Information Asymmetry, Information Dissemination and the Effect of Regulation FD on the Cost of Capital

September 7, 2006

Abstract

This paper considers the impact of Regulation FD on firms' information environments and costs of capital. We find that the net impact of Regulation FD was to increase firms' costs of capital. However, the increase was small in economic terms, only about seven basis points per annum. We also document substantial cross-sectional variation in the cost of capital changes. We find that cost of capital changes were negatively related to both pre-regulation firm size and PIN.

JEL classification: G14; G38
Keywords: Regulation FD; Cost of Capital; Information Asymmetry

1 Introduction

This research considers the impact of Regulation Fair Disclosure (FD) on informed trading and the cost of capital[1]. Regulation FD was adopted by the Securities and Exchange Commission (SEC) in October 2000, and was intended to increase confidence and fairness in capital markets by prohibiting managers from selectively releasing material non-public information to market professionals or institutional shareholders, but not to the public at large. Before the implementation of Regulation FD, proponents argued that requiring managers to release all material disclosures to the public at large rather than select market professionals would reduce the information advantage of these professionals and thus decrease the information asymmetry in the market. Others argued that the regulation could have a 'chilling' effect, leading managers to reduce the quality and quantity of disclosures, both formal and informal, because of uncertainty about whether a particular informal disclosure might later be judged in court to be 'material' or whether a particular disclosure was sufficiently broad.

This study adds to the literature by considering how Regulation FD changed firms' information environments and how these changes impacted firms' expected returns. We perform this analysis on a broad cross-section of firms and control for other contemporaneous events that may have impacted firms' information environments but are not related to Regulation FD. In our analysis, we appeal to recent theoretical and empirical work in finance that

[1] Throughout this study, we use the term 'cost of capital' to refer to a firm's cost of equity capital. We leave an assessment of the impact of Regulation FD on the cost of debt capital to future research. Also, we use the term 'expected return' and 'cost of capital' interchangeably. Clearly, in a market with asymmetric information, expected returns will differ between agents. However, we use the term 'expected return' to refer to the expected return as observed by econometricians. This is consistent with the usage of the terms in Easley and O'Hara (2004).

suggests that elements of firms' information environments are important determinants of firms' expected returns. For instance, Easley and O'Hara (2004) present a rational expectations model where the cost of capital depends on the split between the amount of public and private information as well on how widely private information is disseminated. The intuition is that increasing the extent to which information is disseminated reduces the cost of capital by increasing the informativeness of stock prices, which reduces the risk to uninformed investors and thus reduces the return they demand. On the other hand, if information that was previously public becomes private, expected returns increase. This happens because informed investors can use their additional information advantage to trade with uninformed investors and hold portfolios more heavily weighted to stocks with positive private information and weighted against stocks with negative private information. The additional asymmetry increases the risk to the uninformed investors, who cannot adjust their portfolios to take account of the private information. Easley, Hvidkjaer and O'Hara (2002) examine this notion empirically and show that information asymmetry is priced in the cross-section using a measure of information asymmetry from a structural microstructure model, the probability of informed trade or PIN.

This paper applies these insights to an examination of the effects of Regulation FD on firms' costs of capital. A primary contribution of this study is that we use the cost of capital as a natural measure to assess the economic consequences of Regulation FD's impact on information asymmetry and information dissemination. For instance, suppose, as opponents of the regulation suggested, that after Regulation FD's implementation, managers decided to decrease the frequency or quality of their disclosures. The resulting decrease in the dissemination of information would tend to increase firms' costs of capital. If, on the other hand, Regulation FD induces firms to make public information that was formerly private, the amount of information asymmetry and thus firms' capital costs would decline. The economic impact of these effects is important for our overall understanding of the effect of the regulation.

To measure the impact of changes in firms' information environments on expected returns, we use an asset pricing model estimated on a broad cross-section of firms to measure the market 'prices' of information asymmetry and information dissemination. We then use these 'prices' in conjunction with proxies for both to evaluate Regulations FD's impact on capital costs. This provides a natural way to assess an important aspect of the economic impact of Regulation FD[2]. Furthermore, we contribute to the emerging literature on the relation between firms' information environments and capital costs by providing evidence of the extent to which information asymmetry and dissemination affect expected returns for a broad cross-section of firms.

A number of studies have considered the effect of Regulation FD on various aspects of firms' information environments with mixed results[3]. Among these studies, the three most closely related to ours are Gomes, Gorton and Madureira (2006), Jorion, Liu and Shi

[2]Other economic impacts might include the welfare impacts of Regulation FD on various market participants such as informed versus uninformed investors and investors versus managers.

[3]Heflin, Subramanyam and Zhang (2003), Bailey, Li, Mao and Zhong (2003), Straser (2002) argue that firms increased disclosures after Regulation FD. Bushee, Matsumoto and Miller (2004), Gintschel and Markov (2004), Topaloglu (2003), Eleswarapu, Thompson and Venkataraman (2004) and Chiyachantana, Jiang, Taechapiroontong and Wood (2004) document decreases in effective bid-ask spreads after Regulation FD. On the other hand, Sidhu, Smith and Whaley (2005), and Straser (2002) find that the adverse selection component of the bid-ask spread has risen after Regulation FD.

(2005) and Straser (2002). While focusing on changes in disclosure, Gomes, Gorton and Madureira (2006) briefly consider the impact of Regulation FD on the Fama-French size factor loadings. They find that after the regulation the size factor loadings increased for small firms but decreased for large firms. In contrast, we estimate the changes in cost of capital from Regulation FD using an asset pricing model, motivated by the theoretical work of Easley and O'Hara (2004), which explicitly allows firms' expected returns to vary based on changes in information asymmetry and information dissemination. To proxy for information asymmetry, we use the PIN measure for a broad cross-section of firms. Jorion, Liu and Shi (2005) examine the price impact of credit downgrades and upgrades before and after Regulation FD and find that credit rating changes are more informative after Regulation FD. This suggests that information was less widely disseminated after the implementation of Regulation FD. Straser (2002) also considers the impact of Regulation FD on information asymmetry using the PIN measure, albeit for a small sample of firms. We differ from Straser (2002) by considering the impact of Regulation FD on PIN for a broad cross-section of firms, including most NYSE, NASDAQ and AMEX stocks. Furthermore, we use the cost of capital to measure the economic size of the change in PIN. Also, we consider the impact of Regulation FD on how widely information is disseminated and how changes in information dissemination impact the cost of capital. This is important because, as Easley and O'Hara (2004) argue, information dissemination can have important effects on the cost of capital and Regulation FD is likely to have changed how widely information is disseminated. Lastly, this study controls for other events, coincident with Regulation FD, that may have altered firms' information environments but are unrelated to the change in regulation.

The results indicate that after Regulation FD's implementation the average firm experienced increased information asymmetry and decreased information dissemination. For the average firm, these changes are associated with an increase in expected return of around seven basis points per annum. Furthermore, we find substantial cross-sectional variation in cost of capital changes, with the most important determinants of this variation being PIN and firm size. In particular, we find that changes in capital costs are decreasing in both PIN and firm size.

The remainder of the paper is structured as follows. Section 2 explains the two hypotheses about how Regulation FD affected firms' cost of capital. Section 3 discusses our empirical methods and the results. Section 4 presents concluding remarks.

2 Hypotheses

We advance two hypotheses regarding Regulation FD's impact on firms' expected returns. Our first hypothesis summarizes the SEC's intent in implementing Regulation FD.

> *Hypothesis 1 - The Effective Regulation Hypothesis: The net result of Regulation FD was to decrease capital costs by either increasing information dissemination or decreasing information asymmetry or both.*

The Effective Regulation Hypothesis posits that prior to Regulation FD, managers were selectively disclosing information and receiving private benefits from this selective disclosure. This practice hurts uninformed investors and leads them to require higher costs of capital, because as small shareholders, they do not have the power to force managers to stop the selective disclosure. The Effective Regulation Hypothesis holds that Regulation FD could have either of two potential effects. First, the Regulation could force managers to disclose information more broadly because managers do not have enough flexibility under SEC rules to cut back on disclosures. Thus, managers could be forced to disseminate information more broadly, by making additional voluntary disclosures. Second, managers could act to make formerly private signals public, for instance by making public announcements of information that was previously disclosed only to select market professionals, or by including previously private information in required disclosures. As a result of either or both of these changes, the net result would be a decrease in expected returns.

