Regulation Fair Disclosure and Capital Structure

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Abstract

This study examines the impact of Regulation Fair Disclosure (FD) on corporate financing choices. Regulation FD puts more constraints on corporate disclosure in the equity market than in the debt market. After the regulation, although firms are no longer able to selectively disclose material information to market professionals in the equity market, they can still do so to banks and rating agencies in the debt market. Consistent with the expectation that FD affects firms differentially, I find substantial cross-sectional variation in changes in information asymmetry in the equity market. I further find that firms experiencing greater increases in information asymmetry increase their leverage more after FD. The results suggest that firms who cannot perfectly replace private disclosure with public disclosure are likely to experience increases in information asymmetry and that they may turn to the debt market for capital where private disclosure is still available.

1 Introduction

This study examines the change in capital structure as an economic consequence of Regulation Fair Disclosure (FD). Regulation FD, implemented by the Securities and Exchange Commission (SEC) in October 2000, puts more constraints on corporate disclosure in the equity market than in the debt market. In the equity market, the regulation prohibits any selective disclosure of material information by firms to favored market professionals.[1] In the debt market, on the other hand, it grants an exemption to credit rating agencies and does not apply to banks.[2] Because firms are likely to be affected by FD differentially, although some firms may be able to replace the loss of the selective disclosure channel with other information transmission channels, other firms may not be able to do so (Gomes et al. (2007); Wang (2007)). Less disclosure leads to greater asymmetric information among investors (Brown et al. (2004); Brown and Hillegeist (2007)). Given that information asymmetry among investors is positively related to the cost of capital (Easley and O'Hara (2004); Easley et al. (2002)), these firms now face higher costs of equity capital and have incentives to turn to the debt market where private disclosure is still available.

By providing equal access to firm disclosures, Regulation FD aims to mitigate information asymmetry across different classes of investors. This information asymmetry is different from the asymmetry between firm insiders and outside investors. The information asymmetry between the firm and its investors is intrinsic to the firm and arises because firm managers have better information than outside investors. In

[1] Rule 100(b)(1) enumerates four categories of persons to whom selective disclosure may not be made absent a specified exclusion. The first three are securities market professionals: (1) broker-dealers and their associated persons, (2) investment advisers, certain institutional investment managers and their associated persons, and (3) investment companies, hedge funds, and affiliated persons. The fourth category of person is any holder of the issuer's securities, under circumstances in which it is reasonably foreseeable that such person would purchase or sell securities on the basis of the information.

[2] Rule 100(b)(2) grants an exemption to an entity whose primary business is the issuance of credit ratings, provided the information is collected solely for the purpose of developing a credit rating and the entity's ratings are publicly available.

contrast, the information asymmetry between market participants represents heterogeneity of investor beliefs and can be viewed extrinsic to the firm.[3] Because the goal of FD is to reduce information asymmetry across groups of investors, in this study I focus on extrinsic information asymmetry among investors and control for intrinsic information asymmetry in the tests. I measure extrinsic information asymmetry using the probability of information-based trading (PIN), which is based on the market microstructure model developed by Easley, Kiefer, O'Hara, and Paperman (1996). The PIN is the probability that a particular trade originates from a privately informed investor. The higher the PIN, the greater the information asymmetry among investors.

I find substantial cross-sectional variation in changes in PIN after controlling for other contemporaneous factors that could have impacted firms' information environments but are unrelated to FD. Specifically, I sort firms into quintiles based on the estimated change in PIN and find that, on average, firms in the first quintile experience a decrease in PIN (lower extrinsic information asymmetry) of 5.8%, while firms in the fifth quintile experience an increase in PIN (higher extrinsic information asymmetry) of 3.3%. Combined with the results in Easley, Hvidkjaer, and O'Hara (2002) on the association between PIN and cost of equity, my finding suggests that the first quintile firms experience a decrease of 145 basis points in their annual cost of equity, while the fifth quintile firms experience an increase of 82.5 basis points in theirs. I further investigate pre-regulation firm characteristics that may explain the cross-sectional impact of Regulation FD. I find that firms positively affected by FD tend to be larger firms with better earnings performance, greater financial information complexity, higher litigation costs, more sophisticated investors, and a higher probability of having a credit rating. They also tend to have larger decreases in both analyst forecast dispersion and analyst forecast error after the regulation.

[3] The definitions of extrinsic information asymmetry and intrinsic information asymmetry follow Agarwal and O'Hara (2007).

I find that the cross-sectional variation in the effects of Regulation FD on extrinsic information asymmetry explains changes in capital structure in the post-FD period. Specifically, firms experiencing greater increases in PIN following the adoption of FD tend to have greater increases in leverage. Robustness tests show that the finding is robust to different model specifications and cannot be explained by changes in cost of debt. I further investigate through which components does leverage change and find that the increase in leverage comes from more debt issuances and fewer equity issuances. Overall my finding is consistent with the notion that managers make a trade-off to increase the use of debt when facing increased costs of equity.

Early papers on Regulation FD primarily investigate the average effects of FD (e.g., Irani and Karamanou (2003); Bailey et al. (2003); Heflin et al. (2003); Eleswarapu et al. (2004)), but these studies present conflicting evidence. For example, Heflin, Subramanyam, and Zhang (2003) examine the flow of financial information to the equity market prior to earnings announcements and find no evidence of impairment in the information environment. Eleswarapu, Thompson, and Venkataraman (2004) find that the degree of the information asymmetry reflected in trading costs has declined following the introduction of FD, consistent with SEC goals to level the playing field. However, Sidhu, Smith, Whaley, and Willis (2008), using the adverse selection component of the spread as the proxy for information asymmetry, report opposite results.

Recent papers start to consider cross-sectional variation in the effects of FD. For example, Wang (2007) explores how Regulation FD affects the disclosure policies and information environments of firms that provide earnings guidance pre-FD relative to firms that do not provide guidance. Gintschel and Markov (2004) examine market reactions to analyst announcements. They find that analyst announcements have a smaller price impact after Regulation FD and the drop varies systematically with brokerage house and stock characteristics. Mohanram and Sunder (2006) study cross-analyst differences in forecast accuracy. They find that analysts who were likely to have had preferential access to firms in the pre-FD period are more likely to be adversely affected in the post-FD period. Finally, Gomes, Gorton, and Madureira (2007) study the effects of FD by partitioning firms based on size. They find that Regulation FD caused a reallocation of information-producing resources, resulting in a welfare loss for small firms, which now face a higher cost of equity capital.

My paper contributes to the research on Regulation FD by connecting the regulatory effects on the information environment to an economic outcome, the change in capital structure. Most academic researchers have focused on FD's impact on the information environment. My paper extends the research by empirically showing that, through its influences on the information environment, Regulation FD also influences corporate financing choices. This result is of interest to policymakers who wish to assess the overall consequences of Regulation FD and to evaluate the likely effects of disclosure requirements on corporate financing behavior.[4]

This paper relates to two streams of research. The first investigates the link between equity market information risk and capital structure. This research shows that firms with higher extrinsic information asymmetry in the equity market tend to have higher leverage (e.g., Bharath et al. (2008); Agarwal and O'Hara (2007)). My work complements this stream of research, but I differ along several important dimensions. First, my focus is not on studying the general relation between information risk and capital structure, but on investigating the potential impact of FD on corporate financing behavior. Second, these studies relate the level of extrinsic information asymmetry to capital structure and such a level approach is subject to a possibly severe omitted variable problem. I use Regulation FD as an exogenous shock

[4] A concurrent paper by Albring, Banyi, Dhaliwal, and Pereira (2008) also explores the impact of FD on firm financing decisions. Rather than focusing on capital structure, they focus on public debt and equity issuances. They find that although on average firms are more likely to issue equity in the post-FD period, firms with high proprietary cost of public disclosure increase their reliance on public debt financing after FD.

that stimulates changes in the degree of extrinsic information asymmetry. I then test whether changes in extrinsic information asymmetry are associated with simultaneous changes in capital structure. The change approach is less likely to suffer from omitted variable bias. Finally, the differential impacts of FD on the equity market and the debt market provide me with a more powerful setting. While previous studies have established a link between equity market information risk and capital structure, this link is less clear because information risk can also affect cost of debt. In contrast, because Regulation FD primarily affects the equity market and has virtually no impact on the debt market, it is reasonable to assume that the information risk does not change in the debt market and therefore, the change in capital structure is associated with the change in information risk in the equity market.

A second stream of related research explores the effect of Regulation FD on firms' costs of equity capital (Gomes et al. (2007); Duarte et al. (2008); Chen et al. (2008)). These studies use different cost of equity constructs and provide mixed results. For example, Gomes, Gorton, and Madureira (2007) and Duarte, Han, Harford, and Young (2008) use realized returns as the measure of cost of equity capital and find that the cost of capital increases for some firms post-FD. In contrast, Chen, Dhaliwal, and Xie (2008) examine implied cost of equity capital and show that the cost of capital is reduced after Regulation FD. Cost of equity capital is known to be difficult to measure. Prior research has shown that the correlation between expected returns and realized returns is weak (Elton (1999)) and that firm-specific estimates of cost of equity based on realized returns are very imprecise (Fama and French (1997)). Implied cost of equity is popular in accounting literatures, but it relies crucially on the underlying assumptions. I opt to study the effect of Regulation FD on capital structure which is more easily measured. If FD has a differential impact on cost of equity across firms, we should observe cross-sectional variation in the change in capital structure post-FD.

The paper proceeds as follows. Section 2 develops the hypothesis. I discuss the measure of extrinsic information asymmetry in Section 3. Section 4 conducts capital structure analysis and Section 5 concludes.

2 Hypothesis development

Regulation FD has a much smaller impact on the debt market information environment than on the equity market information environment. In the private debt market, firms with high costs of public disclosure can still privately convey information to banks. In the public debt market, rating agencies still have access to selective information. Although Regulation FD applies to debt analysts, it should have small influences on the level of information asymmetry among bond investors. Unlike the equity market, the bond market is essentially an institutional market. There are smaller differences in bond investors' technical expertise to acquire and process information.

