Rational Information Acquisition Screens*

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Abstract

We develop and empirically test a model of information acquisition in capital markets. In the model, investors are uncertain about the returns to acquiring private information *before* they acquire it. This results in a novel reason for why past price movements impact future capital market outcomes: investors use public information, including past prices, as a screen to estimate the returns to acquiring private information and efficiently allocate their limited information-processing capacity across firms. The model predicts that larger unexplained price movements lead to more private information acquisition, higher future price volatility, and higher future trading volume. Using fine-grained data measuring information acquisition on Edgar and Bloomberg, we provide empirical evidence in support of the model's predictions.

Keywords: Information Acquisition; Market for Information; Higher-Moment Uncertainty; Investor Attention; Edgar Downloads; Bloomberg; Earnings Announcements; Big Data

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1 Introduction

Investment screens based on easily acquired public metrics are widespread in the marketplace. One role for such investment screens involves their use in excess return portfolio formation rules. The efficacy of this role for screens, which is premised on markets failing to be semi-strong form efficient, is mixed at best (e.g., Green, Hand, and Zhang, 2017). A second role for screens is to aid investors' formation of portfolios with desired risk exposures. The use of screens to determine risk exposures, which is premised on the screening variables capturing firm-specific sensitivity to relevant risk factors, is consistent with the existence of relatively passive investment funds tied to screens (e.g., high dividend yield funds) and with academic studies using screens to form factor portfolios (e.g., Fama and French, 2015). Regardless of which of these two roles is played by a particular screen, the screen dictates the investment portfolio, so the investor is largely passive once a screen is chosen. In contrast, many investors are quite active in that they engage in costly private information activities for particular firms, such as expending analyst attention to analyze firm filings and other disclosures, making payments to engage with expert scientists or engineers to assess a firm's products or pipelines, or incurring analyst time and travel costs to visit with supplies or customers. Because information acquisition resources are limited, these active investors must determine which firms should be targeted for information acquisition endeavors.[1] Given the observation that active investors must allocate limited information acquisition resources, we develop and test a theory for another role for an investment screen, an information acquisition screen. In essence, our theory pertains to how screens are employed for allocating limited information acquisition (or attention) resources, rather than how they are employed for allocating investment funds in a portfolio.

We motivate our theory with research documenting that investors allocate differential amounts of attention across firms, consistent with investors facing information-processing constraints.[2] Little is known, however, about how investors manage these constraints and why they allocate more attention to some firms than to others. To address these questions, we construct a model that

[1] Conversations with investment professionals describe a multi-step investment process that begins with identifying a set of firms to consider for further information collection and analysis. Examples: https://www.fe.training/free-resources/investment-banking/investment-research/, https://finimize.com/content/how-use-stock-screener-find-hidden-gems.

[2] For example, studies have assumed or documented that investors focus their information acquisition activities on firms with negative or extreme returns (e.g., Drake, Roulstone, and Thornock, 2012, 2015; Kempf, Manconi, and Spalt, 2017; Abramova, Core, and Sutherland, 2020), positive earnings surprises (e.g., Brown, Hillegeist, and Lo, 2009; Koester, Lundholm, and Soliman, 2016), negative earnings shocks (e.g., Drake, Roulstone, and Thornock, 2016), and location or education commonalities with investors (e.g., Chen, Cohen, Gurun, Lou, and Malloy, 2020; Dyer, 2021).

explains how screens based on public information can help investors efficiently allocate their private information acquisition efforts. We extract testable predictions from the model regarding the relation between a simple screen outcome and future investor attention, price volatility, and trading volume. We then test these predictions using a large sample of earnings announcements of publicly traded U.S. firms from 2004 to 2022.

In standard pricing models, prices reflect all available public information about future cash flows, so past price movements and past public information are not useful to investors for allocating their investment funds to generate excess investment profits. Our model has this feature as well, but past public information is useful to investors for allocating the limited information acquisition resources. In particular, in our dynamic information acquisition and trading model, transitory speculators arrive each period and theu much decide where to allocate their information acquisition efforts. The critical assumption we impose is that those transitory speculators are uncertain about which firm's information environment offers the best returns to information acquisition efforts. We illustrate how, in equilibrium, past prices and earnings help resolve some of that uncertainty.

We assume that entering speculators have access to historical prices and earnings, which is information readily available in public databases. This public information, coupled with the belief that the quality of private information is correlated across time, enables the entering speculators to develop a screen that informs their firm-following decision (i.e., which firm to acquire private information about). In particular, the model's explicit, endogenous, and efficient screen is formed based on public information signals represented by past prices and past earnings. The screen is a function of the deviation of the realized price from expected price, where expected price is based on realized earnings.[3] A larger deviation from the expected price suggests that higher-quality private information is driving demand and indicates a more profitable private information acquisition opportunity.[4] All else equal, entering speculators will follow the firm that is expected to offer higher returns to private information acquisition. After they make their choices, all speculators obtain

[3]Throughout the paper, we define public information as information that can be employed to update beliefs without requiring significant information acquisition and processing capacity. Within our model, the public information for information acquisition decisions includes past prices, past earnings, and past investor following, all of which are readily available in standard financial summaries. Private information, in contrast, is information that can be employed to update beliefs only if significant information acquisition and processing capacity is expended on that information source. Our definition of private information includes detailed information from the news and corporate filings, which prior literature has shown to be costly to obtain (Blankespoor, deHaan, and Marinovic, 2020; Indjejikian, 1991). We use 'information acquisition' and 'private information acquisition' interchangeably. See Section 3 for more details.

[4]If the noise trader activity (i.e., variance) is uncertain, the same result would hold because a greater price deviation from expected price would be indicative of greater noise trader activity.

private information about the firm they follow and engage in trade with the dedicated investors and noise traders.

We investigate whether our model explains investors' information acquisition efforts in the data. The literal mechanism in the model is unobservable, because the profitability of private information acquisition opportunities is unobservable. Hence, we test our model by testing its predictions for observable economic outcomes, which is a common means for testing economic theories (e.g., Samuels, Taylor, and Verrecchia, 2021; Kim, 2024). The key testable prediction is that firms with observed prices that deviate more from expected prices should attract more attention (i.e., more entering speculators in the model decide to follow and acquire private information about the firm), because deviations from expected prices suggest more profitable information acquisition opportunities. Our model also provides two additional testable predictions. Specifically, to the extent that the increase in attention is associated with more private information gathering and, as a consequence, more information-based trade, those firms with greater deviations from expected price should exhibit: (i) greater future price volatility and (ii) greater future trading volume.[5]

Earnings announcements offer several advantages for testing the model's predictions. First, they represent a public release of fundamental information, and earnings are one of the most widely disseminated financial metrics. Second, earnings have a well-established relation with prices and a number of investors rely on them as key valuation inputs (Collins and Kothari, 1989), aligning with the model's notion of expected price based on earnings. Third, earnings announcements occur at routine intervals, which mitigates the alternative explanation that investors are responding to underlying events at other times as opposed to using the reflection of those events in earnings. Finally, earnings announcements span a broad sample of firms, enabling us to calculate expected prices based on earnings and price-earnings multiples across a diverse cross-section of companies.

Using a sample of earnings announcements from 2004 to 2022, we test whether proxies for future information acquisition are increasing in abnormal price deviations, defined as the portion of observed price that is not explained by earnings realizations. Consistent with the model's predictions, we find that Edgar downloads and Bloomberg terminal attention for a firm are higher when that firm's observed price immediately after the earnings announcement deviates more from the expected price. Further disaggregating the deviations into positive and negative signed deviations, we find that both Edgar downloads and Bloomberg terminal attention have a U-shaped relation with the

[5] This intuition is similar to the result in Andrei and Hasler (2015), where an exogenous increase in investor attention increases volatility. Similarly, a firm's risk disclosure in Smith (2022) helps investors estimate when it is more lucrative to acquire information.

signed deviation. This finding corroborates the model's prediction that information acquisition is highest when the *absolute* value of the deviation is largest, regardless of the sign of the deviation. In addition, it mitigates alternative explanations (e.g., new growth opportunities) that would predict a monotone relation between signed abnormal prices and information acquisition.

In addition to testing the model's primary prediction, we also test its predictions regarding future price volatility, trading volume, and declines in attention. To test the predictions regarding future price volatility and trading volume, we use a mediated path analysis and document that an increase in investor information acquisition—triggered by a greater deviation of observed price from expected price—is associated with higher future return variance and trading volume. With respect to the model's prediction that a large price deviation at one firm can diminish attention paid toward another firm, we find that, when one firm experiences a larger price deviation from expected price at the earnings announcement, the attention metrics for a matched peer decrease. Hence, the attention afforded to one firm appears to come at the expense of attention to another peer.

We conduct additional analyses to test two main assumptions underlying the model's narrative, to perform a robustness exercise, and to address alternative explanations for our findings. To test the assumption that abnormal prices attract attention from entering speculators, as opposed to pre-existing investors in a firm, our analysis uses IP addresses of the investors to provide empirical evidence that information acquisition from new entering speculators are increasing with abnormal prices. We also find empirical support for the assumption that that returns to information acquisition are correlated over time. Next, we consider alternative measures of abnormal prices as a robustness exercise, which corroborates our main findings. Finally, we provide some evidence that is inconsistent with alternative explanations for our findings. For example, our inferences are robust to controlling for pre-announcement attention and non-recurring events, and we find no evidence that deviations from expected price are associated with predictable mispricing that reverses in the future.

Our study contributes to multiple streams of literature. First, our model and empirical results offer an economic rationale for prior empirical research's assumptions that extreme price movements attract institutional investor attention. For example, many prior papers employ shocks that assume that institutional investors focus attention on holdings that experience extreme returns and consequently become distracted with respect to other, unrelated, parts of their portfolio (e.g., Kempf et al., 2017; Abramova et al., 2020; Chen, Dong, and Lin, 2020; Liu, Low, Masulis, and Zhang, 2020). Our model provides a *rational* explanation for why investors might focus on firms with extreme returns, by introducing the idea that unexplained price deviations suggest a profitable information acquisition opportunity. Our empirical results provide direct evidence of institutional investors' information acquisition increasing in response to large unexplained price movements. Our study also complements research showing that retail investors pay attention to extreme returns (e.g., Barber and Odean, 2008; Blankespoor, Dehaan, Wertz, and Zhu, 2019; Barber, Huang, Odean, and Schwarz, 2022). In contrast to this literature, we provide a rational explanation for why investors can use past prices to allocate attention efficiently, even *absent* cognitive biases or lack of sophistication. Moreover, our predictions focus largely on institutional investors, as opposed to retail investors, and thereby suggest that attention can be attributed to different stimuli for different investor types. By explaining why investors allocate their limited attention in specific ways, we address a promising direction for future research identified in Blankespoor et al. (2020)'s survey of the literature on disclosure processing costs.

Second, our analysis contributes novel insights to the literature on private information acquisition in asset markets by introducing uncertainty about the returns to private information acquisition. Within that literature, various determinants of private information acquisition have been studied, including the direct cost of acquiring the information (Grossman and Stiglitz, 1980; Verrecchia, 1982), uncertainty about firm value (Nagar, Schoenfeld, and Wellman, 2019), the nature of available public information (Demski and Feltham, 1994; Kim and Verrecchia, 1994; McNichols and Trueman, 1998; Gao and Liang, 2013), the mechanisms for profiting from that information through trading or indirect sale (Garcia and Vanden, 2009), private information leakage by informed insiders (Indjejikian, Lu, and Yang, 2014), information-processing biases (Ko and Huang, 2007), status concerns (Garcia and Strobl, 2011), and the nature of the information choice set and nature of information chosen by other investors (Froot, Scharfstein, and Stein, 1992; Fischer and Verrecchia, 1998; Van Nieuwerburgh and Veldkamp, 2009; Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016). Our analysis is most related to the latter determinants, in that we consider an information choice from a constrained set of information choices. In that work, investors generally choose how much information to acquire (i.e., how much variance to eliminate) or the degree to which one's information overlaps with others' (i.e., the covariance of the private information). The attributes of the information that investors can obtain, such as its precision, are commonly known in these models and the only uncertainty pertains to the realization of that information. As a result, past prices are typically not informative about the potential profits to private information acquisition in those settings and screens based on public information such as past prices would not be valuable.

Our paper differs by assuming that entering speculators are uncertain about the returns to acquiring private information prior to making the firm-following decision, and therefore use prior prices and realized earnings as a screen to infer the value of information acquisition.

Third, our findings contribute to the literature on market feedback effects. In this literature, stock price reflects information about a firm's future cash flows. Consequently, managers and investors use stock price to update their beliefs about the firm's future cash flows, which, in turn, affects managers' real investment decisions and investors' portfolio allocation decisions (see Bond, Edmans, and Goldstein, 2012 for a review). For example, Luo (2005) document that companies extract information from the market reaction to their M&A announcement and consider it in closing the deal. Similarly, Chen, Goldstein, and Jiang (2007) find that the sensitivity of corporate investment to stock price increases with price informativeness, suggesting that managers learn about their firms' fundamentals from stock price and incorporate this information in real investment decisions. Our findings complement and extend this stream of literature by showing how investment screens based on public information can be useful in a semi-strong form efficient marketplace, even when the screens do not generate direct trading profits. Given that focus, our modeling framework has three features that deviate significantly from the features in the antecedent literature. First, the entering investors are endeavoring to resolve uncertainty about which firm offers a more profitable information acquisition opportunity. Hence, they are trying to update their beliefs about the precision of private information (i.e., the second moment), and not about the private information signal itself regarding cash flows (i.e., the first moment), which is the case in the antecedent studies. Second, the public information set they employ to resolve uncertainty is completely stale in the sense that it provides no information about any firm's future cash flows that is not already embedded into the past stock price. Hence, they are not employing a *contemporaneous* price to update their beliefs about future cash flows, which is the case in the antecedent studies. Third, they employ that information to make a decision about where they allocate their limited information acquisition capacity. Hence, the information in the price is useful for allocating attention, as opposed to making a managerial investment decision or an investor portfolio allocation decision.

Finally, we contribute to a stream of literature where investors are uncertain about the precision of other investors' beliefs. For example, in Blume, Easley, and O'Hara (1994), one set of investors does not know the precision of other investors' private information and in Schneider (2009) investors do not know the precision of the aggregate information in price.[6] Investors in both models know their own demand and information, and can then use the aggregate trading volume to infer information about the other traders' precision. In Banerjee and Green (2015) rational uninformed investors do not know whether other investors trade on information or on noise. As a result, larger price surprises are associated with higher fundamental uncertainty and higher risk premia, which leads to a seemingly stronger reaction to negative news. In our model, all investors that actively trade know all parameters of the model; that is, conditional on following a firm, there is no uncertainty about the information endowment of other investors following the firm, but investors (in particular, the entering transitory speculators) do not know which firm offers better returns to information acquisition before they decide which firm to follow.[7]

The remainder of the paper begins with a discussion of the model in Section 2 where we describe its critical assumptions, characterize the equilibrium, and identify some testable empirical implications. Section 3 describes the empirical data and measures used in the study and presents descriptive statistics. In Section 4, we discuss the empirical strategy and present results. Section 5 provides concluding remarks.

2 Model

Consider a setting where the equity claims to two firms, a and b, are traded in perfectly competitive markets over an infinite horizon by three types of traders. The participants in a given firm's equity market are transitory speculators who choose to follow the firm as well as a set of dedicated investors and noise traders. A new generation of transitory speculators arrives each period and departs in the subsequent period, whereas the set of dedicated investors and noise traders in each firm's equity market is present in all periods. Consistent with canonical models of trade with asymmetrically informed traders (i.e., Grossman and Stiglitz (1980) and Kyle (1985)), the transitory speculators

[6]Somewhat related are Hughes and Pae (2004), Penno (1996), and Subramanyam (1996), where a firm discloses information with an unknown precision. In contrast to our study, in this stream of literature all investors have homogeneous information. Also related is a stream of research that assumes investors are uncertain about other aspects of the information, such as the veracity of external news (Libgober, Michaeli, and Wiedman, 2023), the precision of current forecast news (Hutton and Stocken, 2021), and the truthfulness of management forecasts (Rogers and Stocken, 2005).

[7]Dye and Sridhar (2007) and Michaeli (2017) allow for an unobservable precision of information in a capital market. Dye and Sridhar (2007) assume that all investors receive the information and do not learn the precision. Michaeli (2017) assumes that a manager acquires information and provides it to users for free. That is, investors do not choose to acquire information (whether or not they observe its precision), and they have as much information as the manager chooses to provide.

are informed traders, the dedicated investors are passive but strategic uninformed traders, and the noise traders are the source of noise in the market each period.

Each period t has three stages. In the first stage, entering transitory speculators arrive and decide which of the two firms to follow (i.e., the firm whose equity market they participate in and who they acquire information about). In the second stage, earnings for each firm $i \in \{a, b\}$ are realized, made public to firm i's market participants, and paid out as a dividend to firm i's equity holders as of the end of period $t-1$. Additionally, entering transitory speculators who decided to follow firm i in the first stage acquire private information about i's subsequent period earnings. Therefore, the firm-following decision in the first stage is effectively an information acquisition decision. In the third stage, trade occurs in a firm's market among the entering transitory speculators following the firm, dedicated investors, noise traders, and the departing transitory speculators who chose to follow the firm in the prior period and are liquidating their prior period trading position. A timeline summarizing the three stages is in Figure 1.