Our second hypothesis mirrors the arguments that have been made against Regulation FD:

> *Hypothesis 2 - The Regulatory Failure Hypothesis: The net result of Regulation FD was to increase capital costs by either decreasing information dissemination or by increasing information asymmetry or both.*

Under the Regulatory Failure Hypothesis, increasing disclosure is costly for managers. These costs include the direct costs of making additional disclosures, such as additional time and effort to prepare formal disclosure documents as well as the costs of maintaining investor relations departments. Perhaps more significantly, if managers disclose information broadly or make it public, they lose the ability to trade on the information and the ability to use that information to curry favor with select analysts and institutional investors. Furthermore, managers may not wish to invite the additional scrutiny that broad disclosures of information may bring or to allow competitors to have access to the information. In addition, managers face uncertainty about which disclosures might trigger SEC enforcement actions, since it is not necessarily clear how the SEC will interpret terms such as 'material non-public information' and 'broad, non-exclusionary distribution'. Thus, in the face of these costs, managers respond to the new regulation by reducing the informativeness or quantity of disclosures and keeping information held within the firm. This reduces the number of investors who are able to be become informed and thus reduces information dissemination. To the extent that the new disclosure policies cause information that would previously have been made public to be kept private, information asymmetry would increase. Furthermore, some informed investors may be better able to adapt to the reduced quality or quantity of disclosures than uninformed investors. The informed traders' superior adaptability could come about because informed traders have relatively cheap access to information sources the firm cannot control but that would be prohibitively expensive to the uninformed. These might include industry experts as well as the firms' suppliers and customers. This would also increase information asymmetry. Each of these two effects would tend to increase firms' costs of capital.

It is worth noting that while the distinction between disclosing private information more broadly and making information public is clear in theoretical models such as Easley and O'Hara (2004), is not necessarily clear outside such models. This is because information that is seemingly 'public' may require costly interpretation in order for its pricing implications to become clear. Thus, financial statements are public in the sense that they are cheaply available, however, those without sufficient training, skill or time may not be able to use them to form signals about firm value that are useful for trading decisions. However, the effect on the cost of capital of the making private information public and disclosing information more broadly is the same. The former reduces information asymmetry and the latter increase information dissemination. We do not attempt to classify specific types of management disclosures as 'private information made public' or 'private information more broadly disseminated' or to identify the effect of specific managerial actions on our proxies for information asymmetry and information dissemination. Instead, we develop proxies for both information asymmetry and information dissemination and use these proxies to capture the regulations' total impact on firms' capital costs from changes in managers' disclosure practices.

It is also worth noting that we implicitly assume that the total amount of information, (i.e. the total number of signals available to potential market participants) remains unchanged[4]. There are two reasons for this assumption. First, we argue that the total amount of information about a firm is ultimately related to the firm's production processes. That is, we assume that the firm produces information as a by-product of producing goods and services. This information is both available to managers and employees as part of their jobs and is necessary for these individuals to perform their jobs. It is worth noting that these people can trade on their information and can thus be considered (at least potential)

[4]The total number of signals is represented in Easley and O'Hara (2004) as I. We assume that I is a fixed constant for each firm and our hypotheses deal with changes to the parameters α (the fraction of private signals) and μ (the number of informed traders).

market participants. We argue that it is unlikely that Regulation FD caused firms to alter their internal information systems or production processes to change the amount of information that the firm produces and makes available to insiders. Rather, we assume that firms would act to change the proportion of signals kept within the firm or to change their policies with respect to whom information can be revealed. We argue that altering the proportion of signals kept internal to the firm and changing to whom the firm decides to disseminate information represent uniformly less costly alternative reactions to the regulation than literally altering the firm's internal information systems in a way that would change the amount of information that the firm produces as part of its daily operations.

3 Empirical Methods and Results

3.1 Proxies for the Information Environment

In order to quantify the effects discussed in the previous section, we need proxies for both information asymmetry and information dissemination. As our proxy for information asymmetry, we use the PIN measure. Computation of PIN requires estimation of a structural market microstructure model introduced by Easley, Hvidkjaer and O'Hara (2002), Easley, Kiefer and O'Hara (1997) and Easley, Kiefer, O'Hara and Paperman (1996), among several others. The model posits the existence of a liquidity provider who observes the flow of buy and sell orders and assesses the probability that the orders come from informed traders when setting bid and ask quotes. The order of events in the model is as follows. First, at the beginning of each day nature decides whether a private information event will occur. Private information events occur with probability a. Conditional on an information event happening on a particular day, the informed traders in the model receive a private signal. The signal is positive with probability d and negative with probability $1 - d$. If the signal is positive, buy order flow for that day arrives according to a Poisson distribution with intensity parameter $u + e_b$ and sell order flow arrives according to a Poisson distribution with intensity parameter e_s. If the signal is negative, buy order flow arrives according to a Poisson distribution with intensity parameter e_b and sell order flow arrives according to a Poisson distribution with intensity parameter $e_s + u$. If there is no signal, buy and sell order flow arrives by Poisson distributions with intensity parameters e_b and e_s, respectively. Using the data on the number of buys and sells for each stock, the econometrician can estimate the parameters of the model via maximum likelihood. The PIN is computed (suppressing the firm subscript) as:

$$PIN = \frac{au}{au + e_s + e_b} \tag{1}$$

The intuition behind PIN is that if information asymmetry increases, the fraction of informed trade will increase in the market. Easley, Hvidkjaer and O'Hara (2002) examine the relation between PIN and the cross-section of average returns and find that PIN is significantly positively related to average returns in both an economic and a statistical sense, even after controlling for volume, bid-ask spreads, size, book-to-market, volatility and the volatility of volume. They find, for instance, that a ten percentage point increase in PIN is associated with an 250 basis point increase in average annual returns. They interpret this finding as consistent with the notion that PIN captures the role of information asymmetry discussed in Easley and O'Hara (2004), namely the number of private signals in the market relative to the number of public signals. We adopt a similar interpretation of PIN.

In order to estimate PIN we need data on the number of buyer and seller initiated trades for each firm-day. We gather these data from the Institute for the Study of Securities Markets (ISSM) (1983-1992) and the NYSE Trade and Quote (TAQ) (1993-2001) databases. We exclude all trades with non-typical settlement conditions since these may be trades under special arrangements from which the PIN model abstracts. We also exclude trades and quotes that occurred before the open, at the open as well as those at the close and after the close. We exclude these trades and quotes to avoid including trades that occurred during the opening and closing auctions. We exclude all quotes with zero bid or ask prices, quotes for which the bid-ask spread was greater than 50 percent of the price and trades with zero prices. We exclude these trades and quotes to eliminate possible data errors. Since neither the TAQ nor the ISSM databases identify trades as buyer or seller initiated, we use the Lee and Ready (1991) algorithm to sign the trades. Briefly stated, trades above (below) the mid-point of the bid-ask spread are considered buyer (seller) initiated. Trades that occur at the mid-point of the spread are classified as buyer (seller) initiated according to a tick test. In addition, if there were no quotes posted during the trading day, we use the tick test to sign any trades made during the day. For each firm, for each day, we compute the number of trades classified as buyer initiated and the number of trades classified as seller initiated. The full sample includes AMEX (1983-2001), NYSE (1983-2001) and NASDAQ (1987-2001) common stocks. We exclude ADR's and closed end funds.

For each firm in the sample we estimate PIN every calendar quarter numerically via maximum likelihood[5]. We require that each firm included in the sample have at least 20 valid observations per quarter from which to compute the PIN. Other studies, for instance Vega (2005), have estimated PIN using similar sample sizes, in Vega's case 40 trading days. Time series graphs of the cross-sectional median and quartiles of PIN can be found in Figure 1. Since the NASDAQ was primarily a dealer market during this period, and thus has different microstructure characteristics that may effect the estimation of PIN, we present the PIN results for the NYSE/AMEX and NASDAQ firms separately. We maintain this separation in the analysis that follows. Panel A shows the median and quartiles for NYSE firms. Panel B shows the median and quartiles for NYSE and AMEX firms. Panel C shows the median and quartiles for the NASDAQ firms. The median, first and third quartile of the PIN estimates in Panel A closely match those in Easley, Hvidkjaer and O'Hara (2002). On the other hand, the estimates in Panel B and C are somewhat higher than the cross-sectional medians and quartiles presented in Easley, Hvidkjaer and O'Hara (2002). We attribute this to the large number of small firms that trade on NASDAQ and AMEX since, as Easley, Hvidkjaer and O'Hara (2002) show, PIN is negatively correlated with size.

Table 1 presents the first quartile, median and third quartile of PIN, but for various portfolios rather than for the different exchanges. The portfolios are formed based on size, book-to-market and PIN. The results indicate that high book-to-market firms and small firms tend to have higher $PIN's$. The median PIN for each portfolio is between 20 and 40 percent. Furthermore, while the cross-sectional variability in PIN within the portfolios increases for small firms, high book-to-market firms and high PIN firms, in all cases the first

[5] The numerical maximization routine converged in virtually all cases.

and third quartiles are no smaller than ten percent and no larger than 60 percent. Table 1 also presents the fraction of the firms within each portfolio for which the estimation resulted in a corner solution for a, that is, a value of zero or one. For each of the portfolios, the fraction of corner solutions is small, usually less than one percent. The exceptions are low PIN firms, large firms and low BM firms, which tend to have around three percent corner solutions. Lastly, Table 1 presents the median as well as the first and third quartile of the $t-$statistics for the individual firm $PIN's$ within each portfolio. The t-statistics indicate that $PIN's$ are precisely estimated[6]. Each portfolio's median $t-$statistic is greater than five. Furthermore, even the first quartiles are all typically larger than four. We conclude from these results that the PIN estimation procedure produced reasonable PIN values for each of the exchanges and we see no evidence of problems with the PIN estimates for any particular group of stocks.