In the equity market, Regulation FD could potentially decrease the quality and quantity of information dissemination, resulting in higher asymmetric information among investors. Regulation FD closed down the private disclosure channel. To the extent that public disclosure is not a perfect substitute for private disclosure, some firms may not be able to increase or maintain the same level of disclosure as before. SEC Commissioner Unger voted against FD and expressed the concerns that the regulation would lead to a chilling of the information flow from issuers to the marketplace (Unger (2000)). Wang (2007) finds that roughly half of the firms that rely on private earnings guidance replace private guidance with nondisclosure instead of public guidance.[5] Less disclosure results in longer-lived and more valuable private

[5] Reasons firms may prefer to convey information to a select audience include reducing proprietary costs, limiting the risk of misinterpretation by less skilled users, avoiding the cost of deciding whether the information is "material" under FD, and decreasing litigation risk given that public disclosure may be subject to stricter scrutiny than private disclosure (Unger (2000); Weber (2000); Unger

information (Sidhu et al. (2008)), which gives greater incentives to investors to search for the undisclosed information. Resourceful investors who can discover the information through other channels may therefore gain an informational advantage. Prior research has also shown an inverse relation between voluntary disclosure and information differences across investors (Brown et al. (2004); Brown and Hillegeist (2007)). Consistent with the view that FD may increase extrinsic information asymmetry, Sidhu, Smith, Whaley, and Willis (2008) find that the adverse selection component of the bid-ask spread increases approximately 36% after the adoption of the standard.

The impact of FD on firms' equity market information environments is not uniform across firms. Gomes, Gorton, and Madureira (2007) find that big firms are able to replace the loss of selective disclosure with other information transmission channels, but small firms are not able to do so. This information-producing reallocation results in a higher cost of equity capital for small firms and no significant change for big firms. Wang (2007) finds that firms with lower information asymmetry (measured by PIN) and higher proprietary costs tend to replace private disclosure with nondisclosure after FD, and these firms suffer significant deterioration in their equity market information environments. Since Regulation FD affects firms of different characteristics differently, I expect to observe cross-sectional differences in changes in extrinsic information asymmetry in the equity market. That is while some firms may enjoy a decrease in extrinsic information asymmetry, others may experience an increase.

Extrinsic information asymmetry among security investors is positively related to cost of capital. Easley and O'Hara (2004) demonstrate theoretically that securities with greater private information relative to public information have higher required returns (i.e., higher costs of capital). The higher return reflects the fact that private information increases the risk to uninformed investors of holding the security because informed investors are better able to adjust their portfolio weights to incorporate

(2001)).

the new information. In equilibrium, uninformed investors require compensation for bearing such risk. Easley, Hvidkjaer, and O'Hara (2002) provide empirical support that information risk is priced.

Under the assumptions that information risk is priced and that the information environment of the debt market is less affected by FD, I predict greater increases in leverage after Regulation FD for firms experiencing greater increases in extrinsic information asymmetry in the equity market. Higher extrinsic information asymmetry increases the cost firms face in raising equity capital. If their optimal disclosure strategy does not allow them to disclose more to resolve the information risk, these firms have incentives to turn to the debt market where they face fewer constraints in privately communicating with capital providers and can, therefore, obtain relatively lower costs of capital. In contrast, the null hypothesis (of no economic consequences) predicts that firms' capital structure remains unaffected by the standard.

3 The measure for extrinsic information asymmetry

3.1 The probability of information-based trading (PIN)

I measure extrinsic information asymmetry using the probability of information-based trading (PIN), which is based on the market microstructure model developed by Easley, Kiefer, O'Hara, and Paperman (1996).[6] Several papers have used PIN to study

[6] Besides PIN, measures of extrinsic information asymmetry are usually based on bid-ask spreads. The spread is comprised of three types of costs facing market makers: order processing costs, inventory holding costs, and adverse selection costs. The adverse selection costs compensate market makers for the risk of trading with the better informed, and hence, reflect the degree of information asymmetry among investors. Spread-based measures suffer from many interpretation difficulties because it is empirically challenging to estimate the three components accurately (see Callahan, Lee, and Yohn (1997) for discussions on limitations of using the bid-ask spread as an empirical proxy). Unlike spreads, PIN directly measures the risk of private information. This is because PIN is derived from a theoretical model that does not incorporate factors other than information.

a broad range of topics in accounting and finance.[7] The PIN model is a sequential trade model in which a group of informed and uninformed traders trade an asset with a market maker. At the beginning of each trading day, nature determines whether there is new information about the asset (an information event) with probability α. When an information event occurs it is either bad news with probability δ, or good news with probability $1-\delta$. Only informed traders observe the information event.

After nature determines the information signal, trading begins with orders arriving sequentially to the market according to independent Poisson processes. Informed traders observe the information signal and only trade on information-event days. They buy if they have seen good news and sell if they have seen bad news.[8] Orders from informed traders arrive at rate μ. Uninformed traders do not observe the information signal and trade independently of any news event. Orders from uninformed traders arrive at rate ε_b for buy orders and at rate ε_s for sell orders. Figure 1 depicts graphically the trading process.

PIN is uninformed market participants' perceived probability that a particular trade is information-based:[9]

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_b + \varepsilon_s} \tag{1}$$

The greater the PIN, the greater is the information asymmetry. I outline the estimation process and the descriptive statistics of PIN in Appendix A.

[7] For example, Brown, Hillegeist, and Lo (2004), Brown and Hillegeist (2007), Duarte, Han, Harford, and Young (2008), and Wang (2007) use PIN to study the impact of firms' disclosure policies. Vega (2006) uses PIN to study the effect of private and public information on the post-announcement drift. Ferreira and Laux (2007) use PIN to study the association between corporate governance and information flow.

[8] The information event in the model represents the information only known by the informed traders. Empirically it can be pure private information that is only disclosed to the informed traders. For example, insider information. Or it can be information produced by the informed traders from a public information event. For example, the information extracted from a public earnings announcement.

[9] Strictly speaking, PIN is the market maker's expected probability that the opening trade is information based.

3.2 Sample Selection

This paper explores the potential impact of FD on capital structure. Given that firms' capital structures are sticky over time (Leary and Roberts (2005); Lemmon et al. (2008)), I need a sufficiently long sample period.[10] I use a 10 year sample period from 1995 to 2005. I specify 1995 to 1999 as the period before Regulation FD (pre-FD) and 2001 to 2005 as the period after Regulation FD (post-FD), omitting the regulatory change year of 2000.

The initial sample consists of all firms with ordinary common stocks listed on the New York Stock Exchange (NYSE) and traded both before and after the adoption of Regulation FD. I limit the analysis to NYSE firms because the NYSE's specialist market structure most closely fits to that of the PIN model. Following Easley, Hvidkjaer, and O'Hara (2002), I exclude companies incorporated outside of the U.S., real estate investment trusts, and closed-end funds. I also exclude any firm-year observation which does not have at least 60 days with both quotes and trades because I cannot estimate the PIN model reliably. Finally, all firms in the sample need to have required data from COMPUSTAT, CRSP, I/B/E/S and CDA/Spectrum. The final sample consists of 1039 firms with firm-year observations ranging from 6814 to 9301, depending on the empirical specification.

4 Capital structure analysis

4.1 Measuring changes in extrinsic information asymmetry

I use changes in PIN to proxy for changes in extrinsic information asymmetry after the implementation of Regulation FD. Since a firm's information environment may change with the passage of time even without the introduction of a new regulation, I

[10] A long sample period increases the probability of confounding events. To mitigate this problem, I use a regression analysis to control for concurrent factors affecting firms' information environments. (see Section 4.1).

use a regression analysis to control for contemporaneous changes in the information environment unrelated to FD. The model takes the form:

$$PIN_{i,t} = \beta_{1,i} + \beta_{2,i} FD_t + \gamma_1 Size_{i,t} + \gamma_2 InstOwn_{i,t} + \gamma_3 Coverage_{i,t} + \gamma_4 MTB_{i,t} + \eta_{i,t} \quad (2)$$

where i indexes the firm and t indexes the calendar year. FD is a dummy variable, which equals 1 if the observation is from the post-FD sample period, and 0 otherwise.

My goal is to estimate firm-specific changes in the information environment and thus ideally I would like to estimate equation (2) by firm. However, because each firm only has a maximum of 10 observations (recall that the sample period is 10 years), firm-specific regressions would be highly inaccurate. Instead I estimate equation (2) by industry with firm-specific intercepts: β_1 and β_2. I define industry according to the Fama and French (1997) 48-industry classifications.

The ratio $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$ captures firm-specific change in PIN relative to the firm's pre-FD PIN after controlling for other factors also affecting PIN.[11] I use $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$ to estimate the impact of FD on the firm's information environment. To reduce the potential measurement error associated with $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$, I adopt an ordinal transformation of the variable in which the firm with the smallest $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$ is assigned a rank of one. I then divide the ordinal variable by the total number of firms in the sample (1039) so that the range of the ordinal variable is between zero and one. As Llorente, Michaely, Saar, and Wang (2002) point out, this kind of monotonic transformation preserves the intuition of the differences between the low and high values of the variable without reading too much into the specific differences in magnitude. The transformed variable, $GrowthPIN$, is my proxy for the change in extrinsic information asymmetry.

Control variables include firm size, institutional ownership, analyst coverage, and

[11] Given the bounded nature of PIN, the scaling by the pre-FD PIN allows me to capture the impact of FD more precisely. For example, a 0.05 increase in PIN has a larger impact on a firm with a pre-FD PIN value of 0.001 than a firm with a pre-FD PIN value of 0.1.

growth opportunities. Large firms tend to have better public information environment that can potentially mitigate information asymmetry among investors.[12] *Size* is the log of net sales (COMPUSTAT Annual Item 12). Institutions have an influence on a firm's information environment and price informativeness (El-Gazzar (1998); Jiambalvo et al. (2002)). I define institutional ownership, *InstOwn*, as the proportion of the firm's shares held by institutions. Prior research finds that extrinsic information asymmetry is lower for firms with a larger analyst following (e.g., Brennan and Subrahmanyam (1995); Easley et al. (1998)). *Coverage* is the number of analysts making annual EPS forecasts in the year. Growth opportunities are associated with disclosure behavior (Frankel et al. (1999)). Since disclosure behavior is associated with extrinsic information asymmetry (Brown et al. (2004)), growth opportunities may also be associated with extrinsic information asymmetry. I use market-to-book, MTB, to proxy for growth opportunities. MTB is market value (MV) of assets divided by book value (BV) of assets.[13]

4.2 Descriptive statistics

Table 1, Panel A presents the average $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$ from equation (2) by quintiles. On average firms in the first quintile experience a decrease in PIN by 23%, whereas firms in the fifth quintile experience a growth in PIN by 43%. Firms in the three middle quintiles have very small changes in PIN.[14] Because Regulation FD has little impact on firms in the three middle quintiles, I group these firms together. I present descrip-

[12] Easley, Hvidkjaer, and O'Hara (2002) find a negative correlation between PIN and firm size.