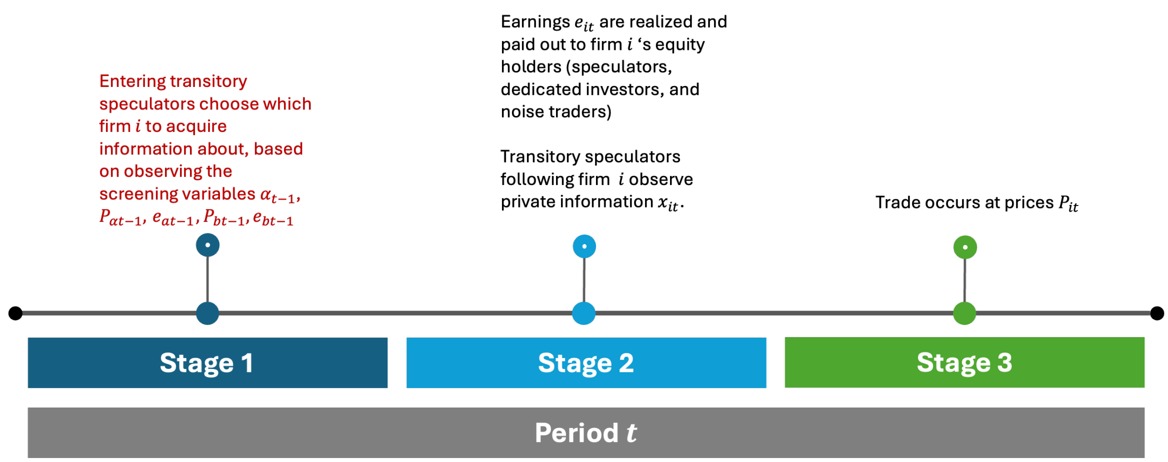


Figure 1 Timeline. This figure summarizes the timeline of the model. We assume an infinite time horizon. The same period t timeline repeats in period $t+1$, during which a new group of entering transitory speculators arrives, and the old transitory speculators from period t liquidate their position and depart from the model.

The earnings process for each firm i is common knowledge and follows the AR(1) process

$$e_{it+1} = \lambda e_{it} + \tilde{\varepsilon}_{it+1}, \tag{1}$$

where $\lambda \in (0, 1]$ is a persistence parameter, and $\tilde{\varepsilon}_{it} \sim N\left(0, s^2\right)$ is independent of $\tilde{\varepsilon}_{j\tau}$ for all $j \in \{a, b\}$ and $\{j, t\} \neq \{i, \tau\}$. All traders participating in firm i's market observe the period-t earnings realization. Entering transitory speculators that follow firm i, and who trade in firm i's shares in period t, also observe information about the innovation in i's period $t+1$ earnings. In particular, the speculators observe the realization $\tilde{x}_{it} = x_{it}$, where $\tilde{x}_{it}$ is normally distributed with mean 0, variance $q_{it}^2 < s^2$, covariance with $\tilde{\varepsilon}_{it+1}$ of q_{it}^2, and is independent of all other random variables in the model. In effect, q_{it}^2 represents the quality of the speculators' private information.

The market is perfectly competitive and, accordingly, we model all traders as atomistic. The set of transitory speculators entering in each period has measure 1. The variable $\alpha_{at} = \alpha_t \in [0, 1]$ denotes the proportion of transitory speculators that follow firm a in period t. Accordingly, the proportion following firm b is $\alpha_{bt} = 1 - \alpha_t$. The set of noise traders in each firm's market has measure 1. We normalize the supply of shares of each firm to 0 per dedicated investor and the set of dedicated investors in each market has measure 1. Furthermore, while we treat the dedicated investors in each market as different individuals and assume that transitory speculators participate in only the market of the firm they follow, we note that the model equilibrium is identical if we assume dedicated investors in each market are the same set of individuals, and/or allow the transitory speculators to participate in both markets but still constrain them to receiving private information about just the firm they follow.[8]

Dedicated investors in the market for firm i's equity are risk neutral and invest in i's equity as well as a risk-free security in each period. Formally, a dedicated investor d in the market for firm i's equity chooses their period t demand (i.e., their holdings from period t to $t+1$), denoted d_{dit}, to maximize the expectation of their period $t+1$ wealth

$$E\left[d_{dit}(\tilde{e}_{it+1} + \tilde{P}_{it+1}) + (1+r)\left(W_{td} - d_{dit}P_{it}\right)|\Omega_{it}\right], \tag{2}$$

where $\tilde{P}_{it+1}$ is the period $t+1$ price, which is uncertain at t, P_{it} is the observed period-t price, r is the net return for the risk free security, W_{td} is their initial wealth, and Ω_{it}, is the information available to all of i's market participants at date t, which includes: (i) the past history of prices, earnings, and the proportion of speculators following i and (ii) the quality of the private information that is acquired by the speculators participating in i's market at date t, q_{it}^2.

Noise traders in the market for firm i's equity in period t demand a random amount that is unrelated to the firm's fundamentals (i.e., prices and earnings). Formally, their demand is n_{it}, where n_{it} is the

[8]This equivalence arises because dedicated investors are risk neutral, which implies: (i) their behavior in one market would not influence their behavior in the other market, so they effectively behave in each market like two separate risk neutral investors, and (ii) their discounted expectation of subsequent period earnings and price is the current equilibrium price and, at that price, an uninformed transitory speculator participating in the market would not take a position due to their aversion to variation in payoffs.

realization of a mean 0 normally distributed random variable with variance σ^2, which is independent of all other random variables.

A transitory speculator who enters in period t and decides to follow firm i and participate in its equity market takes a position in firm i's equity claim as well as the risk-free security in period t, which are then closed out when they depart the model in period $t+1$. Formally, after entering the market for i in period t, a speculator learns all information regarding i that is available to i's equity market participants, Ω_{it}, and the private information realization regarding i, x_{it}. The speculator then chooses their demand d_{sit}, where the subscript s denotes the speculator, to maximize

$$E\left[d_{sit}\left(\tilde{e}_{it+1}+\tilde{P}_{it+1}\right)+(1+r)\left(W_{ts}-d_{sit}P_{it}\right)-\frac{c}{2}d_{sit}^{2}|\Omega_{it},x_{it}\right], \tag{3}$$

where W_{ts} is their initial wealth, and $c>0$ is an incremental cost parameter for holding a position in i's equity. The incremental $\frac{c}{2}d_{sit}^2$ crudely reflects the cost of being exposed to the risks of holding i over that time frame. It captures the idea that speculators tend to be less diversified than typical investors and, accordingly, more sensitive to firm-specific risks. From a modeling perspective, the introduction of this additional cost is a parsimonious way to bound demands.[9]

An important, and novel, assumption in our model concerns the evolution of private information quality in each period, as well as the knowledge of that evolution. In particular, one of the two firms offers greater information gathering opportunities in each period, which we model by assuming that $q_{at}\in\{q_h,q_l\}$ and $q_{bt}\in\{q_h,q_l\}$, where $q_h>q_l$, and that, if firm a's private information quality is q_h (q_l), then b's private information quality is q_l (q_h). The firms' relative information qualities follow a simple Markov process, where $\rho\in\left(\frac{1}{2},1\right)$ denotes the persistence of the relative information quality. In particular, if firm a offers the high (low) quality private information in period t, the probability that it offers the high (low) quality private information in period $t+1$ is ρ.

Given the evolution of the two firms' information environments, the critical assumption in the model is that the transitory speculators arriving at date t know all of the model primitives except for the values of q_{at} and q_{bt} *before* making their firm-following decisions. Instead, we assume they must make their decision based upon a small set of information, which is the extent to which each firm was followed in period $t-1$, α_{t-1} and $1-\alpha_{t-1}$, as well as the previous periods' prices and

[9]To bound informed demands in models such as ours, a common assumption is that speculators are risk averse with a negative exponential utility function. Such an assumption yields parsimonious linear demand functions and information gathering decisions when state variables are normally distributed. That is not the case in our model because period-t beliefs about prices in period $t+1$ are not normally distributed due to the time-varying quality of private information.

earnings, $\{P_{at-1}, e_{at-1}, P_{bt-1}, e_{bt-1}\}$. This information set is consistent with the kind of data that actual speculators could easily access prior to deciding where to focus their information gathering efforts, in the sense that standard databases include simple financial statistics as well as analyst following measures.[10] With this information, the entering transitory speculators employ a screen to determine which firm offers a greater opportunity for profitable private information acquisition. Finally, *after* entering transitory speculators decide to follow firm i and begin to participate in its equity market, they learn firm i's private information quality because they become knowledgeable about that firm's information environment. We assume that the dedicated investors participating in firm i's equity market are also knowledgeable about the firm's information environment (i.e., private information quality) due to their continuing presence.

We make one technical assumption to ensure that in every period both firms are followed by at least some speculators (i.e., we have an interior solution in the information/acquisition game). In particular, we assume that $q_l^2 > \frac{\sigma^2}{\left(\frac{1}{c}\right)^2\left(\frac{1+r}{1+r-\lambda}\right)^2 q_h^2+\sigma^2} q_h^2$. This condition ensures that even when investors are extremely certain that the private information about one firm is of low quality, some investors will still follow that firm.

2.1 Equilibrium Characterization

Our model extends a standard static noisy rational expectations equilibrium structure into an infinite horizon model involving transitory speculators. As such, an equilibrium is defined by a pricing function for each firm and period, P_{it}, that is a function of the state in that period (i.e., earnings and price history, private information, speculator following, and noise trade), and by a transitory speculator following for each firm and period, α_{it}, that is a function of the entering transitory speculators' information. The equilibrium should satisfy three conditions: (i) the pricing functions clear the market each period, (ii) no transitory speculator can be made better off by altering their firm-following decision, and (iii) the beliefs of all investors/speculators are formed in a Bayesian manner and are equilibrium consistent (i.e., satisfy rational expectations). Accordingly, we begin our characterization of equilibrium by determining an equilibrium pricing function for each period given that period's allocation of transitory speculators. We use that pricing characterization to then determine the allocation of transitory speculators each period as a function of their beliefs

[10] Note that, in equilibrium, the simple information set that we impose, and α_{t-1} in particular, is a sufficient statistic for the entire history of firm-following, prices, and earnings up until $t-1$ with respect to inferring q_{at} and q_{bt} (and q_{at-1} and q_{bt-1}). Hence, augmenting the entering transitory speculators information set to include the entire past history of prices and earnings would have no effect on our equilibrium characterization.

about each firm's information environment, as characterized by the probability that each firm offers the higher quality private information gathering opportunities. Finally, given the pricing functions and transitory speculator allocations, we characterize how entering transitory speculator beliefs must evolve over time. During each step of the process, we satisfy the third requirement of equilibrium by forcing investor/speculator beliefs to be formed in a Bayesian manner and to be equilibrium consistent. In our characterization of the equilibrium in the main text below, we intuitively describe the equilibrium, which is supported with a more rigorous equilibrium derivation in Appendix A.

Infinite horizon overlapping generations models such as ours are known to have multiple equilibria absent some other restrictions on equilibrium (e.g. transversality conditions) that effectively rule out, say, bubbles or sunspot equilibria. As a consequence, we follow the antecedent literature and focus on highly intuitive dynamic linear equilibria in which price is linear in the contemporaneous state variables, e, x_{it}, and n_{it}, and in which the coefficient on e is the same across periods whereas those on x_{it} and n_{it} vary over time. Such equilibria are not only consistent with antecedent literature, but also result in equilibrium pricing that is consistent with discounted expected earnings/cash flows valuation frameworks.

Because dedicated investors are risk neutral, the market clearing price in each period must make them indifferent to holding shares. As a result, we can pin down a linear equilibrium price function,

$$P_{it} = Me_{it} + \beta_{ixt}x_{it} + \beta_{int}n_{it}, \tag{4}$$

where $M = \frac{\lambda}{1+r-\lambda}$, $\beta_{ixt} = \frac{1}{1+r-\lambda}\frac{\left(\frac{\alpha_{it}}{c}(M+1)q_{it}\right)^2}{\left(\frac{\alpha_{it}}{c}(M+1)q_{it}\right)^2+\sigma^2}$, $\beta_{int} = \frac{1}{1+r-\lambda}\frac{\frac{\alpha_{it}}{c}(M+1)q_{it}^2}{\left(\frac{\alpha_{it}}{c}(M+1)q_{it}\right)^2+\sigma^2}$, and P_{it} is the discounted expectation of the sum of firm i's period $t+1$ price and dividend, which equals the period $t+1$ earnings.

The coefficient M (or multiple) on earnings, e_{it}, is constant over time and reflects the capitalization of current period earnings. That capitalization is decreasing in the discount rate, r, and is increasing in earnings persistence, λ. When earnings follow a random walk, $\lambda = 1$, the coefficient effectively reflects the value of the perpetuity of expected earnings. With mean reversion, $\lambda < 1$, the multiple is smaller as investors do not expect current earnings to be paid in perpetuity.

The coefficient β_{ixt} on the private information, x_{it}, equals a capitalization multiple, $\frac{1}{1+r-\lambda}$, times an information content coefficient, $\frac{\left(\frac{\alpha_{it}}{c}(M+1)q_{it}\right)^2}{\left(\frac{\alpha_{it}}{c}(M+1)q_{it}\right)^2+\sigma^2}$, that determines the extent to which price or, equivalently, total net demand reflects x_{it}. The capitalization multiple differs from that on current earnings by a factor of λ because the expectation of next period earnings, e_{it+1}, conditioned on this period's earnings, e_{it}, is λe_{it}, whereas the expectation of next period earnings conditioned upon x_{it} is x_{it}. The information content coefficient is increasing in the proportion of speculators in the firm's market, α_{it}, and decreasing in the incremental cost the informed speculators bear to hold a position, c, because more private information is impounded into price when there are more speculators trading more aggressively on their information. The information content coefficient is also increasing in the quality of the private information, q_{it}^2, and decreasing in the extent of noise trade, σ^2, because the signal-to-noise ratio about the private information captured from price is increasing in the quality of the signal, captured by q_i^2, and decreasing in the noise, captured by σ^2. Finally, the coefficient on the noise trade is very similar to that on the private information. The reason for this commonality stems from the fact that dedicated investors effectively use the demand implied by the price to infer the private information. Because the demand is an aggregation of the private information and noise trade, the noise trade has a similar coefficient to that on the private information.

When entering transitory speculators decide which firm to follow in period t, their decision is determined by their beliefs regarding which firm offers a greater expected profit from informed trade. The expected profit for following each firm, in turn, is increasing in the quality of the private information that will be obtained about the firm and decreasing in the proportion of transitory speculators who follow the firm. Hence, in equilibrium, transitory speculators will gravitate toward the firm that is expected to offer the higher quality private information and they will do so until the higher following for that firm equates the expected profits for following each firm.

The novel aspect of our model is that entering transitory speculators do not know the private information quality. Instead, they determine the probability that a and b offer the higher quality private information given the information available to them, which is the following choices of previous transitory speculators, α_{t-1} and $1-\alpha_{t-1}$ respectively, and the prices, P_{at-1} and P_{bt-1}, and earnings, e_{at-1} and e_{bt-1}. The variables in their information set, in equilibrium, convey information about the private information quality offered by each firm in period t because of the assumed persistence of the information environment (i.e., if $q_h = q_{at-1} > q_{bt-1} = q_l$ then it is more likely than not that $q_h = q_{at} > q_{bt} = q_l$). The period $t-1$ following decision informs beliefs about the quality of private information offered by each firm in period t because those decisions convey the previous generation's beliefs about which firm offered the higher quality private information in $t-1$. The previous period prices and earnings are informative about which firm actually offered higher quality private information in $t-1$, because the deviation of the realized price from the expected price conditional upon the earnings conveys the extent of other information impacting price, which is directly related to the quality of private information the informed speculators traded upon. Given that $\{\alpha_{t-1}, P_{at-1}, e_{at-1}, P_{bt-1}, e_{bt-1}\}$ determines the entering transitory speculator beliefs about which firm will offer the higher quality private information in period t, those beliefs, in turn, determine the equilibrium speculator following for period t.

In summary, we offer Proposition 1, which as noted earlier, is formally derived in the appendix.

Proposition 1. *There exists a unique dynamic linear equilibrium characterized by: (i) the pricing function* $P_{it} = Me_{it} + \beta_{ixt}x_{it} + \beta_{int}n_{it}$ *for each period* t *as a function of the allocation of transitory speculators for period* t*; and (ii) the evolution of the allocation of transitory speculators over time, where the allocation for period* t, α_t, *is a function of entering transitory speculator beliefs about each firm's likelihood of offering the higher quality private information in period* t, *which are determined by* $\{\alpha_{t-1}, P_{at-1}, e_{at-1}, P_{bt-1}, e_{bt-1}\}$.

2.2 Empirical Implications: Attention and Price Deviations

Our model provides three clear testable empirical implications related to realized price deviations from expected prices conditioned upon earnings. Those implications are summarized in the following Corollary.