Finding proxies for information dissemination is a more difficult task. We identify three proxies for information dissemination. Our first proxy for information dissemination, $CDUM$, is a dummy equal to one if a firm has a credit rating. We argue that $CDUM$ is a proxy for the degree of information dissemination since firms with credit ratings are analyzed by rating agencies which then distribute information about the firms. Thus, firms with credit ratings should have more widely disseminated information than firms without credit ratings. In fact, evidence in Jorion, Liu and Shi (2005) suggests that post Regulation FD, credit rating agencies publically disseminate information that would otherwise be private.

[6] We compute the standard error of PIN using the delta method and the standard errors of the parameters of the structural model.

We collect the credit rating data from the quarterly COMPUSTAT files.

Our second proxy for information dissemination, $SDUM$, is a dummy equal to one if the firm's institutional ownership percentage is higher than the full sample median ownership fraction[7]. The intuition for this proxy is that institutional owners are more likely to be informed than non-institutional owners. Thus, the more institutional ownership a firm has, the more informed investors exist for this firm. We collect the institutional ownership data from the Thomson Financial CDA/Spectrum Institutional Money Manager (13f) Holdings database.

Our third proxy for information dissemination, $ADUM$, is a dummy equal to one if the firm is covered by analysts. The intuition behind this proxy is that if a firm is covered by analysts, information is more widely distributed to potentially informed traders. In this context, analysts can be viewed in two ways. First, analysts can be viewed as agents who analyze information and produce private signals which they then disburse to investors. Investors who receive the signals are then informed investors. Second, analysts can be viewed as dispensers of information for the company. Under this view, analysts are agents who pass private signals to investors, who become more informed as a result of receiving the signal. Thus, we do not require that analysts necessarily produce information. Rather, we assume only that analysts spread information, regardless of its source. As Easley, Hvidkjaer and O'Hara (2002) and Merton (1987) note, in either case, increased analyst coverage would tend to reduce the cost of capital by increasing the dissemination of information. We collect

[7]Note that the results are similar if we use the fraction of institutional ownership rather than $SDUM$ as a proxy for information dissemination.

the analyst coverage information from I/B/E/S. $ADUM$ is equal to one if the firm has analysts listed in I/B/E/S. Firms that do not have analysts listed in I/B/E/S have $ADUM$ equal to zero.

Table 2 presents the average and standard deviation for PIN, $ADUM, SDUM$, and $CDUM$ as well as book-to-market and size for each year in the sample. It is worth noting that all of the information dissemination proxies decline dramatically in 1987, the year that the NASDAQ firms enter the sample. This reflects the fact that NASDAQ firms are less likely to have credit ratings, significant institutional ownership or analyst coverage than NYSE or AMEX firms.

To analyze the change in the cost of capital associated with the implementation of Regulation FD, we begin by computing the PIN, $ADUM, SDUM$ and $CDUM$ for each stock in the sample for which data are available for a period immediately preceding the passage of Regulation FD and the period immediately following implementation of Regulation FD. The post-event period for this study runs from October 23, 2000 to January 23, 2001. The post-event period was chosen to end at the point where decimalization came into effect for NYSE/AMEX. We stop the post-event period at this point so we can avoid having to disentangle the effects of decimalization on PIN. Zhao and Chung (2006) find that $PIN's$ are significantly larger in the post-decimalization period. Furthermore, we wish to avoid contaminating the effects of Regulation FD with the effects of the Sarbanes-Oxley Act which took effect in 2002. The pre-event period was chosen to mirror the post-event period in length. The pre-event period runs from July 21, 2000 to October 21, 2000 for NYSE. We exclude all stocks involved in the NYSE decimalization pilot program (159 stocks) since these stocks experienced the change to decimal trading increments before the rest of the market and thus have pre- and post-event periods contaminated by decimalization.

For each stock we compute pre- and post- event $PIN's$ using data for the dates mentioned above. Table 3 presents the fraction of corner solutions and the first quartile, median and third quartile of the ratio of firms' PIN to their standard errors. The results are similar to the full sample in the fraction of corner solutions for a. Furthermore, for each group of stocks, the PIN estimates are large relative to their standard errors. Thus, it appears that $PIN's$ both before and after Regulation FD are relatively precisely estimated. In sum, we see no indication of problems with the PIN estimates in either the period before or the period after Regulation FD.

Analyst data, institutional ownership data and credit rating data are only available quarterly. This being the case, we use the quarterly data that most closely approximates the pre- and post-event period. Thus, the pre-event values for $ADUM$, $SDUM$ and $CDUM$ are computed using data for the calendar quarter beginning in July of 2000 and ending in September of 2000. The post-event values for these variables are computed using data for the calendar quarter beginning in October of 2000 and ending in December 2000.

Table 4 shows that the average firm experienced an increase in PIN between the pre- and post-event periods. The fraction of firms covered by analysts and the fraction of firms with credit ratings also increased. NYSE/AMEX firms experienced decreases in the fraction of firms with large institutional positions, however NASDAQ firms experienced increases in the fraction of firms with large institutional positions, though neither of these changes is statistically significant. Thus, it appears that for the average firm, Regulation FD had a mixed effect. That is, the Regulation seems to have increased information asymmetry but, at the same time, increased information dissemination.

The economic impact and the economic significance are unclear, however, without further analysis. There are several reasons for this. First, since the direction of the changes in information asymmetry and information dissemination offset one another in terms of their impact on the cost of capital, we must assess the net impact of the changes in order to make an inference about which of our two hypotheses better explain the data. Second, the changes outlined above do not allow us to make a judgement about the economic size of Regulation FD's effect. To make these judgments, we need to calculate the market 'prices' of information asymmetry and information dissemination so that we can calculate the direction and economic size of the net effect of the changes in Table 4 on the cost of capital. Lastly, we must account for other events that occurred in this time frame, but have nothing to do with Regulation FD. In the analysis that follows, we estimate the impact of Regulation FD on the cost of capital in order to judge the economic impact of the regulation. Furthermore, we introduce controls for other events coincident with the implementation of Regulation FD.

3.2 Estimating the Change in the Cost of Capital

To measure Regulation FD's impact on expected returns we estimate asset pricing models that include PIN and the proxies for information dissemination as well as beta, size and book-to-market ratios. This model mirrors that employed by Easley, O'Hara and Hvidkjaer

(2002), except we explicitly account for the effects of information dissemination. Specifically, we estimate the following cross-sectional regression:

$$r_i = a + (\theta_1 + \theta_2 ID_i)\, PIN_i + \gamma_1 \beta_i + \gamma_2 size_i + \gamma_3 bm_i + e_i \tag{2}$$

Where $ID_i \in \{ADUM_i, SDUM_i, CDUM_i\}$.

In the above, we expect that $\theta_1 > 0$ and $\theta_2 < 0$. This reflects the intuition that increasing information asymmetry increases expected returns. At the same time, increasing the amount of information dissemination tends to reduce the premium uninformed traders demand for information asymmetry because prices become more informative as information is more widely distributed[8].

Recall that we estimate the models separately to account for the fact that NASDAQ was primarily a dealer market during the estimation period. Furthermore, NASDAQ is known to 'double-count' volume. These considerations could affect the NASDAQ PIN estimates, making them structurally different from the NYSE $PIN's$.

The price and shares outstanding data to compute size come from CRSP. Size is the logarithm of the December market equity for year $t-1$. We compute the log of the book-to-market ratio in June of year t using the book common equity (BE) for the fiscal year ending in calendar year $t-1$, divided by market value of the stock at the end of December of $t-1$. BE is the COMPUSTAT book value of stockholders' equity, plus balance sheet deferred taxes

[8]This specification and the signs of the coefficients can be rigorously justified by considering the formula for expected return in Easley and O'Hara (2004). Approximating the expected return formula via a Taylor series expansion yields an expression involving the sum of the information asymmetry parameter and an interaction between the information asymmetry and information dissemination parameter.

and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, we use redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. We eliminate negative BE firms. We compute the beta using the two step procedure outlined in Fama and Macbeth (1973). Each month, we form 40 portfolios based on betas computed for the past 60 months. We then compute the full period post ranking betas for each portfolio and assign this beta to each firm in the portfolio. The return data come from CRSP.

For each month with the necessary data for all variables we run cross-sectional regressions of firm returns on beta, size, book-to-market, PIN and PIN interacted with either $ADUM$, $SDUM$ or $CDUM$. For the purposes of the regressions, for each month in the quarter, $ADUM$, $SDUM$ and $CDUM$ are set equal to the value for the calender quarter in which the month in question falls. For the NYSE/AMEX regressions involving PIN and $SDUM$ the estimation period is January 1984 through December 2000. Due to the availability of data, the estimation period for the NYSE/AMEX regressions involving $ADUM$ and $CDUM$ is January 1985 through December 2000. All NASDAQ regressions are estimated using data from January 1988 to December 2000 since the trade and quote data necessary to compute PIN are not available in ISSM for earlier years. Following Easley, O'Hara and Hvidkjaer (2002), we employ the weighted least-squares procedure outlined by Litzenberger and Ramaswamy (1979) to obtain efficient coefficient estimates.