[13] I define MV of assets as BV of assets (Item 6) minus BV of equity plus MV of equity. I define BV of equity as total assets less total liabilities (Item 181) and preferred stock (Item 10) plus deferred taxes (Item 35). When deferred taxes is missing, it is set to zero. When preferred stock is missing, it is replaced with the redemption value of preferred stock (Item 56) if available, else with the carrying value (Item 130). MV of equity is defined as common shares outstanding (Item 25) times price (Item 199). These definitions follow Fama and French (2002).

[14] Recall that $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$ measures a firm's change in PIN relative to its pre-FD PIN after controlling for factors that may affect the change in the information environment (i.e., firm size, institutional ownership, analyst coverage, and growth opportunities).

tive statistics in Panel B by the following three groups: the first group encompasses firms in the lower quintile of $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$; the second group includes firms in the three middle quintiles, and the third group has those firms in the upper quintile.

Table 1, Panel B provides descriptive information on capital structure and the variables in equation (2) before and after Regulation FD. The descriptive data are based on the mean values of the variables; results based on the median values yield similar inferences and are not reported. I define book leverage as debt to BV of assets and market leverage as debt to MV of assets. Firms in group 1 and group 2 are larger firms and they experience a reduction in PIN after FD (from 0.165 to 0.107 for group 1 and from 0.147 to 0.122 for group 2). In contrast, firms in group 3, which are smaller firms, experience an increase in PIN (from 0.153 to 0.186). The data indicate that while large firms enjoy a decrease in extrinsic information asymmetry subsequent to the FD adoption, small firms experience an increase. This result supports Gomes, Gorton, and Madureira (2007), who find that the information environment deteriorates for small firms after FD. Combined with the findings in Easley, Hvidkjaer, and O'Hara (2002) on the association between PIN and cost of equity, my result suggests that, on average, firms in group 1 (group 2) experience a decrease of 145 (62.5) basis points in the annual cost of equity, while firms in group 3 experience an increase of 82.5 basis points.

Turning to capital structure, both book leverage and market leverage increase significantly for group 3, while the leverage does not change significantly for group 1 and only market leverage increases significantly for group 2. Overall the results in Panel A and Panel B are consistent with the view that firms experiencing larger increases in extrinsic information asymmetry are relatively more levered after Regulation FD. The higher leverage may be due to the increased cost of equity resulting from the increased information risk.

Table 1, Panel C reports descriptive data on selected ex ante firm characteristics and changes in analyst behavior to explore why some firms experience increases in extrinsic information asymmetry, but others do not. The ex ante firm characteristics are the means of the variables in the pre-FD period, and the change in analyst behavior is the difference in the means between the post-FD and the pre-FD periods. Since Regulation FD has the greatest impact on firms in group 1 and group 3, I compare the variables between these two groups.

Firms with complex financial information are more likely to supply information directly to investors rather than filter it through analysts (Bushee et al. (2003)). Because these firms make less use of selective disclosure, they are less exposed to the rule change and thus may be less likely to be adversely affected by FD. Following Bushee, Matsumoto, and Miller (2003), I use membership in a high technology industry and revenue volatility as proxies for financial information complexity.[15] Consistent with the prediction, firms in group 1 have relatively more complex financial disclosures: they are more likely to be in the high-tech industries and have larger revenue volatility.

Firms with higher litigation costs are more likely to disclose publicly (Skinner (1994); Kasznik and Lev (1995)). These firms are less likely to choose nondisclosure after Regulation FD and therefore should be less likely to experience increases in extrinsic information asymmetry.[16] Credit rating agencies are exempt from Regulation FD. Jorion, Liu, and Shi (2005) find that the information content of credit ratings increases after FD, possibly because credit analysts at rating agencies have access to

[15] Following Bushee, Matsumoto, and Miller (2003), SIC codes classified as high-tech industries include: Drugs (2833-2836); Electric Distribution Equipment (3612-3613); Electrical Industrial Apparatus (3621-3629); Household Audio & Video Equipment (3651-3652); Communications Equipment (3661-3669); Electron Tubes (3671); Printed Circuit Boards (3672); Semiconductors & Related Devices (3674); Magnetic and Optical Recording Media (3695); Telephone Communications (4812-4822); Radio & TV Broadcasting (4832-4899); Computer and Data Processing Services (7370-7379). I measure revenue volatility as the standard deviation of quarterly revenue, measured over three years including and preceding the current year.

[16] I denote a firm to have high litigation costs if it is in a high litigation risk industry and also suffers an earnings decrease for at least 4 quarters during the pre-FD period. Following Francis, Philbrick, and Schipper (1994), SIC codes classified as high litigation risk industries include: Biotechnology (2833-2836, 8731-8734); Computers (3570-3577, 7370-7374); Electronics (3600-3674); Retailing (5200-5961).

confidential information that is no longer made available to equity analysts. Because credit ratings are publicly available, I expect Regulation FD to have a smaller impact on the information environment of firms with ratings. Consistent with these expectations, relative to group 3 firms, group 1 firms have higher litigation costs and are more likely to have a bond rating.

Miller (2002) finds that firms increase public disclosure when they experience sustained strong earnings performance. Greater disclosure reduces information risk. Consistent with this view, group 1 firms have stronger firm performance than group 3 firms, as measured by ROE or ROA. Using institutional ownership as a measure of investor sophistication, I find that firms experiencing increases in extrinsic information asymmetry tend to have fewer sophisticated investors (48% institutional ownership for group 3 versus 61% for group 1). The result is consistent with Barron, Byard, and Enis (2002) who show that providing unsophisticated investors unfiltered access to information increases the likelihood that such investors form diverse opinions about the firm.

If Regulation FD has increased differences in opinion among analysts, then, to the extent that analyst reports are an information source to investors, differences in opinion among investors should increase too. I measure analyst disagreement by analyst forecast dispersion.[17] Consistent with the prediction, firms in group 3 experience larger increases in forecast dispersion than firms in group 1. Moreover, firms in group 3 also experience larger increases in analyst forecast error.[18]

[17] I define forecast dispersion as the standard deviation of individual analysts' most recent earnings forecast in the 90 days prior to the earnings announcement.

[18] I define forecast error as the absolute value of the difference between the actual earnings per share and the median of individual analysts' most recent earnings forecast in the 90 days prior to the earnings announcement. I scale the forecast error by the stock price at the fiscal quarter end.

4.3 Multiple regression to explain changes in capital structure

To test whether changes in extrinsic information asymmetry in the equity market explain cross-sectional variation in changes in capital structure, I estimate the following regression equation:

$$\begin{aligned} Leverage_{i,t} &= \beta_1 + \beta_2 FD_t + \beta_3 GrowthPIN_i + \beta_4 GrowthPIN_i * FD_t \\ &\quad + \gamma Controls_{i,t-1} + \eta_{i,t} \end{aligned} \tag{3}$$

where *Leverage* denotes either book leverage or market leverage. To reduce the likelihood of simultaneity bias, I measure leverage ratios at year t, and all control variables at year $t-1$. I cluster standard errors by firm and by year to correct for possible correlations across observations of a given firm and of a given year (Rogers (1993); (Petersen 2007)).

The key idea behind equation (3) is to filter out confounding macroeconomic changes since β_2 summarizes the way that all firms are influenced by time. β_3 captures time-invariant differences in leverage among firms with different $GrowthPIN$. β_4 represents the additional increase in leverage post-FD associated with an increase in $GrowthPIN$. The hypothesis predicts that firms experiencing larger increases in extrinsic information asymmetry will have relatively higher leverage after FD, and hence, $\beta_4 > 0$.

Following the literature (e.g., Rajan and Zingales (1995); Hovakimian et al. (2001); Fama and French (2002); Agarwal and O'Hara (2007)), I include a set of firm characteristics as controls. They are intrinsic information asymmetry between the firm and its investors, growth opportunities, dividend payout, nondebt tax shields, asset tangibility, profitability, and firm size. Previous studies have found that firms with higher leverage tend to have higher intrinsic information asymmetry, lower growth opportunities, lower dividend payouts, lower nondebt tax shields, more tangible assets, lower profitability, and are larger in size.

Intrinsic information asymmetry can confound the interpretation of the results if it is correlated with extrinsic information asymmetry across investors. I use abnormal returns around quarterly earnings announcements, $AbRet$, as the proxy for intrinsic information asymmetry. Higher abnormal returns indicate more unanticipated information in the earnings announcements and thus larger information gaps between firm managers and outside investors. $AbRet$ is the average of the absolute cumulative abnormal returns ($ACAR$) of the quarterly earnings announcements for the year. I compute absolute cumulative abnormal return around earnings announcement day 0 as $ACAR = |\Pi_{t=-1}^{+1}(1 + AR_t) - 1|$ where AR is abnormal return computed based on market model residuals estimated over the pre-announcement window (-200, -11).

I measure growth opportunities using market-to-book ratio, MTB, and research and development expenditure, $R\&D$. $R\&D$ is research and development expense (Item 46) divided by total assets.[19] Dividend payout, $Dividend$, is a dummy variable which equals 1 if common stock dividends (Item 21) is positive, and 0 otherwise. I use depreciation expenses to proxy for nondebt tax shields. $Depreciation$ is depreciation and amortization expense (Item 14) divided by total assets. Asset tangibility, PPE, is defined as net plant, property, and equipment (Item 8) divided by total assets. Profitability, $Profit$, is defined as operating income before interest, taxes, and depreciation (Item 13) divided by total assets.

Table 2 reports the regression results of equation (3) using book leverage and then market leverage. In both models (columns (1) and (2)), the coefficient on $GrowthPIN * FD$ is significantly positive, consistent with the hypothesis that the

[19] When firms do not separately report R&D expenses, the variable is missing in COMPUSTAT. About 70% of COMPUSTAT firms have reported missing R&D expenses. 56% of firm-year observations in my final sample have missing R&D expenses. To avoid serious sample attrition, I assume any firms that report total assets but not R&D expenses to have zero R&D expenses in that year. The results are very similar if I set the missing R&D expenses to the industry-year mean.

greater the increase in extrinsic information asymmetry, the greater the increase in leverage post-FD. Moving $GrowthPIN$ from the 25th to the 75th percentile raises the change in book leverage by 2.6 percentage points.[20] The average total assets in the sample is $12,529 million. Therefore moving $GrowthPIN$ from the 25th to the 75th percentile increases the change in debt by $326 million. I also find that consistent with pecking order theory, intrinsic information asymmetry between managers and investors tends to increase leverage (by 1.18 percentage points per standard deviation increase) and profitability tends to reduce leverage (by 8.03 percentage points per standard deviation increase).[21]

A stronger test is provided in columns (3) and (4), where I have added Fama and French industry dummies. These dummies control for unobserved industry heterogeneity that is constant over time and identify the regulatory impact by comparing changes in capital structure among firms within the same industry. Although FD may have different influences across industries and including the industry dummies eliminates this cross-industry variation, an industry fixed effects specification helps verify that the documented results are not completely driven by differences between industries. The addition of the industry dummies attenuates the coefficient on $GrowthPIN * FD$. However, it does not alter the main result; $GrowthPIN * FD$ remains significantly positive. The attenuation confirms that the regulatory effects vary among industries because some of the variation in leverage is explained by industry.

