122	0.101	0.026*†	0.070*	-0.375	0.195*†	0.406*†	1.184	1.043
	(0.000)	(0.006)	(0.112)		(0.004)	(0.008)	(0.184)	(0.024)	(0.056)	(0.114)	(0.104)
Quartile 4	0.007*†	0.046*†	-0.376†	0.170	0.021*†	0.018	-0.675*†	0.350*†	0.376*†	1.039	1.138*†
	(0.000)	(0.007)	(0.139)		(0.001)	(0.007)	(0.174)	(0.016)	(0.020)	(0.046)	(0.028)
Ψ											
Quartile 1	0.008*†	0.061*†	-0.293†	0.157	0.022*†	0.028	-0.855†	0.322*†	0.357*†	1.024†	1.072*†
	(0.000)	(0.007)	(0.150)		(0.003)	(0.010)	(0.332)	(0.019)	(0.029)	(0.015)	(0.018)
Quartile 2	0.009*†	0.059*†	-0.400†	0.151	0.024*†	0.046*	-0.531†	0.270*†	0.411*†	1.188	1.043
	(0.001)	(0.008)	(0.137)		(0.003)	(0.009)	(0.178)	(0.021)	(0.034)	(0.072)	(0.069)
Quartile 3	0.009*†	0.058*†	-0.291*†	0.188	0.022*†	0.025	-0.429*†	0.322*†	0.458*†	1.009	1.006
	(0.001)	(0.007)	(0.082)		(0.002)	(0.009)	(0.130)	(0.027)	(0.040)	(0.016)	(0.027)
Quartile 4	0.009*†	0.049*†	-0.291*†	0.200	0.022*†	-0.020	-0.584*†	0.325*†	0.529*†	1.001	1.051
	(0.001)	(0.006)	(0.087)		(0.004)	(0.016)	(0.196)	(0.026)	(0.034)	(0.013)	(0.034)

Table 5: Double-Sorted Investment Regressions

Calculations are based on a sample of unregulated and non-financial firms from the annual 2005 COMPUSTAT industrial files. The sample period is 1990 to 2004. $SDEV$ is the standard deviation of analysts' earning estimates, rescaled as a fraction of the capital stock. Ψ is a measure of idiosyncratic volatility from Durnev, Morck, and Yeung (2004). Size is calculated as total book assets. Overhang is the debt-overhang correction term from Hennessy (2004). ρ^2 is a measurement error consistent estimate of the regression coefficient of determination; τ^2 is the ratio of signal to the sum of signal and noise for the observable q-proxy, τ_p^2 is a version of τ^2 in which a measure of price non-synchronicity has been filtered out of the observable q-proxy; and τ_m^2 is a version of τ^2 in which a the standard deviation of analysts' earnings estimates has been filtered out of the observable q-proxy. Fama-MacBeth (1973) standard errors are in parentheses under the parameter estimates. An asterisk indicates that the t-statistic associated with the standard error exceeds its 5% bootstrapped critical value. A dagger indicates that over half of the t-statistics corresponding to the yearly estimates exceed their 5% bootstrapped critical values.

