The effect of meeting or missing earnings expectations on information asymmetry[*]

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Abstract: We examine whether the previously documented pricing premium for firms' equity when they meet or beat earnings expectations (MBE) is attributable to a reduction in the cost of equity capital via a reduction in information asymmetry. We measure the latter using the probability of informed trading (PIN) from Easley *et al.* (1997). We find that PIN decreases (increases) when firms meet or beat (miss) earnings expectations and that these changes increase with the magnitude of the earnings surprise. In addition, firms that regularly MBE show a stronger decline in PIN compared with those achieving MBE irregularly. Furthermore, we find that the reduction in asymmetry for MBE firms disappears in cases where *expectations* management was likely used to meet the earnings benchmark, but we find no evidence that *earnings* management affects the reduction in asymmetry attributable to MBE. Broadly, our results correspond to findings regarding the pricing premium associated with MBE, suggesting that the MBE pricing premium is at least partially attributable to a "denominator effect" where investors discount future cash flows at lower rates because of reduced levels of information asymmetry.

Key Words: Information asymmetry; meeting or beating expectations; earnings expectations; expectation management; investor recognition hypothesis.

JEL Classification: G12; G14; M41; M43.

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1. Introduction

Several recent studies, including Barth *et al.* (1999), Bartov *et al.* (2002), and Kasznik and McNichols (2002), have documented that investors assign a valuation premium to firms that meet or beat a benchmark level of earnings expectations (MBE). In searching for a rational explanation for the MBE premium, prior literature has focused on a signaling explanation whereby MBE signals better than expected future performance (cash flow or earnings).[1] We label this explanation the "numerator effect," consistent with common valuation terminology.

We examine an alternative but mutually non-exclusive explanation that we term the "denominator effect" whereby meeting (missing) earnings expectations leads to a decrease (increase) in the cost of capital (COC). Kasznik and McNichols (2002) speculate that the premium could be partly due to changes in COC since they find that the numerator effect does not fully explain the MBE valuation premium. We analyze the relation between MBE and the level of information asymmetry, which is positively associated with the COC (Easley *et al.* (2002), Easley *et al.* (2004), and Healy *et al.* (1999)). (As explained below, we choose this indirect approach because we cannot generate reliable evidence by directly examining the association between MBE and the COC.) We hypothesize that MBE (its complement, "Miss") firms experience changes in their trading and information environments that lead to a decrease (increase) in information asymmetry.

We conduct time-series tests of the association between a firm's earnings performance in one quarter and the change in information asymmetry in the subsequent quarter. Our proxy for

[1] While not disputing the extant evidence, the signaling story is unsatisfying because it is unlikely that meeting earnings expectations can serve as an economically-valid separating signal; conditional on the current level of earnings, it is not clear that exceeding a benchmark imposes additional costs that would vary between firms with different earnings prospects. The signaling explanation is more applicable in cases when (differentially) costly earnings management techniques are used to meet expectations.

information asymmetry is the probability of informed trade, or PIN, which we estimate using an extension of the popular EKO market microstructure model (Easley *et al.* (1997)). We rely on the consensus analysts forecast to proxy for the market's earnings expectations because Brown and Caylor (2004) find that the MBE phenomenon has the strongest association with this earnings benchmark during our sample period.

We find that information asymmetry declines significantly when a firm meets or beats its earnings expectations but rises significantly when a firm misses the benchmark level of earnings. Utilizing the components of the PIN measure, we examine the underlying link between earnings performance and information asymmetry. We find that MBE firms experience an increase in the volume of trading by uninformed investors both in absolute and relative terms (compared with investors who trade on private information). This evidence suggests good earnings performance increases the firm's investment visibility and attracts unsophisticated investors.[2] Such a dynamic is consistent with the Investor Recognition Hypothesis of Merton (1987).

The MBE pricing literature has examined the association between MBE and the market premium in more detail and has documented a number of cross-sectional differences in the MBE premium. We conduct supplementary tests that correspond to several of these results because evidence that parallels prior pricing premium results increases the likelihood that the information asymmetry effect is capturing the denominator effect. First, we find that the change in information asymmetry is positively related to the magnitude of the earnings surprise. Second, our evidence indicates the decrease (increase) in information asymmetry is larger for MBE (Miss) firms who have regularly met/beaten expectations over the prior eight quarters. Indeed,

[2] This finding suggests that MBE firms experience improved liquidity. Archarya and Pedersen (2005) and Brennan and Subrahmanyam (1996) find liquidity is negatively associated with the COC. Together, these findings suggest a complementary MBE denominator effect. Also, if more uninformed trading represents an expansion of the shareholder base, then MBE firms experience an improvement in aggregate risk sharing, further reducing the COC.

our results indicate that the average reduction in asymmetry that arises through MBE is significant only when it is part of a repeated pattern. Finally, we examine firms that are likely to have used expectations management or earnings management in order to meet expectations. We find the decrease in information asymmetry is largely eliminated for expectations management firms. For earnings management firms, we find no evidence for any differences in the MBE effect on information asymmetry. Overall, these findings articulate with corresponding results in Barth *et al.* (1999), Bartov *et al.* (2002) and Kasznik and McNichols (2002), further supporting the existence of a denominator effect.[3]

Graham *et al.* (2005) provide survey evidence consistent with the MBE premium. They report that more than eighty percent of Chief Financial Officers (CFOs) agree that meeting earnings benchmarks helps "maintain or increase the stock price" and "build credibility with capital markets." Seventy-eight percent of CFOs also believe that missing a benchmark "creates uncertainty about the firm's future prospects." Our evidence that information asymmetry is related to earnings benchmarks gives credence to CFOs' beliefs about the cost of capital benefits of meeting earnings benchmarks. In addition, our evidence is more direct as it reflects what investors actually do, rather than what CFOs believe investors do.

This paper contributes to the literature by providing evidence consistent with an alternative but non-exclusive "denominator" explanation for the MBE pricing premium documented in the prior literature. Indirectly, our evidence suggests that changes in the cost of capital, caused by changes in information asymmetry, contribute to the MBE valuation premium. The associations between MBE patterns and information asymmetry articulate with

[3] The expectations management results are not fully congruent with Bartov *et al.* (2002) in that Bartov *et al*. show evidence that there is only a partial reduction in the pricing premium for expectations management firms. However, additional tests show that in our sample, the MBE pricing premium essentially disappears in cases where expectations management had likely occurred; these findings are consistent with our information asymmetry results.

corresponding relations between MBE patterns and market pricing documented in the prior literature. By providing evidence consistent with the denominator effect, this paper suggests a rational explanation for why firms and analysts play the "earnings game" whereby firms engage in costly activities to meet external forecasts: firms receive cost of capital benefits while analysts benefit from more accurate earnings forecasts and higher trading volumes. Thus, the efforts taken by managers to meet earnings expectations are not necessarily contrary to the interests of shareholders, as is often implied (Jensen (2005)).

We also contribute to the literature by providing insights into the role earnings benchmarks play in affecting investors trading decisions and information search activities. We document how informed and uninformed investors alter their trading behaviors based on how actual earnings compare to earnings benchmarks. These findings are consistent with the Investor Recognition Hypothesis (Merton (1987)) whereby good (bad) earnings performance increases (decreases) a firm's investment visibility.

We do not follow an alternative and more direct approach of analyzing the relation between MBE and the COC for several reasons. First, Easton and Monahan (2005) find that accounting-based *ex ante* proxies for the COC are generally unreliable. Second, existing techniques rely on the current stock price and analyst forecasts of future earnings or cash flows. As a result, increases (decreases) in stock prices mechanically lead to decreases (increases) in the implied COC when there are delays in the updating of analysts' forecasts. Kasznik and McNichols (2002) find that the future profitability of MBE firms is not immediately reflected in analyst forecasts made after earnings are released. Thus, implied COC techniques have systematic errors that are biased in favor of the hypothesized denominator effect. Third, relying on *ex post* realized returns to measure expected returns is invalid when expected returns are changing, as we expect to be the case in our setting, because realized and expected returns move in opposite directions. Given the limitations surrounding the use of COC estimates in our setting, we instead rely on prior theoretical and empirical research that has documented a positive association between PIN and the equity COC (Easley *et al*., 2002) and indirectly proxy for the COC by using PIN.