Overall, I find evidence consistent with the hypothesis that Regulation FD affects capital structure through its influences on the information environment. Specifically, firms experiencing larger increases in extrinsic information asymmetry in the equity market also experience larger increases in leverage post-FD. Because FD has a smaller impact on the debt market and cost of capital is increasing in the level of extrinsic

[20] Moving $GrowthPIN$ from the 25th to the 75th percentile increases book leverage by 0.9% in the pre-FD period and by 3.5% in the post-FD period. $2.6\% = 3.5\% - 0.9\%$. All control variables are set to their mean values.

[21] The calculation is based on the coefficients in column (2) of Table 2.

information asymmetry, my results suggest that managers make a trade-off to increase the use of debt when facing higher costs of equity.[22]

4.4 Alternative model specifications

4.4.1 Relax the assumption of linearity

One limitation of equation (3) is that it is looking at the linear effect of $Leverage$ and $GrowthPIN$. It assumes that a one-unit increase in $GrowthPIN$ has a constant effect on $Leverage$. To relax this assumption, I divide firms into three groups based on $GrowthPIN$ and modify equation (3) into:

$$\begin{aligned} Leverage_{i,t} &= \beta_1 + \beta_2 FD_t + \beta_3 Group2_i + \beta_4 Group3_i \\ &\quad +\beta_5 Group2_i * FD_t + \beta_6 Group3_i * FD_t \\ &\quad +\gamma Controls_{i,t-1} + \eta_{i,t} \end{aligned} \tag{4}$$

where $Group2$ ($Group3$) is a dummy variable, which equals 1 if the $GrowthPIN$ is in the three middle quintiles (the upper quintile).[23]

Equation (4) relaxes the assumption of linearity, but it also reduces potentially important heterogeneity in $GrowthPIN$. Nevertheless, since the exact functional

[22] I am aware of two alternative explanations for my findings. First, Duarte and Young (2007) show that the PIN component related to asymmetric information is not priced, while the PIN component related to illiquidity is priced. Ng (2008) finds that information quality lowers cost of equity capital through lowering liquidity risk. These findings imply that Regulation FD may affect liquidity risk through its influences on disclosure quality and that it is because of the lowered liquidity that firms experiencing greater increases in PIN now have higher leverage post-FD. Second, recent work by Lambert, Leuz, and Verrecchia (2008) shows that in models of perfect competition, a firm's cost of capital is related to investors' average information precision. Information asymmetry, defined as information precision across investors, has no effect on cost of capital. Based on their findings, my results can be driven by changes in average information precision, and not by changes in extrinsic information asymmetry. However, it is empirically challenging to separate these two effects because Regulation FD is likely to affect average precision and information asymmetry simultaneously.

[23] I choose to group quintile 2, 3, and 4 together because firms in these three middle quintiles have very small changes in PIN. Recall from Table 1 that the mean growth in PIN for these three quintiles are only -0.046 (quintile 2), -0.003 (quintile 3), and 0.049 (quintile 4). The results are very similar for a quintile specification in equation (4).

form between leverage and extrinsic information asymmetry is unknown, equation (4) serves as an alternative specification to verify that the results are not sensitive to the linear assumption. The hypothesis predicts firms experiencing larger increases in information asymmetry to have higher leverage after Regulation FD. Since equation (4) defines $Group1$ (i.e., firms in the first quintile of $GrowthPIN$) as the base group, I expect both β_5 and β_6 to be greater than zero and β_6 to be greater than β_5.

Columns (1) and (2) in Table 3 report the results of equation (4). Independent of how I measure leverage, I find positive coefficients and an increase in the magnitude of the coefficients on the interaction terms: $Group2 * FD$, $Group3 * FD$. Moreover, for both equation (3) and equation (4), the results are robust to the inclusion of a full set of interaction terms between the control variables and the FD dummy (not tabulated). These results confirm my earlier findings that the greater the increase in extrinsic information asymmetry in the equity market, the greater the increase in leverage post-FD.

4.4.2 Firm heterogeneity

In Table 2 the coefficient on $GrowthPIN$ is positive and significant in the market leverage specification (columns (2) and (4)). This indicates that firms experiencing greater increases in extrinsic information asymmetry have higher market leverage even before the adoption of Regulation FD. One potential concern is that the post-FD larger increases in market leverage for high $GrowthPIN$ firms are driven by unobserved firm characteristics unrelated to FD. For example, high $GrowthPIN$ firms tend to be smaller firms with low MV of equity (i.e., high market leverage). Since the post-FD period coincides with an economic slowdown, smaller firms may be more negatively affected by the low economic activity and experience larger decreases in MV of equity (and hence, larger increases in market leverage).

I sort firms into deciles based on $GrowthPIN$. Indeed, in the pre-FD period high

$GrowthPIN$ firms tend to have smaller MV of equity than low $GrowthPIN$ firms (e.g., firms in decile 10 have a mean MV of equity of 695 million, whereas firms in decile 1 have a mean of 7203 million). The smaller MV of equity explains the positive coefficient on $GrowthPIN$ for the market leverage specification in Table 2. However, in the post-FD period high $GrowthPIN$ firms have *larger* increases in MV of equity than low $GrowthPIN$ firms (e.g., firms in decile 10 have increased their MV of equity by 58%, whereas firms in decile 1 have increased theirs by only 11%). It is therefore unlikely that changes in MV of equity are an alternative explanation for my market leverage results.

To address the concern that other unobserved firm heterogeneity is correlated with $GrowthPIN$ and drives the results, I employ a change model:[24]

$$\Delta Leverage_i = \beta_1 + \beta_2 GrowthPIN_i + \gamma \Delta Controls_i + \Delta\eta_i \tag{5}$$

where $\Delta Leverage$ is the change in mean book leverage or market leverage from pre-FD to post-FD. $\Delta Controls$ is the change in mean control variables from pre-FD to post-FD. I expect $GrowthPIN$ to be positively associated with $\Delta Leverage$.

Equation (5) eliminates any time-constant, unobserved firm effects. By averaging the data before and after FD, it also ignores the time-series information and thus mitigates a potential serial correlation problem with leverage.[25] The downside of equation (5) is that it reduces the variation in the explanatory variables. While $Controls_{i,t}$ frequently has substantial variation in the cross section, $\Delta Controls_i$ may not have much variation and can therefore have large standard errors.

Columns (3) and (4) in Table 3 report the results of equation (5). Consistent with

[24] Note that I cannot simply use a firm fixed effects model because my variable of interest $GrowthPIN$ does not change over time.

[25] Because capital structure is highly stable (Leary and Roberts (2005); Lemmon et al. (2008)), leverage could be positively serially correlated. Serial correlation leads to understated standard errors. Bertrand, Duflo, and Mullainathan (2004) show that collapsing the time series information into a pre- and post-period successfully mitigates the serial correlation problem.

my primary results, the coefficient on $GrowthPIN$ is significantly positive for both change in book leverage and change in market leverage. Therefore, unobservable firm characteristics are unlikely to explain FD's differential effects on leverage.

4.4.3 Robustness checks and other issues

A recent paper by Mohanram and Rajgopal (2008) suggests that PIN is not priced risk. Their finding, however, does not distinguish between whether information risk is not priced or PIN is simply not a good proxy for extrinsic information asymmetry. In order to further validate my results, in Appendix B I examine the private information trading ($Private$) suggested by Llorente, Michaely, Saar, and Wang (2002) as an alternative proxy for extrinsic information asymmetry. My findings are robust to this alternative measure. Appendix B also shows that the findings are robust to alternative measures of intrinsic information asymmetry, different specifications of equation (2), and the exclusion of financial and utility firms.

I explore the possibility of using American Depository Receipts (ADRs) and non-U.S. companies with securities listed on the U.S. exchanges as a control sample to the adoption of Regulation FD. Although ADRs and foreign firms are legally exempt from FD, anecdotal evidence shows that foreign issuers may be following the practice of U.S. firms and voluntarily complying with the regulation.[26] These securities may not be a perfect control sample. I repeat the analysis on a sample of ADRs and foreign common stocks traded on the NYSE. I find evidence of cross-sectional variation in changes in extrinsic information asymmetry for these foreign firms (not reported, available upon request). The result is consistent with the anecdotal evidence that foreign issuers may voluntarily comply with FD and thus experience changes in information environments in the equity market. However, the change in extrinsic information

[26] For example, Citigroup's 2005 Depository Receipts Information Guide states that "many Non-U.S. companies with securities trading in the U.S. (including DR issuers) have voluntarily opted to comply with the requirements of Regulation FD."

asymmetry does not explain the concurrent change in capital structure. This finding is expected because foreign firms have more financing choices than U.S. firms. When facing higher cost of equity in the post-FD period, foreign firms can raise capital not only in the U.S. debt market, but also in their own home countries. Therefore, it is harder to detect a capital structure shift in the U.S. market for foreign firms.

Because the period surrounding the implementation of Regulation FD contains other events (e.g., the economic recession, the internet bust, and the decimalization of the stock exchanges), it is possible that these confounding events are driving the results. To address the concern, I rerun the tests using 1998, 1999, and 2001 as the hypothetical implementation years of Regulation FD. I find weaker results when using these hypothetical implementation years. For example, with 2001 as the implementation year (i.e., pre-FD period is from 1996-2000 and post-FD period is from 2002-2006), the coefficient on $GrowthPIN * FD$ is significant only for book leverage and is not significant for market leverage. When I use 1999 as the implementation year (i.e., pre-FD period is from 1994-1998 and post-FD period is from 2000-2004), the coefficients on $GrowthPIN * FD$ are smaller for both book leverage (decreases from 0.052 in Table 2 to 0.021) and market leverage (decreases from 0.040 in Table 2 to 0.033). When I use 1998 as the implementation year (i.e., pre-FD period is from 1993-1997 and post-FD period is from 1999-2003), the coefficient on $GrowthPIN * FD$ is significant only for book leverage and insignificant for market leverage. The fact that year 2000 gives the strongest result, while not conclusive proof that the effects are exclusively due to FD, provides strong evidence of Regulation FD being an important driving force behind the findings.