	OLS Estimates				GMM Estimates						
	q	Cash Flow	Overhang	R^2	q	Cash Flow	Overhang	ρ^2	τ^2	τ_p^2/τ^2	τ_m^2/τ^2
$SDEV$											
Low $SDEV$, Small	$0.009^{*\dagger}$	$0.072^{*\dagger}$	$-0.346^{\dagger}$	0.131	$0.026^{*\dagger}$	$0.071^{*\dagger}$	$-0.528^{\dagger}$	$0.245^{*\dagger}$	$0.469^{*\dagger}$	$0.816^{*\dagger}$	$0.915^{\dagger}$
	(0.001)	(0.005)	(0.140)		(0.004)	(0.011)	(0.215)	(0.019)	(0.064)	(0.052)	(0.048)
High $SDEV$, Small	$0.008^{*\dagger}$	$0.050^{*\dagger}$	$-0.534^{\dagger}$	0.163	$0.023^{*\dagger}$	0.039^{*}	$-0.602^{*\dagger}$	$0.336^{*\dagger}$	$0.361^{*\dagger}$	$0.915^{\dagger}$	0.994
	(0.001)	(0.005)	(0.180)		(0.002)	(0.006)	(0.254)	(0.023)	(0.021)	(0.082)	(0.007)
Low $SDEV$, Large	$0.009^{*\dagger}$	$0.097^{*\dagger}$	0.049	0.136	$0.018^{*\dagger}$	0.012	-0.125	$0.189^{*\dagger}$	$0.600^{*\dagger}$	1.005	1.028
	(0.002)	(0.014)	(0.083)		(0.009)	(0.072)	(0.126)	(0.031)	(0.059)	(0.016)	(0.019)
High $SDEV$, Large	$0.007^{*\dagger}$	$0.063^{*\dagger}$	-0.101	0.200	$0.021^{*\dagger}$	-0.047	-0.477	$0.316^{*\dagger}$	$0.579^{*\dagger}$	1.027	$1.253^{*\dagger}$
	(0.001)	(0.009)	(0.092)		(0.004)	(0.031)	(0.284)	(0.021)	(0.021)	(0.097)	(0.071)
Ψ											
Low Ψ, Small	$0.008^{*\dagger}$	$0.061^{*\dagger}$	$-0.293^{\dagger}$	0.157	$0.029^{*\dagger}$	0.028^{*}	$-0.855^{*\dagger}$	$0.322^{*\dagger}$	$0.357^{*\dagger}$	1.024	0.985
	(0.000)	(0.007)	(0.150)		(0.003)	(0.010)	(0.332)	(0.019)	(0.029)	(0.015)	(0.038)
High Ψ, Small	$0.009^{*\dagger}$	$0.059^{*\dagger}$	$-0.400^{*\dagger}$	0.151	$0.024^{*\dagger}$	$0.046^{*\dagger}$	$-0.531^{*\dagger}$	$0.270^{*\dagger}$	$0.411^{*\dagger}$	$0.892^{*\dagger}$	1.093
	(0.001)	(0.008)	(0.137)		(0.003)	(0.009)	(0.178)	(0.021)	(0.034)	(0.026)	(0.047)
Low Ψ, Large	$0.009^{*\dagger}$	$0.058^{*\dagger}$	$-0.291^{*\dagger}$	0.188	$0.024^{*\dagger}$	0.024^{*}	$-0.462^{*\dagger}$	$0.334^{*\dagger}$	$0.506^{*\dagger}$	$1.234^{*\dagger}$	$1.241^{*\dagger}$
	(0.001)	(0.007)	(0.082)		(0.002)	(0.007)	(0.130)	(0.025)	(0.038)	(0.081)	(0.081)
High Ψ, Large	$0.009^{*\dagger}$	$0.049^{*\dagger}$	$-0.291^{*\dagger}$	0.200	$0.022^{*\dagger}$	-0.020	$-0.584^{*\dagger}$	$0.325^{*\dagger}$	$0.629^{*\dagger}$	1.014	1.049
	(0.001)	(0.006)	(0.087)		(0.004)	(0.016)	(0.196)	(0.026)	(0.034)	(0.018)	(0.025)

Table 6: Double-Sorted Investment Regressions: The Bubble Years

Calculations are based on a sample of unregulated and non-financial firms from the annual 2005 COMPUSTAT industrial files. The sample period is 1997 to 2000. $SDEV$ is the standard deviation of analysts' earning estimates, rescaled as a fraction of the capital stock. Ψ is a measure of idiosyncratic volatility from Durnev, Morck, and Yeung (2004). Size is calculated as total book assets. Overhang is the debt-overhang correction term from Hennessy (2004). ρ^2 is a measurement error consistent estimate of the regression coefficient of determination; τ^2 is the ratio of signal to the sum of signal and noise for the observable q-proxy, τ_p^2 is a version of τ^2 in which a measure of price non-synchronicity has been filtered out of the observable q-proxy; and τ_m^2 is a version of τ^2 in which a the standard deviation of analysts' earnings estimates has been filtered out of the observable q-proxy. Fama-MacBeth (1973) standard errors are in parentheses under the parameter estimates. An asterisk indicates that the t-statistic associated with the standard error exceeds its 5% bootstrapped critical value. A dagger indicates that over half of the t-statistics corresponding to the yearly estimates exceed their 5% bootstrapped critical values.