Corollary 1. *In the unique dynamic linear equilibrium, if the deviation of firm* i*'s period* $t-1$ *price from the expected price conditioned on* i*'s period* $t-1$ *earnings increases,* $|P_{it-1} - Me_{it-1}|$, *then*

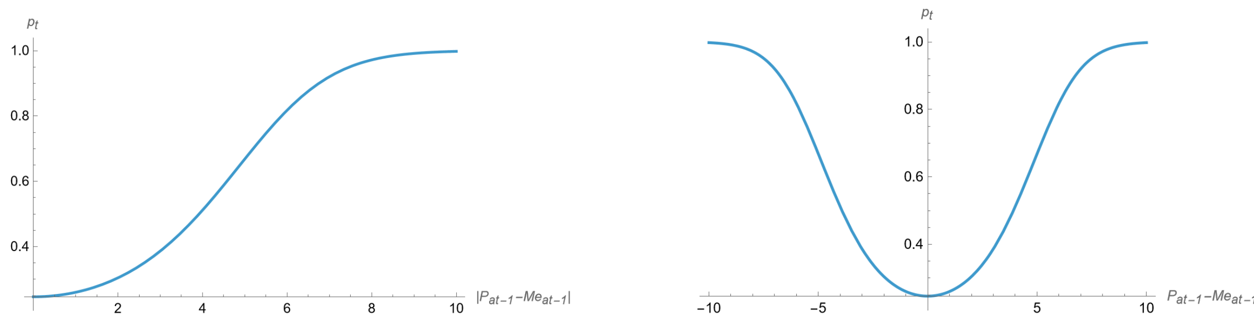
(i) *the proportion of period* t *transitory speculators following firm* i *increases and the proportion following firm* j *decreases;*

(ii) *the variance of the period* t *price change for firm* i*'s claims increases and that for firm* j*'s claims decreases; and*

(iii) *the period* t *trading volume for firm* i*'s claims increases and that for firm* j*'s claims decreases.*

Part (i) of Corollary 1 suggests that a firm whose price deviates more from the expected price given the screening variables, which is a simple multiple in our model, should naturally attract more attention from speculators who rely on screens to determine which firm to follow. Deviations from that expected price suggest to entering transitory speculators that there is more private information being impounded into the price. However, the deviation from the expected price could also be due to noise trade, which makes the deviation an imperfect signal of the quality of private information.

Figure 2 shows that the probability that a firm has a high private information quality is increasing in the absolute price deviation, $|P_{it-1} - Me_{it-1}|$. Because a higher information quality increases the expected profits from informed trading, more speculators will follow the firm. This further implies that the attention by speculators in a firm is a U-shaped function of the firm's signed price deviation.



(a) absolute price deviation

(b) signed price deviation

Figure 2 Conditional probability that firm a has a high private information quality as a function of firm a's absolute unexplained price deviation (Panel a) and firm a's absolute unexplained price deviation (Panel b).

As an aside, we emphasize that the equilibrium price at any point in time reflects a correct expectation given the information available to all market participants. This implies that the deviation from the expected price itself is not informative about the content of the private information and, thus, does not offer a trading opportunity. Instead, it signals an information acquisition opportunity. Hence, the deviation is informative in the market for information even though it is not informative in the market for cash flows. This reasoning further implies that when there is no uncertainty about the quality of private information (i.e., when $q_h = q_l$), or if there is no persistence in the information environment (i.e., when $\rho = \frac{1}{2}$), then entering speculators will not use past prices and earnings at all.

Part (i) also suggests that when a peer firm exhibits a larger deviation from expected price given the screening variables, a firm will attract less attention from speculators who rely on screens. This implication arises from the screen informativeness regarding uncertain private information quality coupled with the assumption that a speculator can follow only one firm due to limited attention. The real-world implication of this part of Corollary 1 is, perhaps, somewhat tenuous given that individuals could choose to allocate their attention to many different firms, so that we do not know which set of peer firms the average investor is looking at.

Parts (ii) and (iii) of Corollary 1 establish links between unexplained price deviations in one period and observable market characteristics in a subsequent period, which arise because of the link between unexplained prices and transitory speculator following. The intuition underlying part (ii) of Corollary 1 is quite straightforward: a larger realization for $|P_{i1} - Me_{i1}|$ increases period t entering transitory speculators' probabilistic assessment that firm i offers higher quality private information, which implies that i's market attracts a greater proportion of speculators and j's market attracts a smaller proportion of speculators. As a consequence there is more (less) informed trade for firm i (j) claims, which leads to more (less) movement in prices for i (j). The intuition for part (iii) of Corollary 1 is identical to that for part (ii). That is, a larger unexplained price attracts more speculators to the market, which increases trading volume associated with informed speculator demands.

Finally, we close the discussion linking speculator following and unexplained price deviations by offering an aside about the other state variable in the period t entering speculators' information set, which is the prior period speculator following, α_{t-1}. There is, not surprisingly, a positive relation between prior period following and *unconditional* expected current period following (i.e., when the unexplained price deviations are not known). However, there is no monotonic relation between prior period speculator following and current period speculator following *conditional* upon a set of prior period unexplained price deviations. We do not focus on the relation between prior period speculator following and current period speculator following in our empirical analysis for two reasons. First, as just noted, the relation given the entering speculators full information set is theoretically ambiguous. Second, the model omits any notion of a dedicated following (that is, investors that acquire information over multiple periods). While introducing dedicated following into the model has no substantive impact on Proposition 1 or Corollary 1, it would clearly have implications for any assessment of the lagged relation in following. That is, a positive relation between prior period following and current period following would be expected to arise in the cross section of firms even if the past following contains no information about the quality of private information. While the relation between prior period following and current period following is not the focus of our empirical analysis, however, we do endeavor to control for prior period following in our empirical assessment of the relation between unexplained price deviations and speculator following.

3 Sample and Data

We use a comprehensive sample of publicly traded U.S. firms' earnings announcements from 2004 to 2022 to test Corollary 1. Our sample of earnings announcements comes from the intersection of Compustat and IBES. We use the next trading day if the announcement is after trading hours and use the earlier of the Compustat and IBES announcement dates if they differ, following DellaVigna and Pollet (2009). We obtain stock price and trading volume data from CRSP. We also use Compustat to obtain control variables such as financial leverage, total assets, and short interest, Thomson Reuters to obtain institutional ownership data, WRDS SEC Analytics Suite to obtain voluntary disclosure data, RavenPack to obtain data on media stories, and IBES to obtain management guidance information.

We empirically test whether deviations of observed price from expected price (e.g., based on earnings realizations) are related to investors' subsequent information acquisition activities. If investors are using these types of screens to allocate their information acquisition efforts, we would observe that investors acquire more information when a firm has large positive or negative price deviations, because such deviations suggest higher returns to information acquisition.

In our model, the expected price is calculated as a simple multiple of earnings. To capture this intuition from our model, we calculate our empirical measure of abnormal price, $AbnPrice$, as the absolute difference between the observed price and the expected price, scaled by the expected price. We compute the expected price as realized earnings multiplied by an industry-and-size-matched price-to-earnings multiple, which serves as a proxy for the analytical model's multiple on earnings. Although we expect investors in practice to base expected price on other publicly available metrics in addition to earnings, our empirical tests base price expectations on earnings and prices, which are simple and commonly available.[11]

Next, to capture investors' private information acquisition, we employ two empirical measures, one based on the SEC Edgar downloads and the other based on Bloomberg terminal attention. These measures represent private information acquisition as a costly process of extracting value-relevant information about firms from publicly available sources (Blankespoor et al., 2020; Indjejikian, 1991). Examples of investors' private information acquisition activities include reading contracts and com-

[11] Since price-to-earnings multiples cannot be interpreted when earnings is negative, we calculate $AbnPrice$ only for those observations where earnings is positive. In robustness tests, we use an alternative, changes-based measure of abnormal price which does not require earnings to be positive. This alternative measure uses a firm as its own benchmark, allowing us to account for firm-specific variation in abnormal price deviations. We also include firm fixed effects throughout our analyses to account for firm-specific variation in expected prices.

plex filings (which can be downloaded from Edgar), analyzing the news through proprietary data platforms (e.g., via Bloomberg), and talking with suppliers or conducting site visits (which are unobservable). We download Edgar search volume data from the SEC's Edgar website and remove robot downloads, following Drake et al. (2015).[12] We download Bloomberg attention data from Bloomberg terminals, which captures the intensity of Bloomberg users attention to different firms. Both measures have the advantage of capturing information acquisition from investors with some degree of sophistication. Users downloading company filings from Edgar are sophisticated enough to be aware of and read financial statements, and Bloomberg terminals are primarily used by institutional investors. These measures are available for different sample periods and they encompass information acquisition from different sources, enhancing the robustness of our findings through triangulation. We measure Edgar search volume and Bloomberg abnormal institutional investor attention over the quarter, beginning after the earnings announcement date and ending before the next earnings announcement date. This window maps directly to the current period's firm-following decision from Corollary 1, which is a function of the prior period's price and earnings (i.e., $|P_{it-1} - Me_{it-1}|$). In additional analyses, we assess the robustness of our results to using a shorter window of five days after the earnings announcement.

Our primary sample consists of 87,493 firm-quarters when examining Edgar search volume, due to the Edgar search volume coverage from 2004 to 2016.[13] Our primary sample when examining Bloomberg attention consists of 59,895 firm-quarters, due to the Bloomberg data coverage from 2010 to 2022. Table 1 reports summary statistics for the variables used in our analysis. For ease of interpretation, we present summary statistics for the raw variables prior to ranking or log transformations. The unit of analysis is a firm-quarter. Panel A reports statistics for the 2004-2016 sample used in the Edgar analysis. Panel B reports statistics for the 2010-2022 sample used in the Bloomberg analysis. All variables are defined in Appendix B. The summary statistics in Panel A reveal that the average firm-quarter has 2,025.11 Edgar downloads after the earnings announcement. The summary statistics in Panel B reveal that the average firm-quarter has a sum of 21.50 in Bloomberg readership, which is the sum of the Bloomberg heat index ranging from 0 to 4 on each firm-day.

[12]Raw data on Edgar filing downloads is available at https://www.sec.gov/about/data/edgar-log-file-data-sets. Ryans (2017) provides a processed version of the log file that removes robot downloads.

[13]We begin our sample in 2004, because Edgar downloads are sparsely populated in 2003.

4 Empirical Results

4.1 Main Results: Abnormal Price and Information Acquisition

We begin by testing part (i) of Corollary 1. Specifically, we test whether larger deviations of price from expected price attract greater information acquisition from speculative investors. We estimate the following regression using the sample of firm-quarters with available data to compute each information acquisition proxy:

$$InfoAcq_{i,t+1} = \beta_1 AbnPrice_{i,t} + \gamma Controls_{i,t} + \Sigma\beta_i Firm_i + \Sigma\beta_t Year\text{-}Quarter_t + \epsilon_{i,t+1}, \tag{5}$$

where $InfoAcq_{i,t+1}$ is one of several measures of information acquisition for firm i in a particular period $t+1$ following the earnings announcement. $AbnPrice_{i,t}$ is the within-quarter percentile rank of the abnormal price, calculated as the absolute percentage difference between firm i's observed price at the earnings announcement and its expected price based on realized earnings and a price-to-earnings multiple matched by industry and firm size. Ranking this variable mitigates the impact of outliers and, compared to using the raw values, better reflects the spirit of the model.[14] A positive β_1 suggests that larger deviations from expected price attract greater information acquisition from speculative investors using information acquisition screens to make a firm-following decision.

Our primary specification includes a vector of control variables, $Controls_{i,t}$, to account for factors that affect information acquisition but that do not directly reflect the profitability of private information acquisition opportunities. These controls include financial leverage, firm size, the presence of a bundled management forecast, institutional ownership, short interest, voluntary 8-K disclosures, and media stories. The inclusion of the control variables $log(Assets)$, $BundledForecast$, $Voldisc8k$, and $MediaStories$ accounts for the general extent to which information about the firm is available. We include $Leverage$, $Instown$, and $Shortsell$ to control for variation in demand for information, based on the type and sophistication of investors that seek information about the firm (i.e., creditors, institutional investors, and short sellers, following Drake et al., 2015).[15]

[14] Specifically, in the model, a speculative investor's capacity to acquire information is limited to only one of two firms. Therefore, the relative ranking of the firm's price deviation matters when making the firm-following decision (e.g., if speculators only have enough capacity to acquire information about the top X firms, whether or not a firm is in the set of top X firms matters more than the difference in raw price deviation between the firm with rank X and the firm with rank $X+1$).

[15] As each of these control variables affects the supply of or demand for information, investors potentially use the control variables as inputs to their information acquisition screens. Our intuition from the model is that a simple screen based on stock price can help investors assess the returns to information acquisition. Therefore, by controlling

We include Firm and Year-Quarter fixed effects, which subsume any variation constant within firm and quarter. For our main results, we also estimate an alternative specification that includes a control for lagged information acquisition and replaces Firm fixed effects with Industry fixed effects defined by 2-digit SIC codes. Reflecting the model's assumption that historical information acquisition decisions are publicly observable, Firm fixed effects absorb firm-specific variation in information acquisition and the control for lagged information acquisition directly controls for the speculators' information acquisition from the previous period.[16] Year-Quarter fixed effects address potential time trends in the nature of information and noise trade properties such as those driven by technological changes, regulations, or other macroeconomic shocks. We cluster standard errors by Firm, which allows for within-firm correlation over time.

Table 2 presents regression results estimating several versions of Equation (5). Columns 1 and 4 estimate versions of Equation (5) that exclude control variables, columns 2 and 5 estimate the primary specification, and columns 3 and 6 estimate versions of Equation (5) that include a lagged dependent variable and replace the Firm fixed effects with Industry fixed effects. Across all columns, we find support for the prediction in part (i) of Corollary 1. Information acquisition is greater when $AbnPrice$ reflects larger deviations from expected price. The results in Table 2 imply that an increase in $AbnPrice$ is associated with more Edgar downloads (columns 1 to 3) and more Bloomberg news attention (columns 4 to 6) in the subsequent quarter. Overall, the results in Table 2 are consistent with the model's prediction that information acquisition increases in the absolute value of the deviation of price from it's conditional expectation.

To strengthen our inferences, we further test whether the data support the model's prediction about the information that speculators can learn from past prices. In particular, because the conditional probability that the private information is of high quality is increasing the absolute value of the price deviation, $|P_{it-1} - Me_{it-1}|$ (see panel a of 2), the model implies that information acquisition is U-shaped in the *signed* price deviation (as in panel b of figure 2). To test whether this U-shape is present in the data, we plot Edgar downloads and Bloomberg attention against the signed price deviation, $AbnPrice\_Signed$. Specifically, to account for firm and time effects, we first regress Edgar downloads on Firm and Year-Quarter fixed effects and obtain the residuals. In Panel (a) of

for non-price-based variables, our empirical tests measure the relation between future information acquisition and price deviations that is incremental to other information environment indicators. Nevertheless, for completeness, we present results with and without the inclusion of these control variables.

[16] We do not implement Firm fixed effects and the control for the lagged dependent variable both in the same specification because they require different identifying econometric assumptions. Angrist and Pischke (2009) suggest assessing the robustness of the findings to multiple identifying assumptions and using them to bound the effect size.

Figure 2, we plot the average residual for each value of *AbnPrice_Signed* (ranks ranging from 1 to 100), along with the quadratic fitted value prediction. In Panel (b), we use the same methodology with the Bloomberg attention measure. The plots suggest that information acquisition on both Edgar and Bloomberg tends to be U-shaped in the signed abnormal price deviation.

Corollary 1 not only predicts that information acquisition about firm i is greater when its *AbnPrice* reflects larger deviations from its expected price, but also that it is smaller when a peer firm j's *AbnPrice* reflects larger deviations from firm j's expected price. In effect, abnormal prices elsewhere in the market draw attention away from the focal firm because these two firms compete for investors' limited information acquisition capacity.[17]

To test this prediction, we conduct a matched-peer analysis, in which we match each firm with a peer firm from the same industry that announces earnings on the same day as the focal firm and is closest in asset size. To ensure that the two firms are comparable in terms of asset size, we retain matches where the larger firm's asset size is less than 1.5 times the smaller firm's, and the size difference between the two firms is less than \$100 billion. When there are multiple such matches, we retain the matched peer with the smallest difference in asset size. This process results in a smaller sample than in Table 2, consisting of 45,619 firm-quarters in the Edgar sample and 29,597 firm-quarters in the Bloomberg sample. Using this sample, we estimate versions of Equation (5) that include the abnormal price of the peer firm (*AbnPricePeer*) as an additional explanatory variable.[18] Table 3 reports the estimation results. The results are broadly consistent with Corollary 1's prediction that a larger *AbnPricePeer* is associated with reduced information acquisition about the focal firm. Table 3 finds that *AbnPrice* and *AbnPricePeer* have opposite associations with Edgar downloads (columns 1 to 3) and Bloomberg news attention (columns 4 to 6) in the subsequent quarter. In sharp contrast to the results for the focal firm's abnormal price, *AbnPricePeer* is associated with *fewer* Edgar downloads about the focal firm. Similarly, *AbnPricePeer* is associated with *reduced* Bloomberg attention about the focal firm. Collectively, our empirical findings suggest that entering speculators rely on abnormal price deviations as screens to allocate their information acquisition

[17] Our model only includes two firms, and it does not account for the possibility that deviations in a peer firm's price can draw additional attention to the focal firm, if investors acquire information about comparable firms. Although outside of the model, we acknowledge that this possibility makes it unclear ex-ante whether the empirical tests will find a negative association between a peer firm's abnormal price and the focal firm's information acquisition. To account for industry-specific and market-wide sources of shared variation in information acquisition across firms, we use Industry fixed effects and Year-Quarter fixed effects in one of our regression specifications.