4.5 Decompose changes in capital structure

So far I have documented that firms experiencing greater increases in extrinsic information asymmetry increase their leverage more after Regulation FD. The increase in leverage may come from more debt issued, less equity issued, or lower retained earnings. To have a more complete picture of how the capital structure changes, I examine the components related to change in leverage: net equity issues ($EIssue$), newly retained earnings (ΔRE), and net debt issues ($DIssue$). I regress each of these three components on $GrowthPIN$ to determine through which components does leverage change. The model takes the form:

$$Component_i = \beta_1 + \beta_2 GrowthPIN_i + \gamma Control_i + \eta_i \tag{6}$$

where $Component$ is either $EIssue$, ΔRE, or $DIssue$.

Following the balance sheet measures in Baker and Wurgler (2002), I define net equity issues ($EIssue$) as the change in mean BV of equity minus the change in mean retained earnings (Item 36) from pre-FD to post-FD all divided by post-FD mean assets. ΔRE is the change in mean retained earnings from pre-FD to post-FD divided by post-FD mean assets. I define net debt issues ($DIssue$) as the residual change in mean assets from pre-FD to post-FD divided by post-FD mean assets. I measure the control variables using their pre-FD means.

Table 4 reports the regression results of equation (6). The results indicate that the effect of changes in extrinsic information asymmetry on changes in capital structure comes through new equity and new debt issues. Columns (1) and (2) show that $GrowthPIN$ is negatively related to net equity issues and positively related to net debt issues.[27] Firms experiencing greater increases in information risk after Regulation FD issue relatively less equity and more debt, and therefore have higher leverage. A one standard deviation increase in $GrowthPIN$ reduces net equity issues by 1.22 percentage points and raises net debt issues by 2.16 percentage points. Given that the average total assets in the post-FD period is $16,187 million, a one standard deviation

[27] Notice that the $DIssue$ model has 1 more observation than the $EIssue$ and the ΔRE models. This is because one sample firm does not have retained earnings data and therefore I cannot calculate $EIssue$ and ΔRE.

increase in $GrowthPIN$ leads to a decrease in net equity issues by \$197 million and an increase in net debt issues by \$350 million. Column (3) shows that $GrowthPIN$ is not related to newly retained earnings.

Because Regulation FD has the least impact on banks, I expect the positive association between net debt issues and $GrowthPIN$ to come from bank debt issues. I calculate the difference in the average amount of bonds and bank loans issued between the post-FD period and the pre-FD period deflated by the post-FD average assets for the three groups of firms defined in Section 4.2.[28] Consistent with the expectation, I find that firms in group 1 (i.e., low $GrowthPIN$ firms) increase the amount of bonds issued by 0.79% and the amount of bank loans by 0.76%, while firms in group 3 (i.e., high $GrowthPIN$ firms) increase their bond issues by 0.9% and their bank loans by 1.42% (not tabulated).

Overall Table 4 shows that fewer new equity issues and more new debt issues contribute to the higher leverage of firms with greater increases in extrinsic information asymmetry following the adoption of FD. Moreover, the higher new debt issues are more likely to come from new bank loans.

4.6 Changes in cost of debt

One alternative explanation for the documented results is that firms experiencing greater increases in information asymmetry in the equity market also experience greater decreases in cost of debt. The lower cost of debt makes debt a cheaper capital source and thus increases leverage. To investigate this explanation, I examine bonds issued and bank loans raised during the sample period and employ a regression model

[28] The bond data are from Mergent database and the bank loan data are from Dealscan.

similar to equation (3) with cost of debt as the dependent variable:

$$\begin{aligned} Spread_{i,t} &= \beta_1 + \beta_2 FD_t + \beta_3 GrowthPIN_i + \beta_4 GrowthPIN_i * FD_t \\ &\quad + \gamma Controls + \eta_{i,t} \end{aligned} \tag{7}$$

For bank loans, *Spread* is the number of basis points above LIBOR charged on the loan. For bonds, *Spread* is the number of basis points above the yield of Treasury bond with similar maturity and coupon rate.

Following the literature (Beatty et al. (2002); Datta et al. (1999)), I include a set of control variables related to debt pricing. The variables that are common to both public and private debt pricing are: the credit rating ($S\&PRating$), leverage ($MktLev$) and size ($Size$) of the borrower, the maturity ($Maturity$) and size ($DebtSize$) of the debt, the credit spread ($CreditSpread$), and the yield spread ($YieldSpread$). The variables that are specific to public debt pricing are: whether or not the issuer can redeem the bond before maturity ($Redeem$) and the age of the issuer (Age). The variables that are specific to private debt pricing are: whether or not the loan is a revolving loan ($Revolve$), and whether or not the purpose of the loan is for a takeover ($Takeover$).[29]

Table 5 reports the results of equation (7). In column (1) I combine public and private debt and include control variables common to both types of debt. Since public debt and private debt may have different attributes, in columns (2) and (3) I estimate

[29] I follow the procedure in Barth, Hodder, and Stubben (2008) to estimate the firm's S&P bond rating. $S\&PRating$ ranges from 1 for AAA to 22 for D; $MktLev$ is market leverage (using book leverage yields similar results); $Maturity$ is the number of years between the start and the end date of the debt; $DebtSize$ is the amount of the debt raised divided by the total assets of the borrower; $CreditSpread$ is the difference between the Baa corporate bond and 30-year yield on the U.S. Treasury bonds; $YieldSpread$ is the difference in the 10-year and 3-month yield on the U.S. Treasury bonds; $Redeem$ is a dummy variable, which equals 1 if the issuer can redeem the bond before maturity, and 0 otherwise; Age is the number of days the firm appears on CRSP when the bond is issued; $Revolve$ is a dummy variable, which equals 1 if the loan is a revolving loan, and 0 otherwise; $Takeover$ is a dummy variable, which equals 1 if the purpose of the loan is for takeover, and 0 otherwise. $S\&PRating$, $MktLev$, and $Size$ are measured at the fiscal year end preceding the debt contract.

the model separately for each type of debt. The results offer no support for the cost of debt explanation. The coefficient on $GrowthPIN * FD$ is insignificant under all three specifications. We cannot infer that cost of debt changes around Regulation FD any differently for firms that experience large increases in extrinsic information asymmetry in the equity market relative to those that do not. In contrast, the results support the assumption that Regulation FD has virtually no impact on the debt market information environment. Firms faced with higher costs of equity may lower their cost of capital by turning to the debt market where they face fewer constraints communicating with capital providers.

5 Conclusion

This paper examines the change in capital structure as an economic consequence of Regulation FD. Implemented in October 2000, Regulation FD was intended to reduce information asymmetry among investors by preventing selective disclosure by firms to analysts and institutional investors. However, to the extent that public disclosure is not a perfect substitute for private disclosure, some firms may overall disclose less information after the regulation. Less disclosure increases extrinsic information asymmetry among investors which leads to higher costs of capital. Because FD has a smaller impact on the information environment of the debt market, firms faced with higher information asymmetry in the equity market may turn to the debt market to raise capital.

Using a large sample of NYSE firms over the period 1995-2005, I find substantial cross-sectional variation in changes in extrinsic information asymmetry in the post-FD equity market. I further find that firms experiencing greater increases in extrinsic information asymmetry in the equity market become more highly levered after Regulation FD. The increases in leverage are driven by more debt issuances and fewer equity issuances. This finding is robust to different model specifications and cannot be explained by changes in cost of debt. Given that cost of capital is increasing in the level of extrinsic information asymmetry, my results are consistent with the view that managers adjust the target leverage ratios to rely more on debt when facing increased costs of equity. The paper thus provides empirical evidence of the effect of FD on corporate financing choices.

My study is not without limitations. Because capital structure is sticky, I need to rely on a long sample period to capture its change. Although I have controlled for other factors that might have affected the information environment to isolate the effects of Regulation FD, I cannot fully eliminate the possibility that other confounding events are affecting the results and might add noise to the analysis. Moreover, I rely on the probability of information-based trading developed by Easley, Kiefer, O'Hara, and Paperman (1996) as the proxy for extrinsic information asymmetry. As with any empirical proxy, mine is subject to measurement error and certain limitations (e.g., see Duarte and Young (2007)).

Appendix

A Estimation of PIN

The likelihood function of order arrivals is a weighted average of the likelihood on a no, bad, and good news day. The weights are the probabilities of each type of day occurring: $1-\alpha$ for a no news day, $\alpha\delta$ for a bad news day, and $\alpha(1-\delta)$ for a good news day. The likelihood function for a given stock on a trading day t is:

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

where B and S are the total buys and sells per day, and $\theta = (\alpha, \delta, \mu, \varepsilon_b, \varepsilon_s)$ is the parameter vector. Assuming independence across trading days gives the likelihood function across T days:

$$L(\theta|M) = \prod_{t=1}^{T} L(\theta|B_t, S_t) \tag{8}$$

where (B_t, S_t) is the buy and sell data for day $t = 1, ..., T$ and $M = (B_1, S_1), ...(B_T, S_T)$ is the data set.

I estimate the parameters of the model (i.e., α, δ, μ, ε_b, ε_s) by maximizing the likelihood function (8) given daily buys and sells data. To obtain daily buys and sells, I use transactions data from Trade And Quote (TAQ) database. All trades and quotes are first run through a series of error filters described in Hvidkjaer (2006).[30] I then

[30] Trades with the following condition codes are excluded: A, C, D, G, L, N, O, R, X, Z, 8, 9, so are quotes with the condition codes: 4, 5, 7–9, 11, 13–17, 19, 20. Further, trades with a correction code greater than 1 are excluded. Only NYSE trades and quotes are used. The filer to exclude possible errors is following: (1) Quotes are deleted if the ask price is not greater than the bid price, or the bid–ask spread is greater than 75% of the midquote, or the ask (bid) price is more than double or less than half of the previous ask (bid) price; (2) Only trades within the opening hours of the exchange are included; and (3) Trades at prices of more than double or less than half of the previous trade are excluded.

classify trades into buys and sells according to Lee and Ready (1991) algorithm.[31] I maximize (8) for every firm in the sample over an annual period. After all parameters are estimated, I compute firm-year PINs via equation (1).