	OLS Estimates				GMM Estimates						
	q	Cash Flow	Overhang	R^2	q	Cash Flow	Overhang	ρ^2	τ^2	τ_p^2/τ^2	τ_m^2/τ^2
$SDEV$											
Low $SDEV$, Small	0.010*†	0.068*†	-0.110	0.142	0.030*†	0.055	-0.037	0.296*†	0.421*†	0.758*†	0.859*†
	(0.001)	(0.006)	(0.212)		(0.008)	(0.029)	(0.281)	(0.012)	(0.083)	(0.021)	(0.035)
High $SDEV$, Small	0.007*†	0.052*†	-0.483*†	0.161	0.021*†	0.050*†	-0.630*†	0.356*†	0.347*†	0.858*†	0.957
	(0.000)	(0.005)	(0.043)		(0.002)	(0.004)	(0.159)	(0.038)	(0.035)	(0.014)	(0.059)
Low $SDEV$, Large	0.007*†	0.089*†	0.081	0.120	0.015*†	0.152	0.074	0.146*†	0.421*†	0.973	0.911
	(0.002)	(0.022)	(0.096)		(0.004)	(0.111)	(0.082)	(0.068)	(0.156)	(0.015)	(0.073)
High $SDEV$, Large	0.007*†	0.054*†	0.035	0.218	0.024*†	-0.108	0.021	0.387*†	0.566*†	0.996	1.163*†
	(0.001)	(0.007)	(0.096)		(0.004)	(0.053)	(0.096)	(0.064)	(0.041)	(0.003)	(0.027)
Ψ											
Low Ψ, Small	0.008*†	0.060*†	-0.698*†	0.167	0.027*†	0.079*†	-0.680*†	0.339*†	0.313*†	0.991	1.019
	(0.001)	(0.007)	(0.179)		(0.010)	(0.019)	(0.192)	(0.099)	(0.073)	(0.023)	(0.019)
High Ψ, Small	0.007*†	0.052*†	0.041	0.122	0.022*†	0.052*	-0.151	0.274*†	0.373*†	0.783*†	0.875†
	(0.001)	(0.004)	(0.201)		(0.004)	(0.011)	(0.366)	(0.020)	(0.079)	(0.065)	(0.073)
Low Ψ, Large	0.007*†	0.059*†	0.003	0.204	0.020*†	-0.079	-0.133	0.343*†	0.505*†	0.974	1.003
	(0.001)	(0.014)	(0.147)		(0.004)	(0.056)	(0.093)	(0.030)	(0.062)	(0.019)	(0.024)
High Ψ, Large	0.009*†	0.059*†	0.066	0.216	0.019*†	-0.040	0.027	0.309*†	0.571*†	0.981	0.879*
	(0.001)	(0.010)	(0.077)		(0.002)	(0.027)	(0.068)	(0.048)	(0.039)	(0.007)	(0.037)

Table 7: Double-Sorted Investment Regressions: Alternate Price Informativeness Measure

Calculations are based on a sample of unregulated and non-financial firms from the annual 2005 COMPUSTAT industrial files. The sample period is 1992 to 2001. "Probability of informed trading" (or PIN) is a measure of price informativeness from Easley, Kiefer, and O'Hara (1996). Overhang is the debt-overhang correction term from Hennessy (2004). ρ^2 is a measurement error consistent estimate of the regression coefficient of determination; τ^2 is the ratio of signal to the sum of signal and noise for the observable q-proxy, τ_p^2 is a version of τ^2 in which PIN been filtered out of the observable q-proxy; and τ_m^2 is a version of τ^2 in which $SDEV$ has been filtered out of the observable q-proxy. $SDEV$ is the standard deviation of analysts' earning estimates, rescaled as a fraction of the capital stock. Fama-MacBeth (1973) standard errors are in parentheses under the parameter estimates. An asterisk indicates that the t-statistic associated with the standard error exceeds its 5% bootstrapped critical value. A dagger indicates that over half of the t-statistics corresponding to the yearly estimates exceed their 5% bootstrapped critical values.