Next, we develop our hypotheses regarding the association between earnings performance and information asymmetry. In Section 3, we introduce the PIN measure of information asymmetry. Section 4 discusses data sources, variable construction, and descriptive statistics. Section 5 presents the results of our empirical tests, and Section 6 concludes the paper.

2. Relation between meeting or beating earnings expectations and information asymmetry

In the idealized setting of informationally efficient stock markets, all potential investors are assumed to costlessly process all public information. However, these idealized conditions are not met in practice. Investors must at least be aware of the firm before they can consider it as a potential investment. While investors will not buy the stock of every firm of which they become aware, they cannot buy the stock of a firm of which they are unaware. Merton (1987) and Fishman and Hagerty (1989) show that decreases in costs of obtaining and processing public information about a firm leads to increases in the number of non-privately informed investors. This "Investor Recognition Hypothesis" is supported by several studies that demonstrate the importance of visibility on the size and composition of the firm's ownership base.[4] For example, Falkenstein (1996) shows that mutual funds have significant preferences for stocks with heavy newspaper coverage while Barber and Odean (2005) find that individuals are net buyers of

[4] Aggarwal *et al.* (2002) and Demers and Lewellen (2003) find that IPO underpricing is reduced by increased attention by the media and non-affiliated analysts. Similarly, Grullon *et al.* (2004) find that firms with greater product market advertising expenditures have more individual and institutional investors. Also see Foerster and Karolyi (1999) and Kadlec and McConnell (1994).

stocks on days when the firms are in the news. In addition, Lehavy and Sloan (2005) provide more direct support for the Investor Recognition Hypotheis by documenting an association between recognition and current and future stock returns.

We expect that reporting good earnings news (i.e., above expectations) generally increases the number of investors who are both aware of the firm and, given the good earnings performance, more likely to invest. Consistent with our expectation, Nofsinger (2001) finds that individuals significantly increase their buying activity after good earnings news, but not following bad earnings news. His evidence indicates that while bad news may generate increased attention from uninformed investors, it does not lead them to invest in the stock.[5] Thus, we expect that good earnings performance results in more uninformed trading because it increases investment visibility and reduces the costs of obtaining public information about the firm. Accordingly, we expect that good earnings performance is associated with relatively more trading by uninformed investors, and hence, lower information asymmetry.

Good earnings performance also decreases the level of information asymmetry by reducing the incentives to search for private information. We hypothesize that when a firm meets or beats its earnings target, investors believe that it is more likely to hit its target in the future.[6] In this case, there are fewer short-term incentives to search for private information about next period's earnings (Goel and Thakor (2003)).[7] In addition, the expansion of the investor base discussed above will further reduce the incentives to search for private information. Peress (2004) demonstrates that a broader investor base will reduce the incentives for existing

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[5] Nofsinger (2001) also finds that individuals respond more strongly to good news than institutional investors do, which suggests that good news predominantly draws in uninformed traders.

[6] In our sample, the unconditional probability of a firm meeting or beating its earnings expectations is 0.76, while the probability conditional on MBE in the prior quarter is 0.84.

[7] There are still incentives to discover information about the extent to which firms will beat or miss expectations. However, this is the same as searching for private information to predict the level of earnings. We are interested in whether there is an additional effect for meeting or missing a benchmark.

shareholders to produce private information. Since we expect the new investors to be predominantly uninformed, the net effect is less private information production. Accordingly, we expect that after good earnings performance, there will be fewer days on which certain investors are trading on private information (which we refer to as private information events).

We expect bad earnings performance will lead to an increase in information asymmetry through a similar but not identical dynamic. While missing the market's earnings expectations may generate additional investor recognition (through negative press coverage), it is unlikely to generate additional investment activity. Instead, bad earnings performance will cause the level of uninformed trading to decrease. In addition, the expected amount of private information about the firm's future earnings performance will increase. Ciccone (2003) finds that analysts typically disagree more after bad news than good news, which indicates there is increased uncertainty and more private information available after bad news. The findings in Graham *et al.* (2005) are also consistent with this notion. They report that CFOs commonly believe that not meeting an earnings target will be interpreted by the market as evidence of hidden problems. Increased uncertainty about the firm's future prospects after it fails to meet its earning expectations will lead to more search activities, and hence, more frequent private information events. Accordingly, we examine the following hypotheses (all hypotheses are stated in alternate form):

> **H1:** Meeting or beating (missing) earnings expectations is associated with less (more) information asymmetry during the subsequent period.
>
> **H2:** Meeting or beating (missing) earnings expectations is associated with:
> **(a)** more (less) trading by uninformed investors,
> **(b)** relatively less (more) trading by privately-informed investors, and
> **(c)** less (more) frequent private information events in the subsequent period.

Prior literature on the MBE phenomenon indicates that MBE premium is generally larger when firms routinely deliver good earnings performance compared to firms which only sporadically meet their earnings targets. One possible explanation for these findings is that it takes repeated good earnings performance to substantially increase the firm's investment visibility and/or alter incentives to search for private information. In this case, we also expect that the effect of a Miss will be greater for firms that had previously delivered good earnings performance on a routine basis. Consistent with this reasoning, Barth *et al.* (1999) find a significant decrease in the valuation premium when a firm breaks a previously increasing earnings pattern. Thus, if the valuation premium is related to differences in information asymmetry as we propose, then the relation between information asymmetry and both good and bad earnings performance should be stronger when firms have routinely delivered good earnings performance. Thus, we test the following hypothesis:

> **H3:** Firms that have repeatedly met or beaten earnings expectations in prior periods experience larger decreases (increases) in information asymmetry after meeting or beating (missing) earnings expectations.

We hypothesize that the effects of good earnings performance on firm visibility will depend on how the earnings target was met. To the extent that a firm uses either earnings management or expectations management to meet an earnings target and these efforts are partially observable, then we expect the reduction in information asymmetry will be lessened for two reasons. First, the benefits of increased investment visibility will be lower to the extent the market believes that the firm did not actually achieve good earnings performance. Second, there will be more uncertainty about future earnings, which will increase incentives to search for private information. We expect these factors will ameliorate the negative association between information asymmetry and good earnings performance when either expectations or earnings management techniques have been used. Thus, we test the following hypothesis:

H4: The association between meeting or beating expectations and information asymmetry is less negative when it is more likely that the good earnings performance is due to:

(a) expectations management, or

(b) earnings management.

3. The PIN measure of information asymmetry

Information asymmetry manifests itself when certain investors trade on private information. Hence, information asymmetry results in abnormally large imbalances between buy and sell orders on days when informed investors are trading on their private information. This observation forms the intuition behind the EKO microstructure model of information asymmetry (Easley *et al.* (1997)), which we use to estimate the unconditional probability of information-based trading for a given stock based on the observed order flow.

Easley *et al.* (1997) models trading as a repeated game between the market maker and two types of traders: informed and uninformed. At the beginning of each trading day, nature determines whether a private information event occurs with probability α. On such days, informed traders receive private information about the firm's value. The private information contains bad (good) news with probability δ $(1-\delta)$, where bad (good) news indicates that the profit maximizing trade is to sell (buy) the stock.[8]

Uninformed traders submit buy and sell orders each day according to independent Poisson processes at the daily rate ε. On days with good (bad) news, informed buy (sell) orders also arrive at a rate proportional to the amount of uninformed trading, $\nu\varepsilon$. Therefore, on a no-news day, both buys and sells are Poisson distributed with parameter ε. On bad-news days, buys are Poisson distributed with parameter ε and sells are Poisson distributed with parameter

[8] By assuming that the type of news is unambiguous, the model does not allow for both informed buying and selling on the same day, as in Kim and Verrecchia (1991); instead, information asymmetry is one-sided, as in Kyle (1985).

$(\varepsilon + \nu\varepsilon) = \varepsilon(1+\nu)$; vice versa on good-news days. The market maker sets prices to buy or sell one unit of stock and executes orders as they randomly arrive.[9] The market maker knows the unconditional probability of, and expected order flow associated with, a private information event and uses the actual order flow to update her beliefs throughout the trading day. By the end of the day, all private information has been impounded into price through informed trading.