Table 5 contains the estimated coefficients from the above specifications as well as a specification that includes PIN only. Consistent with Easley, O'Hara and Hvidkjaer (2002), the estimated coefficients on PIN are positive, economically significant and large relative to their standard errors in all of the regressions. For NYSE/AMEX firms, the estimates indicate that a ten percentage point increase in PIN is associated with an approximately 90 basis point increase in the annual cost of capital. This is consistent with the results in Easley, Hvidkjaer and O'Hara (2002), if somewhat smaller, perhaps owning to a different sample period and the inclusion of the AMEX stocks in our sample. The estimates for NASDAQ are closer to those found in Easley, Hvidkjaer and O'Hara (2002) and indicate that a ten percentage point increase in PIN is associated with a 230 basis point increase in the cost of capital. The coefficient on PIN declines somewhat after including the interaction with $ADUM$, $SDUM$ and $CDUM$ but remains significant. The coefficient on the interaction terms are negative, consistent with their interpretation as proxies for information dissemination. The coefficients on $CDUM$ are highly significant for both exchanges, while those on $SDUM$ and $ADUM$ are not, indicating that the $CDUM$ coefficients are more precisely estimated than the $ADUM$ and $SDUM$ coefficients. However, despite the fact that $CDUM$ is the only information dissemination proxy that produces a significant interaction term, in the analysis that follows the economic and statistical significance of the results is nearly identical for each of the proxies.

Before proceeding, note that the each of the information dissemination proxies could also be a proxy for information asymmetry. At least with respect to analyst coverage, the extant literature is mixed on this point. For instance, Brennan and Subrahmanyan (1995) find that greater analyst tends to reduce adverse selection costs. Thus, $ADUM$, could be a proxy for PIN. On the other hand, Easley, O'Hara and Paperman (1998) find that analyst coverage is not a good proxy for PIN. Table 6 presents the correlations between PIN and the information dissemination proxies for our sample. Each of the pair-wise correlations between PIN and the information dissemination proxies is negative and between .3 and .4. Thus, it is possible that the information dissemination proxies are simply capturing variation in PIN and this explains the negative signs on the interaction terms in the regressions in Table 5. To examine the possibility that $ADUM$, $CDUM$ and $SDUM$ are actually weak proxies for PIN rather than information dissemination, we re-estimate the regression in Table 5, however we include a PIN^2 term in the regression. To understand the logic behind the inclusion of PIN^2, suppose that each of the information dissemination proxies is simply a noisy proxy for PIN. For instance, assume that:

$$CDUM_i = bPIN_i + u_i \tag{3}$$

where u is that portion of $CDUM$ that is not related to PIN.

Now, if u_i is unrelated to cross-sectional variation in information dissemination, θ_2 would be non-zero only if there was a non-linear relation between expected returns and PIN. Therefore, if $CDUM$ is simply a weak proxy for PIN we expect that including a PIN^2 term in the regression would result in an estimated coefficient of zero for $CDUM \times PIN$.

Table 7 presents the results of the Fama-Macbeth regressions, including PIN^2. For each of the regressions, the coefficient on the information dissemination variables is nearly unchanged. For instance, the coefficient on the $CDUM \times PIN$ remains -.0065 and significant for NYSE/AMEX firms and for NASDAQ firms changes from -.0133 to -.0136 while remaining significant. From this we conclude that the information dissemination proxies are not simply noisy proxies for PIN. In the analysis that follows we compute the cost of capital changes using the results in Table 5. The results are essentially identical if we instead compute the changes in the cost of capital using the results in Table 7.

We compute the change in cost of capital due to changes in firms' information environments before and after Regulation FD as:

$$\Delta r_i = \theta_1 \left[PIN_{After,i} - PIN_{Before,i} \right] + \theta_2 \left[PIN_i \times ID_{After,i} - PIN_i \times ID_{Before,i} \right] \quad (4)$$

Where $ID_i \in \{ADUM, SDUM, CDUM\}$.

Of course, other events occurred during the period coincident with the implementation of Regulation FD that may impact PIN and information dissemination but have nothing to do with the regulation. Therefore, we do not wish to attribute the entire change in cost of capital due to changes in firms' information environments in this period to Regulation FD. To control for other contemporaneous events, we estimate the following cross-sectional regression:

$$\Delta r_i = c_0 + c_1 \Delta VOL_i + c_2 \Delta LARGE_i + c_3 HIGHTECH_i + c_5 SIZE_i + c_6 BM_i + c_7 PIN_i + w_i \quad (5)$$

The term ΔVOL is the change in average share volume (expressed in units of ten million shares) before and after Regulation FD and $\Delta LARGE$ is the change in the number of trades involving more than 10,000 shares before and after the regulation (expressed in units of 100 trades). $HIGHTECH$ is a dummy variable equal to one if a firm is classified as being in the technology industry according to the ten Fama-French industry classifications. ΔVOL and $\Delta LARGE$ are meant to capture changes in market that occurred in the same time period as the implementation of Regulation FD, such as the abrupt price declines in internet related stocks, that may have impacted market volume and thus PIN and the information dissemination proxies, but are not the result of Regulation FD. We include $HIGHTECH$ to account for the fact that the collapse of the internet bubble may have had effects on PIN and the information dissemination proxies that are not captured by the volume variables.

We include $SIZE$, BM and PIN in the regression to assess the cross-sectional determinants of Regulation FD's effect on firms' costs of capital. $SIZE$ and BM are the logarithm of the firm's size and book-to-market ratio at the end of 1999. The value of PIN in the regression is computed using data from the period April through June 2000. All of the explanatory variables, except the dummy variables, are demeaned. Therefore, the constant in this regression reflects the change in the cost of capital purged of effects not related to Regulation FD and for firms with average $SIZE$, BM and PIN.

Table 8 contains the results of various versions of the above regression and the average unadjusted change in the cost of capital, for the full sample, the NYSE/AMEX and NASDAQ sub-samples and for each of the information dissemination proxies. The results indicate that the average firm experienced a cost of capital increase of about 12 basis points per annum. After accounting for the control variables, the average change in the cost of capital attributable to Regulation FD is seven basis points per year. However, it is possible that Regulation FD had an impact on the control variables as well, so the actual cost of capital change appears to be between seven and 12 basis points per year. For all of the information dissemination proxies, the estimated increase is large relative to its standard error. However, the change does not appear to be large, in an economic sense. To see this note that we can use the results in Vuolteenaho (2002) to assess the amount of expected return news that would result from a seven basis point permanent increase in the cost of capital. Vuolteenaho (2002) implements a Campbell-Shiller log-linear decomposition of the variance of individual stock returns. To do so, he uses a discount coefficient of .967. This coefficient emerges from the log-linearization of stock returns. Using this coefficient, we estimate that the expected return news from a permanent seven basis point increase in expected return is $-\left[\frac{1}{1-.967}\right].07 \simeq -2$ percent. By comparison, Vuolteenaho (2002) estimates that the standard deviation of expected return news for a typical firm is about two percent per month. Thus, if Regulation FD was a complete surprise to the market in the month it was implemented, the expected return news resulting from the regulation would have been about the same magnitude as the expected return news in a typical month.

While the regulation appears to have had only a small effect on the average firm's cost of capital, there is considerable cross-sectional variation in the regulation's effect. To see this first note that the results in Table 8 indicate that the cost of capital changes are different for the NYSE/AMEX and NASDAQ samples. After accounting for the control variables, the average firm in the NYSE/AMEX sample experienced a statistically significant decrease in cost of capital of around six basis points per annum. On the other hand, the average firm on the NASDAQ experienced an increase of around 12 basis points per annum. Further evidence of cross-sectional variation can be found by examining the coefficients on $SIZE$, BM and PIN in the regressions. For the sample as a whole, the cost of capital change is significantly decreasing in both $SIZE$ and PIN. The estimates indicate that everything else constant, a firm one percent larger than the mean has a cost of capital reduction of around eight basis points smaller than the average firm. For the NYSE/AMEX firms, there appears to be little or no relation between size and the cost of capital change. For NASDAQ firms, however, a firm one percent larger than average would have a cost of capital change around 14 basis points smaller than the average NASDAQ firm. The same is true of the relation between the cost of capital change and PIN. That is, there is little relation between the cost of capital change and PIN for NYSE/AMEX firms, but a large, statistically significant negative relation for NASDAQ firms. For whole sample, a firm with a PIN ten percentage points larger than the average PIN would have a cost of capital change around 11 basis points smaller than the average firm, everything else constant. For NASDAQ firms, a firm whose PIN was ten percentage points larger than NASDAQ average would have a cost of capital change of about 17 basis points. For the sample as a whole, as for the NYSE/AMEX and NASDAQ samples, there appears to be no significant relation between the cost of capital changes and the book-to-market ratio.

What do we make of these results? Regulation FD increased the average firm's cost of capital, consistent with the Regulatory Failure Hypothesis. However, the size and sign of the change in cost of capital depend on firm size and PIN. Furthermore, given the size of the coefficients on $SIZE$ and PIN it is clear that large stocks and high PIN stocks could actually experience cost of capital decreases, consistent with the Effective Regulation Hypothesis. In fact, the average NYSE/AMEX firm, which is larger than the average NASDAQ firm, experienced a decrease in capital costs, while NASDAQ firms experienced increases.