[18] Consistent with the rest of the analyses, we percentile-rank the matched peer's abnormal price, *AbnPricePeer*, within each Year-Quarter.

efforts toward firms with abnormal price deviations, and away from other firms, consistent with the model's intuition that such deviations imply higher returns to information acquisition.

4.2 Main Results: Abnormal Price and Market Outcomes

An important outcome of the model is that, as larger price deviations attract more information acquisition, such information acquisition generates more trade. Thus, part (ii) (and part (iii)) of Corollary 1 posits that subsequent price variance (trading volume) increases with larger price deviations.

We empirically test parts (ii) and (iii) of Corollary 1, including the mechanism underlying their predictions (i.e., information acquisition), by performing a mediated (path) analysis. Our goal with this analysis is to descriptively assess the importance of information acquisition in explaining the association between abnormal price deviations and market outcomes.[19] Prior accounting research has used path analysis to test whether a relationship between X and Y arises through path Z (e.g., Bonsall IV, Green, and Muller III, 2018, 2020). Our analysis mirrors this research design to test whether information acquisition is an important mechanism underlying the association between larger price deviations and increased return variance and trading volume (MacKinnon, 2012). Specifically, we use a structural equation model to estimate the mediation effect as the change in the coefficient on *AbnPrice* when information acquisition (*EdgarSearch*, *Bloomberg*) is included as a mediator in the regression of future market outcomes on *AbnPrice* (MacKinnon and Dwyer, 1993). We first estimate the association between *AbnPrice* and future market outcomes (the total effect) as follows:

$$\begin{aligned} MarketOutcome_{i,t+1} = \beta_1 AbnPrice_{i,t} + \\ \gamma Controls_{i,t} + \Sigma\beta_i Firm_i + \Sigma\beta_t Year\text{-}Quarter_t + \epsilon_{i,t+1}, \end{aligned} \tag{6}$$

where $MarketOutcome_{i,t+1}$ is either the standard deviation of returns ($RetVariance$) or trading volume ($TradingVol$), measured over the subsequent quarter. Then, to estimate the importance of information acquisition in explaining this association, we include information acquisition in the

[19] This analysis is descriptive, as we acknowledge that there could be unobserved variables omitted from the regressions that could lead to the patterns we document. Mediated analysis, just like the ordinary-least-square (OLS) analysis, relies on the identifying assumption that the error terms in the mediator equation and the dependent variable equation are uncorrelated. To the extent these identifying assumptions are violated, our results are subject to endogeneity concerns, which limits our ability to draw strong causal inferences. Please see (Lennox and Payne-Mann, 2023) for further discussion of mediated analysis and recommendations for best practices.

regression:

$$
\begin{aligned}
MarketOutcome_{i,t+1} = \beta_1 AbnPrice_{i,t} + \beta_2 InfoAcq_{i,t+1} + \\
\gamma Controls_{i,t} + \Sigma\beta_i Firm_i + \Sigma\beta_t Year\text{-}Quarter_t + \epsilon_{i,t+1},
\end{aligned}
\tag{7}
$$

where $InfoAcq_{i,t+1}$ is either Edgar downloads or Bloomberg investor attention, measured over the subsequent quarter. Comparing the estimates from equation (6) to the estimates from equation (7) allows us to decompose the total effect as the sum of: (i) the direct effect from abnormal price to future market outcomes (path I: $AbnPrice \rightarrow MarketOutcome$, estimated by equation (7)), and (ii) the indirect effect through information acquisition as the mediated path. The indirect effect is the product of the mediated paths between abnormal price and information acquisition (path II: $AbnPrice \rightarrow InfoAcq$, estimated by equation (5)) and between information acquisition and future market outcomes (path III: $InfoAcq \rightarrow MarketOucome$, estimated by equation (7)).

Table 4 reports the results of the path analysis.[20] In Panel A, columns 1 and 2, we decompose the relation between abnormal price ($AbnPrice$) and subsequent return variance ($RetVariance$) into the direct path, and the indirect mediated path through information acquisition on Edgar ($EdgarSearch$). The direct path (path I) between abnormal price and subsequent return variance is positive and significant after accounting for the mediator variable $EdgarSearch$. The mediated path has two components, the path between abnormal price and information acquisition (path II) and the path between information acquisition and return variance (path III). The mediated path (path II $\times$ path III) is also positive and significant, suggesting an indirect effect of 0.0001, which is 3.3% of the total effect of 0.003. Note that the total effect is the sum of the direct and indirect effects. Panel B reports the underlying mediated regression results using ordinary least squares. Column 1 estimates equation (6), and column 2 estimates equation (7) after including $EdgarSearch$ as the $InfoAcq$ variable. Consistent with abnormal price affecting return variance through information acquisition on Edgar, $EdgarSearch$ loads significantly once included in the regression and its inclusion lowers the significance of the $AbnPrice$ variable.[21] Overall, the estimation results support our inference

[20] In an untabulated analysis, we repeat the path analysis using our alternative research design that includes an explicit control for lagged information acquisition with industry fixed effects instead of firm fixed effects. All our inferences remain unchanged.

[21] As expected, the coefficient estimate on $AbnPrice$ in column 1 corresponds to the total effect (I + II $\times$ III) reported in Panel A. The coefficient estimates on $AbnPrice$ and $EdgarSearch$ in column 2 correspond to the direct path (path I) and the mediated path from $EdgarSearch$ to $RetVariance$ (path III), respectively. The mediated path from $AbnPrice$ to $EdgarSearch$ (path II) is estimated as part of our main analysis reported in Table 2.

that information acquisition on Edgar explains the positive association between abnormal price deviations and subsequent return variance.

Similarly, the results in Table 4, Panel A, columns 3 and 4 decompose the relation between abnormal price and subsequent trading volume ($TradingVol$) into the direct path and the mediated path through information acquisition on Edgar. The direct path (path I) between abnormal price and subsequent trading volume is positive but insignificant after accounting for the mediator variable $EdgarSearch$. In contrast, the mediated path through information acquisition on Edgar (path II $\times$ path III) is positive and significant, and the estimated indirect effect is 0.008, which is more than half of the total effect of 0.014. We report the underlying mediated regression results in Panel B. The mediating variable, $EdgarSearch$ is positive and significant in column 4 of Panel B, and its inclusion lowers the significance of the $AbnPrice$ variable compared to the results reported in column 3.[22] Overall, the findings support our inference that information acquisition on Edgar explains a substantial portion of the positive association between abnormal price deviations and subsequent trading volume.

Panels C and D of Table 4 use information acquisition on Bloomberg ($Bloomberg$) as the mediating variable to find similar results. Panel C reports the direct, indirect, and total effects from the path analysis, and Panel D reports the underlying regressions for these effects.[23] The results in Panel C, columns 1 and 2, suggest that abnormal price affects subsequent return variance both directly and indirectly through information acquisition on Bloomberg terminals. The direct path (path I) between abnormal price and subsequent return variance is positive and significant after accounting for the mediator variable $Bloomberg$. The mediated path (path II $\times$ path III) is also positive and significant. The mediated path has two components, the path between abnormal price and information acquisition (path II) and the path between information acquisition and return variance (path III). The product of these two paths is the indirect effect (0.0001), which is 10% of the total effect of 0.001. This finding suggests that information acquisition on Bloomberg explains the positive association between abnormal price deviations and subsequent return variance.

[22] The coefficient estimate on $AbnPrice$ in column 3 corresponds to the total effect (I + II $\times$ III) reported in Panel A. The coefficient estimates on $AbnPrice$ and $EdgarSearch$ in column 4 correspond to the direct path (path I) and the mediated path from $EdgarSearch$ to $TradingVol$ (path III), respectively. The mediated path from $AbnPrice$ to $EdgarSearch$ (path II) is estimated as part of our main analysis reported in Table 2.

[23] Columns 1 and 3 of Panel D report results from estimating equation (6). Columns 2 and 4 of Panel D report results from estimating equation (7) after including $Bloomberg$ as the $InfoAcq$ variable. The coefficient estimates on $AbnPrice$ in columns 1 and 3 correspond to the total effects (I + II $\times$ III) reported in Panel C. The coefficient estimates on $AbnPrice$ and $Bloomberg$ in columns 2 and 4 correspond to the direct paths (path I) and the mediated paths from $Bloomberg$ to the outcome variables (path III), respectively. The mediated path from $AbnPrice$ to $Bloomberg$ is estimated as part of our main analysis reported in Table 2.

In Table 4, Panel C, columns 3 and 4, we repeat the analysis to examine whether information acquisition on Bloomberg is an important channel through which abnormal price deviations affect subsequent trading volume. We find that the direct path (path I) between abnormal price and subsequent trading volume is positive and significant after accounting for the mediator variable $Bloomberg$, and the mediated path through information acquisition on Bloomberg (path II $\times$ path III) is also positive and significant. The estimated indirect effect is 0.004, which is 13.8% of the total effect of 0.029. This finding suggests that information acquisition on Bloomberg explains the positive association between abnormal price deviations and subsequent trading volume. Combined with the matched-peer analysis results from Table 3, the results in this section imply that subsequent price variance and trading volume are increasing in the focal firm's abnormal price and decreasing in the matched-peer firm's abnormal price through their effects on information acquisition.

4.3 Additional Analyses

Our main results show that information acquisition is greater when firms' prices deviate more from expected prices. In this section, we present several additional analyses that address alternative explanations and provide more refined insights into the model's predictions.

First, we address the alternative explanation that our results reflect reverse causality. A positive relation between post-announcement attention and abnormal prices could be explained by higher pre-announcement attention that both leads to higher announcement returns and continues post-announcement. Our regression specifications presented in columns (3) and (6) of Table 2 address this concern to some extent by controlling for the pre-announcement information acquisition measured over the previous quarter. Nonetheless, to further address this alternative explanation, we re-estimate the relation between abnormal price movements and subsequent information acquisition after incorporating an explicit control for pre-announcement attention in the short window (i.e., 5 days) before the announcement. We continue to find a significantly positive relation between abnormal price movements and subsequent information acquisition (untabulated).

Next, to explicitly remove the effects of the existing investors from the earlier periods who could continue their pre-announcement attention, we focus only on *new* entering speculators. By definition, these speculators did not follow the firm pre-announcement and their attention therefore cannot simply continue from the pre-announcement period. We estimate a version of Equation (5) in which our measures of $InfoAcq$ are $EdgarNew$ and $EdgarNewIPs$, the number of Edgar downloads from new IP addresses and the number of unique new IP addresses, respectively, summed over the subsequent quarter. New IP addresses are those that did not download the firm's filings in the previous period. Table 5 reports results showing that greater price deviations attract information acquisition from new speculators, whose pre-announcement activity by definition could not have caused any abnormal price deviations at the announcement. This finding also provides evidence in support of the model's intuition that entering speculators rely on screens to allocate their information acquisition capacities.[24]

Second,we empirically test an important underlying assumption in the model—that the quality of private information is correlated over time. To this end, we assess the persistence of the extent of price deviation from expected price, which reflects the quality of private information. We present a rank transition matrix in Table 6 Panel A. The matrix shows that firms with $AbnPrice$ decile rank X in one period (row) are more likely to have the same or similar $AbnPrice$ decile rank in the next period (column) than they are to move several decile rankings up or down. This persistence is especially discernible for firms in the top decile of $AbnPrice$, of which 44.8% remain in the top decile in the next quarter. To ensure that this persistence does not stem from price-to-earnings ratios that persistently differ from the industry benchmark per se, we repeat this analysis using abnormal price deviations measured using $AbnPriceChange$, which does not reference an industry price-to-earnings ratio benchmark. We continue to observe a similar pattern of persistence, with 41.4% of firms in the top decile of $AbnPriceChange$ remaining in the top decile in the next quarter (untabulated).

Temporal correlation in returns to information acquisition also suggests that current period price deviations could predict information acquisition for multiple subsequent periods. We investigate this possibility by estimating versions of Equation (5) that replace $InfoAcq_{i,t+1}$ with $InfoAcq_{i,t+2}$ and $InfoAcq_{i,t+3}$. Table 6 Panel B, columns 1 to 3 present results using Edgar downloads. Column 1 reports the main specification for the subsequent quarter (also see Table 2 column 2), column

[24] In an untabulated analysis, we also refine our measures of Edgar downloads by distinguishing between downloads from financial institutions versus non-professional investors. We use WhoWas reports from the American Registry of Internet Numbers (ARIN) to identify the organizations associated with the top 1,500 IP address blocks downloading Edgar filings during our sample period. Following Drake, Johnson, Roulstone, and Thornock (2020), we manually identify financial institutions and internet service providers (ISPs) based on the names of the organizations owning a block of these IP addresses, because the last three digits of the IP address are masked. Financial institutions include investment banks, hedge funds, commercial banks, insurance companies, and other financial institutions. ISPs, such as Comcast and Verizon, could reflect non-professional investors or professional investors working outside of the office. We expect both types to use screens to allocate their attention, as both professional and non-professional investors' information acquisition activities are associated with other firm outcomes (e.g., Kim, 2024). In addition, even the non-professional investors in the Edgar log file data are relatively "sophisticated," because they actively acquire information on Edgar. We find that abnormal price deviations are associated with more information acquisition on Edgar from both financial institutions and non-professional investors.

2 reports results using two-quarters-ahead Edgar downloads, and column 3 reports results using three-quarters-ahead Edgar downloads. Compared to the coefficient of interest in column 1, column 2's coefficient is significantly positive, but smaller in magnitude and column 3's coefficient is significantly positive and even smaller in magnitude. Table 6 Panel B, columns 4 to 6 present results using Bloomberg attention. Column 4 reports the main specification for the subsequent quarter (also see Table 2 column 5), column 5 reports results using two-quarters-ahead Bloomberg attention, and column 6 reports results using three-quarters-ahead Bloomberg attention. Compared to the coefficient of interest in column 4, the coefficients in columns 5 and 6 are smaller in magnitude and significantly positive.

Taken together, our findings suggest that the returns to private information acquisition have some degree of persistence, which provides empirical evidence in support of the assumption that the quality of private information is correlated over time. Furthermore, this persistence in information acquisition suggests that abnormal price deviations reflect persistent gains from high-quality private information as opposed to one-time price spikes due to confounding, non-recurring events. These results are also consistent with speculators relying on the screens to allocate their information acquisition efforts, which in turn signals higher returns to information acquisition in the subsequent period. Consequently, large price deviations predict greater future information acquisition, although this predictability generally decreases over time.

In our third set of additional analyses, we further address concerns about confounding events. To rule out the possibility that investors may be responding directly to non-recurring events, which affect abnormal prices, we obtain a list of non-earnings related 8-K filings that reflect significant but idiosyncratic non-recurring events in the $[t-5, t+5]$ window around earnings announcements. We repeat our analysis after removing the earnings announcements that occur around these unanticipated 8-K filings. We also explicitly control for the number of unanticipated 8-Ks released around our main sample of earnings announcements. In both analyses (untabulated), we continue to find a significantly positive association between abnormal price deviations and information acquisition.

To rule out the possibility that investors may be responding to confounding information events after the earnings announcement, we next assess the robustness of our results to measuring information acquisition using a shorter window of five days [+1, +5] after the earnings announcement. An advantage of using this shorter window is that information acquisition immediately after the earnings announcement is more likely to be motivated by abnormal price at the earnings announcement, thus mitigating confounds. In Table 7, we report the results of estimating versions of Equation (5) that replace the dependent variables with Edgar search and Bloomberg news attention measured in the five days after the earnings announcement. Across all specifications, we find support for the model's prediction using this alternative measurement window. The results in Table 7 imply an increase in $AbnPrice$ is associated with more Edgar downloads (columns 1 to 3) and more Bloomberg news attention (columns 4 to 6) in days $[t+1, t+5]$ after the earnings announcement.

We next rule out the possibility that our results can be explained by confounding industry shocks or firm-specific growth opportunities that are correlated with both unexplained price deviations and information acquisition. To account for unobserved industry-level events, we include Industry $\times$ Year-Quarter fixed effects in all of our main regressions and continue to find similar results (untabulated). To address the concern that information acquisition could increase in response to a firm-specific growth opportunity that is typically associated with high stock prices, we show in Figure 2 that information acquisition on both Edgar and Bloomberg is U-shaped in the signed abnormal price deviation. In the spirit of identification by functional form, the U-shaped relation we document mitigates concerns about alternative explanations and correlated omitted variables that predict a monotone relation between information acquisition and the signed abnormal price deviation. For an omitted variable to be able to explain our results, it would need to posit an alternative economic theory for why the relation flips in sign across the distribution of signed price deviations.

We also examine announcements of unexpected interest rate changes from the Federal Open Market Committee (FOMC) meetings as as an exogenous source of price shocks. Unexpected interest rate changes are macroeconomic events that lead to stock price movements, and individual firms' stock price reactions to such a shock combines both a predictable component shared across firms and an abnormal component specific to each firm, reflecting each firm's exposure, or 'beta,' to interest rate changes. Therefore, it is important to isolate the component of the stock price reaction that is unrelated to firm-specific exposures. Using the industry return as an appropriate benchmark for investors' expectations about a firm's price movement in response to this macroeconomic shock, we decompose the stock price reaction into two parts: one that captures the industry-wide expected component, which is unrelated to firm-specific exposures, and the firm-specific information component, measured by the firm's industry-adjusted return. Consistent with our expectation, in untabulated results, we find that the abnormal firm-specific portion of the price movement is positively and significantly associated with subsequent information acquisition. However, we do not find such an association for the more predictable, industry-wide portion of the price movement.