An important simplifying assumption of the EKO model is that the daily arrival rates of uninformed buy and sell orders are drawn from independent Poisson distributions that have constant parameters over the estimation period. This assumption causes the daily numbers of uninformed buys and sells to be uncorrelated. However, this assumption is violated in practice because certain public information events affect the trading intensity of both uninformed buyers and sellers on a particular day. These events can be both firm-specific, such as earnings announcements, and market-wide, such as the release of macroeconomic statistics (Chordia *et al.* (2000)). If these events affect the trading intensities of all uninformed traders similarly, then the daily arrival rates of uninformed buy and sell orders will be positively correlated. Evidence in Brown and Hillegeist (2005) and Venter and de Jongh (2004) strongly supports the idea that there are common shocks to the daily level of uninformed trading, and thus, the assumption of identical daily Poisson distributions does not hold in practice.

To overcome this limitation, Venter and de Jongh (2004) extend the EKO model by specifying the arrival of uninformed buy and sell orders as a bivariate Inverse Gaussian Poisson process. The extended model assumes that on each trading day, the average trading intensities of uninformed investors are subject to a scaling factor W_t, where W_t is drawn from an inverse

[9] The model assumes that each trade is equally informative regardless of its size. This assumption is plausible as informed investors disguise their private information by mimicking the trade sizes of uninformed traders (Barclay and Warner (1993), Chakravarty (2001)). Jones *et al.* (1994) provide evidence suggesting that the loss of information due to ignoring trade size is small.

Gaussian distribution with parameter $\psi > 0$. As $E[W_t] = 1$ (and $Var[W_t] = (1/\psi^2)$), the unconditional expectation of the daily number of uninformed buys (sells) remains equal to $E[\varepsilon W_t] = \varepsilon$.[10] Since the scaling factor affects both uninformed buyers and sellers equally, the extended model induces a positive correlation between the daily number of buy and sell orders. We provide a more detailed description of the extended model in the Appendix.

The extended model's parameters (α, δ, ψ, ε, ν) are estimated by maximizing the likelihood function given in Equation (A5) in the Appendix using the daily number of buys and sells as inputs. PIN is calculated as follows:

$$PIN = \frac{\alpha\nu\varepsilon}{\alpha\nu\varepsilon + 2\varepsilon}. \tag{1}$$

PIN is the unconditional expectation of the fraction of total daily trades that are based on private information since $\alpha\nu\varepsilon$ is the expected number of orders from privately informed investors and $\alpha\nu\varepsilon + 2\varepsilon$ is the expected number of total orders. Equation (1) shows that asymmetry increases with the frequency of private information events (α), and the relative intensity of informed trading (ν), and decreases in the level of uninformed trading (ε).

4. Sample and measurement

The data originates from three primary sources. Intraday trade data comes from the Trades and Quotes (TAQ) database. Second, earnings expectations are based on the consensus of analysts' forecasts computed by First Call. For consistency with forecasted numbers, we also use First Call's record of the actual earnings to determine whether a company meets/beats or misses its

[10] As $\psi \rightarrow \infty$, the mass of the distribution becomes concentrated at $W = 1$ and the extended model reduces to the original EKO model. To be consistent with prior literature, we also replicate our analyses using PINs from the original model. The untabulated results are qualitatively similar to those reported in the tables in that when significant results are reported, they remain significant at conventional revels using the basic PINs. However, consistent with basic PINs estimates being more noisy, the significance levels are reduced and the absolute values of the coefficient estimates are closer to zero.

earnings expectations. Third, we use data from Compustat to estimate the likelihood of earnings management and to measure firm size.

The sample comprises all firm-quarters in the intersection of these data sources, with First Call being the most restrictive database. The sample period begins in the first quarter of 1995, when First Call data seems to have become reliable, and ends with the second quarter of 2004, the time when the First Call data was obtained. We use non-linear optimization procedures to maximize the likelihood functions in equation (A5) to estimate the PIN and its component parameters. We exclude observations in the few cases where the average daily number of buys or sells is greater than 2,000 as the computational costs of estimating the likelihood function is prohibitive. In total, we have 65,619 firm-quarter observations.

We measure PIN in event time, with the five trading days centered on the quarterly earnings announcement date acting as the divider between quarters. Thus, each firm-quarter estimate is based on trade data over approximately 12 weeks. As shown in Table 1, the mean and median PIN estimates are 18.40% and 16.15%, respectively. These values are similar to the values reported in Brown *et al.* (2004) even though that paper uses the original, as opposed to the extended, EKO model. This similarity is not surprising because the correlation between PIN computed under both models is high (untabulated Pearson correlation coefficient = 0.80). However, we find that the extended model fits the trade data significantly better. In our sample, the median value of ψ is 2.31 and 99% of all estimated values are less than 10.2. Recall that the original model is a subset of the extended model, but with $1/\psi$ equal to 0.[11]

We define $MBE_{i,t}$ as an indicator variable that equals 1 if firm *i*'s actual EPS is greater than or equal to the consensus forecast of EPS for quarter *t*, where the consensus is the latest

[11] Further examination indicates that the basic EKO model fits the data approximately as well as the extended model only when the trading intensity is extremely low; for ψ to reach 25 or higher (indicating the original model fits the data reasonably well), the median level of total uninformed trading is less than three trades per day.

value prior to the actual earnings release date reported by First Call. In our sample, firms meet or beat expectations 76% of the time. In comparison, Bartov et al. report that 70% of their sample observations in 1994-1997, and 50% in 1983-1993, meet or beat expectations. Thus, it appears that the incidence of MBE has increased over time.

As discussed more thoroughly in the next section, our analysis focuses on quarter-to-quarter changes in information asymmetry. Consequently, we only need to employ control variables that change substantially from one quarter to the next. We use two control variables: (changes in) the number of analysts and firm size. $Analysts_{i,t}$ is the number of analysts contributing to the consensus estimate of EPS reported by First Call for firm i and quarter t. $Size_{i,t}$ is the natural log of firm i's market value of equity (in millions of dollars) at the end of the fiscal quarter corresponding to the EPS report. The mean (median) number of analysts is 5.99 (4) and the mean (median) firm size is \$608 (\$550) million.

Table 2 presents the matrix of Pearson correlations. All values are significant at the 0.01 level. By construction, *PIN* and the *PIN* parameters (α, ν, ε) have high correlations. The correlations between *MBE* and *PIN* (and its component parameters α, ν, and ε), are all consistent with the hypothesized relations, although the correlation with α is modest (-0.04). In addition, the large negative correlations between *PIN* and *Size* (-0.57) and between *PIN* and *Analysts* (-0.47) are expected and consistent with the prior literature.

5. Analysis and results

In this section, we describe the regression analyses we carry out to test our hypotheses. Before doing so, we first present preliminary evidence based on a bivariate analysis relating PIN to the number of consecutive quarters for which a firm has met/beaten or missed expectations. We then formally test the association between PIN and MBE (H1), and between the component parameters of PIN and MBE (H2). Next, we test whether there is an incremental association between PIN and MBE when a firm habitually meets or beats expectations (H3). Finally, we examine whether the relation between PIN and MBE depends on whether the good earnings performance was likely achieved through expectations or earnings management (H4).

5.1. Preliminary evidence

Table 3 and Figure 1 show the level of PIN according the number of consecutive quarters for which a firm meets/beats or misses the analyst consensus forecast of earnings. Negative values indicate the number of consecutive quarters that a firm has missed expectations. Data for the numbers of quarters below –4 and exceeding +24 have been winsorized at –4 and +24, respectively, because there are relatively few observations with values exceeding these cutoffs. Figure 1 clearly shows an almost monotone decrease in PIN from just over 20% down to just over 11% as the *MBE* string increases from 1 to 24 quarters. This preliminary evidence supports our expectation that meeting or beating earnings expectations is associated with the level of information asymmetry. Firms that have missed expectations experience higher PIN than MBE firms. While there is no apparent pattern between PIN and the number of consecutive *Miss* quarters, the average value of PIN (over 20.5%) is quite high for these firms.

The above analysis is only suggestive since it does not control for other confounding effects, such as the negative correlation between Size and PIN and the positive correlation between Size and MBE. We address such issues with our formal regression analyses.