The fact that small stocks tended to experience larger increases in expected return after the regulation than large firms may be a reflection of the difference in relative disclosure costs across firms. Since disclosure involves fixed costs, such as maintaining public and investor relations departments, small firms may have decided to cut back more drastically on private disclosures. Managers at these firms may also have reduced the number and quality of public disclosures in effort to avoid the cost of deciding which disclosures are and are not appropriate under the regulation and thus avoid the potential for SEC enforcement actions. At the same time, informed investors have recourse to alternative sources of private information that managers cannot control such as industry insiders, customers, and suppliers. These alternative sources of information allow them to partially replace the selective disclosures they no longer receive. As a result, the relative advantage of the informed increased. On the other hand, managers at large firms have additional resources to allow them to interpret the regulation and make additional disclosures with less fear of misinterpreting the regulation and drawing attention from the SEC. Thus, their increased information dissemination and reduced information asymmetry were the result of increased public disclosures and more broadly disseminated private disclosures.

The negative relation between PIN and changes in capital costs may simply reflect the fact that high PIN firms tended to be the firms for which the uninformed investors were at the biggest disadvantage prior to the implementation of the regulation. It is perhaps not surprising that the regulation tended to have a positive impact on these firms. Nonetheless, for the average firm, especially considering compliance costs, the regulation appears to have had a net negative impact on value.

4 Conclusion

The intent behind the SEC's implementation of Regulation FD was to 'level the playing field' by forcing managers to stop making disclosures to select individuals. The hope was that managers would make information available more broadly, and thus increase information dissemination or reduce information asymmetry, thereby reducing capital costs. This study presents evidence that, for the average firm, the opposite has occurred. We find that the net effect of Regulation FD has been to increase firms' expected returns. This finding is consistent with our Regulatory Failure Hypothesis. However, for the average firm, the change in expected returns is not large, only about seven basis point per annum. We further find that the economic impact of the regulation varies widely among firms, with the small firms and low PIN firms experiencing significantly larger cost of capital increases.

References

[1] Bailey, Warren, Haitao Li, Connie X. Mao, and Rui Zhong, 2003, Regulation fair disclosure and earnings information: market, analyst, and corporate responses, Journal of Finance 58, 2487-2514.

[2] Brennan, Michael and Avanidhar Subrahmanyam, 1995, Investment analysis and price formation in securities markets, *Journal of Financial Economics*, 38, 361-381.

[3] Bushee, Brian J., Dawn A. Matsumoto, and Gregory S. Miller, 2004, Managerial and investor responses to disclosure regulation: the case of Reg FD and conference calls, *Accounting Review* 79, 617-643.

[4] Chiyachantana, Chiraphol N., Christine X. Jiang, Nareerat Taechapiroontong, and Robert A. Wood, 2004, The impact of regulation fair disclosure on information asymmetry and trading: an intraday analysis, *Financial Review* 39, 549-577.

[5] Campbell, John, 1991, A variance decomposition for stock returns, *Economic Journal* 101, 157-179.

[6] Campbell, John, and John Ammer, 1993, What moves stock and bond markets? A variance decomposition for long-term asset returns, *Journal of Finance* 48, 3-37.

[7] Dimson, Elroy, 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 7, 197-206.

[8] Easley, David, Nicholas M. Kiefer, Maureen O'Hara, and Joseph B. Paperman, 1996, Liquidity, information, and infrequently traded stocks, *Journal of Finance* 51, 1405-1436.

[9] Easley, David, Nicholas M. Kiefer, and Maureen O'Hara, 1997, One day in the life of a very common stock, *Review of Financial Studies* 10, 805-835.

[10] Easley, David, Maureen O'Hara and Joseph B. Paperman, 1998, *Journal of Financial Markets*, 1, 175-201.

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

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

[13] Eleswarapu, Venkat R., Rex Thompson, and Kumar Venkataraman, 2004, The impact of regulation fair disclosure: trading costs and information asymmetry, *Journal of Financial and Quantitative Analysis* 39, 209-225.

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

[15] Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

[16] Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55-84.

[17] Fama, Eugene F., and James D. MacBeth, 1973, Risk, return and equilibrium: Empirical tests, *Journal of Public Economy* 81, 607-636.

[18] Gintschel, Andreas, and Stanimir Markov, 2004, The effectiveness of regulation FD, *Journal of Accounting Economics* 37, 293-314.

[19] Gomes, Armando, Gary Gorton, and Leonardo Madureira, 2006, SEC regulation fair disclosure, information, and the cost of capital, Case Western Reserve University working paper.

[20] Heflin, Frank, K.R. Subramanyam, and Yuan Zhang, 2003, Regulation FD and the financial information environment: early evidence, *Accounting Review* 78, 1-37.

[21] Jorion, Philippe, Zhu Liu and Charles Shi, 2005, Informational effects of Regulation FD: Evidence from rating agencies, *Journal of Financial Economics*, 76, 309-330.

[22] Lee, Charles M.C., and Mark J. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733-746.

[23] Lewellen, Jonathan, and Stefan Nagel, 2006, The conditional CAPM does not explain asset-pricing anomalies, Journal of Financial Economics forthcoming.

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

[25] Sidhu, Baljit, Tom Smith, and Robert E. Whaley, 2006, Regulation fair disclosure and the cost of adverse selection, Vanderbilt University working paper.

[26] Straser, Vesna, 2002, Regulation fair disclosure and information asymmetry, University of Notre Dame working paper.

[27] Topaloglu, Selim, 2003, Institutional trading activity around earnings announcements: evidence on the effects of regulation FD, Queen's University working paper.

[28] U.S. Securities and Exchange Commission, 2000, Final rule: selective disclosure and insider trading, available from http://www.sec.gov/rules/final/33-7881.htm.

[29] Vega, Clara, 2005, Stock price reaction to public and private information, *Journal of Financial Economics*, forthcoming.

[30] Vuolteenaho, Tuomo, 2002, What drives firm-level stock returns? *Journal of Finance* 57, 233-264.

[31] Zhao, Xin and Kee H. Chung, 2006, Decimal Pricing and Information-Based Trading: Tick Size and Informational Efficiency of Asset Price, *Journal of Business Finance & Accounting*, 33, 753-766.

Table 1: Corner Solution and Summary Statistics of PIN Estimated Each Quarter

This table reports the fraction of corner solutions for parameter a and summary statistics on PIN for BM, Size and PIN portfolios. The a and PIN are estimated using Easley, Hvidkjaer and O'Hara (2002) model, for each quarter from 1983 to 2001. The parameter a denotes the probability of an information event. The corner solution is the case when a is equal to one or zero. PIN is a composite variable measuring the probability of information-based trading. The book-to-market ratio (BM) is the book common equity for the fiscal year ending in calendar year t-1, divided by year-end market value of equity in year t-1. Size is the year-end market value of equity for year t-1, in billion dollars.

BM Portfolio	Corner Solutions a	PIN Q1	PIN Median	PIN Q3	PIN/SE(PIN) Q1	PIN/SE(PIN) Median	PIN/SE(PIN) Q3
Low 10%	0.02	0.14	0.20	0.27	4.93	6.20	7.40
2nd 10%	0.02	0.15	0.21	0.28	4.82	6.05	7.29
3rd 10%	0.02	0.14	0.20	0.28	4.75	6.03	7.28
4th 10%	0.01	0.15	0.21	0.30	4.57	5.87	7.22
5th 10%	0.01	0.15	0.23	0.34	4.34	5.71	7.13
6th 10%	0.01	0.16	0.24	0.37	4.28	5.68	7.11
7th 10%	0.01	0.17	0.26	0.39	4.24	5.63	7.09
8th 10%	0.01	0.19	0.29	0.45	4.16	5.60	7.11
9th 10%	0.00	0.22	0.32	0.47	4.17	5.56	7.12
High 10%	0.00	0.22	0.32	0.46	3.92	5.25	6.78

SIZE Portfolio	Corner Solutions a	PIN Q1	PIN Median	PIN Q3	PIN/SE(PIN) Q1	PIN/SE(PIN) Median	PIN/SE(PIN) Q3
Low 10%	0.00	0.32	0.43	0.55	3.92	5.33	6.97
2nd 10%	0.00	0.28	0.40	0.53	3.97	5.43	7.04
3rd 10%	0.00	0.27	0.36	0.48	4.06	5.50	7.08
4th 10%	0.00	0.24	0.31	0.43	4.22	5.63	7.16
5th 10%	0.00	0.21	0.27	0.36	4.16	5.52	7.03
6th 10%	0.00	0.19	0.24	0.32	4.38	5.77	7.14
7th 10%	0.01	0.17	0.22	0.28	4.38	5.71	7.11
8th 10%	0.01	0.15	0.19	0.25	4.50	5.81	7.15
9th 10%	0.02	0.13	0.17	0.23	4.63	5.88	7.12
High 10%	0.04	0.10	0.14	0.19	5.10	6.25	7.47