	OLS Estimates				GMM Estimates						
	q	Cash Flow	Overhang	R^2	q	Cash Flow	Overhang	ρ^2	τ^2	τ_p^2/τ^2	τ_m^2/τ^2
PIN											
Low PIN, Small	$0.007^{*\dagger}$	$0.102^{*\dagger}$	-0.624	0.117	$0.040^{*\dagger}$	0.023	$-0.986^{*\dagger}$	$0.232^{*\dagger}$	$0.242^{*\dagger}$	1.022	0.984
	(0.001)	(0.015)	(0.251)		(0.010)	(0.024)	(0.168)	(0.030)	(0.040)	(0.039)	(0.051)
High PIN, Small	$0.010^{*\dagger}$	$0.106^{*\dagger}$	$-0.526^{*\dagger}$	0.182	$0.034^{*\dagger}$	0.062	$-0.983^{*\dagger}$	$0.269^{*\dagger}$	$0.388^{*\dagger}$	0.872	$0.836^{\dagger}$
	(0.002)	(0.018)	(0.102)		(0.006)	(0.019)	(0.124)	(0.035)	(0.069)	(0.078)	(0.092)
Low PIN, Large	$0.004^{*\dagger}$	$0.116^{*\dagger}$	-0.002	0.161	$0.020^{*\dagger}$	-0.062	-0.551	$0.204^{*\dagger}$	$0.576^{*\dagger}$	1.001	1.015
	(0.001)	(0.019)	(0.182)		(0.007)	(0.078)	(0.396)	(0.017)	(0.046)	(0.008)	(0.012)
High PIN, Large	$0.007^{*\dagger}$	$0.107^{*\dagger}$	-0.016	0.156	$0.017^{*\dagger}$	0.018	-0.079	$0.184^{*\dagger}$	$0.677^{*\dagger}$	0.971	$1.068^{*\dagger}$
	(0.002)	(0.038)	(0.167)		(0.005)	(0.036)	(0.196)	(0.048)	(0.042)	(0.015)	(0.015)

Table 8: Monte Carlo Performance of GMM and OLS Estimators

Indicated expectations and probabilities are estimates based on 10,000 Monte Carlo samples of size 336. The samples are generated by

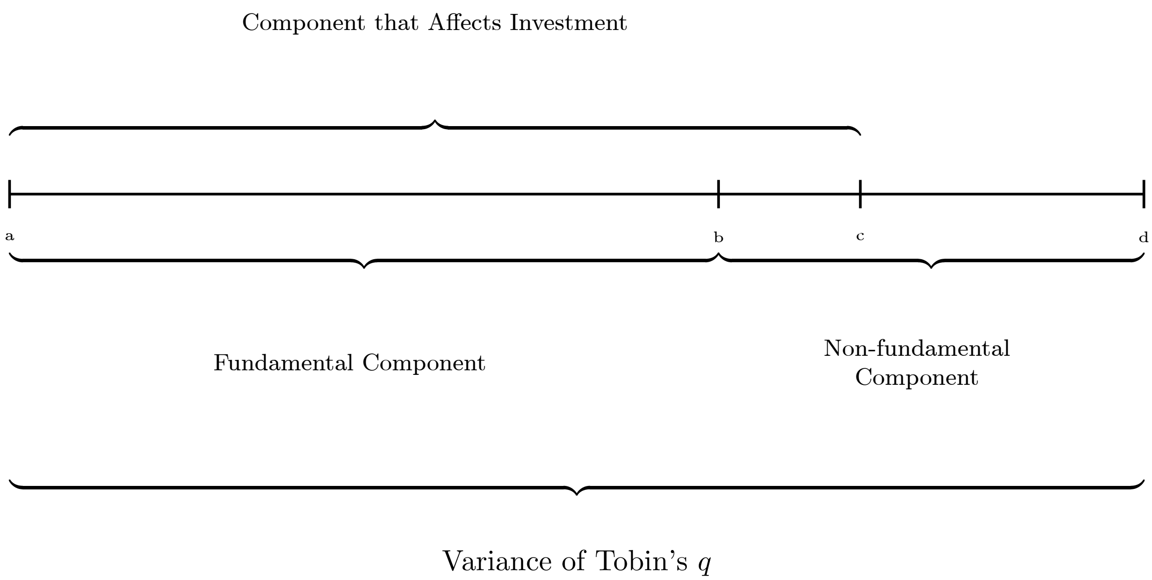
$$
\begin{aligned}
y_i &= q_i\beta + u_i \\
x_i &= \gamma + q_i + \varepsilon_i,
\end{aligned}
$$