Table 6 presents summary statistics on the parameters of the PIN model across all firm-years. The median firm-year has a PIN of 0.135. The small standard errors of the estimates indicate that the model is relatively precisely estimated. In general, my parameter estimates are consistent with the ones in Easley, Hvidkjaer, and O'Hara (2002), except that my arrival rates, μ, ε_b, ε_s, are larger. The larger arrival rates are because I use a more recent sample period which contains larger trading volume.[32]

B Robustness tests for changes in capital structure

Table 7 presents four robustness tests for changes in capital structure. To save space, I report the results for market leverage. The results for book leverage are qualitatively similar. The first robustness test (Amount of private information trading) uses the private information trading ($Private$) measure of Llorente, Michaely, Saar, and Wang (2002) as an alternative measure of extrinsic information asymmetry. The measure is based on the argument that hedging trades generate negative autocorrelated returns and speculative trades generate positive autocorrelated returns.[33]

[31] Trades at prices above the bid and ask midpoint are called buys (i.e., buyer-initiated trades), and those below the midpoint are called sells (i.e., seller-initiated trades). Trades occur at the midpoint are classified using the "tick test", under which trades executed at a price higher than that of the previous trade are called buys, and those executed at a lower price are called sells. If the trade is executed at the midpoint and also at the same price as the previous trade, then its price is compared to the next most recent trade. The comparison continues until the trade is classified. To adjust for differences in reporting times between quotes and trades, trades used to matched with quotes are assumed to have occurred five seconds before being reported. Opening trades not preceded by a quote are eliminated.

[32] Easley, Hvidkjaer, and O'Hara (2002) use a sample period from 1983 to 1998, while I use a sample period from 1995 to 2005 (excluding the regulatory change year of 2000).

[33] Hedging trades are defined as trades initiated by investors to rebalance their portfolios for risk sharing, while speculative trades are initiated by investors to speculate on their private information.

$Private$ is $\widehat{c}_2$ from the firm-year regression: $R_{i,t+1} = c_0 + c_1 R_{i,t} + c_2 V_{i,t} * R_{i,t} + \varepsilon_{i,t+1}$, where R is daily stock return and V is the log of daily turnover detrended by subtracting a 200 trading day moving average. Stocks with positive $\widehat{c}_2$ are associated with speculative trade (i.e., high amount of private information trading), while stocks with negative $\widehat{c}_2$ are associated with hedging trade (i.e., low amount of private information trading). To measure changes in $Private$, I re-estimate equation (2) with $Private$ as the dependant variable. Since $Private$ can be negative, I use $\frac{\widehat{\beta}_2}{|\widehat{\beta}_1|}$ to measure the impact of FD on the amount of private information trading. I then apply an ordinal transformation to reduce potential measurement error and denote $GrowthPrivate$ as the transformed variable.

The second robustness test (Idiosyncratic volatility) uses idiosyncratic volatility (Ψ) as an alternative proxy for intrinsic information asymmetry between the firm and its shareholders. Higher idiosyncratic volatility indicates a larger amount of firm-specific information that is not shared by the market and thus higher information asymmetry between the firm and its shareholders (Krishnaswami et al. (1999); Krishnaswami and Subramaniam (1999)). I measure idiosyncratic volatility as $\Psi = ln(\frac{1-R^2}{R^2})$, where R^2 is estimated from a firm-year regression of daily returns on contemporary market returns and lagged market returns.[34]

The third robustness test (Include $Coverage * FD$ in Equation (2)) includes an interaction term, $Coverage * FD$, in equation (2) to account for potential changes in analyst following after Regulation FD (Mohanram and Sunder (2006); Gomes et al. (2007)). The last robustness test (Exclude financial and utility firms) excludes firms in the financial sector (6000s SICs) and the utility sector (4900-4999 SICs) because their capital structures are likely to be different from other firms in the sample. These robustness tests confirm earlier results.

[34] I include lagged market returns to avoid the problem of thin trading. For stocks with low liquidity, stock prices may not incorporate new information immediately, but with a lag. I also estimate Ψ by regressing daily returns on contemporary market returns and both lead and lag market returns. The results are very similar.

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Figure 1
Tree Diagram of the Trading Process

This figure presents the structure of the trading process in the PIN model. α is the probability of an information event; δ is the probability of bad news conditional on an information event has happened; μ is the arrival rate of informed trades; ε_b is the arrival rate of uninformed buys; ε_s is the arrival rate of uninformed sells. Nodes to the left of the dotted line occur once per day.

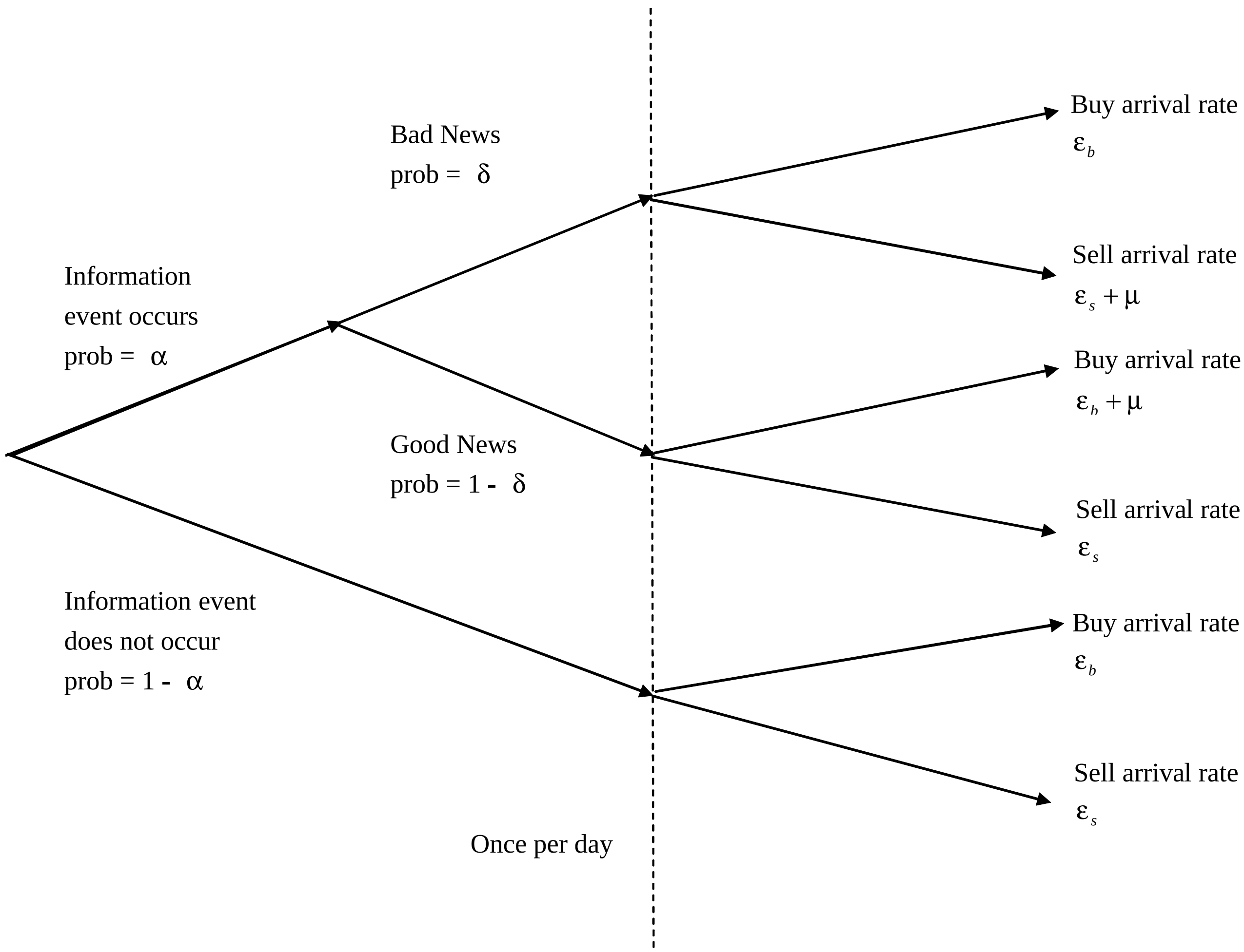

Figure 1: Tree Diagram of the Trading Process

Table 1
Descriptive Statistics

Panel A presents the estimated impact of Regulation FD on extrinsic information asymmetry by quintiles of firms formed based on $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$.

$$PIN_{i,t} = \beta_{1,i} + \beta_{2,i}FD_t + \gamma_1 Size_{i,t} + \gamma_2 InstOwn_{i,t} + \gamma_3 Coverage_{i,t} + \gamma_4 MTB_{i,t} + \eta_{i,t}$$

PIN is the probability of information-based trading; $FD = 1$ if the observation is from the post-FD period, and 0 otherwise; $Size$ is the log of net sales; $InstOwn$ is the proportion of the firm's shares held by institutions; $Coverage$ is the number of analysts making annual EPS forecasts; MTB is MV of assets divided by BV of assets. Panel B presents the means of the capital structure variables and the variables in equation (2) pre- and post-FD. Group 1 includes firms in the first quintile of $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$; Group 2 includes firms in the three middle quintiles of $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$; Group 3 includes firms in the upper quintile of $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$; $BookLev$ is debt to BV of assets; $MktLev$ is debt to MV of asset; $Sales$ is net sales measured in millions. Panel C presents descriptive information on selected firm characteristics existing prior to FD and changes in analyst behavior. The pre-FD firm characteristics are measured at the means in the pre-FD period, and the change in analyst behavior is the difference in the means pre- and post-FD. *High-tech industry* $= 1$ if the firm belongs to high-tech industries, and 0 otherwise; *Rev volatility* is the standard deviation of quarterly revenue, measured over three years including and preceding the current year; *Litigation cost* $= 1$ if the firm is in a high litigation risk industry and also suffers an earnings decrease for at least 4 quarters in the pre-FD period; *Rating availability* $= 1$ if the firm has a S&P bond rating, and 0 otherwise; ROE is operating income before depreciation divided by BV of equity; ROA is operating income before depreciation divided by total assets; $Herfindahl\ index$ is the sum of the squares of the market shares of the firms in the industry (2-digit SIC), where market share is defined as firm sales divided by total industry sales; $Forecast\ dispersion$ is the standard deviation of individual analysts' most recent earnings forecast in the 90 days prior to the earnings announcement; $Forecast\ error$ is the absolute value of the difference between the actual earnings per share and the median of individual analysts' most recent earnings forecast in the 90 days prior to the earnings announcement, scaled by the stock price at the fiscal quarter end. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively (two-tailed test).