Fourth, we corroborate the model's intuition using alternative measures of abnormal prices. Our main empirical proxy for abnormal price constructs a screen based on observed prices and realized earnings. Although this measure is a simple proxy for unexplained price movements, the model assumes that the prior means of both the level of earnings and changes in earnings are 0, effectively yielding the same theoretical predictions for levels and changes. Therefore, we use a changes-based version of our abnormal price screen as an alternative proxy. $AbnPriceChange$ is defined as the absolute difference between the change in price (e.g., 3-day return) over the short window surrounding the earnings announcement, scaled by unexpected earnings, and the firm's historical average of this scaled return. This variable effectively calculates a short-window earnings response coefficient on each earnings announcement day, and uses the pre-announcement expectations as the benchmark to measure abnormal price movements.[25] We report the results of estimating several versions of Equation (5) that replace $AbnPrice$ with $AbnPriceChange$ in Table 8. Across all specifications, we find that information acquisition is greater when $AbnPriceChange$ reflects larger unexplained price movements.

We also repeat this analysis using two other measures of abnormal price movements. These measures compute expected price based on price-to-earnings multiple benchmarks that incorporate analysts' price targets and/or earnings forecasts. Specifically, we calculate expected price in two ways: (i) realized earnings $\times$ a price-to-earnings multiple based on analysts' median price forecast scaled by the median earnings consensus, and (ii) realized earnings $\times$ a median price-to-earnings multiple derived from market price at the time of each individual analyst earnings forecast. In untabulated analyses, we continue to find robust evidence that post-announcement information acquisition increases with absolute deviations from both measures of expected prices based on analyst forecasts.

Finally, we address the alternative explanation that our abnormal price deviation measure, rather than alerting entering speculators about the returns to private information acquisition, is associated with mispricing. "Mispricing" in the sense that private information acquisition can correct the

[25]This measure has the advantage of controlling for potential correlated omitted variables that stay constant in the short window around the earnings announcement. In addition, comparing the return per unit of unexpected earnings to the firm's historical average of this value means that the measure does not require an assumption about the set of comparable firms investors use to form price expectations. An additional advantage of this measure is that, unlike $AbnPrice$, it is available for firm-quarters with negative earnings. Therefore, in our regressions using $AbnPriceChange$, we include an additional control for loss quarters. A disadvantage of this alternative measure is that it is difficult to interpret the short-window earnings response coefficient when earnings surprise (UE) and abnormal returns (CAR) move in opposite directions, and that such cases cannot be directly compared to the majority of the cases where the two move in the same direction. Therefore, we calculate this variable only for those observations where UE and CAR have the same sign.

price is consistent with our model and empirical results, because prices correctly reflect all public information in our model (semi-strong efficient market). However, to the extent prices fail to reflect public information, speculators could trade on mispricing without acquiring information, because abnormal price deviations will reverse in the future. Under this alternative explanation, firms with abnormally high positive returns would have future negative returns, so speculators know to short these stocks without needing to acquire additional information. Inconsistent with trading on price deviations directly, our main results show an association between unexplained price deviations and future information acquisition.

To further alleviate this concern, we assess whether unexplained price deviations are associated with return reversals in the 6 months after the earnings announcement. Prior research examines mispricing using reversals in returns (e.g., Keloharju, Linnainmaa, and Nyberg, 2021). We follow this approach and estimate the following regression equation:

$$\begin{aligned} Return[t+2,t+180]_{i,t} = \beta_1 Return[t-1,t+1]_{i,t} + \gamma Controls_{i,t} + \Sigma\beta_i Firm_i + \\ \Sigma\beta_t Year\text{-}Quarter_t + \epsilon_{i,t}, \end{aligned} \tag{8}$$

where $Return[t+2,t+180]_{i,t}$ is the buy-and-hold abnormal return on days $[t+2,\ t+180]$ after the announcement and $Return[t-1,t+1]_{i,t}$ is the buy-and-hold abnormal return in the 3 days centered around the announcement. In column 1, we estimate equation (8) in the sample of firms with extreme price deviations, defined as those in the top decile of $AbnPrice$. Columns 2 and 3 estimate equation (8) in the subsamples of firms with large positive and large negative price deviations, defined as those in the top and bottom deciles of signed abnormal price deviations ($AbnPrice\_Signed$), respectively. A significantly negative β_1 would be consistent with return reversals, indicating mispricing among firms with high abnormal price deviations. We find insignificant β_1 coefficients, which suggests that return reversals or return predictability are unlikely to exist in high $AbnPrice$ firms. Column 4 estimates a version of Equation (8) that interacts $Return[t-1,t+1]$ with $AbnPrice$ in the full sample of announcements and finds an insignificant coefficient on the interaction term. The falsification test results presented in Table 9 mitigate concerns that $AbnPrice$ represents mispricing on which speculators could directly trade, because $AbnPrice$ is not associated with earnings announcement returns that are more likely to reverse.

5 Conclusion

An information event that offers profitable trading opportunities to investors who know about it and can assess its implications can occur for any tradeable asset at any time. As a result, it is challenging for a given investor to know where to focus their information acquisition efforts. Price-based screens that quickly sort large numbers of assets can guide these efforts and increase investors' expected trading profits. To provide some insight into why, how, and when screens are effective, and to identify some implications of their use for asset prices, we develop and analyze a model in which speculators can only follow one of two firms and are uncertain about the quality (i.e., profitability) of the private information that can be obtained by following each firm. When those speculators have access to past prices and earnings, they optimally employ a screen using those statistics to inform their firm-following decisions. Within the context of this model of screens, speculators are more inclined to follow firms that have a larger deviation between price and the expectation of price conditioned on earnings. They do so because larger unexplained price deviations suggest that there is more private information in the marketplace. While intuitive, this observation stands in contrast to the prior literature in which past prices are irrelevant for information acquisition decisions. In addition, because firms whose prices deviate from database-driven expectations are more likely to attract the attention of speculators, our model also predicts that those firms will be more inclined to experience increased price volatility and trading activity.

Our empirical analysis using abnormal price deviations at earnings announcements and investors' information acquisition on Edgar and Bloomberg finds results consistent with these predictions. Collectively, our evidence for the model's proposed mechanism is strong: information acquisition is increasing in a firm's (absolute) abnormal price deviation, U-shaped in the firm's signed price deviation, and decreasing in a peer firm's (absolute) abnormal price deviation. Our analyses address a number of alternative explanations and provide additional analyses that support the model's intuition and assumptions. For example, the U-shaped association between a firm's signed price deviation and information acquisition mitigates alternative explanations that would predict a monotone relation (e.g., growth opportunities).

We note a few limitations of our tests of the theory. First, an empirical price-to-earnings benchmark is hardly a sophisticated screen incorporating all data available in common databases. Hence, it is an imperfect proxy for actual investor information acquisition screens. Most screens, however, likely rely in part on the use of some combination of earnings and multiples and, as a consequence, our simple empirical screen should be a reasonable proxy for more complex screens. Accordingly, deviations from earnings-based expectations should predict subsequent investor attention even if more complex screens are used to allocate constrained information gathering capacity. Second, our tests cannot prove that all investors rely on the screen to identify private information acquisition opportunities. In particular, it is conceivable that some investors could obtain the information in our simple empirical screen from other non-screen sources (e.g., private meetings or data, as in Solomon and Soltes, 2015; Bushee, Gerakos, and Lee, 2018; Zhu, 2019). With that point acknowledged, our results still imply that investors can use simple and readily available screens to identify firms with private information acquisition opportunities. In summary, although imperfect, our empirical setting and tests provide evidence that screens are useful for identifying private information acquisition opportunities.

Future research could explore a more general version of our framework by allowing for screens that include more information than just earnings to derive unexplained price movements and identify profitable information acquisition opportunities. Additionally, although we have focused on investors' response to past prices, our model allows for an endogenous attention such that managers may be able to influence the attention that their firm receives from investors. For example, it would be interesting to analyze a setting where managers can manipulate reported earnings with the intent of attracting or discouraging institutional investors' information acquisition.

Appendix A Formal Derivations

Derivation of Linear Equilibrium Characterized in Proposition 1

The model's linear equilibrium is established through the three observations. Below, we first describe the observations, followed by detailed derivations. The first observation is analogous to a static noisy rational expectations linear equilibrium pricing function.

Observation 1. *In any linear equilibrium, the pricing function is:*

$$P_{it} = Me_{it} + \beta_{ixt}x_{it} + \beta_{int}n_{it}, \tag{9}$$

where $M = \frac{\lambda}{1+r-\lambda}$, $\beta_{ixt} = \frac{1}{1+r-\lambda}\frac{\left(\frac{\alpha_{it}}{c}\frac{1+r}{1+r-\lambda}q_{it}\right)^2}{\left(\frac{\alpha_{it}}{c}\frac{1+r}{1+r-\lambda}q_{it}\right)^2+\sigma^2}$, *and* $\beta_{int} = \frac{1}{1+r-\lambda}\frac{\frac{\alpha_{it}}{c}\frac{1+r}{1+r-\lambda}q_{it}^2}{\left(\frac{\alpha_{it}}{c}\frac{1+r}{1+r-\lambda}q_{it}\right)^2+\sigma^2}$.

In the dynamic model, the α_{it} in each pricing function is determined endogenously by the entering transitory speculators' firm following decisions. When entering transitory speculators decide which firm to follow in period t, their decision is determined by their beliefs regarding which firm offers the better opportunity for profitable informed trade. We denote the expected profits for a transitory speculator who follows firm i in period t as $\pi\left(q_{it}^2, \alpha_{it}\right)$. This expected profit is an increasing function of the quality of private information quality for i during t, q_{it}, and a decreasing function of the proportion of transitory speculators who follow firm i in period t, α_{it}. Hence, transitory speculators, all else equal, will prefer to follow a firm with the higher private information quality and lower following. The novel aspect of our model, however, is that entering transitory speculators do not know the private information quality prior to making the firm following decision. Let p_t (and $1 - p_t$, respectively) denote the entering transitory speculators' belief that firm a (b) offers information quality q_h. In any equilibrium, an entering transitory speculator must be indifferent to following a and b given the beliefs regarding the qualities of the private information offered by each firm. Observation 2 states that there is a unique allocation of transitory speculators to each firm given any set of beliefs.

Observation 2. *For any beliefs regarding which firm offers the higher quality private information,* $p_t \in [0, 1]$, *there exists a unique equilibrium allocation of entering transitory speculators at date* t. *The equilibrium allocation to firm* a, α_t, *is increasing in the probability that* a *offers the higher quality information environment,* p_t.

Observation 2 implies that, in equilibrium, the proportion of speculators following a firm is increasing in their beliefs as to whether that firm offers the higher quality private information.

To complete the characterization of the linear equilibrium, we must determine how p_t evolves in equilibrium. Given that α_t, the equilibrium allocation of transitory speculators in period t, is monotone and increasing in p_t, we can infer the entering transitory speculators' beliefs in period t, p_t. Let that function be denoted $p(\alpha_t)$, which is useful for characterizing the evolution of beliefs. Furthermore, the characterization of entering transitory speculator beliefs about which firm offers superior private information acquisition opportunities is facilitated by introducing a bit of notation. In particular, let $f(P_{it-1} - Me_{it-1}|q_\kappa, \alpha_{it-1})$ be a probability density function for the distribution of $P_{it-1} - Me_{it-1}$ for firm i in period $t-1$, conditional upon $q_{it-1} = q_\kappa$, where $\kappa \in \{h, l\}$, the quality of private information attained from following firm i in $t-1$, and α_{it-1}, the proportion of transitory speculators following firm i in $t-1$. That density function is a normal density with mean 0 and variance $\left(\frac{\alpha_{it-1}}{c}\right)^2 M^2 q_\kappa^2 + \sigma^2$. Using this notation, the beliefs of the transitory speculators entering the market at t are characterized in Observation 3.

Observation 3. *Given the screening variables employed by entering transitory speculators, $\{\alpha_{t-1}, P_{at-1}, e_{at-1}, P_{bt-1}, e_{bt-1}\}$, the equilibrium date t entering transitory speculators believe firm a will yield high quality private information with probability:*

$$p_t = \rho \frac{p(\alpha_{t-1})\Gamma(\alpha_{t-1})}{p(\alpha_{t-1})\Gamma(\alpha_{t-1}) + (1 - p(\alpha_{t-1}))} + (1-\rho) \frac{(1 - p(\alpha_{t-1}))}{p(\alpha_{t-1})\Gamma(\alpha_{t-1}) + (1 - p(\alpha_{t-1}))} \tag{10}$$

where $\Gamma(\alpha_{t-1}) = \frac{f(P_{at-1}-Me_{at-1}|q_h,\alpha_{t-1})f(P_{bt-1}-Me_{bt-1}|q_l,1-\alpha_{t-1})}{f(P_{at-1}-Me_{at-1}|q_l,\alpha_{t-1})f(P_{bt-1}-Me_{bt-1}|q_h,1-\alpha_{t-1})}$ *and* $f(P_{it-1} - Me_{it-1}|q, \alpha)$ *is a mean 0 normal density function with variance* $\left(\frac{1+M}{1+r}\right)^2 \left(\frac{\left(\frac{\alpha}{c}(1+M)q\right)^2}{\left(\frac{\alpha}{c}(1+M)q\right)^2 + \sigma^2}\right) q^2$.

The first ratio in the probability characterization in Observation 3, $\frac{p(\alpha_{t-1})\Gamma(\alpha_{t-1})}{p(\alpha_{t-1})\Gamma(\alpha_{t-1})+(1-p(\alpha_{t-1}))}$, is the probability that $q_{at-1} = q_h$ and $q_{bt-1} = q_l$, and it is weighted by ρ, the probability that the state of the information environment remains unchanged. The second ratio, $\frac{(1-p(\alpha_{t-1}))}{p(\alpha_{t-1})\Gamma(\alpha_{t-1})+(1-p(\alpha_{t-1}))}$, is the probability that $q_{at-1} = q_l$ and $q_{bt-1} = q_h$, and it is weighted by $(1-\rho)$, the probability that the state of the information environment changes.

Derivations for Observation 1.

To characterize equilibrium behaviors within a period, we work backwards from the equity market trading to the firm following decisions. The demand of an informed speculator following firm i in period t, d_{sit}, is given by the first order condition from maximizing the expectation of their objective function, which is

$$d_{sit} = \frac{(1+M)(\lambda e_{it} + x_{it}) - (1+r) P_{it}}{c} \tag{11}$$

The term $(1+M)(\lambda e_{it}+x_{it})$ reflects an informed speculator's expectation of the next period dividend, $(\lambda e_{it}+x_{it})$, plus price, $M(\lambda e_{it}+x_{it})$, given the linear pricing function and the speculator's private information about the innovation to earnings in the next period. The demand of the dedicated investors is infinitely positive (negative) if the following expression is positive (negative), and is any value if it is 0:

$$(1+M)\left(\lambda e_{it}+E\left[\tilde{x}_{it}|\Omega_{it}\right]\right)-(1+r)\,P_{it}, \tag{12}$$

where $E\left[\tilde{x}_{it}|\Omega_{it}\right]$ is the expectation of $\tilde{x}_{it}$ conditional upon the dedicated investors' information at date t, which includes, among other things, the date t price, which in a noisy rational expectations equilibrium is used to draw an inference about the entering transitory speculators' private information.

Given the dedicated investors' bang-bang demand function, which follows from their risk neutrality, the market clears if and only if the price makes the dedicated investors indifferent to holding shares, which means that the equilibrium price must satisfy

$$P_{it}=\frac{(1+M)\left(\lambda e_{it}+E\left[\tilde{x}_{it}|\Omega_{it}\right]\right)}{1+r}. \tag{13}$$

We determine the expectation $E\left[\tilde{x}_{it}|\Omega_{it}\right]$ in the same manner as Grossman and Stiglitz (1980). Specifically, given the relationship between current period price and demands, the dedicated investors can infer the statistic $y_{it}=\frac{\alpha_{it}}{c}(1+M)\,x_{it}+n_{it}$, which is sufficient statistic for $\{\Omega_{it},y_{it}\}$ with respect to $\tilde{x}_{it}$.

Given $y_{it}=\left(\frac{\alpha_{it}}{c}\right)(1+M)\,x_{it}+n_{it}$, the expectation of $\tilde{x}_{it}$ is:

$$\begin{aligned} E\left[\tilde{x}_{it}|y_{it}\right] &= \frac{\frac{\alpha_{it}}{c}(1+M)\,q_{it}^2}{\left(\frac{\alpha_{it}}{c}(1+M)\,q_{it}\right)^2+\sigma^2}\left(\left(\frac{\alpha_{it}}{c}\right)(1+M)\,x_{it}+n_{it}\right) \\ &= \frac{\left(\frac{\alpha_{it}}{c}(1+M)\,q_{it}\right)^2}{\left(\frac{\alpha_{it}}{c}(1+M)\,q_{it}\right)^2+\sigma_i^2}x_{it}+\frac{\frac{\alpha_{it}}{c}(1+M)\,q_{it}^2}{\left(\frac{\alpha_{it}}{c}(1+M)\,q_{it}\right)^2+\sigma^2}n_{it}. \end{aligned}$$

Therefore, the linear pricing function must satisfy:

$$P_{it}=\frac{1+M}{1+r}\lambda e_{it}+\frac{1+M}{1+r}\frac{\left(\frac{\alpha_{it}}{c}(1+M)\,q_{it}\right)^2}{\left(\frac{\alpha_{it}}{c}(1+M)\,q_{it}\right)^2+\sigma^2}x_{it}+\frac{1+M}{1+r}\frac{\frac{\alpha_{it}}{c}(1+M)\,q_{it}^2}{\left(\frac{\alpha_{it}}{c}(1+M)\,q_{it}\right)^2+\sigma^2}n_{it}. \tag{14}$$

Using the observation that $M=\frac{1+M}{1+r}\lambda$, and solving for M, the observation follows directly.