5.2. Association of PIN and MBE – tests of H1 and H2

We examine whether PIN decreases in the quarter after a firm meets or beats its benchmark level of earnings. To accomplish this, we express changes in PIN as a function of MBE and changes in the control variables, as follows:

$$\Delta PIN_{i,t+1} = \beta_0 + \beta_1 MBE_{i,t} + \beta_2 \Delta Analyst_{i,t+1} + \beta_3 \Delta Size_{i,t+1} + \mu_{i,t+1} \quad (2)$$

where $\Delta PIN_{i,t+1} = PIN_{i,t+1} - PIN_{i,t}$, and analogously for $\Delta Analyst_{i,t+1}$ and $\Delta Size_{i,t+1}$. Recall that $PIN_{i,t}$ is measured in event time, so $\Delta PIN_{i,t+1}$ measures the change in PIN from the approximately twelve-week period immediately prior to the earnings announcement for quarter t to the twelve-week period immediately afterwards. The intercept (β_0) represents the average change in PIN for firms that miss expectations (i.e., MBE = 0) conditional on no changes in size or analyst following. Based on Hypothesis H1, we predict that $\beta_0 > 0$ and $\beta_1 < 0$.

Panel A of Table 4 shows that there is a significant increase in PIN when a firm fails to meet or beat its earnings expectations. On average, PIN increases by a significant 0.23% (t-statistic = 5.17) during the following quarter after missing its earnings benchmark. In contrast, the significant negative coefficient on *MBE* (t-statistic = -4.98) indicates that PINs are lower by 0.27% when a firm meets or beats, rather than misses, its target level of earnings. We also estimate a levels version of equation (2) where PIN_t is included as an additional control variable. The untabulated results are similar as the coefficient on MBE_t is -0.35 (t-statistic = -6.46).[12] Together, these findings provide strong support for hypothesis H1. To the extent the type of information risk captured by PIN is priced in the market, the MBE valuation premium is at least partially explained by a reduction in the cost of capital for MBE firms. In addition, the coefficients for the control variables are strongly significant and consistent with our expectations. Specifically, increases in firm size and the extent of analyst coverage are associated with reductions in the level of information asymmetry.

We next examine the association between MBE and the components that comprise the PIN estimate using equations that are analogous to equation (2), but with the dependent variable

[12] In addition, the results of levels versions of the analyses presented in Tables 5 – 7 are all qualitatively similar to the changes specifications and the inferences remain the same except where specifically noted.

being an individual PIN parameter (α, ν, and ε). These analyses provide insights into the source of the negative association between MBE and information asymmetry. As shown in Panel B of Table 4, we find no evidence that the probability of an information event (α) is affected by whether a firm meets or misses expectations. However, as predicted, we do find in Panel C that the amount of informed relative to uninformed trading (ν) decreases (coefficient = -0.018, *t*-statistic = -4.19) and in Panel D that the absolute amount of uninformed trading (ε) increases (coefficient = 4.10, *t*-statistic = 11.87) in the following quarter when a firm meets or beats its earnings benchmark. The magnitude of the *MBE* coefficient in the ε regression indicates that in the quarter after a firms meets or beats its benchmark the number of trades by uninformed investors increases on average by about 8 trades per day (2×4.099). This represents an increase of 3.4% (10.0%) relative to the mean (median) value of ε shown in Table 1. In comparison, the change in ν is more modest, at 2% (2.5%) of the mean (median) value.

In summary, the results in Panels B – D provide partial support for hypothesis H2. The results indicate that MBE firms experience a significant increase in the amount of trading by uninformed investors, both in absolute terms and relative to the amount of informed trading. However, we find no evidence indicating that MBE is associated with reduced incentives to search for private information about earnings.

To further explore the relation between MBE/Miss and the level of information asymmetry, we examine whether the magnitude of the earnings surprise is incrementally associated with the change in information asymmetry. That is, we look at whether the association between asymmetry and earnings performance varies depending on whether the firm just meets or slightly beats (misses) its earnings benchmark or exceeds (misses) the target by a wide margin. We categorize firms into four groups using four indicator variables:

- *BigMeet* = 1 if *MBE* = 1 and (actual EPS – consensus EPS forecast) > \$0.02;
- *SmallMeet* = 1 if *MBE* = 1 and (actual EPS – consensus EPS forecast) ≤ \$0.02;
- *SmallMiss* = 1 if *MBE* = 0 and (actual EPS – consensus EPS forecast) ≥ -\$0.02;
- *BigMiss* = 1 if *MBE* = 0 and (actual EPS – consensus EPS forecast) < -\$0.02.[13]

We examine whether the association between PIN and earnings performance varies depending on the size of the earnings surprise using equations that are analogous to equation (2), but including in the regression three of the four indicators (*BigMeet*, *SmallMeet*, and *SmallMiss*) in place of *MBE*. The interpretation of these coefficients is relative to the effect of a relatively large earnings shortfall (*BigMiss* = 1) on information asymmetry.

The results of these analyses are presented in Table 5 and show the effect of different magnitudes of earnings surprises on the quarterly change in PIN. The coefficients on all three earnings surprise variables are significantly negative, indicating that relatively large misses result in the largest increases in information asymmetry. Consistent with larger positive surprises leading to larger declines in PIN, the coefficient on *BigMeet* (-0.47) is more negative than the *SmallMeet* coefficient (-0.33), which in turn is more negative than the *SmallMiss* coefficient (-0.24). F-tests indicate that the *BigMeet* coefficient is significantly more negative than the other two coefficients (both *p*-values < 0.01), but that the *SmallMeet* and *SmallMiss* coefficients are not significantly different from each other (*p*-value = 0.25).[14] These results suggest that bigger positive earnings surprises lead to increased investor recognition, which in turn leads to larger reductions in information asymmetry. Likewise, larger negative earnings surprises lead to larger increases in asymmetry compared to smaller earnings shortfalls.

[13] These cutoffs were determined to ensure an adequate number of observations in each category. Approximately 14%, 10%, 49%, and 26% of observations fall into the *BigMiss*, *SmallMiss*, *SmallMeet*, and *BigMeet* categories, respectively. The results are not sensitive to using alternative cutoff values.
[14] Untabulated results for the levels specification are similar except the *SmallMiss* coefficient is no longer significant, but the difference between the *SmallMeet* and *SmallMiss* coefficients becomes significant.

5.3. Association of PIN and MBE history – test of H3

According to hypothesis H3, MBE (Miss) firms that have repeatedly met or beaten expectations in prior periods experience larger decreases (increases) in the level of information asymmetry compared to firms that have done so less regularly. We define an indicator variable, $Habitual_{i,t}$, that equals 1 if in quarter *t*, firm *i* has met or beaten expectations in at least six out the eight previous quarters (i.e., quarters *t–8* to *t–1*). We then estimate the following equation:

$$\begin{aligned}\Delta PIN_{i,t+1} = \delta_0 + \delta_1 MBE_{i,t} + \delta_2 Habitual_{i,t} + \delta_3 MBE_{i,t} \times Habitual_{i,t} \\ + \delta_4 \Delta Analysts_{i,t+1} + \delta_5 \Delta Size_{i,t+1} + \eta_{i,t+1}\end{aligned} \tag{3}$$

To avoid survival bias, we include only observations that have at a minimum of 8 quarters of past data. Hypothesis H3 predicts that $\delta_2 > 0$ and $\delta_3 < 0$. Note that δ_2 captures the incremental effect of a quarter *t* Miss for firms that had habitually met expectations in quarters prior to *t*.

The results in Table 6 show that there are indeed additional benefits to repeatedly meeting or beating expectations, consistent with hypothesis H3. The coefficient on *MBE×Habitual* is significantly negative (*t*-statistic = -1.89; one-sided *p*-value = 0.03). In addition, the *MBE* coefficient is no longer significant, as it was in Table 4. F-tests strongly reject the hypotheses that the coefficients on *MBE×Habitual* and *MBE* are both equal to zero (F-statistic = 4.51; *p*-value = 0.02) and that the sum of the two coefficients is equal to zero (F-statistic = 8.26; *p*-value < 0.01). Together, the results indicate that the average reduction in PIN that arises through meeting or beating expectations is minimal unless it is part of a repeated pattern. The significant positive coefficient on *Habitual* ($\delta_2 = 0.233$, t = 2.16) indicates that PIN increases more when a habitual beater misses expectations compared with non-*Habitual* firms that miss expectations. This relation between information asymmetry and MBE (Miss) for firms that had habitually met or beaten the benchmark level of earnings is similar to the association between the MBE valuation premium and habitual MBE firms documented in Barth *et al.*

(1999), Bartov *et al.* (2002) and Kasznik and McNichols (2002), among others. This similarity further supports our argument that the observed pricing premium associated with MBE is at least partially explained by a denominator effect driven by changes in information asymmetry.