Table 1: *continued*

Panel A: The impact of Regulation FD on extrinsic information asymmetry

	Overall	Quintile				
		1	2	3	4	5
$\hat{\beta}_2/\hat{\beta}_1$	0.041	-0.231	-0.046	-0.003	0.049	0.434

Panel B: Differences between pre-FD and post-FD

	Pre-FD							
	Obs	PIN	Book Lev	Mkt Lev	Sales	MTB	Coverage	InstOwn
Group 1	831	0.165	0.540	0.377	4802	1.892	12.094	0.607
Group 2	2614	0.147	0.566	0.397	4757	1.849	11.887	0.610
Group 3	757	0.153	0.543	0.437	1402	1.586	6.777	0.484
	Post-FD							
	Obs	PIN	Book Lev	Mkt Lev	Sales	MTB	Coverage	InstOwn
Group 1	929	0.107***	0.524	0.393	6524**	1.676***	10.395***	0.685***
Group 2	2809	0.122***	0.568	0.424***	7179***	1.662***	9.807***	0.704***
Group 3	847	0.186***	0.578***	0.509***	2716***	1.359***	5.712***	0.595***

Panel C: Pre-FD firm characteristics and changes in analyst behavior

	Group 1	Group3	Test of difference (*p* -value)
Pre-FD firm characteristics			
High-tech industry	0.134	0.034	< 0.0001
Rev volatility	180.397	61.753	< 0.0001
Litigation cost	0.170	0.104	< 0.0001
Rating availability	0.605	0.432	< 0.0001
ROE	0.372	0.329	0.008
ROA	0.149	0.135	< 0.0001
Herfindahl index	0.049	0.052	0.176
InstOwn	0.607	0.484	< 0.0001
Sales	4802	1402	< 0.0001
Changes in analyst behavior			
ΔAnalyst following	-1.139	-1.352	0.615
ΔForecast dispersion	-0.001	0.022	0.008
ΔForecast error x 1000	-0.194	3.496	0.007

Table 2
Changes in Capital Structure

This table presents regression analysis of changes in capital structure associated with Regulation FD.

$$\begin{aligned} Leverage_{i,t} &= \beta_1 + \beta_2 FD_t + \beta_3 GrowthPIN_i + \beta_4 GrowthPIN_i * FD_t \\ &\quad + \gamma_1 AbRet_{i,t-1} + \gamma_2 MTB_{i,t-1} + \gamma_3 R\&D_{t-1} + \gamma_4 Dividend_{i,t-1} \\ &\quad + \gamma_5 Depreciation_{i,t-1} + \gamma_6 PPE_{i,t-1} + \gamma_7 Profit_{i,t-1} + \gamma_8 Size_{i,t-1} + \eta_{i,t} \end{aligned}$$

$Leverage$ is either book leverage, defined as debt to BV of assets, or market leverage, defined as debt to MV of assets; $FD = 1$ if the observation is from the post-FD period, and 0 otherwise; $GrowthPIN$ is $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$ from equation (2) after the ordinal transformation; $AbRet$ is abnormal returns around quarterly earnings announcements; MTB is MV of assets divided by BV of assets; $R\&D$ is research and development expense divided by total assets; $Dividend = 1$ if the firm distributes common stock dividends in the year, and 0 otherwise; $Depreciation$ is depreciation and amortization expense divided by total assets; PPE is net property, plant, and equipment divided by total assets; $Profit$ is operating income before interest, taxes, and depreciation divided by total assets; $Size$ is the log of net sales. t-statistics are in parentheses and are calculated based on standard errors clustered by firm and by year. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively (two-tailed test).

Table 2: *continued*

	(1) Book Leverage	(2) Market Leverage	(3) Book Leverage	(4) Market Leverage
Intercept	0.436	0.494	0.465	0.410
	(12.32)***	(12.91)***	(7.82)***	(7.70)***
FD	-0.060	-0.036	-0.055	-0.031
	(-4.45)***	(-1.88)*	(-5.47)***	(-2.07)*
GrowthPIN	0.018	0.048	0.022	0.049
	(1.17)	(2.86)***	(1.64)	(3.09)**
GrowthPIN*FD	0.052	0.040	0.043	0.035
	(4.55)***	(2.81)***	(4.05)***	(1.99)*
Control Variables				
$AbRet_{t-1}$	0.053	0.367	0.355	0.648
	(0.51)	(3.79)***	(5.08)***	(9.88)***
MTB_{t-1}	-0.016	-0.067	-0.015	-0.062
	(-3.69)***	(-8.94)***	(-3.64)***	(-7.99)***
$R\&D_{t-1}$	-0.640	-0.906	-0.175	-0.387
	(-3.92)***	(-5.09)***	(-1.15)	(-2.48)**
$Dividend_{t-1}$	0.018	0.006	-0.011	-0.022
	(1.68)*	(0.75)	(-1.18)	(-3.02)**
$Depreciation_{t-1}$	0.097	-0.441	0.642	0.332
	(0.46)	(-1.57)	(3.80)***	(1.55)
PPE_{t-1}	-0.104	-0.012	-0.050	0.004
	(-4.61)***	(-0.51)	(-1.81)*	(0.14)
$Profit_{t-1}$	-0.712	-0.957	-0.569	-0.789
	(-7.87)***	(-9.89)***	(-8.71)***	(-9.79)***
$Size_{t-1}$	0.039	0.024	0.045	0.029
	(11.65)***	(6.13)***	(14.66)***	(8.96)***
Industry Fixed Effects	No	No	Yes	Yes
Observations	8787	8782	8787	8782
Adj R^2	0.27	0.47	0.42	0.59

Table 3
Changes in Capital Structure: Alternative Specifications

This table uses two alternative specifications to examine the change in capital structure associated with Regulation FD. The first specification relaxes the assumption of linearity:

$$\begin{aligned} Leverage_{i,t} &= \beta_1 + \beta_2 FD_t + \beta_3 Group2_i + \beta_4 Group3_i \\ &+\beta_5 Group2_i * FD_t + \beta_6 Group3_i * FD_t \\ &+\gamma_1 AbRet_{i,t-1} + \gamma_2 MTB_{i,t-1} + \gamma_3 R\&D_{i,t-1} + \gamma_4 Dividend_{i,t-1} \\ &+\gamma_5 Depreciation_{i,t-1} + \gamma_6 PPE_{i,t-1} + \gamma_7 Profit_{i,t-1} + \gamma_8 Size_{i,t-1} + \eta_{i,t} \end{aligned}$$

The second specification addresses the issue of unobserved firm heterogeneity:

$$\begin{aligned} \Delta Leverage_i &= \beta_1 + \beta_2 GrowthPIN_i \\ &+\gamma_1 \Delta AbRet_i + \gamma_2 \Delta MTB_i + \gamma_3 \Delta R\&D_i + \gamma_4 \Delta Dividend_i \\ &+\gamma_5 \Delta Depreciation_i + \gamma_6 \Delta PPE_i + \gamma_7 \Delta Profit_i + \gamma_8 \Delta Size_i + \Delta\eta_i \end{aligned}$$

$Leverage$ is either book leverage, defined as debt to BV of assets, or market leverage, defined as debt to MV of assets; $FD = 1$ if the observation is from the post-FD period, and 0 otherwise; $GrowthPIN$ is $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$ from equation (2) after the ordinal transformation; $Group2$ and $Group3 = 1$ if the firm belongs to the appropriate group of $GrowthPIN$, and 0 otherwise; $AbRet$ is abnormal returns around quarterly earnings announcements; MTB is MV of assets divided by BV of assets; $R\&D$ is research and development expense divided by total assets; $Dividend = 1$ if the firm distributes common stock dividends in the year, and 0 otherwise; $Depreciation$ is depreciation and amortization expense divided by total assets; PPE is net property, plant, and equipment divided by total assets; $Profit$ is operating income before interest, taxes, and depreciation divided by total assets; $Size$ is the log of net sales. The second specification takes the difference in the mean values of the variables between the post-FD period and the pre-FD period. t-statistics are in parentheses and are calculated based on standard errors clustered by firm and by year. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively (two-tailed test).

Table 3: *continued*

	Relax Assumption of Linearity			Change Model	
	(1)	(2)		(3)	(4)
	Book Leverage	Market Leverage		Δ Book Leverage	Δ Market Leverage
Intercept	0.439	0.501	Intercept	-0.032	-0.025
	(12.85)***	(12.98)***		(-3.30)***	(-2.82)***
FD	-0.057	-0.032	GrowthPIN	0.058	0.060
	(-4.23)***	(-1.36)		(3.96)***	(4.26)***
Group2	0.013	0.011			
	(1.15)	(1.03)			
Group3	0.019	0.045			
	(1.35)	(2.95)***			
Group2*FD	0.024	0.016			
	(3.78)***	(2.59)***			
Group3*FD	0.042	0.034			
	(4.03)***	(2.79)***			
Control Variables					
$AbRet_{t-1}$	0.054	0.358	ΔAbRet	0.649	1.086
	(0.52)	(3.74)***		(4.42)***	(6.46)***
MTB_{t-1}	-0.016	-0.067	ΔMTB	0.003	-0.049
	(-3.74)***	(-9.09)***		(0.49)	(-4.22)***
$R\&D_{t-1}$	-0.629	-0.908	ΔR&D	0.291	0.019
	(-3.82)***	(-5.03)***		(0.84)	(0.04)
$Dividend_{t-1}$	0.017	0.005	ΔDividend	-0.042	-0.055
	(1.60)	(0.70)		(-2.57)**	(-3.09)***
$Depreciation_{t-1}$	0.091	-0.445	ΔDepreciation	0.641	0.977
	(0.44)	(-1.59)		(1.94)*	(2.58)**
PPE_{t-1}	-0.102	-0.011	ΔPPE	-0.078	-0.089
	(-4.54)***	(-0.47)		(-1.36)	(-1.50)
$Profit_{t-1}$	-0.715	-0.949	ΔProfit	-0.409	-0.496
	(-7.92)***	(-9.89)***		(-3.34)***	(-3.41)***
$Size_{t-1}$	0.039	0.024	ΔSize	0.009	0.020
	(11.53)***	(6.14)***		(0.90)	(2.12)**
Observations	8787	8782		1039	1039
Adj R^2	0.27	0.47		0.14	0.35

Table 4
Decompose Changes in Capital Structure

This table examines components related to changes in capital structure

$$\begin{aligned} Component_i &= \beta_1 + \beta_2 GrowthPIN_i \\ &\quad + \gamma_1 AbRet_i + \gamma_2 MTB_i + \gamma_3 R\&D_i + \gamma_4 Dividend_i \\ &\quad + \gamma_5 Depreciation_i + \gamma_6 PPE_i + \gamma_7 Profit_i + \gamma_8 Size_i + \eta_i \end{aligned}$$

$Component$ is one of the 3 components related to change in leverage: net equity issues ($EIssue$), net debt issues ($DIssue$), and newly retained earnings (ΔRE); $GrowthPIN$ is $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$ from equation (2) after the ordinal transformation; $AbRet$ is abnormal returns around quarterly earnings announcements; MTB is MV of assets divided by BV of assets; $R\&D$ is research and development expense divided by total assets; $Dividend = 1$ if the firm distributes common stock dividends in the year, and 0 otherwise; $Depreciation$ is depreciation and amortization expense divided by total assets; PPE is net property, plant, and equipment divided by total assets; $Profit$ is operating income before interest, taxes, and depreciation divided by total assets; $Size$ is the log of net sales. All the control variables are measured at their pre-FD means. t-statistics are in parentheses and are calculated based on White heteroscedastic consistent standard errors. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively (two-tailed test).