PIN Portfolio	Corner Solutions a	PIN Q1	PIN Median	PIN Q3	PIN/SE(PIN) Q1	PIN/SE(PIN) Median	PIN/SE(PIN) Q3
Low 10%	0.03	0.11	0.15	0.20	4.74	5.97	7.20
2nd 10%	0.02	0.13	0.17	0.23	4.57	5.84	7.13
3rd 10%	0.01	0.15	0.19	0.25	4.53	5.82	7.13
4th 10%	0.01	0.17	0.21	0.28	4.45	5.75	7.07
5th 10%	0.01	0.18	0.23	0.30	4.40	5.69	7.04
6th 10%	0.00	0.21	0.26	0.34	4.26	5.66	7.07
7th 10%	0.00	0.24	0.30	0.39	4.31	5.75	7.25
8th 10%	0.00	0.26	0.35	0.45	4.14	5.61	7.21
9th 10%	0.00	0.28	0.40	0.51	4.08	5.59	7.24
High 10%	0.00	0.35	0.48	0.60	4.04	5.61	7.39

Table 2: Summary Statistics

This table presents yearly cross-sectional means and standard deviations on some key variables in our sample. All statistics are calculated for the whole sample of NYSE, AMEX and NASDAQ firms. Size is the year-end market value of equity for year t-1, in billion dollars. The book-to-market ratio (BM) is the book common equity for the fiscal year ending in calendar year t-1, divided by year-end market value of equity in year t-1. The probability of informed trading (PIN) is estimated using Easley, Hvidkjaer and O'Hara (2002) model, for each quarter from 1984 to 2001. ADUM is equal to one if a firm has one or more analysts, otherwise zero. The SDUM denotes whether the fraction of shares held by large institutions exceeds the median level for the entire sample. The CDUM is equal to one if a firm has credit rating, otherwise zero.

	Firm	**Size ($Bils)**		**BM**		**PIN**		**CDUM**		**ADUM**		**SDUM**	
Year	**No.**	**Ave**	**Std.**	**Ave**	**Std.**	**Ave**	**Std.**	**Ave**	**Std.**	**Ave**	**Std.**	**Ave**	**Std.**
Ave	5086	1.016	5.241	0.801	0.984	0.298	0.129	0.181	0.376	0.587	0.465	0.464	0.474
1984	2067	0.711	2.665	0.784	0.452	0.288	0.135	.	.	.	.	0.470	0.477
1985	2014	0.775	2.679	0.910	0.569	0.279	0.125	0.261	0.439	0.700	0.446	0.508	0.477
1986	1953	0.912	3.014	0.768	0.461	0.267	0.116	0.323	0.458	0.701	0.445	0.544	0.471
1987	4415	0.579	2.384	0.702	0.566	0.301	0.116	0.179	0.376	0.502	0.469	0.388	0.463
1988	4593	0.505	2.198	0.932	1.600	0.324	0.126	0.177	0.379	0.491	0.465	0.383	0.463
1989	4372	0.583	2.491	0.797	0.669	0.314	0.127	0.182	0.382	0.537	0.467	0.426	0.469
1990	4159	0.647	2.711	0.811	1.074	0.324	0.131	0.178	0.379	0.546	0.469	0.453	0.478
1991	4058	0.682	3.038	1.273	2.124	0.310	0.127	0.174	0.376	0.556	0.470	0.469	0.476
1992	4984	0.714	3.308	0.842	1.318	0.311	0.134	0.143	0.347	0.494	0.479	0.418	0.473
1993	5752	0.719	3.266	0.728	1.154	0.300	0.123	0.142	0.343	0.510	0.478	0.419	0.471
1994	6177	0.766	3.387	0.645	0.620	0.304	0.124	0.140	0.343	0.550	0.474	0.438	0.475
1995	6454	0.712	3.322	0.722	0.641	0.298	0.117	0.143	0.346	0.569	0.473	0.461	0.475
1996	6659	0.941	4.555	0.649	0.710	0.296	0.116	0.144	0.347	0.604	0.467	0.463	0.473
1997	7125	1.108	5.678	0.612	0.792	0.292	0.123	0.152	0.354	0.629	0.463	0.485	0.476
1998	7280	1.376	7.563	0.559	0.558	0.293	0.135	0.168	0.364	0.640	0.461	0.489	0.476
1999	6853	1.854	12.057	0.735	0.882	0.288	0.137	0.181	0.381	0.662	0.454	0.500	0.477
2000	6484	2.308	15.122	0.747	0.861	0.284	0.146	0.188	0.387	0.651	0.456	0.504	0.479
2001	6142	2.398	14.892	1.204	2.654	0.300	0.156	0.206	0.401	0.632	0.464	0.533	0.480

Table 3: Corner Solution and Summary Statistics of PIN/SE(PIN) Estimated Around Reg. FD

This table reports the fraction of corner solutions for a and summary statistics on the ratio of PIN/SE(PIN), where a and PIN are estimated for the 3-month period before regulation FD (21 July, 2000 ~ 21 October, 2000) and the 3-month period after regulation FD (23 October, 2000 ~ 23 January, 2001), using Easley, Hvidkjaer and O'Hara (2002) model. The parameter a denotes the probability of an information event. The corner solution is the case when a is equal to one or zero. PIN is a composite variable measuring the probability of information-based trading. The book-to-market ratio (BM) is the book common equity for the fiscal year ending in calendar year t-1, divided by year-end market value of equity in year t-1. Size is the year-end market value of equity for year t-1, in billion dollars.

BM	***Corner Solutions for a***		**PIN/SE(PIN) Before FD**				**PIN/SE(PIN) After FD**			
Portfolio	**Before**	**After**	**Ave**	**Q1**	**Med**	**Q3**	**Ave**	**Q1**	**Med**	**Q3**
Low 10%	0.04	0.05	7.00	5.20	6.26	7.59	7.22	5.72	6.95	8.06
2nd 10%	0.03	0.02	6.74	5.16	6.44	7.68	7.28	5.86	6.79	7.93
3rd 10%	0.04	0.01	6.79	5.11	6.44	7.79	6.98	5.71	6.79	8.02
4th 10%	0.02	0.01	6.81	5.35	6.56	7.99	7.71	5.87	6.97	8.06
5th 10%	0.00	0.01	6.52	5.11	6.40	7.90	7.11	5.66	6.87	8.39
6th 10%	0.00	0.01	6.60	4.94	6.44	8.01	7.12	5.42	7.07	8.40
7th 10%	0.01	0.00	9.68	5.20	6.61	8.00	7.02	5.59	6.90	8.49
8th 10%	0.00	0.00	6.64	4.85	6.61	8.24	7.03	5.39	6.88	8.37
9th 10%	0.00	0.00	6.66	4.95	6.55	8.06	7.15	5.55	7.09	8.60
High 10%	0.00	0.00	6.41	4.53	6.20	7.95	6.69	4.90	6.64	8.51

SIZE	***Corner Solutions for a***		**PIN/SE(PIN) Before FD**				**PIN/SE(PIN) After FD**			
Portfolio	**Before**	**After**	**Ave**	**Q1**	**Med**	**Q3**	**Ave**	**Q1**	**Med**	**Q3**
Low 10%	0.00	0.00	6.98	5.08	6.84	8.52	7.48	5.60	7.63	9.53
2nd 10%	0.00	0.00	6.85	5.12	6.77	8.45	7.19	5.39	7.12	8.87
3rd 10%	0.00	0.00	6.66	4.74	6.75	8.34	7.18	5.63	7.24	8.67
4th 10%	0.00	0.00	6.68	5.26	6.59	8.11	7.11	5.47	7.04	8.62
5th 10%	0.00	0.00	6.39	4.72	6.17	7.88	6.93	5.37	6.85	8.26
6th 10%	0.00	0.00	6.47	4.92	6.26	8.00	6.88	5.51	6.79	8.14
7th 10%	0.00	0.00	6.49	5.11	6.35	7.61	6.65	5.46	6.52	7.78
8th 10%	0.02	0.02	6.19	5.10	6.07	7.13	6.85	5.66	6.66	7.62
9th 10%	0.02	0.02	9.39	5.15	6.25	7.40	7.47	5.66	6.68	7.52
High 10%	0.10	0.07	8.18	5.45	6.45	7.67	7.83	5.88	6.89	7.99

PIN	***Corner Solutions for a***		**PIN/SE(PIN) Before FD**				**PIN/SE(PIN) After FD**			
Portfolio	**Before**	**After**	**Ave**	**Q1**	**Med**	**Q3**	**Ave**	**Q1**	**Med**	**Q3**
Low 10%	0.09	0.04	6.89	4.48	5.64	7.04	6.93	5.57	6.51	7.52
2nd 10%	0.02	0.04	8.76	4.62	5.65	6.88	7.60	5.46	6.61	7.55
3rd 10%	0.01	0.01	6.28	4.96	6.02	7.15	6.61	5.49	6.56	7.54
4th 10%	0.01	0.01	6.21	4.81	5.95	7.14	6.50	5.42	6.48	7.46
5th 10%	0.00	0.00	6.30	5.07	6.34	7.47	6.86	5.59	6.72	8.08
6th 10%	0.00	0.00	6.40	5.09	6.31	7.53	7.06	5.63	6.96	8.46
7th 10%	0.00	0.00	6.78	5.51	6.76	8.24	7.17	5.70	7.11	8.55
8th 10%	0.00	0.00	7.20	5.53	7.21	8.81	7.35	5.77	7.37	8.91
9th 10%	0.00	0.00	7.32	5.94	7.32	8.68	7.61	5.72	7.62	9.35
High 10%	0.01	0.00	7.93	5.90	7.95	10.20	7.70	5.55	7.63	9.62

Table 4: Average Changes in PIN and Information Dissemination

This table reports the average change in probability of informed trading (PIN) and various proxies for information dissemination around regulation FD. We compare the 3-month period before regulation FD (21 July, 2000 ~ 21 October, 2000) to the 3-month period after regulation FD (23 October, 2000 ~ 23 January, 2001), for the sample of NYSE, AMEX and NASDAQ firms. The PIN is estimated following Easley, Hvidkjaer and O'Hara (2002) model. The ADUM is equal to one if a firm has one or more analysts, otherwise zero. The SDUM denotes whether the fraction of shares held by large institutions exceeds the median level for the entire sample. The CDUM is equal to one if a firm has credit rating, otherwise zero. The corresponding T-statistics are below the changes in parenthesis.