5.4. Effect of expectations or earnings management on the association between PIN and MBE – tests of H4

In this section, we examine whether the relation between MBE and information asymmetry is weakened when a firm is more likely to have managed expectations or earnings in order to meet the earnings benchmark (H4). As expectations and earnings management activities are not directly observable, we can only identify instances in which such activities are more or less likely to have occurred. Following Bartov *et al.* (2002), we compare the consensus forecast at two points in time to identify instances where expectations management is more likely to have occurred. We identify MBE firms where the latest EPS forecast before the earnings announcement date for firm *i* is lower than the earliest EPS forecast following the prior quarter's earnings announcement, *and* actual EPS is less than the earliest EPS forecast. In other words, the firm did not MBE its beginning-of-period earnings target but did so relative to its end-of-period target. In these cases, we set the indicator variable $ExpMan_{i,t} = 1$; otherwise the variable equals zero. This classification scheme causes 27% of observations to be identified as likely to have managed expectations downwards in order to meet or beat their earnings target.

To identify firms that are more likely to have managed earnings, we estimate the level of discretionary accruals using the residuals from the following modified-Jones model:

$$TotAccr_{i,t} / TA_{i,t-1} = \kappa_0 + \kappa_1(1/TA_{i,t-1}) + \kappa_2(\Delta Sales_{i,t} - \Delta Rec_{i,t}) / TA_{i,t-1} + \kappa_3 PPE_{i,t} / TA_{i,t-1} + \iota_{i,t} . \quad (4)$$

TotAccr is total accruals, measured as the change in non-cash current assets (Compustat quarterly item 40 – item 36) less the change in non-debt current liabilities (item 49 – item 45) less depreciation (item 5). *TA* is total assets (item 44), *Sales* is item 2, *Rec* is accounts receivable (item 37), and *PPE* is property, plant and equipment (item 42). The model is estimated separately for each quarter t and for each 2-digit SIC code. We require a minimum of 8 observations per regression. Based on these estimates of discretionary accruals, we classify firms as having managed earnings upwards in quarter t if the residual from equation (4) is positive, $MBE = 1$, but *MBE* would have equaled zero if discretionary accruals had been zero. That is, when the firm was only able to meet the earnings target because it had positive discretionary accruals, we set the indicator variable $EarnMan_{i,t}$ equal to 1; otherwise, it equals zero. This classification scheme results in 40% of observations being identified as likely to have managed earnings upwards in order to meet or beat their earnings benchmark.

We then estimate the following equation to test hypothesis H4:

$$\Delta PIN_{i,t+1} = \phi_0 + \phi_1 MBE_{i,t} + \phi_2 ExpMan_{i,t} + \phi_3 EarnMan_{i,t} + \phi_4 \Delta Analyst_{i,t+1} + \phi_5 \Delta Size_{i,t+1} + \xi_{i,t} \quad (5)$$

We continue to expect that firms benefit from meeting or beating expectations, so $\phi_1 < 0$. However, we predict that firms that are more likely to have managed expectations or earnings will have an attenuated MBE effects to the extent these efforts are observed by the market. Therefore, we expect $\phi_2 > 0$ and $\phi_3 > 0$.

Table 7 presents the results of this regression. The sample is reduced to about half of that used in Table 4 because of the additional data requirements. We find that the *MBE* coefficient is significantly negative ($\phi_1 = -0.418$, t-statistic = -5.24) and similar in magnitude to that reported in Table 4. We find that the coefficient on *ExpMan* is significantly positive as predicted ($\phi_2 = 0.510$, t-statistic = 7.93) and in fact is slightly larger than the *MBE* coefficient in magnitude. Thus, the MBE effect is attenuated to such an extent that there are no significant benefits for meeting or beating expectations ($\phi_1 + \phi_2 = 0.092$, F-statistic = 1.06, p-value = 0.30) when it likely has been accomplished by managing expectations. In comparison, we find no evidence that engaging in earnings management reduces the association between *PIN* and *MBE*. The coefficient on *EarnMan* is quite small in magnitude and is insignificantly different from zero (ϕ_3 = 0.089, t-statistic = 1.41).

Overall, we find evidence that the association between information asymmetry and meeting/beating expectations substantially weakens for firms that manage expectations but not earnings. We conjecture that the differences in results for the two management techniques are due to the relative ease of identifying expectations management, which only requires that one is able to observe analyst forecasts at the beginning and end of each quarter. In contrast, it is much more difficult to conclusively identify cases of earnings management. The results are also consistent with there being substantially more measurement error for the earnings management variable (Dechow *et al.* (1995)). However, it is unclear if investors have a better measure of earnings management.

5.5. Effect of expectations and earnings management on the association between MBE and returns.

The analyses in the prior section correspond to similar analyses in Bartov *et al.* (2002). Based on a sample period (1983 – 1997) that largely predates ours (1995 – 2004), they find that the reduction in the pricing premium remains statistically significant although somewhat small in magnitude in cases where earnings management is suspected, while the premium is reduced by over 50% in cases where expectations management is likely. As such, their findings and our information asymmetry results are not fully consistent with each other.

One possible explanation for the differences between results is that the reported earnings "game" between analysts, investors, and firms has evolved over time (Brown and Caylor (2004)). Accordingly, we examine the associations between MBE and the pricing premium in the presence of expectations and earnings management in our sample, and determine to what extent they correspond to the asymmetry results in Table 7. Following Bartov *et al*. (2002), we use the following regression equation to assess the MBE pricing premium in cases where earnings or expectations management were likely to have been used to meet the earnings expectations:

$$CAR_{i,t} = \alpha_0 + \alpha_1 FCError_{i,t} + \alpha_2 MBE_{i,t} + \alpha_3 MBE_{i,t} \times Manage_{i,t} + \varepsilon_{i,t} \quad (6)$$

where *Manage* equals *ExpMan* or *EarnMan* depending on the specification. *CAR* is the cumulative abnormal (beta-adjusted) return beginning two days following the date of the first forecast for the quarter subsequent to the prior quarter's earnings announcement to one day after the current earnings announcement. *FCError* is the difference between the actual earnings per share and the earliest consensus (median) forecast during the quarter deflated by beginning of quarter share price.[15] Due to the additional data requirements, the number of firm-quarter observations is reduced to 21,025.

The results from estimating equation (6) when *Manage* ≡ *ExpMan* are presented in Table 8, Panel A. Consistent with the prior literature, the coefficient on *MBE* is positive and significant (t-statistic = 16.84). The magnitude of the coefficient indicates that MBE firms are priced at a 5.4% premium relative to other firms, which is consistent with the prior literature. As expected, the MBE pricing premium is significantly lower in cases where expectations management is more likely to have taken place. Adding the interaction coefficient with the *MBE* coefficient ($\phi_2 + \phi_3$) indicates that the MBE premium is reduced to 1.7% in cases where expectations management is likely. This amount, while statistically significant (p-value = 0.0001), is economically small. Furthermore, untabulated analyses indicate that when we

[15] Untabulated analyses show that our results are qualitatively unchanged if cumulative raw returns are used instead of cumulative abnormal returns or if the first forecast is used instead of the first consensus forecast.

include *ExpMan* as a separate variable in the regression (i.e., the main effect, in addition to the interaction with *MBE*), the MBE premium in cases of expectations management is reduced to an insignificant 0.67%. This finding corresponds to the result in Table 7 that there is no significant reduction in information asymmetry for MBE firms that likely engaged in expectations management.

The results from estimating equation (6) when *Manage* ≡ *EarnMan* are presented in Table 8, Panel B. The *MBE* coefficient remains positive and significant (3.7%, *t*-statistic = 11.18), andthe interaction term is close to zero and is not statistically significant (*t*-statistic = 0.04). Thus, we find no evidence of a reduction in the MBE premium in cases where it is more likely that the firm used earnings management in order to meet its earnings benchmark. Our inferences remain the same when *EarnMan* is included as an additional regressor. This finding corresponds to the result in Table 7 that the reduction in information asymmetry for MBE firms does not depend on whether they likely engaged in earnings management.