Derivations for Observation 2

Given the equilibrium pricing function anticipated in Observation 1, the quality of private information that can be acquired about firm i in period t, and the firm following for i in period t, the equilibrium expected profits for a speculator following firm i are

$$\frac{c}{2}E[d_{sit}^2] + (1+r)W_{ts} = \frac{1}{2c}\frac{(M+1)^2\, q_{it}^2\sigma^2}{\left(\frac{\alpha_{it}}{c}\right)^2 (M+1)^2\, q_{it}^2 + \sigma^2} + (1+r)W_{ts}$$

$$= \pi\left(q_{it}^2, \alpha_{it}\right) + (1+r)W_{ts}, \tag{15}$$

where $\pi\left(q_{it}^2, \alpha_{it}\right)$ denotes the expected profits from following, and trading on the private information about, firm i. The expected profits are increasing in the quality of the private information, q_{it}^2, and decreasing in the proportion of transitory speculators who follow i. Hence, transitory speculators, all else equal, will prefer to follow a firm with the higher information quality and lower following.

When transitory speculators make their firm following decision, however, they only have beliefs regarding the quality of private information that can be attained from following firm i and the equilibrium firm following choices of other entering transitory speculators. Let p_t $(1-p_t)$ denote the entering transitory speculator beliefs that firm a (b) offers information quality q_h. Given that specification of beliefs, an interior equilibrium allocation of the transitory speculators for period t, $\alpha_t \in (0,1)$, is sustained if and only if the expected profits from following firm a equal that for following firm b given the allocation α_t.

$$p_t\left(\pi\left(q_h^2, \alpha_t\right) - \pi\left(q_l^2, (1-\alpha_t)\right)\right) + (1-p_t)\left(\pi\left(q_l^2, \alpha_t\right) - \pi\left(q_h^2, (1-\alpha_t)\right)\right) = 0. \tag{16}$$

For any $p_t \in [0,1]$, the left hand side is decreasing in α_t, and, given the assumption that $q_l^2 > \frac{\sigma^2}{\left(\frac{1}{c}\right)^2\left(\frac{1+r}{1+r-\lambda}\right)^2 q_h^2+\sigma^2}q_h^2$, is strictly positive at $\alpha_t = 0$ and strictly negative at $\alpha_t = 1$. Furthermore, comparative statics analysis yields

$$\begin{aligned}
\frac{d\alpha_t}{dp_t} &= -\frac{\left(\pi\left(q_h^2, \alpha_t\right) - \pi\left(q_l^2, (1-\alpha_t)\right)\right) - \left(\pi\left(q_l^2, \alpha_t\right) - \pi\left(q_h^2, (1-\alpha_t)\right)\right)}{p_t\left(\frac{\partial\pi\left(q_h^2,\alpha_t\right)}{\partial\alpha_t} - \frac{\partial\pi\left(q_l^2,1-\alpha_t\right)}{\partial\alpha_t}\right) + (1-p_t)\left(\frac{\partial\pi\left(q_l^2,\alpha_t\right)}{\partial\alpha_t} - \frac{\partial\pi\left(q_h^2,1-\alpha_t\right)}{\partial\alpha_t}\right)} \\
&= \frac{\left(\pi\left(q_h^2, \alpha_t\right) - \pi\left(q_l^2, \alpha_t\right)\right) + \left(\pi\left(q_h^2, (1-\alpha_t)\right) - \pi\left(q_l^2, (1-\alpha_t)\right)\right)}{p_t\left(\frac{\partial\pi\left(q_l^2,1-\alpha_t\right)}{\partial\alpha_t} - \frac{\partial\pi\left(q_h^2,\alpha_t\right)}{\partial\alpha_t}\right) + (1-p_t)\left(\frac{\partial\pi\left(q_h^2,1-\alpha_t\right)}{\partial\alpha_t} - \frac{\partial\pi\left(q_l^2,\alpha_t\right)}{\partial\alpha_t}\right)},
\end{aligned}$$

which is strictly positive. Observation 2 naturally follows.

Derivations for Observation 3

Given $\{\alpha_{t-1}, P_{at-1}, e_{at-1}, P_{bt-1}, e_{bt-1}\}$, the probability that $q_{at} = q_h$ is

$$\begin{aligned} p_t &= \rho \frac{p(\alpha_{t-1})\, g(\Phi_{t-1}|q_h, \alpha_{t-1})}{p(\alpha_{t-1})\, g(\Phi_{t-1}|q_h, \alpha_{t-1}) + (1 - p(\alpha_{t-1}))\, g(\Phi_{t-1}|q_h, \alpha_{t-1})} \\ &\quad + (1-\rho) \frac{(1 - p(\alpha_{t-1}))\, g(\Phi_{t-1}|q_l, \alpha_{t-1})}{p(\alpha_{t-1})\, g(\Phi_{t-1}|q_h, \alpha_{t-1}) + (1 - p(\alpha_{t-1}))\, g(\Phi_{t-1}|q_l, \alpha_{t-1})}, \end{aligned}$$

where $\Phi_{t-1} \equiv \{P_{at-1}, e_{at-1}, P_{bt-1}, e_{bt-1}\}$, $g(\Phi_{t-1}|q_h, \alpha_{t-1})$ is the probability of Φ_{t-1} conditional upon $q_{at-1} = q_h$, $q_{bt-1} = q_l$, $\alpha_{at-1} = \alpha_{t-1}$, and $\alpha_{bt-1} = 1 - \alpha_{t-1}$, and $g(\Phi_{t-1}|q_l, \alpha_{t-1})$ is the probability of Φ_{t-1} conditional upon $q_{at-1} = q_l$, $q_{bt-1} = q_h$, $\alpha_{at-1} = \alpha_{t-1}$, and $\alpha_{bt-1} = 1 - \alpha_{t-1}$. Note that $\{P_{at-1}, e_{at-1}\}$ and $\{P_{bt-1}, e_{bt-1}\}$ are statistically independent, the joint density for $\{P_{at-1}, e_{at-1}\}$ is not a function of q_{bt-1}, the joint density for $\{P_{bt-1}, e_{bt-1}\}$ is not a function of q_{at-1}, the density for e_{at-1} is not a function of q_{at-1} or α_{t-1}, and the density for e_{bt-1} is not a function of q_{bt-1} or α_{t-1}. It follows that $g(\Phi_{t-1}|q_a, \alpha_{t-1})$ can be written as

$$\begin{aligned} & g(\Phi_{t-1}|q_{at-1}, \alpha_{t-1}) \\ & \quad = h_a(P_{at-1}|e_{at-1}, q_{at-1}, \alpha_{t-1})\, k_a(e_{at-1})\, h_b(P_{bt-1}|e_{bt-1}, q_{bt-1}, \alpha_{t-1})\, k_b(e_{bt-1}), \end{aligned} \tag{17}$$

where h_a and h_b are normal density functions, with means Me_{at-1} and Me_{bt-1}, respectively, and variances that are a function of the quality of private information and the proportion of speculators following firm a, α_{t-1}. We can transform the conditional density functions into mean 0 normally distributed random variables as follows:

$$h_a(P_{at-1}|e_{at-1}, q_{at-1}, \alpha_{t-1}) = f(P_{at-1} - Me_{at-1}|q_{at-1}, \alpha_{t-1}) \tag{18}$$

and

$$h_b(P_{bt-1}|e_{bt-1}, q_{bt-1}, \alpha_{t-1}) = f(P_{bt-1} - Me_{bt-1}|q_{bt-1}, 1 - \alpha_{t-1}) \tag{19}$$

where $f(x|q, \alpha)$ is a mean 0 normally distributed random variable with variance

$$v(q, \alpha) = \left(\frac{1+M}{1+r}\right)^2 \left(\frac{\left(\frac{\alpha}{c}\right)^2 (1+M)^2 q^2}{\left(\frac{\alpha}{c}\right)^2 (1+M)^2 q^2 + \sigma^2}\right) q^2. \tag{20}$$

It follows that

$$p_t = \rho \frac{p(\alpha_{t-1})\, \Gamma(\alpha_{t-1})}{p(\alpha_{t-1})\, \Gamma(\alpha_{t-1}) + (1 - p(\alpha_{t-1}))} + (1-\rho) \frac{(1 - p(\alpha_{t-1}))}{p(\alpha_{t-1})\, \Gamma(\alpha_{t-1}) + (1 - p(\alpha_{t-1}))}, \tag{21}$$

where

$$\Gamma\left(\alpha_{t-1}\right)=\frac{f\left(P_{at-1}-Me_{at-1}|q_h,\alpha_{t-1}\right)f\left(P_{bt-1}-Me_{bt-1}|q_l,1-\alpha_{t-1}\right)}{f\left(P_{at-1}-Me_{at-1}|q_l,\alpha_{t-1}\right)f\left(P_{bt-1}-Me_{bt-1}|q_h,1-\alpha_{t-1}\right)}. \tag{22}$$

Derivation of Comparative Statics Characterized in Corollary 1

The following two observations facilitate Corollary 1.

Observation 4. *$\Gamma\left(\alpha_{t-1}\right)$ is increasing in $\left(P_{at-1}-Me_{at-1}\right)^2$ and decreasing in $\left(P_{bt-1}-Me_{bt-1}\right)^2$.*

Proof. We can write $\Gamma\left(\alpha_{t-1}\right)$ as follows:

$$\begin{aligned}
\Gamma\left(\alpha_{t-1}\right) &= \frac{\frac{1}{\sqrt{2\pi v(q_h,\alpha_{t-1})}}\exp\left(-\frac{\left(P_{at-1}-Me_{at-1}\right)^2}{2v(q_h,\alpha_{t-1})}\right)\frac{1}{\sqrt{2\pi v(q_l,1-\alpha_{t-1})}}\exp\left(-\frac{\left(P_{bt-1}-Me_{bt-1}\right)^2}{2v(q_l,1-\alpha_{t-1})}\right)}{\frac{1}{\sqrt{2\pi v(q_l,\alpha_{t-1})}}\exp\left(-\frac{\left(P_{at-1}-Me_{at-1}\right)^2}{2v(q_l,\alpha_{t-1})}\right)\frac{1}{\sqrt{2\pi v(q_h,1-\alpha_{t-1})}}\exp\left(-\frac{\left(P_{bt-1}-Me_{bt-1}\right)^2}{2v(q_h,1-\alpha_{t-1})}\right)} \\
&= \sqrt{\frac{v(q_l,\alpha_{t-1})}{v(q_h,\alpha_{t-1})}}\exp\left(\left(P_{at-1}-Me_{at-1}\right)^2\left(\frac{v(q_h,\alpha_{t-1})-v(q_l,\alpha_{t-1})}{2v(q_h,\alpha_{t-1})v(q_l,\alpha_{t-1})}\right)\right)\times \\
&\quad \sqrt{\frac{v(q_h,1-\alpha_{t-1})}{v(q_l,1-\alpha_{t-1})}}\exp\left(\left(P_{bt-1}-Me_{bt-1}\right)^2\left(\frac{v(q_l,1-\alpha_{t-1})-v(q_h,1-\alpha_{t-1})}{2v(q_h,1-\alpha_{t-1})v(q_l,1-\alpha_{t-1})}\right)\right).
\end{aligned}$$

Noting that $v(q,\alpha)$ is increasing in q, it follows that $\Gamma\left(\alpha_{t-1}\right)$ is increasing in $\left(P_{at-1}-Me_{at-1}\right)^2$ and decreasing in $\left(P_{bt-1}-Me_{bt-1}\right)^2$.

Observation 5. *p_t is increasing in $\Gamma\left(\alpha_{t-1}\right)$.*

Proof. Differentiating p_t with respect to $\Gamma\left(\alpha_t\right)$ yields

$$\begin{aligned}
\frac{\partial p_t}{\partial\Gamma\left(\alpha_{t-1}\right)} &= \rho\frac{p\left(\alpha_{t-1}\right)\left(1-p\left(\alpha_{t-1}\right)\right)}{\left(p\left(\alpha_{t-1}\right)\Gamma\left(\alpha_{t-1}\right)+\left(1-p\left(\alpha_{t-1}\right)\right)\right)^2}-\left(1-\rho\right)\frac{p\left(\alpha_{t-1}\right)\left(1-p\left(\alpha_{t-1}\right)\right)}{\left(p\left(\alpha_{t-1}\right)\Gamma\left(\alpha_{t-1}\right)+\left(1-p\left(\alpha_{t-1}\right)\right)\right)^2} \\
&= \left(2\rho-1\right)\frac{p\left(\alpha_{t-1}\right)\left(1-p\left(\alpha_{t-1}\right)\right)}{\left(p\left(\alpha_{t-1}\right)\Gamma\left(\alpha_{t-1}\right)+\left(1-p\left(\alpha_{t-1}\right)\right)\right)^2} \\
&> 0,
\end{aligned}$$

because $\rho>\frac{1}{2}$.

Proof of Corollary 1 (i).

Note that Observations 4 and 5 imply that p_t is increasing in $|P_{at-1}-Me_{at-1}|$ and decreasing in $|P_{bt-1}-Me_{bt-1}|$. The proof is completed by showing that α_t increases in p_t. Let:

$$K=p_t\left(\pi\left(q_h^2,\alpha_t\right)-\pi\left(q_l^2,\left(1-\alpha_t\right)\right)\right)+\left(1-p_t\right)\left(\pi\left(q_l^2,\alpha_t\right)-\pi\left(q_h^2,\left(1-\alpha_t\right)\right)\right), \tag{23}$$

which is used to determine the equilibrium α_t and equals 0 at the equilibrium α_t. It follows that $\frac{d\alpha_t}{dp_t}=-\frac{\frac{\partial K}{\partial p_t}}{\frac{\partial K}{\partial\alpha_t}}\propto\frac{\partial K}{\partial p_t}$ because we have established that K is decreasing in α_t, $\frac{\partial K}{\partial\alpha_t}<0$. It follows that

$\frac{d\alpha_t}{dp_t} > 0$ because:

$$\begin{aligned}\frac{\partial K}{\partial p_t} &= \left(\pi\left(q_h^2, \alpha_t\right) - \pi\left(q_l^2, (1-\alpha_t)\right)\right) - \left(\pi\left(q_l^2, \alpha_t\right) - \pi\left(q_h^2, (1-\alpha_t)\right)\right) \\ &= \left(\pi\left(q_h^2, \alpha_t\right) - \pi\left(q_l^2, \alpha_t\right)\right) + \left(\pi\left(q_h^2, (1-\alpha_t)\right) - \pi\left(q_l^2, (1-\alpha_t)\right)\right) \\ &> 0.\end{aligned}$$

The proof follows from the fact that $\alpha_{at} = \alpha_t$ and $\alpha_{bt} = 1 - \alpha_t$.

Proof of Corollary 1 (ii).

The variance of firm i's period t change in price is

$$Var[P_{it} - P_{it-1}] = \left(\frac{\lambda}{1+r-\lambda}\right)^2 Var[\tilde{x}_{t-1}|P_{t-1}] + \left(\frac{\lambda}{1+r-\lambda}\right)^2 \left(1 - q_{it-1}^2\right) s^2 + \beta_{ixt}^2 q_{it}^2 + \beta_{int}^2 \sigma^2, \tag{24}$$

where

$$\beta_{ixt} = \frac{1}{1+r-\lambda} \frac{\left(\frac{\alpha_{it}}{c}\right)^2 \left(\frac{1+r}{1+r-\lambda}\right)^2 q_{it}^2}{\left(\frac{\alpha_{it}}{c}\right)^2 \left(\frac{1+r}{1+r-\lambda}\right)^2 q_{it}^2 + \sigma^2} \tag{25}$$

and

$$\beta_{int} = \frac{1}{1+r-\lambda} \frac{\left(\frac{\alpha_{it}}{c}\right) \left(\frac{1+r}{1+r-\lambda}\right) q_{it}^2}{\left(\frac{\alpha_{it}}{c}\right)^2 \left(\frac{1+r}{1+r-\lambda}\right)^2 q_{it}^2 + \sigma^2} \tag{26}$$

are the pricing coefficients derived previously. The proof follows by noting that β_{ixt} and β_{int} are both positive and increasing in α_{it}, which by Corollary 1 (i) is increasing in $|P_{it-1} - Me_{it-1}|$ and decreasing in $|P_{jt-1} - Me_{jt-1}|$ where $j \neq i$.

Proof of Corollary 1 (iii).