in which q_i is distributed as a normal variable raised to the fourth power, and ε_i and u_i are chi-squared variables with one degree of freedom. GMMn denotes the GMM estimator based on moments up to order $M = n$. OLS denotes estimates obtained by regressing y_i on x_i.

True Values: $\beta = 0.04$, $\rho^2 = 0.356$, $\tau^2 = 0.420$.

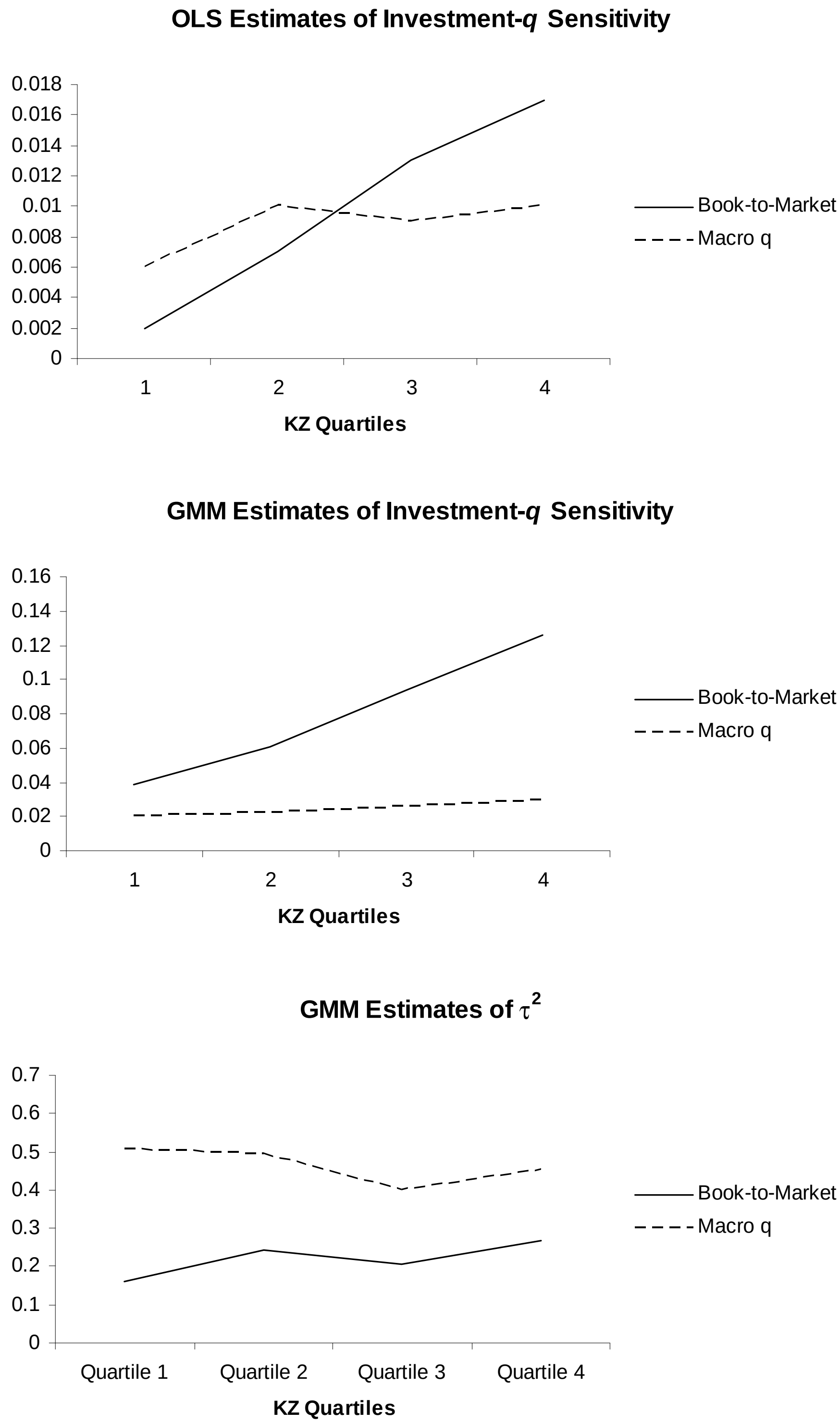
	OLS	GMM3	GMM4	GMM5
$E(\hat{\beta})$	0.013	0.038	0.039	0.036
MAD($\hat{\beta}$)	0.027	0.003	0.003	0.005
P($\mid \hat{\beta} - \beta \mid \leq 0.2\beta$)	0.000	0.960	0.975	0.864
$E(\hat{\rho}^2)$	0.218	0.377	0.371	0.422
MAD($\hat{\rho}^2$)	0.178	0.069	0.047	0.071
P($\mid \hat{\rho}^2 - \rho^2 \mid \leq 0.2\rho^2$)	0.000	0.755	0.917	0.783
$E(\hat{\tau}^2)$	—	0.456	0.416	0.453
MAD($\hat{\tau}^2$)	—	0.053	0.044	0.049
P($\mid \hat{\tau}^2 - \tau^2 \mid \leq 0.2\tau^2$)	—	0.881	0.933	0.908