6. Summary and Conclusions

This study proposes a discount rate "denominator effect" explanation for the previously documented pricing premium for firms that are able to meet or beat investors' earnings expectations. We hypothesize that meeting or beating (missing) earnings expectations leads to real changes in firms' trading and information environments that result in a decrease (increase) in information asymmetry. Relying on prior theoretical and empirical studies that link the cost of equity capital to the level of information asymmetry, documenting a negative relation between MBE and information asymmetry provides indirect evidence supporting the proposed denominator effect.

The results of our time-series tests indicate that information asymmetry decreases over the subsequent quarter when a firm meets or beats earnings expectations and increases after a firm misses its earnings expectations. We conduct additional analyses that correspond to several of the findings in the MBE pricing literature in order to provide additional evidence on cross-sectional variations in the relations. These tests indicate (1) the magnitude of the change in asymmetry is positively related to the absolute magnitude of the earnings surprise; (2) the decrease (increase) in information asymmetry is larger for MBE (Miss) firms who have regularly met or beaten expectations over the prior eight quarters; and (3) the decrease in information asymmetry is unaffected (eliminated) for firms that likely used earnings (expectations) management in order to MBE. Overall, these findings mimic corresponding MBE pricing results in Barth *et al.* (1999), Bartov *et al.* (2002) and Kasznik and McNichols (2002) and provide further support for our proposed denominator effect.

Our analyses of the components of our information asymmetry proxy reveal that the benefits of MBE derive primarily from an increase in the amount of uninformed trading, which causes the relative amount of informed trading to decrease. These results are consistent with the "Investor Recognition Hypothesis" of Merton (1987) and Fishman and Hagerty (1989). In addition, we do not find that the probability that a private information event occurs is associated with a firm's earnings performance, suggesting that the MBE does not strongly affect the incentives to search for private information.

Our results provide support for a denominator explanation for the observed MBE pricing premium: MBE firms experience a decrease in information asymmetry, which lowers the COC, which in turns leads to higher stock prices. Identifying the relative contribution of various numerator (cash flow or earnings) effects and denominator effects is an unresolved issue that is beyond the scope of this paper. We leave this question for future research.

Appendix: Venter and de Jongh (2004) Extension of EKO Model

While the extended EKO model maintains the assumption that uninformed buy and sell orders arrive each day based on a Poisson distribution, it allows the daily intensity of the arrival rate to vary. The arrival rate of uninformed buys and sells is given by εW_t, where W_t is a random variable with E[W] = 1. On good-news (bad-news) days, informed traders also place buy (sell) orders at arrival rate $\nu\varepsilon W_t$; thus, the distribution of buys (B) and sells (S) on day t is given by:

(B_t, S_t) | no-news, W_t ~ Independent Bivariate Poisson (εW_t, εW_t)
(B_t, S_t) | bad-news, W_t ~ Independent Bivariate Poisson (εW_t, $\varepsilon(1+\nu)W_t$)
(B_t, S_t) | good-news, W_t ~ Independent Bivariate Poisson ($\varepsilon(1+\nu)W_t$, εW_t) .

The likelihood function induced by the model for a particular trading day, conditional on the Poisson trading intensities λ_{Bt} and λ_{St} for buys and sells, respectively, is given by:

$$L_t(B_t,S_t \mid \lambda_{Bt},\lambda_{St}) = f_{POISS}(B_t,S_t \mid \lambda_{Bt},\lambda_{St}) = \frac{(\lambda_{Bt})^{B_t}}{B_t!} * \frac{(\lambda_{St})^{S_t}}{S_t!} * e^{-\lambda_{Bt}-\lambda_{St}} \quad . \tag{A1}$$

The overall likelihood function is a "mixture" model where the weights on the three components (no news, bad news, and good news) reflect the probabilities of their occurrence in the data. Denote the trading intensity of both buys and sells that arises on a particular "no-news" day by: $\lambda_{Nt} = \varepsilon W_t$, so the trading intensity depends on the day-specific value of the random variable, W. Similarly, the combined trading intensity (by both informed and uninformed) on a "news" day is: $\lambda_{It} = \varepsilon(1+\nu)W_t$. Therefore, we can write the likelihood of observing a pattern of B_t buys and S_t sells, conditional on these parameters, as: $L_t(B_t,S_t \mid \lambda_{Nt},\lambda_{It}) = L_t(B_t,S_t \mid \varepsilon,\mu,W_t)$

$$=(1-\alpha)f_{POISS}(B_t,S_t \mid \lambda_{Nt},\lambda_{Nt}) + \alpha\delta f_{POISS}(B_t,S_t \mid \lambda_{Nt},\lambda_{It}) + \alpha(1-\delta)f_{POISS}(B_t,S_t \mid \lambda_{It},\lambda_{Nt})$$

where $f_{POISS}(B_t , S_t \mid \lambda_{Bt}, \lambda_{St})$ denotes the probability of observing B_t buys and S_t sells on a particular day given that buy orders are arriving with Poisson intensity λ_{Bt}, and sell orders are arriving with Poisson intensity λ_{St}. Hence: $L_t(B_t, S_t \mid \lambda_{Nt}, \lambda_{It}) =$

$$(1-\alpha)\frac{\lambda_{Nt}^{B_t}}{B_t!}*\frac{\lambda_{Nt}^{S_t}}{S_t!}*e^{(-2\lambda_{Nt})}+\alpha\delta\frac{\lambda_{Nt}^{B_t}}{B_t!}*\frac{\lambda_{It}^{S_t}}{S_t!}*e^{(-\lambda_{Nt}-\lambda_{It})}+\alpha(1-\delta)\frac{\lambda_{It}^{B_t}}{B_t!}*\frac{\lambda_{Nt}^{S_t}}{S_t!}*e^{(-\lambda_{It}-\lambda_{Nt})}. \quad \text{(A2)}$$

The extended EKO model assumes that the random variable W has a unit inverse Gaussian distribution with parameter $\psi > 0$. The expected value equals one and the variance equals $1/\psi^2$. Thus, as $\psi \rightarrow \infty$, the variance in daily trading intensities induced by general market conditions goes to zero and the extended model reduces to the original EKO model. Formally:

$$f_{UIG}(w;\psi)=\frac{\psi\exp(\psi^2)}{\sqrt{2\pi}}w^{-\frac{3}{2}}\exp(-\frac{1}{2}\psi^2(w^{-1}+w)),\ \ w>0. \quad \text{(A3)}$$

The distributional assumption for W implies that the joint distribution of B_t and S_t is given by a multivariate Poisson inverse Gaussian distribution (Stein *et al.* (1987)). If λ_1 and λ_2 are the base level of trading intensity for buys and sells respectively on a particular day (i.e., $\lambda_{Bt} = W_t\lambda_1$ and $\lambda_{St} = W_t\lambda_2$), then the likelihood function for observing the mixed Poisson distribution of B_t buys and S_t sells is given by: $f_{PIG} = f_{PIG}(B_t, S_t \mid \lambda_1, \lambda_2, \psi)$ =

$$\frac{(\lambda_1)^{B_t}}{B_t!}*\frac{(\lambda_2)^{S_t}}{S_t!}*\left[\frac{\psi^2}{\psi^2+2(\lambda_1+\lambda_2)}\right]^{\frac{B_t+S_t}{2}}*e^{(\psi^2-\psi\sqrt{(\psi^2+2(\lambda_1+\lambda_2))})}*\hat{K}_{(B_t+S_t-\frac{1}{2})}(\psi\sqrt{(\psi^2+2(\lambda_1+\lambda_2))}) \quad \text{(A4)}$$

where $\hat{K}_n(z) = K_n(z)/K_{0.5}(z)$ and $K_n(z)$ is the modified Bessel function of the second kind. Then, E[B_t] = E[$B_t|W_t$]= E[$\lambda_1|W_t$]= λ_1 and Var(B_t) = $\lambda_1 + (\lambda_1/\psi)^2$; similarly for S_t. The covariance of B_t and S_t is given by Cov(B_t, S_t) = $(\lambda_1\lambda_2)/\psi^2$. Therefore, the expected values of B_t and S_t are given by λ_1 and λ_2 – as in the original EKO model. However, in the extended model, if $\psi << \infty$, the dispersions of B_t and S_t are higher than those in the EKO model and the daily values of buys and sells are positively correlated. Hence, $L_t(B_t,S_t|\alpha,\delta,\psi,\varepsilon,\nu)$ =

$$(1-\alpha) f_{PIG}(B_t, S_t \mid \varepsilon, \varepsilon, \psi) + \alpha\delta f_{PIG}(B_t, S_t \mid \varepsilon, \varepsilon(1+\nu), \psi) + \alpha(1-\delta) f_{PIG}(B_t, S_t \mid \varepsilon(1+\nu), \varepsilon, \psi) \quad \text{(A5)}$$

We use optimization procedures in matlab and/or proc NLP in SAS to maximize the likelihood function by firm-time period. We set initial parameter estimates at: [α, δ, ψ, ε, ν] = [0.5, 0.5, 5, 0.4*mean(buys+sells), 0.2*mean(buys+sells)].