Table 4: *continued*

	(1)	(2)	(3)
	EIssue	DIssue	Δ RE
Intercept	0.222	0.200	0.016
	(5.58)***	(4.17)***	(0.32)
GrowthPIN	-0.042	0.075	-0.038
	(-2.03)**	(2.97)***	(-1.52)
Control Variables			
AbRet	0.066	-1.077	0.004
	(0.24)	(-2.66)***	(0.01)
MTB	0.018	0.028	0.043
	(1.68)*	(3.10)***	(3.82)***
R&D	0.980	-0.552	-1.501
	(2.80)***	(-2.64)***	(-2.23)**
Dividend	-0.038	0.019	0.014
	(-2.87)***	(1.01)	(0.71)
Depreciation	1.095	-0.669	-0.930
	(3.44)***	(-1.89)*	(-2.22)**
PPE	0.039	-0.003	0.000
	(1.53)	(-0.10)	(0.02)
Profit	-0.723	-0.229	0.685
	(-4.85)***	(-1.54)	(3.03)***
Size	-0.017	0.002	-0.007
	(-4.64)***	(0.48)	(-1.75)*
Observations	1038	1039	1038
Adj R^2	0.13	0.05	0.15

Table 5
Changes in Cost of Debt

This table examines changes in cost of debt around Regulation FD.

$$\begin{aligned} Spread_{i,t} &= \beta_1 + \beta_2 FD_t + \beta_3 GrowthPIN_i + \beta_4 GrowthPIN_i * FD_t \\ &\quad + \gamma Controls + \eta_{i,t} \end{aligned}$$

For bank loans, $Spread$ is the number of basis points above LIBOR charged on the loan and for public bonds, it is the number of basis points above the yield of Treasury bond with similar maturity and coupon rate; $FD = 1$ if the observation is from the post-FD period, and 0 otherwise; $GrowthPIN$ is $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$ from equation (2) after the ordinal transformation; $S\&PRating$ is the predicted S&P rating following the procedure in Barth, Hodder, and Stubben (2008) and ranges from 1 for AAA to 22 for D; $MktLev$ is debt to MV of assets; $Size$ is the log of net sales; $Maturity$ is the number of years between the start and the end date of the debt; $DebtSize$ is the amount of the debt raised divided by the total assets of the borrower; $CreditSpread$ is the difference between the Baa corporate bond and 30-year yield on the U.S. Treasury bonds; $YieldSpread$ is the difference in the 10-year and 3-month yield on the U.S. Treasury bonds; $Redeem$ =1 if the issuer can redeem the bond before maturity, and 0 otherwise; Age is the number of days the firm appears on CRSP when the bond is issued; $Revolve$ =1 if the loan is a revolving loan, and 0 otherwise; $Takeover$ =1 if the purpose of the loan is for takeover, and 0 otherwise. $S\&PRating$, $MktLev$, and $Size$ are measured at the fiscal year end preceding the debt contract. t-statistics are in parentheses and are calculated based on standard errors clustered by firm and by year. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively (two-tailed test).

Table 5: *continued*

	(1) Public & Private D	(2) Public D	(3) Private D
Intercept	-91.782	-177.891	8.292
	(-2.61)***	(-3.15)***	(0.22)
FD	13.643	28.569	9.581
	(1.29)	(1.43)	(0.99)
GrowthPIN	7.421	22.163	5.244
	(0.61)	(1.44)	(0.57)
GrowthPIN*FD	7.850	-32.645	14.485
	(0.57)	(-1.29)	(0.96)
Control variables			
S&PRating	13.537	16.747	10.812
	(7.99)***	(8.47)***	(7.28)***
MktLev	163.633	151.277	183.059
	(7.21)***	(7.55)***	(5.77)***
Size	-12.150	-10.689	-18.881
	(-4.69)***	(-2.04)**	(-6.74)***
Maturity	2.426	0.745	8.432
	(3.93)***	(3.38)***	(4.43)***
DebtSize	-22.156	178.010	-31.644
	(-1.79)*	(3.39)***	(-2.57)**
CreditSpread	57.754	91.538	28.670
	(7.15)***	(8.33)***	(3.18)***
YieldSpread	1.625	-3.163	6.983
	(0.45)	(-0.67)	(3.14)***
Redeem		34.632	
		(5.88)***	
Age		0.393	
		(2.43)**	
Revolve			-36.504
			(-10.39)***
Takeover			25.952
			(4.27)***
Observations	5745	2261	3484
Adj R^2	0.41	0.57	0.46

Table 6
Descriptive Statistics on the Estimated PIN Parameters

This table presents the means, medians, and the standard deviations of the estimated PIN parameters, and the median of parameter standard errors. Standard errors are calculated using the delta method. α is the probability of an information event; δ is the probability of bad news conditional on an information event has happened; μ is the arrival rate of informed trades; ε_b is the arrival rate of uninformed buys; ε_s is the arrival rate of uninformed sells.

Variable	Mean	Median	Std. Dev.	Median Std. Err.
α	0.325	0.341	0.127	0.032
δ	0.303	0.293	0.189	0.052
μ	137.310	77.966	148.408	1.823
ε_b	240.330	78.555	378.515	0.832
ε_s	220.423	75.785	345.703	0.694
PIN	0.141	0.135	0.065	0.011

Table 6: Parameter Summary Statistics

Table 7
Changes in Capital Structure: Robustness Tests

This table presents four robustness tests for changes in capital structure associated with Regulation FD. The regressions use equation (3) as the model.

$$\begin{aligned} Leverage_{i,t} &= \beta_1 + \beta_2 FD_t + \beta_3 GrowthPIN_i + \beta_4 GrowthPIN_i * FD_t \\ &\quad + \gamma_1 AbRet_{i,t-1} + \gamma_2 MTB_{i,t-1} + \gamma_3 R\&D_{t-1} + \gamma_4 Dividend_{i,t-1} \\ &\quad + \gamma_5 Depreciation_{i,t-1} + \gamma_6 PPE_{i,t-1} + \gamma_7 Profit_{i,t-1} + \gamma_8 Size_{i,t-1} + \eta_{i,t} \end{aligned}$$

$Leverage$ is market leverage, defined as debt to MV of assets; $FD = 1$ if the observation is from the post-FD period, and 0 otherwise; $GrowthPIN$ is $\frac{\widehat{\beta}_2}{\widehat{\beta}_1}$ from equation (2) after the ordinal transformation; $AbRet$ is abnormal returns around quarterly earnings announcements; MTB is MV of assets divided by BV of assets; $R\&D$ is research and development expense divided by total assets; $Dividend = 1$ if the firm distributes common stock dividends in the year, and 0 otherwise; $Depreciation$ is depreciation and amortization expense divided by total assets; PPE is net property, plant, and equipment divided by total assets; $Profit$ is operating income before interest, taxes, and depreciation divided by total assets; $Size$ is the log of net sales. The first robustness test uses the amount of private information trading constructed based on Llorente, Michaely, Saar, and Wang (2002) as the proxy for extrinsic information asymmetry. The second robustness test uses idiosyncratic volatility, Ψ, as the proxy for intrinsic information asymmetry between managers and investors. The third robustness test adds an interaction term, $Coverage * FD$, in equation (2). The fourth robustness test excludes firms in financial and utility industries. t-statistics are in parentheses and are calculated based on standard errors clustered by firm and by year. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively (two-tailed test).

Table 7: *continued*

	(1) Amount of private information trading	(2) Idiosyncratic volatility	(3) Include *Coverage*FD* in Equation (2)	(4) Exclude financial and utility firms
Intercept	0.569	0.464	0.532	0.331
	(20.48)***	(14.69)***	(14.85)***	(11.00)***
FD	-0.035	-0.027	-0.030	-0.034
	(-4.42)***	(-3.28)***	(-1.55)	(-4.06)***
GrowthPrivate	-0.030			
	(-2.05)**			
GrowthPrivate*FD	0.034			
	(2.44)**			
GorwthPIN		0.045	0.011	0.075
		(2.76)***	(0.78)	(4.33)***
GrowthPIN*FD		0.035	0.029	0.031
		(2.36)**	(2.55)**	(1.92)*
Control variables				
Ψ_{t-1}		0.014		
		(5.92)***		
$AbRet_{t-1}$	0.274		0.371	0.624
	(2.98)***		(3.71)***	(6.76)***
MTB_{t-1}	-0.069	-0.063	-0.068	-0.067
	(-11.87)***	(-11.51)***	(-8.71)***	(-12.17)***
$R\&D_{t-1}$	-1.026	-0.926	-0.946	-0.579
	(-7.06)***	(-7.34)***	(-5.09)***	(-5.16)***
$Dividend_{t-1}$	0.009	0.004	0.004	-0.023
	(1.13)	(0.50)	(0.53)	(-2.72)***
$Depreciation_{t-1}$	-0.480	-0.387	-0.495	0.092
	(-1.64)	(-1.34)	(-1.76)*	(0.39)
PPE_{t-1}	-0.024	-0.024	-0.014	0.073
	(-1.06)	(-1.09)	(-0.57)	(2.92)***
$Profit_{t-1}$	-0.947	-1.000	-0.951	-0.636
	(-9.75)***	(-9.82)***	(-9.75)***	(-6.95)***
$Size_{t-1}$	0.021	0.027	0.022	0.028
	(6.89)***	(8.41)***	(5.78)***	(8.70)***
Observations	9301	8790	8782	6814
Adj R^2	0.47	0.48	0.46	0.43