Figure 1: Decomposition of the Variance of q



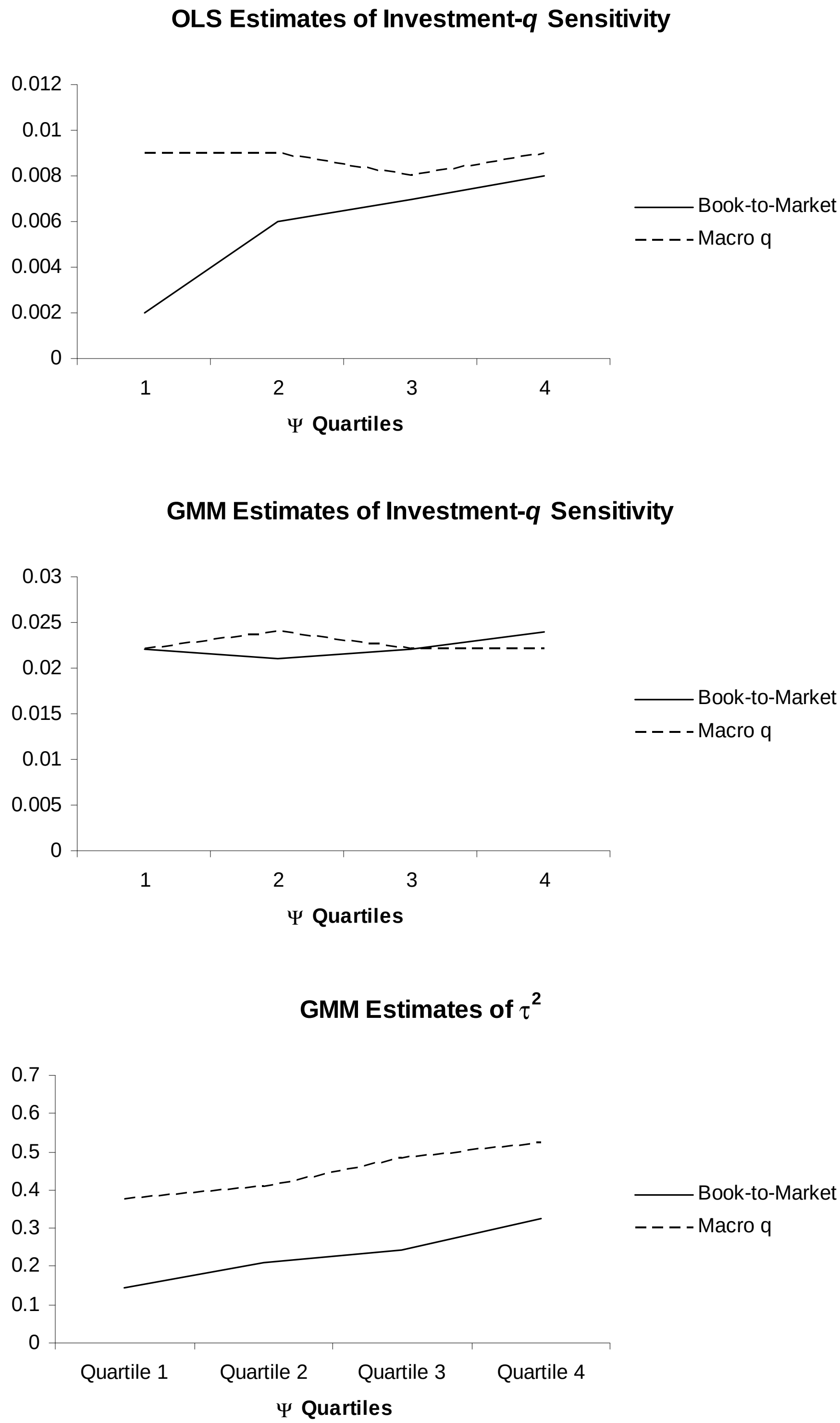
The distance between points a and d represents the variance of Tobin's q. The distance between points a and b represents the component that is due to fundamentals, the distance between points b and d represents the component that is due to non-fundamental factors, and the distance between points b and c represents the portion of the non-fundamental component to which the manager reacts.

Figure 2: KZ-Sorted Investment Regressions



Calculations are based on a sample of unregulated and non-financial firms from the annual 2005 COMPUSTAT industrial files. Estimation is done by OLS and the GMM4 estimator in Erickson and Whited (2002). The sample period is 1991 to 2004. In all cases, the horizontal axit respresents sub-samples stratified by the KZ index, which is an index of financial constraints from Kaplan and Zingales (1997). Tobin's q has been removed from the KZ index. A higher number indicates a greater likelihood both of needing external finance and facing costly external finance. "Macro-q" refers to estimates from regressions in which all regressors are deflated by the capital stock. "Market-to-Book" refers to estimates from regressions in which all regressors are deflated by total book assets. τ^2 is the ratio of signal to the sum of signal and noise for an observable q proxy.

Figure 2: Ψ-Sorted Investment Regressions



Calculations are based on a sample of unregulated and non-financial firms from the annual 2005 COMPUSTAT industrial files. Estimation is done by OLS and the GMM4 estimator in Erickson and Whited (2002). The sample period is 1991 to 2004. In all cases, the horizontal axit respresents sub-samples stratified by the price nonsynchronicity (Ψ), which is a measure of the amount of firm-specific information embedded in the stock price. "Macro-q" refers to estimates from regressions in which all regressors are deflated by the capital stock. "Market-to-Book" refers to estimates from regressions in which all regressors are deflated by total book assets. τ^2 is the ratio of signal to the sum of signal and noise for an observable q proxy.