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Table 1
Descriptive statistics

	Mean	Std. Dev.	5th Percentile	Median	95th Percentile	n
PIN_{t+1}	18.40	9.87	6.92	16.15	37.67	65,619
α_{t+1}	58.43	21.18	26.87	55.80	100	65,619
ν_{t+1}	0.91	0.76	0.28	0.71	2.18	65,619
ε_{t+1}	119.20	218.00	2.54	40.93	489.6	65,619
ψ_{t+1}	49,199	875,532	1.12	2.31	5.47	65,619
MBE	0.76	0.43	0.00	1.00	1.00	65,619
Analysts	5.99	5.11	1.00	4.00	17.00	65,619
Size	6.41	1.69	3.83	6.31	9.38	65,619

Notes:
$PIN_{t+1} = \alpha\nu\varepsilon/(\alpha\nu\varepsilon+2\varepsilon)$ = probability of informed trading.
$\alpha_{i,t}$ = probability of a private information event on any given day, firm *i*, quarter *t*.
$\nu_{i,t}$ = proportional amount of informed trading relative to uninformed trading, firm *i*, quarter *t*.
$\varepsilon_{i,t}$ = amount of uninformed trading, firm *i*, quarter *t*.
$\alpha_{i,t}$, $\nu_{i,t}$, and $\varepsilon_{i,t}$ are estimated according to equation A5 in the Appendix, using trade data in the period beginning day +3 after the earnings announcement for quarter *t* and ending day -3 before the earnings announcement of quarter *t*+1.
$MBE_{i,t}$ = 1 if the reported EPS according to First Call for firm *i*, quarter *t*, is at least as high as the consensus forecast immediately preceding the earnings announcement date; and zero otherwise.
$Analyst_{i,t}$ = number of analysts contributing to the consensus estimate of EPS computed by First Call for firm *i*, quarter *t*.
$Size_{i,t}$ = natural log of firm *i*'s market value of equity in millions of dollars at the end of the fiscal quarter corresponding to the EPS report.

Table 2
Pearson Correlation Matrix (n = 65,613)

	PIN_{t+1}	α_{t+1}	ν_{t+1}	ε_{t+1}	ψ_{t+1}	*MBE*	*Analysts*	*Size*
PIN_{t+1}	1							
α_{t+1}	0.42	1						
ν_{t+1}	0.64	-0.20	1					
ε_{t+1}	-0.44	-0.05	-0.33	1				
ψ_{t+1}	0.08	-0.06	0.18	-0.03	1			
MBE	-0.12	-0.04	-0.09	0.10	-0.01	1		
Analysts	-0.47	-0.07	-0.37	0.55	-0.04	0.15	1	
Size	-0.57	-0.09	-0.46	0.51	-0.06	0.17	0.70	1

See Table 1 for variable definitions.

Table 3

Number of consecutive quarters of meeting or beating (> 0) or missing (< 0) analyst consensus forecast of earnings	Mean PIN (%)	Std. error	No. of obs.	Number of consecutive quarters of meeting or beating (> 0) or missing (< 0) analyst consensus forecast of earnings	Mean PIN (%)	Std. error	No. of obs.
-4	20.23	0.27	1,204	11	14.41	0.23	988
-3	21.25	0.28	1,387	12	13.89	0.22	858
-2	21.19	0.19	3,461	13	14.04	0.25	745
-1	20.31	0.11	10,206	14	13.57	0.25	614
1	20.45	0.09	12,748	15	13.32	0.27	519
2	19.45	0.11	8,124	16	13.46	0.29	469
3	18.58	0.13	5,672	17	13.39	0.32	429
4	17.54	0.14	4,255	18	12.90	0.34	355
5	16.68	0.15	3,374	19	12.89	0.34	303
6	16.51	0.17	2,572	20	12.54	0.36	277
7	16.02	0.18	2,083	21	12.71	0.43	219
8	15.58	0.20	1,769	22	12.18	0.43	174
9	15.09	0.21	1,478	23	11.75	0.44	150
10	14.86	0.22	1,193	24	11.19	0.17	820

The number of quarters is winsorized at -4 and +24.

Figure 1

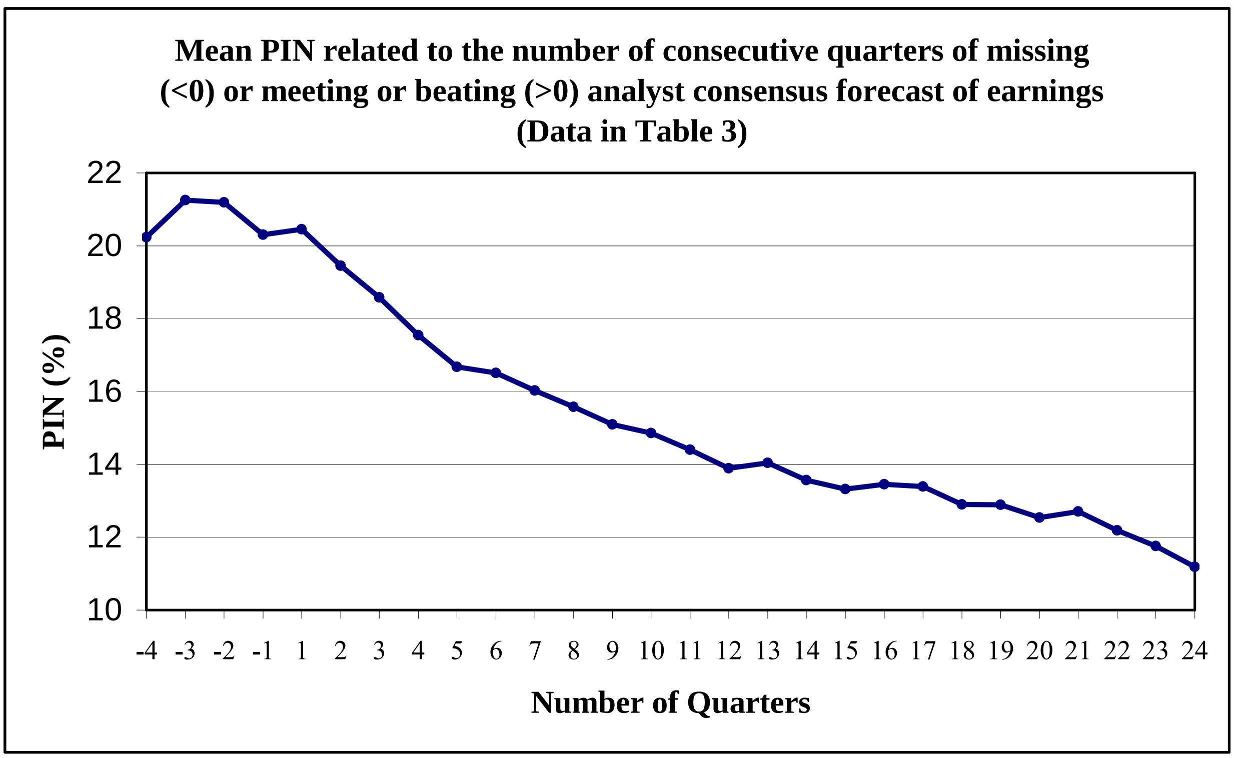

Table 4
Association of PIN and MBE

$$(\Delta PIN_{i,t+1}, \Delta\alpha_{i,t+1}, \Delta\nu_{i,t+1}, \Delta\varepsilon_{i,t+1}) = \beta_0 + \beta_1 MBE_{i,t} + \beta_2 \Delta Analyst_{i,t+1} + \beta_3 \Delta Size_{i,t+1} + \mu_{i,t+1} \quad (2)$$