		Average Changes in			
	No. of Firms	PIN	CDUM	ADUM	SDUM
All Firms	5597	0.0071	0.0047	0.0155	-0.0013
		(4.45)	(4.36)	(5.60)	(-0.44)
NYSE/AMEX	2123	0.0026	0.0068	0.0098	-0.0024
		(0.83)	(3.75)	(2.54)	(-0.63)
NASDAQ	3976	0.0092	0.0034	0.0176	0.0003
		(5.43)	(2.84)	(5.02)	(0.07)

Table 5: Fama-Macbeth Regression Results

The following table contains monthly time-series averages of the estimated coefficients in cross-sectional asset-pricing tests for NYSE and AMEX firms (Panel A), and for NASDAQ firms (Panel B), using the weighted least-square methodology suggested by Litzenberger and Ramaswamy (1979). The dependent variable is the portfolio monthly return. Betas are post-ranked betas estimated using 40 beta portfolios. Size is the logarithm of the December market equity for year t-1, BM is the logarithm of book value divided by market value for year t-1. The analyst dummy (ADUM) is equal to one if a firm has one or more analysts, otherwise zero. The share dummy (SDUM) denotes whether the fraction of shares held by large institutions exceeds the median level for the entire sample. The credit rating dummy (CDUM) is equal to one if a firm has credit rating, otherwise zero. The T-statistics are inside parenthesis.

Panel A: NYSE/AMEX Firms

FM Regressions	(1)	(2)	(3)	(4)	(5)
Beta	-0.0001	-0.0001	0.0000	0.0000	-0.0001
	(-1.91)	(-1.89)	(-0.76)	(-0.84)	(-1.90)
Size	0.0015	0.0019	0.0019	0.0018	0.0019
	(3.01)	(3.80)	(3.45)	(3.10)	(3.79)
BM	0.0028	0.0029	0.0026	0.0026	0.0029
	(3.28)	(3.31)	(2.99)	(2.87)	(3.38)
PIN		0.0070	0.0083	0.0077	0.0077
		(2.64)	(2.56)	(2.11)	(2.36)
PIN*CDUM			-0.0065		
			(-2.15)		
PIN*ADUM				-0.0002	
				(-0.04)	
PIN*SDUM					-0.0013
					(-0.43)

Panel B: NASDAQ Firms

FM Regressions	(1)	(2)	(3)	(4)	(5)
Beta	0.0000	0.0000	0.0000	0.0000	0.0000
	(-1.36)	(-1.19)	(-1.07)	(-1.19)	(-1.20)
Size	0.0008	0.0019	0.0021	0.0020	0.0020
	(1.01)	(2.11)	(2.41)	(2.31)	(2.37)
BM	0.0092	0.0088	0.0089	0.0088	0.0088
	(6.16)	(5.78)	(5.99)	(5.79)	(5.78)
PIN		0.0191	0.0196	0.0192	0.0199
		(2.89)	(2.96)	(2.83)	(2.94)
PIN*CDUM			-0.0133		
			(-2.92)		
PIN*ADUM				-0.0007	
				(-0.22)	
PIN*SDUM					-0.0020
					(-0.55)

Table 6: Correlation between PIN and Information Dissemination Proxies

This table reports the correlation coefficients between the analyst dummy (ADUM), the share dummy (SDUM), the credit rating dummy (CDUM), and probability of informed trading (PIN), estimated quarterly using Easley, Hvidkjaer and O'Hara (2002) model. The correlation coefficients are calculated for the whole sample of NYSE, AMEX and NASDAQ firms, for the period from 1985 to 2000. ADUM is equal to one if a firm has one or more analysts, otherwise zero. The SDUM denotes whether the fraction of shares held by large institutions exceeds the median level for the entire sample. The CDUM is equal to one if a firm has credit rating, otherwise zero. The p-values are in parenthesis below the correlation coefficients.

	PIN	ADUM	SDUM	CDUM
PIN	1	-0.4222 (<.0001)	-0.3445 (<.0001)	-0.2948 (<.0001)
ADUM	-0.4222 (<.0001)	1	0.5143 (<.0001)	0.3026 (<.0001)
SDUM	-0.3445 (<.0001)	0.5143 (<.0001)	1	0.3303 (<.0001)
CDUM	-0.2948 (<.0001)	0.3026 (<.0001)	0.3303 (<.0001)	1

Table 7: Fama-Macbeth Regression Results (With PIN Square)

The following table contains monthly time-series averages of the estimated coefficients in cross-sectional asset-pricing tests for NYSE and AMEX firms (Panel A), and for NASDAQ firms (Panel B), using the weighted least-square methodology suggested by Litzenberger and Ramaswamy (1979). The dependent variable is the portfolio monthly return. Betas are post-ranked betas estimated using 40 beta portfolios. Size is the logarithm of the December market equity for year t-1, BM is the logarithm of book value divided by market value for year t-1. The ADUM is equal to one if a firm has one or more analysts, otherwise zero. The SDUM denotes whether the fraction of shares held by large institutions exceeds the median level for the entire sample. The CDUM is equal to one if a firm has credit rating, otherwise zero. The T-statistics are inside parenthesis.

Panel A: NYSE/AMEX Firms

FM Regressions	(1)	(2)	(3)	(4)	(5)
Beta	-0.0001	-0.0001	0.0000	0.0000	-0.0001
	(-1.91)	(-1.89)	(-0.78)	(-0.85)	(-1.91)
Size	0.0015	0.0019	0.0019	0.0017	0.0019
	(3.01)	(3.80)	(3.52)	(3.16)	(3.92)
BM	0.0028	0.0029	0.0026	0.0025	0.0029
	(3.28)	(3.31)	(2.98)	(2.86)	(3.39)
PIN		0.0070	0.0115	0.0092	0.0107
		(2.64)	(1.44)	(1.13)	(1.54)
PIN Square			-0.0050	-0.0024	-0.0042
			(-0.45)	(-0.23)	(-0.45)
PIN*CDUM			-0.0065		
			(-2.13)		
PIN*ADUM				-0.0002	
				(-0.05)	
PIN*SDUM					-0.0016
					(-0.51)

Panel B: NASDAQ Firms

FM Regressions	(1)	(2)	(3)	(4)	(5)
Beta	0.0000	0.0000	0.0000	0.0000	0.0000
	(-1.36)	(-1.19)	(-1.13)	(-1.23)	(-1.26)
Size	0.0008	0.0019	0.0021	0.0020	0.0020
	(1.01)	(2.11)	(2.38)	(2.33)	(2.35)
BM	0.0092	0.0088	0.0089	0.0088	0.0088
	(6.16)	(5.78)	(6.01)	(5.81)	(5.81)
PIN		0.0191	0.0315	0.0314	0.0318
		(2.89)	(2.75)	(2.81)	(2.83)
PIN Square			-0.0186	-0.0190	-0.0188
			(-1.45)	(-1.55)	(-1.51)
PIN*CDUM			-0.0136		
			(-2.98)		
PIN*ADUM				-0.0017	
				(-0.52)	
PIN*SDUM					-0.0025
					(-0.70)

Table 8: Cross-sectional Cost of Capital Change at the Firm Level

The table reports the estimated coefficients of firm-level cross-sectional regressions. The dependent variable is the change in firms' average cost of capital due to changes in PIN and a proxy for information dissemination, from the period 3-month before regulation FD to the period 3-month after regulation FD. The change in firms' average cost of capital is calculated using the Fama-MacBeth average regression coefficients from regression (3) in Table 5 multiplied by the changes in PIN and analyst dummy (Panel A), or from regression (4) in Table 5 multiplied by the changes in PIN and institutional share dummy (Panel B), or from regression (5) in Table 5 multiplied by the changes in PIN and credit rating dummy (Panel C). The change in cost of capital is annualized. The explanatory variable ΔVOL is the change in firms' average monthly trading volume, from the period 3-month before regulation FD to the period 3-month after regulation FD, expressed in units of ten million shares. The explanatory variable ΔLARGE is the change in firms' average number of large trades with 10,000 shares or more each month, from the period 3-month before regulation FD to the period 3-month after regulation FD, expressed in units of 100 trades. Size is the market value of equity for year-end 1999. BM is the ratio of book equity value ending in 1999 to the market value of equity ending in 1999. PIN is estimated using data from the 2nd quarter of 2000. We also include one dummy variable denoting the HIGHTECH industry. All the explanatory variables except dummies are demeaned. The T-statistics are below regression coefficients inside parenthesis.