The period t speculator trading volume is

$$\begin{aligned}
|d_{sit}| &= \left|\frac{(1+M)(\lambda e_{it}+x_{it})-(1+r)P_{it}}{c}\right| \\
&= \left|\frac{(1+M)x_{it}-(1+r)\beta_{ixt}x_{it}-(1+r)\beta_{int}n_{it}}{c}\right| \\
&= \frac{1}{c}\left|(1+M)x_{it}-(1+r)\beta_{ixt}x_{it}-(1+r)\beta_{int}n_{it}\right| \\
&= \frac{1}{c}\frac{1+r}{1+r-\lambda}\left|\frac{\left(\frac{\alpha_{it}}{c}\right)^2\left(\frac{1+r}{1+r-\lambda}\right)^2 q_{it}^2}{\left(\frac{\alpha_{it}}{c}\right)^2\left(\frac{1+r}{1+r-\lambda}\right)^2 q_{it}^2+\sigma^2}x_{it}+\frac{\left(\frac{\alpha_{it}}{c}\right)\left(\frac{1+r}{1+r-\lambda}\right)q_{it}^2}{\left(\frac{\alpha_{it}}{c}\right)^2\left(\frac{1+r}{1+r-\lambda}\right)^2 q_{it}^2+\sigma^2}n_{it}\right| \\
&= \frac{1}{c}\frac{1+r}{1+r-\lambda}\frac{\left(\frac{\alpha_{it}}{c}\right)\left(\frac{1+r}{1+r-\lambda}\right)q_{it}^2}{\left(\frac{\alpha_{it}}{c}\right)^2\left(\frac{1+r}{1+r-\lambda}\right)^2 q_{it}^2+\sigma^2}\left|\left(\frac{\alpha_{it}}{c}\right)\left(\frac{1+r}{1+r-\lambda}\right)x_{it}+n_{it}\right|.
\end{aligned}$$

The expectation of that volume is therefore

$$\frac{1}{c}\frac{1+r}{1+r-\lambda}\frac{\left(\frac{\alpha_{it}}{c}\right)\left(\frac{1+r}{1+r-\lambda}\right)q_{it}^2}{\left(\frac{\alpha_{it}}{c}\right)\left(\frac{1+r}{1+r-\lambda}\right)q_{it}+\sigma}. \tag{27}$$

This expression is increasing in α_{it}. The proof follows by noting that, by Corollary 1 (i), α_{it} is increasing in $|P_{it-1}-Me_{it-1}|$ and decreasing in $|P_{jt-1}-Me_{jt-1}|$ where $j \neq i$.

Appendix B Variable Definitions

This table presents definitions of the primary variables used throughout the paper. All continuous variables are winsorized at 1% and 99% to limit the influence of outliers.

Variable	**Definition**
AbnPrice	The within-quarter percentile rank of the absolute difference between a firm's observed price on the first trading day after the earnings announcement and the expected price, scaled by the expected price. Expected price is calculated as realized earnings multiplied by the median price-to-earnings multiple of the firms in the same 2-digit SIC industry and asset size quintile, measured four quarters prior. The price-to-earnings multiple is defined only for the observations with positive earnings per share.
AbnPrice_Signed	The within-quarter percentile rank of the (signed) difference between a firm's observed price on the first trading day after the earnings announcement and the expected price, scaled by the expected price. Expected price is calculated as realized earnings multiplied by the median price-to-earnings multiple of the firms in the same 2-digit SIC industry and asset size quintile, measured four quarters prior. The price-to-earnings multiple is defined only for the observations with positive earnings per share.
AbnPriceChange	The within-quarter percentile rank of the absolute difference between the observed price change scaled by the unexpected earnings, and the historical average of this scaled measure. The price change is calculated as the cumulative abnormal returns (CAR) over the three trading days centered on the earnings announcement date, which is then divided by the unexpected earnings (UE) calculated as the quarterly earnings surprise relative to analyst consensus scaled by the quarter-end stock price. Its historical average is calculated across the previous four earnings announcements. This measure is calculated only for those observations where CAR and UE have the same sign.
AbnPricePeer	*AbnPrice* of the matched peer firm. This matched peer is defined as the firm in the same industry (defined based on 2-digit SIC codes) as and that announces earnings on the same day as the focal firm, that is closest in asset size. We only retain matches where the larger firm's asset size is less than 1.5 times the smaller firm's, and the size difference between the two firms is less than \$100 billion.
Bloomberg	Sum of Bloomberg's measure of abnormal institutional investor attention between this quarter's and the subsequent quarter's earnings announcement dates. We log-transform this variable by taking log(1 + Bloomberg raw sum) and multiply the log-transformed variable by 100.
$Bloomberg_{t+2}$	Sum of Bloomberg's measure of abnormal institutional investor attention between next quarter's $(t + 1)$ and the subsequent quarter's $(t + 2)$ earnings announcement dates. We log-transform this variable by taking log(1 + Bloomberg raw sum_{t+2}) and multiply the log-transformed variable by 100.
$Bloomberg_{t+3}$	Sum of Bloomberg's measure of abnormal institutional investor attention between two quarters ahead $(t + 2)$ and three quarters ahead $(t + 3)$ earnings announcement dates. We log-transform this variable by taking log(1+Bloomberg raw sum_{t+3}) and multiply the log-transformed variable by 100.
Bloomberg_5day	Sum of Bloomberg's measure of abnormal institutional investor attention between 1 and 5 trading days subsequent to this quarter's earnings announcement date. We log-transform this variable by taking log(1 + Bloomberg raw sum) and multiply the log-transformed variable by 100.
Bloomberg_lag	*Bloomberg* or *Bloomberg_5day*, measured in the previous quarter.
BundledForecast	Indicator variable set to one if the firm issues earnings guidance on trading days [0,+2] of this quarter's earnings announcement and zero otherwise.
EdgarNew	The total number of Edgar downloads between this quarter's and the subsequent quarter's earnings announcement dates that are initiated from new IP addresses. New IP addresses refer to the ones that did not download the firm's filings in the previous quarter over the same window. The measure includes downloads of all filing forms and excludes bot downloads, following Drake et al. (2015). We log-transform this variable by taking log(1+ EdgarNew raw sum) and multiply the log-transformed variable by 100.

$EdgarNewIP$	Number of unique IP addresses downloading Edgar filings of a firm between this quarter's and subsequent quarter's earnings announcement dates, considering only the new IP addresses that did not download the firm's filings in the previous quarter over the same window. This measure includes IP addresses accessing all filing forms and excludes IP addresses identified as bots, following Drake et al. (2015). We log-transform this variable by taking log(1+EdgarNewIP raw sum) and multiply the log-transformed variable by 100.
$EdgarSearch$	The total number of Edgar downloads between this quarter's and the subsequent quarter's earnings announcement dates. The measure includes downloads of all filing forms and excludes bot downloads, following Drake et al. (2015). We log-transform this variable by taking log(1 + EdgarSearch raw sum) and multiply the log-transformed variable by 100.
$EdgarSearch_{t+2}$	The total number of Edgar downloads between next quarter's $(t+1)$ and the subsequent quarter's $(t+2)$ earnings announcement dates. The measure includes downloads of all filing forms and excludes bot downloads, following Drake et al. (2015). We log-transform this variable by taking log(1+EdgarSearch raw sum$_{t+2}$) and multiply the log-transformed variable by 100.
$EdgarSearch_{t+3}$	The total number of Edgar downloads between two quarters ahead $(t+2)$ and three quarters ahead $(t+3)$ earnings announcement dates. The measure includes downloads of all filing forms and excludes bot downloads, following Drake et al. (2015). We log-transform this variable by taking log(1+EdgarSearch raw sum$_{t+3}$) and multiply the log-transformed variable by 100.
$EdgarSearch\_5day$	The total number of Edgar downloads between 1 and 5 trading days subsequent to this quarter's earnings announcement date. The measure includes downloads of all filing forms and excludes bot downloads, following Drake et al. (2015). We log-transform this variable by taking log(1+EdgarSearch raw sum) and multiply the log-transformed variable by 100.
$EdgarSearch\_lag$	$EdgarSearch$ or $EdgarSearch\_5day$, measured in the previous quarter.
$Instown$	Proportion of institutional ownership from Thomson 13F, multiplied by 100 and measured at the end of the quarter.
$Leverage$	Debt divided by equity, measured at the end of the quarter.
$\log(Assets)$	The natural log of one plus total assets, measured in thousands of dollars at the end of the quarter.
$Loss$	Indicator variable set to one if net income is negative for the quarter and zero otherwise.
$MediaStories$	Number of unique media stories about the firm in a quarter, from RavenPack.
$Return[t-1, t+1]$	Buy-and-hold abnormal earnings announcement returns, measured as firm's buy-and-hold return in the [−1, +1] trading-day window less the buy-and-hold value-weighted market return over the same window.
$Return[t+2, t+180]$	Buy-and-hold abnormal post-announcement returns, measured as firm's buy-and-hold return in the [+2, +180] trading-day window less the buy-and-hold value-weighted market return over the same window.
$RetVariance$	Standard deviation of daily returns between this quarter's and the subsequent quarter's earnings announcement dates, multiplied by 100.
$Shortsell$	Outstanding short-sell interest relative to shares outstanding, from Compustat, multiplied by 100 and measured at the end of the quarter.
$TradingVol$	Sum of the daily percentage turnover, calculated as the volume of shares traded scaled by shares outstanding, between this quarter's and the subsequent quarter's earnings announcement dates and multiplied by 100.
$Voldisc8K$	Number of voluntary Form 8-Ks (Items 2.02, 7.01, 8.01) issued by the firm in a quarter.

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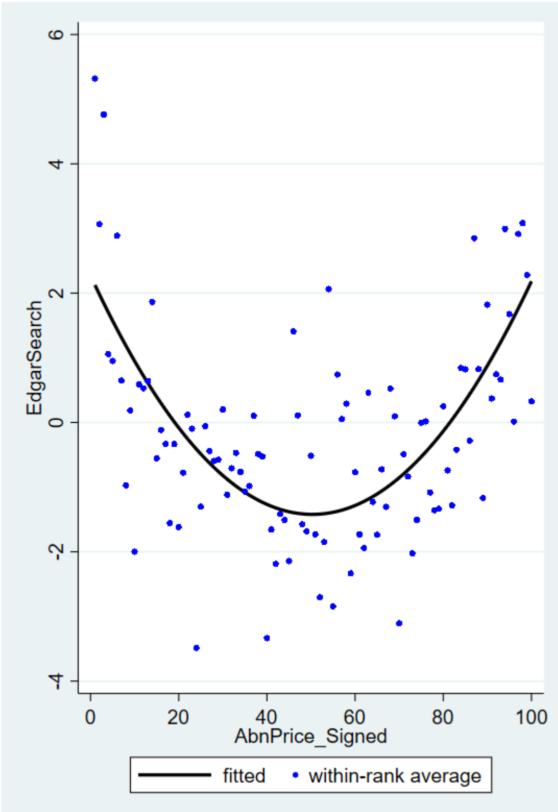
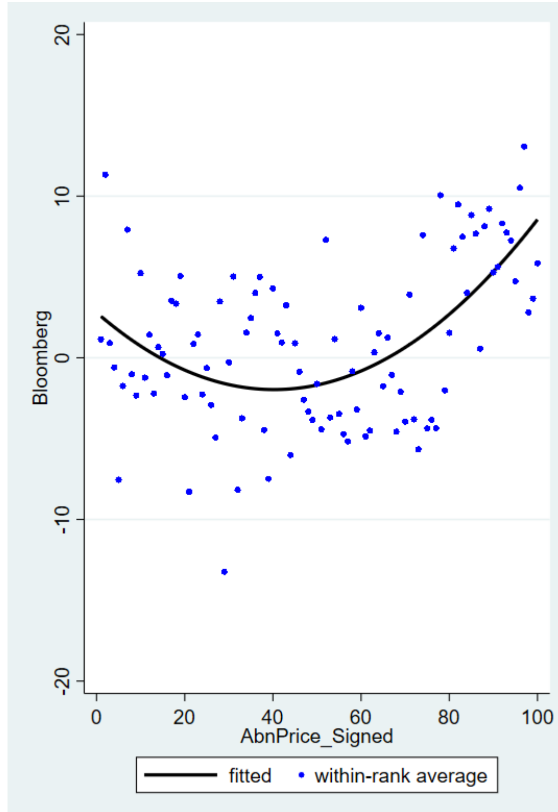


(a) EdgarSearch



(b) Bloomberg

Figure 2 Signed Abnormal Price Deviation and Information Acquisition. This figure plots the relation between the signed abnormal price deviation, *AbnPrice_Signed*, and information acquisition on Edgar (Panel A) and Bloomberg (Panel B).

Table 1
Descriptive Statistics

Panel A. Edgar Downloads Sample: 2004-2016

	Obs.	Mean	Std.Dev.	Q1	Median	Q3
AbnPrice	87,493	0.73	1.41	0.15	0.34	0.63
EdgarSearch	87,493	2,025.11	2,435.86	575.00	1,189.00	2,444.00
TradingVol	87,493	54.30	47.42	24.43	41.61	68.23
RetVariance	87,493	2.26	1.40	1.36	1.89	2.71
Leverage	87,493	0.93	2.10	0.10	0.48	1.11
Assets(in millions)	87,493	11,061.84	31,861.58	563.40	1,803.47	6,269.00
BundledForecast	87,493	0.36	0.48	0.00	0.00	1.00
Instown	87,493	53.32	36.99	8.34	63.32	86.42
Shortsell	87,493	4.15	4.58	1.13	2.69	5.58
Voldisc8K	87,493	2.10	1.66	1.00	2.00	3.00
MediaStories	87,493	38.12	56.11	2.00	18.00	49.00

Panel B. Bloomberg Attention Sample: 2010-2022

	Obs.	Mean	Std.Dev.	Q1	Median	Q3
AbnPrice	59,895	0.86	1.73	0.16	0.35	0.67
Bloomberg	59,895	21.50	30.26	0.00	9.00	30.00
TradingVol	59,895	49.03	41.96	25.90	39.01	58.81
RetVariance	59,895	2.05	1.23	1.30	1.72	2.40
Leverage	59,895	1.02	2.46	0.23	0.63	1.21
Assets(in millions)	59,895	16,135.70	38,210.88	1,096.90	3,193.59	10,618.84
BundledForecast	59,895	0.35	0.48	0.00	0.00	1.00
Instown	59,895	49.56	39.88	0.00	62.28	87.10
Shortsell	59,895	3.78	4.02	1.30	2.47	4.73
Voldisc8K	59,895	2.20	1.58	1.00	2.00	3.00
MediaStories	59,895	68.91	97.62	0.00	42.00	90.00

This table presents descriptive statistics for the raw (i.e., unranked and unlogged) versions of the variables used in our analysis. Panel A presents summary statistics of the variables measured at the firm-quarter level, for the 2004 to 2016 sample examining Edgar downloads. Panel B presents summary statistics of the variables measured at the firm-quarter level, for the 2010 to 2022 sample examining Bloomberg attention. For ease of interpretation, we present summary statistics for the raw variables prior to ranking or log transformations, based on the variable definitions in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers.