Panel A: Dependent variable = $\Delta PIN_{i,t+1}$

Variable	Pred. Sign	Coeff.	*t*-stat.
Intercept	+	0.233	5.17
MBE	–	-0.269	-4.98
Δ*Analysts*	–	-0.098	-7.06
Δ*Size*	–	-1.168	-13.80
Adj. R^2			0.39%
n			63,591

Panel B: Dependent variable = $\Delta\alpha_{i,t+1}$

Variable	Pred. Sign	Coeff.	*t*-stat.
Intercept	+	0.014	0.08
MBE	–	-0.032	-0.15
Δ*Analysts*	–	-0.204	-3.23
Δ*Size*	–	-0.743	-2.34
Adj. R^2			0.02%
n			63,442

Panel C: Dependent variable = $\Delta\nu_{i,t+1}$

Variable	Pred. Sign	Coeff.	*t*-stat.
Intercept	+	0.014	3.90
MBE	–	-0.018	-4.19
Δ*Analysts*	–	-0.004	-3.86
Δ*Size*	–	-0.063	-10.49
Adj. R^2			0.18%
n			63,961

Panel D: Dependent variable = $\Delta\varepsilon_{i,t+1}$

Variable	Pred. Sign	Coeff.	*t*-stat.
Intercept	–	0.474	1.84
MBE	+	4.099	11.87
Δ*Analysts*	+	1.324	8.82
Δ*Size*	+	8.216	10.62
Adj. R^2			0.86%
n			64,373

See Table 1 for variable definitions.

Table 5
Association of PIN and MBE conditional on the size of the earnings surprise

$$\Delta PIN_{i,t+1} = \gamma_0 + \gamma_1 BigMeet_{i,t} + \gamma_2 SmallMeet_{i,t} + \gamma_3 SmallMiss_{i,t} + \gamma_4 \Delta Analysts_{i,t+1} + \gamma_5 \Delta Size_{i,t+1} + \eta_{i,t+}$$

Coefficient	Variable	Predicted Sign	Coefficient Estimate	*t*-statistic
γ_0	Intercept	+	0.340	5.45
γ_1	*BigMeet*	–	-0.469	-6.07
γ_2	*SmallMeet*	–	-0.329	-4.69
γ_3	*SmallMiss*	–	-0.236	-2.32
γ_4	Δ*Analysts*	–	-0.098	-7.06
γ_5	Δ*Size*	–	-1.160	-13.69
F-test			F-statistic	*p*-value
$\gamma_1 = \gamma_2$			7.77	< 0.01
$\gamma_1 = \gamma_3$			7.25	< 0.01
$\gamma_2 = \gamma_3$			1.30	0.25
Adj. R^2				0.41%
n				63,584

Notes:
BigMeet = 1 if *MBE* = 1 and (actual EPS – consensus EPS forecast) > \$0.02; otherwise zero.
SmallMeet = 1 if *MBE* = 1 and (actual EPS – consensus EPS forecast) ≤ \$0.02; otherwise zero.
SmallMiss = 1 if *MBE* = 0 and (actual EPS – consensus EPS forecast) ≥ -\$0.02; otherwise zero.
See Table 1 for definitions of the remaining variables.

Table 6
Association of PIN and MBE conditional on habitual MBE behavior

$$\Delta PIN_{i,t+1} = \delta_0 + \delta_1 MBE_{i,t} + \delta_2 Habitual_{i,t} + \delta_3 MBE_{i,t} \times Habitual_{i,t} + \delta_4 \Delta Analysts_{i,t+1} + \delta_5 \Delta Size_{i,t+1} + \eta_{i,t+1} \quad (3)$$

Coefficient	Variable	Predicted Sign	Coefficient Estimate	t-statistic
δ_0	Intercept	+	0.040	0.51
δ_1	*MBE*	–	0.021	0.20
δ_2	*Habitual*	+	0.233	2.16
δ_3	*MBE×Habitual*	–	-0.254	-1.89
δ_4	Δ*Analysts*	–	-0.075	-4.97
δ_5	Δ*Size*	–	-0.728	-6.93
F-test			F-statistic	p-value
$\delta_1 = \delta_3 = 0$			4.51	0.02
$\delta_1 + \delta_3 = 0$			8.26	< 0.01
Adj. R^2				0.21%
n				38,395

Notes:
$Habitual_{i,t} = 1$ if $\Sigma MBE_{i,\tau} \geq 6$, $\tau = t$-8 to t-1; otherwise zero.
See Table 1 for definitions of the remaining variables.

Table 7
Association of PIN and MBE conditional on expectations and earnings management

$$\Delta PIN_{i,t+1} = \phi_0 + \phi_1 MBE_{i,t} + \phi_2 ExpMan_{i,t} + \phi_3 EarnMan_{i,t} + \phi_4 \Delta Analyst_{i,t+1} + \phi_5 \Delta Size_{i,t+1} + \xi_{i,t} \quad (5)$$

Coefficient	Variable	Predicted Sign	Coefficient Estimate	*t*-statistic
ϕ_0	Intercept	+	0.201	3.41
ϕ_1	*MBE*	–	-0.418	-5.24
ϕ_2	*ExpMan*	+	0.510	7.93
ϕ_3	*EarnMan*	+	0.089	1.41
ϕ_4	*ΔAnalysts*	–	-0.118	-7.52
ϕ_5	*ΔSize*	–	-0.699	-6.69
F-tests			F-stat.	*p*-value
$\phi_1 + \phi_2 = 0$			1.06	0.303
$\phi_1 + \phi_3 = 0$			18.49	<0.0001
Adj. R^2				0.52%
n				31,578

Notes:
$ExpMan_{i,t}$ = 1 if the EPS forecast closest to the earnings announcement date for firm *i* is lower than the earliest EPS forecast made after the prior quarter's earnings announcement, $MBE_{i,t}$ = 1, and actual EPS < earliest EPS forecast; otherwise zero.
$EarnMan_{i,t}$ = 1 if discretionary accruals are positive, $MBE_{i,t}$ = 1 but would have equaled zero if discretionary accruals were non-positive; otherwise zero. Discretionary accruals are proxied by the residuals from the modified Jones model in equation (4), estimated by quarter and by industry at the two-digit SIC code level.
See Table 1 for definitions of the remaining variables.

Table 8
Association of Premium and MBE conditional on expectations and earnings management

Panel A:

$$CAR_{i,t} = \alpha_0 + \alpha_1 FCError_{i,t} + \alpha_2 MBE_{i,t} + \alpha_3 MBE_{i,t} \times ExpMan_{i,t} + \varepsilon_{i,t} \quad (7)$$

Coefficient	Variable	Predicted Sign	Coefficient Estimate	*t*-statistic
ϕ_0	Intercept	–	-0.035	-13.51
ϕ_1	*FCError*	+	2.536	23.19
ϕ_2	*MBE*	+	0.054	16.84
ϕ_3	*MBE×ExpMan*	–	-0.037	-13.14
F-tests			F-stat.	*p*-value
$\phi_2 + \phi_3 = 0$			28.67	<0.0001
Adj. R^2				6.39%
n				21,025

Panel B:

$$CAR_{i,t} = \alpha_0 + \alpha_1 FCError_{i,t} + \alpha_2 MBE_{i,t} + \alpha_3 MBE_{i,t} \times EarnMan_{i,t} + \varepsilon_{i,t} \quad (8)$$

Coefficient	Variable	Predicted Sign	Coefficient Estimate	*t*-statistic
ϕ_0	Intercept	–	-0.032	-12.43
ϕ_1	*FCError*	+	2.858	26.69
ϕ_2	*MBE*	+	0.037	11.18
ϕ_3	*MBE×EarnMan*	–	< 0.000	0.04
F-tests			F-stat.	*p*-value
$\phi_2 + \phi_3 = 0$			131.43	<0.0001
Adj. R^2				5.62%
n				21,025

Notes:
$CAR_{i,t}$ = cumulative beta-adjusted return beginning 2 days after firm *i*'s earnings announcement in quarter *t*-1 and ending 1 day after firm *i*'s earnings announcement in quarter *t*.
$FCError_{i,t}$ = (actual EPS – earliest consensus forecast after quarter *t*-1 earnings announcement) / stock price at beginning of quarter *t* for firm *i*.
See Table 1 and 7 for definition of other variables.