Panel A: Using CDUM as a proxy for information dissemination

	All Firms			NYSE/AMEX			NASDAQ		
Constant	0.0012	0.0009	0.0006	0.0001	-0.0006	-0.0006	0.0017	0.0013	0.0010
	(3.86)	(2.62)	(1.55)	(0.45)	(-1.59)	(-1.60)	(3.92)	(2.37)	(1.51)
ΔVOL			0.0004			0.0002			0.0018
			(0.67)			(0.34)			(1.75)
ΔLARGE			-0.0005			-0.0003			-0.0022
			(-0.89)			(-0.74)			(-1.85)
Log(Size)		-0.0010	-0.0009		0.0001	0.0002		-0.0019	-0.0017
		(-4.38)	(-3.75)		(0.79)	(1.07)		(-4.50)	(-4.01)
Log(BM)		-0.0004	-0.0003		0.0003	0.0003		-0.0005	-0.0004
		(-1.30)	(-0.77)		(0.76)	(0.76)		(-0.96)	(-0.73)
PIN		-0.0123	-0.0114		-0.0029	-0.0023		-0.0197	-0.0188
		(-4.60)	(-4.18)		(-1.24)	(-0.92)		(-4.93)	(-4.63)
HIGHTECH			Yes			Yes			Yes
R-Square	0.000	0.007	0.008	0.000	0.003	0.004	0.000	0.013	0.014
Obs	5222	4422	4421	1733	1511	1511	3489	2911	2910

(To be contined on next page.)

(Contined from previous page.)

Panel B: Using ADUM as a proxy for information dissemination

	All Firms			NYSE/AMEX			NASDAQ		
Constant	0.0012	0.0010	0.0007	0.0001	-0.0006	-0.0007	0.0018	0.0015	0.0012
	(3.98)	(2.85)	(1.69)	(0.30)	(-1.37)	(-1.51)	(4.13)	(2.76)	(1.88)
ΔVOL			0.0016			0.0014			0.0029
			(2.91)			(1.83)			(2.89)
ΔLARGE			-0.0018			-0.0016			-0.0034
			(-3.32)			(-3.40)			(-2.92)
Log(Size)		-0.0010	-0.0008		-0.0001	0.0002		-0.0016	-0.0014
		(-4.32)	(-3.18)		(-0.32)	(0.97)		(-3.88)	(-3.29)
Log(BM)		-0.0004	-0.0003		0.0003	0.0003		-0.0004	-0.0003
		(-1.25)	(-0.81)		(0.77)	(0.72)		(-0.78)	(-0.63)
PIN		-0.0122	-0.0103		-0.0053	-0.0022		-0.0179	-0.0171
		(-4.55)	(-3.77)		(-2.01)	(-0.79)		(-4.55)	(-4.27)
HIGHTECH			Yes			Yes			Yes
R-Square	0.000	0.007	0.010	0.000	0.004	0.015	0.000	0.011	0.014
Obs	5222	4422	4421	1733	1511	1511	3489	2911	2910

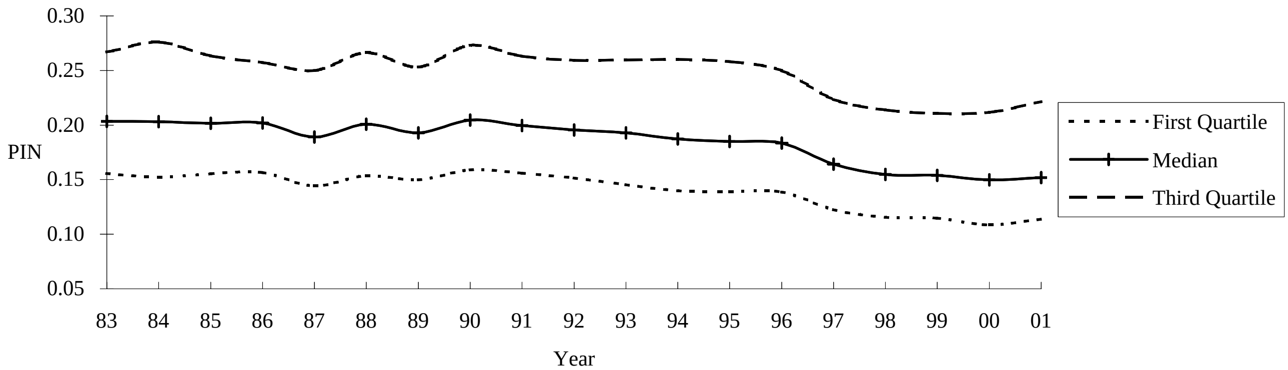
Panel C: Using SDUM as a proxy for information dissemination

	All Firms			NYSE/AMEX			NASDAQ		
Constant	0.0013	0.0011	0.0008	0.0001	-0.0006	-0.0006	0.0019	0.0016	0.0013
	(4.20)	(2.99)	(1.86)	(0.29)	(-1.48)	(-1.56)	(4.33)	(2.88)	(2.01)
ΔVOL			0.0013			0.0011			0.0028
			(2.46)			(1.56)			(2.70)
ΔLARGE			-0.0016			-0.0013			-0.0033
			(-2.84)			(-3.00)			(-2.75)
Log(Size)		-0.0011	-0.0008		0.0000	0.0002		-0.0016	-0.0014
		(-4.35)	(-3.31)		(-0.18)	(0.97)		(-3.89)	(-3.31)
Log(BM)		-0.0005	-0.0003		0.0003	0.0003		-0.0004	-0.0004
		(-1.40)	(-0.95)		(0.86)	(0.79)		(-0.86)	(-0.72)
PIN		-0.0125	-0.0108		-0.0049	-0.0022		-0.0187	-0.0179
		(-4.60)	(-3.90)		(-1.98)	(-0.88)		(-4.63)	(-4.35)
HIGHTECH			Yes			Yes			Yes
R-Square	0.000	0.008	0.010	0.000	0.004	0.013	0.000	0.012	0.015
Obs	5222	4422	4421	1733	1511	1511	3489	2911	2910

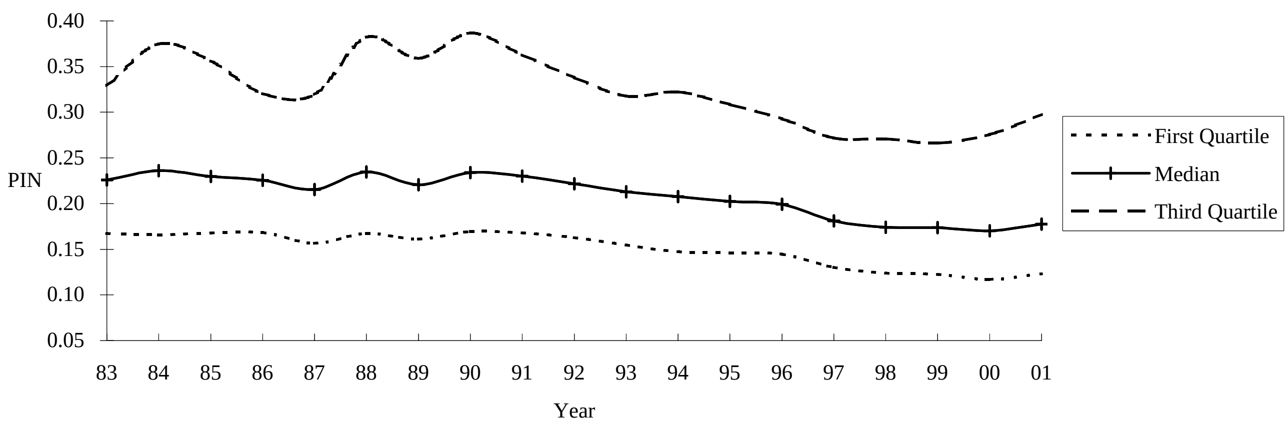
Figure 1 - Time Series of PIN

The figure plots the first quartile, the median, and the third quartile of average PIN each year over the sample period (1983 to 2001), for NYSE firms only (Panel A), for NYSE and AMEX firms (Panel B), and for NASDAQ firms only (Panel C). PIN is a composite variable measuring the probability of information-based trading, estimated each quarter, using Easley, Hvidkjaer and O'hara (2002) probability of informed trading model.

Panel A: Plotting PIN for NYSE Firms Only



Panel B: Plotting PIN for NYSE and AMEX Firms



Panel C: Plotting PIN for NASDAQ Firms Only