Table 2
Abnormal Price and Information Acquisition

	EdgarSearch			Bloomberg		
	(1)	(2)	(3)	(4)	(5)	(6)
AbnPrice	0.040***	0.034***	0.012**	0.090***	0.089***	0.154***
	(6.25)	(5.43)	(2.49)	(3.89)	(3.94)	(9.91)
Leverage		-0.090	-0.060		-0.813**	-0.219
		(-0.68)	(-0.78)		(-2.40)	(-1.29)
log(Assets)		16.324***	5.708***		40.688***	20.431***
		(16.70)	(27.39)		(13.53)	(34.91)
BundledForecast		-2.744***	1.787***		-1.368	2.920**
		(-3.17)	(4.71)		(-0.48)	(2.19)
Instown		-0.086***	0.006		0.027	-0.013
		(-5.09)	(1.16)		(0.63)	(-0.87)
Shortsell		0.867***	0.370***		2.791***	1.616***
		(11.17)	(11.20)		(9.64)	(13.26)
Voldisc8K		2.414***	0.089		2.303***	-1.031***
		(16.31)	(0.81)		(4.74)	(-3.31)
MediaStories		0.047***	0.078***		-0.004	0.039***
		(5.21)	(19.60)		(-0.30)	(6.23)
EdgarSearch_lag			0.764***			
			(140.83)			
Bloomberg_lag						0.700***
						(122.25)
Observations	87,493	87,493	87,493	59,895	59,895	59,895
Adj R-Squared	0.877	0.881	0.880	0.715	0.723	0.762
Firm FE	Yes	Yes	No	Yes	Yes	No
Industry FE	No	No	Yes	No	No	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents an analysis of the relation between abnormal price movement at the earnings announcement and subsequent information acquisition. Columns 1 to 3 examine information acquisition on Edgar. Columns 4 to 6 examine information acquisition on Bloomberg. All variables are defined in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers. t-statistics based on standard errors clustered by Firm are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 3

Matched-Peer Firm Analysis

	EdgarSearch			Bloomberg		
	(1)	(2)	(3)	(4)	(5)	(6)
AbnPrice	0.041***	0.032***	0.020***	0.119***	0.117***	0.185***
	(5.04)	(4.12)	(3.26)	(3.54)	(3.58)	(8.81)
AbnPricePeer	-0.015**	-0.011*	-0.010*	-0.064***	-0.059**	0.003
	(-2.35)	(-1.71)	(-1.71)	(-2.69)	(-2.56)	(0.15)
Leverage		-0.550**	-0.073		-0.976	-0.239
		(-2.19)	(-0.56)		(-1.61)	(-0.78)
log(Assets)		15.254***	5.152***		48.791***	21.645***
		(13.99)	(19.75)		(11.55)	(27.85)
BundledForecast		-4.128***	0.685		-5.468	2.067
		(-4.20)	(1.44)		(-1.37)	(1.17)
Instown		-0.082***	0.008		0.028	-0.029
		(-4.16)	(1.21)		(0.49)	(-1.36)
Shortsell		0.898***	0.353***		2.854***	1.769***
		(8.84)	(7.94)		(7.08)	(10.11)
Voldisc8K		2.500***	-0.190		2.984***	-1.314***
		(13.34)	(-1.41)		(4.77)	(-3.41)
MediaStories		0.069***	0.064***		0.059***	0.079***
		(6.19)	(11.59)		(2.76)	(7.08)
EdgarSearch_lag			0.775***			
			(133.81)			
Bloomberg_lag						0.698***
						(102.85)
Observations	45,619	45,619	45,619	29,597	29,597	29,597
Adj R-Squared	0.874	0.879	0.882	0.669	0.680	0.732
Firm FE	Yes	Yes	No	Yes	Yes	No
Industry FE	No	No	Yes	No	No	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents an analysis of the relation between the focal firm's and a matched peer firm's abnormal price movements at the earnings announcement, and subsequent information acquisition about the focal firm. Columns 1 to 3 (4 to 6) examine information acquisition on Edgar (Bloomberg). All variables are defined in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers. *t*-statistics based on standard errors clustered by Firm are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 4

Abnormal Price, Trading Volume, and Return Volatility: Mediated (Path) Analysis

Panel A. Through Information Acquisition on Edgar: Effects

Outcome:	RetVariance		TradingVol	
	(1)	(2)	(3)	(4)
	Coef	Bootstrap z	Coef	Bootstrap z
Direct Path:				
I. AbnPrice → Outcome	0.003***	22.87	0.006	1.62
Mediated Path:				
II. AbnPrice → EdgarSearch	0.034***	6.58	0.034***	6.58
III. EdgarSearch → Outcome	0.004***	36.92	0.247***	67.12
Indirect Effect (II × III)	0.0001***	6.54	0.008***	6.61
Total Effect (I + II × III)	0.003***	24.06	0.014***	3.38
Controls	Yes		Yes	
Firm FE	Yes		Yes	
Year-Quarter FE	Yes		Yes	

Panel B. Through Information Acquisition on Edgar: Mediated OLS Regressions

	RetVariance		TradingVol	
	(1)	(2)	(3)	(4)
AbnPrice	0.003***	0.003***	0.014***	0.006
	(16.94)	(16.42)	(2.65)	(1.14)
EdgarSearch		0.004***		0.247***
		(25.63)		(38.80)
Leverage	0.018***	0.019***	0.083	0.105
	(4.28)	(4.39)	(0.69)	(0.91)
log(Assets)	-0.040**	-0.098***	1.343	-2.687**
	(-2.18)	(-5.45)	(1.16)	(-2.41)
BundledForecast	-0.085***	-0.075***	-0.503	0.175
	(-5.33)	(-4.73)	(-0.71)	(0.26)
Instown	-0.003***	-0.003***	0.047***	0.068***
	(-8.00)	(-7.26)	(2.97)	(4.53)
Shortsell	0.025***	0.022***	2.895***	2.681***
	(11.45)	(10.20)	(29.62)	(29.10)
Voldisc8K	0.003	-0.006**	0.544***	-0.052
	(0.90)	(-2.02)	(4.70)	(-0.48)
MediaStories	0.000***	0.000	0.019**	0.008
	(2.58)	(1.30)	(2.34)	(0.97)
Observations	87,493	87,493	87,493	87,493
Adj R-Squared	0.632	0.641	0.631	0.665
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes

Table 4

Abnormal Price, Trading Volume, and Return Volatility: Mediated (Path) Analysis (cont'd)

Panel C. Through Information Acquisition on Bloomberg: Effects

Outcome:	RetVariance		TradingVol	
	(1)	(2)	(3)	(4)
	Coef	Bootstrap z	Coef	Bootstrap z
Direct Path:				
I. AbnPrice → Outcome	0.001***	11.16	0.024***	5.42
Mediated Path:				
II. AbnPrice → Bloomberg	0.089***	6.32	0.089***	6.32
III. Bloomberg → Outcome	0.001***	23.48	0.048***	40.83
Indirect Effect (II × III)	0.0001***	5.72	0.004***	6.10
Total Effect (I + II × III)	0.001***	11.58	0.029***	6.68
Controls	Yes		Yes	
Firm FE	Yes		Yes	
Year-Quarter FE	Yes		Yes	

Panel D. Through Information Acquisition on Bloomberg: Mediated OLS Regressions

	RetVariance		TradingVol	
	(1)	(2)	(3)	(4)
AbnPrice	0.001***	0.001***	0.029***	0.024***
	(9.15)	(8.73)	(4.50)	(3.93)
Bloomberg		0.001***		0.048***
		(16.09)		(17.58)
Leverage	0.009***	0.010***	0.123	0.163
	(2.79)	(3.01)	(0.94)	(1.24)
log(Assets)	-0.045**	-0.079***	0.263	-1.706*
	(-2.45)	(-4.25)	(0.26)	(-1.67)
BundledForecast	-0.039*	-0.038*	0.370	0.437
	(-1.92)	(-1.88)	(0.43)	(0.51)
Instown	-0.001***	-0.001***	0.009	0.008
	(-3.49)	(-3.58)	(0.79)	(0.68)
Shortsell	0.016***	0.014***	2.901***	2.766***
	(7.42)	(6.40)	(19.84)	(19.29)
Voldisc8K	-0.011***	-0.013***	0.465***	0.354**
	(-3.38)	(-4.02)	(3.28)	(2.54)
MediaStories	0.000***	0.000***	0.013***	0.013***
	(4.64)	(4.70)	(3.52)	(3.55)
Observations	59,895	59,895	59,895	59,895
Adj R-Squared	0.638	0.642	0.613	0.624
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes

This table presents a mediated (path) analysis of how abnormal price movement at the earnings announcement affects subsequent return volatility and subsequent trading volume through information acquisition. Panels A and B examine information acquisition on Edgar. Panels C and D examine information acquisition on Bloomberg. Panels A and C present the magnitude and the significance of the direct and indirect (e.g., through information acquisition) effects of abnormal price movement on return volatility and trading volume. Following Bonsall IV et al. (2018) we conduct mediated analysis using a structural equation model, and report z-statistics based on bootstrapped standard errors clustered by Firm. Panels B and D compare the baseline regression analysis with a mediated regression analysis that includes measures of information acquisition as an additional explanatory variable. All variables are defined in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers. t-statistics based on standard errors clustered by Firm are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 5

Abnormal Price and Information Acquisition by New Speculators

	EdgarNew	EdgarNewIP
	(1)	(2)
AbnPrice	0.027^{***}	0.026^{***}
	(4.62)	(4.82)
Leverage	-0.031	-0.032
	(-0.26)	(-0.29)
log(Assets)	16.880^{***}	15.221^{***}
	(18.77)	(16.91)
BundledForecast	-2.820^{***}	-2.398^{***}
	(-3.59)	(-3.33)
Instown	-0.075^{***}	-0.058^{***}
	(-5.00)	(-4.02)
Shortsell	0.870^{***}	0.739^{***}
	(12.17)	(11.26)
Voldisc8K	1.691^{***}	1.386^{***}
	(12.39)	(11.16)
MediaStories	0.021^{**}	0.010
	(2.50)	(1.15)
Observations	87,493	87,493
Adj R-Squared	0.872	0.896
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes

This table presents an analysis of the relation between abnormal price movement at the earnings announcement and subsequent information acquisition by new speculators. Column 1 measures new speculators' information acquisition as new Edgar downloads and column 2 as the number of unique new IP addresses downloading Edgar filings. Both measures consider only the new IP addresses that did not download the firm's filings in the previous quarter over the same window. The mean (median) values of raw, unlogged $EdgarNew$ and $EdgarNewIP$ are 1,287.54 (808.00) and 595.14 (366.00), respectively. All variables are defined in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers. t-statistics based on standard errors clustered by Firm are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 6
Correlation in the Quality of Private Information Over Time

Panel A. Rank Transition Matrix

	1	2	3	4	5	6	7	8	9	10
1	18.6%	17.9%	15.5%	12.7%	9.9%	8.3%	5.9%	4.1%	3.8%	3.3%
2	17.7%	16.2%	15.5%	13.3%	10.5%	8.9%	6.4%	4.5%	3.8%	3.2%
3	15.7%	15.1%	15.1%	13.8%	11.7%	9.3%	7.1%	5.3%	4.1%	2.9%
4	12.9%	13.2%	13.4%	13.9%	13.5%	11.1%	8.6%	5.6%	4.2%	3.6%
5	10.7%	10.8%	11.0%	13.3%	14.1%	13.1%	10.9%	7.0%	5.5%	3.6%
6	7.9%	8.8%	9.4%	10.8%	13.7%	14.9%	14.7%	10.1%	6.2%	3.6%
7	5.8%	6.4%	7.4%	8.5%	11.3%	14.3%	18.6%	15.7%	7.6%	4.5%
8	4.8%	4.8%	5.9%	6.7%	7.3%	9.8%	15.9%	22.9%	15.2%	6.6%
9	4.2%	4.8%	4.7%	4.8%	5.4%	6.3%	8.1%	16.0%	29.8%	15.8%
10	3.8%	4.2%	3.9%	3.8%	4.0%	5.6%	5.6%	7.3%	17.3%	44.8%

Panel B. Abnormal Price and Information Acquisition over Time

	EdgarSearch	EdgarSearch_{t+2}	EdgarSearch_{t+3}	Bloomberg	Bloomberg_{t+2}	Bloomberg_{t+3}
	(1)	(2)	(3)	(4)	(5)	(6)
AbnPrice	0.034^{***}	0.021^{***}	0.016^{**}	0.089^{***}	0.071^{***}	0.086^{***}
	(5.43)	(3.27)	(2.46)	(3.94)	(3.13)	(3.69)
Observations	87,493	79,139	74,938	59,895	55,776	54,150
Adj R-Squared	0.881	0.875	0.875	0.723	0.723	0.723
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

This table examines the persistence of abnormal price movements and information acquisition over time. Panel A presents a rank transition matrix of abnormal price movements, using the Edgar Downloads Sample. Each row (column) represents a decile rank of *AbnPrice* this quarter (next quarter). The value in Cell(i,j) represents the percentage of firms with decile rank i this quarter that have decile rank j next quarter. Panel B presents an analysis of the relation between abnormal price movement at the earnings announcement and information acquisition on Edgar (columns 1 to 3) and Bloomberg (columns 4 to 6) over time. All variables are defined in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers. t-statistics based on standard errors clustered by Firm are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 7
Alternative Measurement Window

	EdgarSearch_5day			Bloomberg_5day		
	(1)	(2)	(3)	(4)	(5)	(6)
AbnPrice	0.065***	0.058***	0.066***	0.037***	0.038***	0.102***
	(8.32)	(7.53)	(7.52)	(3.08)	(3.23)	(8.53)
Leverage		-0.154	-0.356**		-0.419**	-0.222
		(-1.05)	(-2.45)		(-2.09)	(-1.50)
log(Assets)		17.591***	12.864***		17.374***	16.352***
		(17.62)	(34.06)		(11.32)	(36.34)
BundledForecast		-5.229***	1.811**		0.029	-1.247
		(-5.66)	(2.35)		(0.02)	(-1.19)
Instown		-0.054***	-0.012		0.012	-0.079***
		(-2.92)	(-1.20)		(0.62)	(-6.58)
Shortsell		0.977***	0.969***		0.606***	0.658***
		(11.33)	(15.67)		(4.53)	(7.03)
Voldisc8K		2.957***	2.751***		1.149***	0.367
		(16.56)	(12.60)		(4.57)	(1.53)
MediaStories		0.057***	0.195***		0.001	0.071***
		(6.49)	(24.61)		(0.09)	(11.98)
EdgarSearch_lag			0.464***			
			(61.98)			
Bloomberg_lag						0.362***
						(44.40)
Observations	87,493	87,493	87,493	59,895	59,895	59,895
Adj R-Squared	0.784	0.790	0.731	0.516	0.522	0.478
Firm FE	Yes	Yes	No	Yes	Yes	No
Industry FE	No	No	Yes	No	No	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

This table repeats the analysis from Table 2, using a shorter, 5-day window to measure information acquisition. Columns 1 to 3 (4 to 6) examine information acquisition on Edgar (Bloomberg). The mean (median) values of raw, unlogged *EdgarSearch_5day* and *Bloomberg_5day* are 183.63 (108.00) and 1.54 (0.00), respectively. All variables are defined in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers. *t*-statistics based on standard errors clustered by Firm are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 8
Abnormal Price Change and Information Acquisition

	EdgarSearch			Bloomberg		
	(1)	(2)	(3)	(4)	(5)	(6)
AbnPriceChange	0.039***	0.023***	0.010**	0.234***	0.169***	0.080***
	(5.66)	(3.68)	(2.00)	(11.11)	(8.49)	(6.05)
Loss		4.806***	3.928***		0.622	10.499***
		(9.52)	(10.87)		(0.39)	(9.71)
Leverage		0.135	-0.070		-0.822***	-0.544***
		(1.45)	(-1.10)		(-3.82)	(-3.73)
log(Assets)		14.255***	5.933***		38.926***	17.488***
		(18.74)	(33.77)		(18.20)	(39.45)
BundledForecast		-2.781***	1.074***		0.235	1.993*
		(-3.61)	(2.86)		(0.09)	(1.65)
Instown		-0.093***	-0.012**		-0.000	-0.045***
		(-6.09)	(-2.48)		(-0.00)	(-3.35)
Shortsell		0.987***	0.470***		2.539***	1.242***
		(15.28)	(15.51)		(11.57)	(13.13)
Voldisc8K		2.290***	0.289***		2.349***	-0.545**
		(16.40)	(2.68)		(5.57)	(-2.00)
MediaStories		0.059***	0.091***		0.008	0.052***
		(7.49)	(23.30)		(0.68)	(9.61)
EdgarSearch_lag			0.733***			
			(155.13)			
Bloomberg_lag						0.696***
						(140.68)
Observations	87,346	87,346	87,346	62,745	62,745	62,745
Adj R-Squared	0.863	0.868	0.863	0.701	0.712	0.754
Firm FE	Yes	Yes	No	Yes	Yes	No
Industry FE	No	No	Yes	No	No	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

This table repeats the analysis from Table 2, using a changes-based measure of abnormal price movement. Columns 1 to 3 (4 to 6) examine information acquisition on Edgar (Bloomberg). The mean (median) values of unranked *AbnPriceChange* are 38.97 (15.70) in the EdgarSearch sample and 45.59 (17.19) in the Bloomberg sample, respectively. All variables are defined in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers. t-statistics based on standard errors clustered by Firm are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 9
Falsification Test: Return Reversals

	Return[t+2,t+180]			
	(1) AbnPrice Top10%	(2) AbnPrice_Signed Top10%	(3) AbnPrice_Signed Bottom10%	(4) Full Sample
Return[t-1,t+1]	-0.020	-0.026	-0.040	-0.015
	(-0.47)	(-0.61)	(-0.86)	(-0.58)
AbnPrice				0.000
				(1.54)
Return[t-1,t+1] × AbnPrice				0.000
				(0.82)
Leverage	0.001	0.001	0.005**	0.002**
	(0.31)	(0.28)	(2.22)	(2.31)
log(Assets)	-0.124***	-0.125***	-0.145***	-0.109***
	(-9.62)	(-9.69)	(-9.80)	(-26.80)
BundledForecast	0.004	0.002	-0.011	-0.009**
	(0.28)	(0.12)	(-0.58)	(-2.14)
Instown	-0.000*	-0.000	-0.000	-0.000**
	(-1.74)	(-1.46)	(-1.13)	(-2.00)
Shortsell	-0.003*	-0.003**	-0.005***	-0.004***
	(-1.95)	(-1.97)	(-3.24)	(-7.62)
Voldisc8K	-0.002	-0.002	0.001	0.000
	(-0.82)	(-0.83)	(0.22)	(0.17)
MediaStories	-0.000	-0.000	0.000	0.000
	(-0.12)	(-0.21)	(1.39)	(1.42)
Observations	13,259	13,259	13,327	132,988
Adj R-Squared	0.198	0.197	0.257	0.126
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes

This table presents a falsification test showing that *AbnPrice* is not associated with return reversals. The sample period for this analysis spans 2004-2022. Columns 1, 2, and 3 examine the association between abnormal returns in the 3-day window around the earnings announcement and future abnormal returns $[t+2,\ t+180]$, in subsamples of announcements with *AbnPrice* in the top decile, *AbnPrice_Signed* in the top decile, and *AbnPrice_Signed* in the bottom decile, respectively. Column 4 examines the association between abnormal returns in the 3-day window around the earnings announcement and future abnormal returns $[t+2,\ t+180]$, and how it varies with *AbnPrice*. The mean (median) values of $Return[t-1,t+1]$ and $Return[t+2,t+180]$ are 0.004 (0.003) and 0.003 (-0.015), respectively. All variables are defined in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers. t-statistics based on standard errors clustered by Firm are in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

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