Capital Market Consequences of Decimalization and Overlapping Regulations

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Current draft: March 2017

ABSTRACT: Several recent policy initiatives identify Decimalization as adversely impacting capital formation by affecting small firms' information environments because it reduced the incentives of analysts to cover these firms. Yet, we argue that these initiatives do not consider the effects of two regulations that overlapped with the implementation of decimalization: Regulation Fair Disclosure (Reg FD) and regulations related to the Global Analyst Research Settlement (GARS). We exploit non-synchronicities in the implementation of the three regulations to examine their impact on informational efficiency and trading costs of U.S. stocks across size partitions. We find that analyst coverage actually increases and analyst forecasts are more informative following Decimalization. Our tests of informational efficiency and trading costs around earnings announcements also fail to show any adverse impact of Decimalization. Our results suggest that the regulatory concern surrounding Decimalization may be misplaced. In addition, our findings suggest that small firms' decline in informational efficiency and increase in trading costs may be attributable to Reg FD and GARS rather than Decimalization.

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1. INTRODUCTION

This study investigates whether and how several U.S. market reforms impacted the information environments and trading costs of U.S. stocks. In the early 2000s, American markets underwent significant regulatory reform. The objectives underlying the regulations varied significantly, ranging from granting investors equal access to price relevant information from firms' management (Regulation Fair Disclosure, "Reg FD"); reducing the costs of trading (Decimalization); and restricting interactions between banks' analyst research and investment banking divisions (Global Analyst Report Settlement, "GARS"). Among these regulations, Decimalization, in particular, has come under increased scrutiny in recent years. The main concern centers on whether Decimalization restricted small firms' access to capital by adversely impacting their information environments. For example, The SEC (2012) and the IPO Task Force (2011) identify Decimalization as adversely impacting small and medium cap stocks, arguing that the adoption of decimal pricing reduced the economic incentives of investment banks and analysts to follow small firms, which, in turn, adversely affected the firms' capital formation. In addition, a report sponsored by Grant Thornton (Weild and Kim 2010, p.22) argues that Decimalization reduced the economic incentive for traders to cover small firms by reducing the spread, which in turn led to lower trading volume and investment in small stocks.

Several recent policy initiatives aim to address the possible adverse impact of Decimalization on small stocks. Specifically, the Jumpstart Our Business Startups (JOBS) Act of April 2012 authorized the SEC to increase the tick size from one cent to up to 10 cents for emerging growth companies with annual revenue less than $1 billion. Meanwhile, U.S. Congress introduced two bills in 2013, the Spread Pricing Liquidity Act and the Small Cap Liquidity Reform Act, both intending to increase tick sizes for smaller firms. This culminated in the SEC implementing a two-year Tick Size Pilot Program on October 3, 2016 that increases the minimum tick size for certain small cap stocks.[1] The regulatory activism regarding Decimalization is especially surprising considering that theory backed by a host of empirical evidence suggesting that Decimalization increased informational efficiency by lowering trading costs (Amihud and Mendelson 1986; Angel 1997; Bessembinder 2003).

In contrast to the recent enhanced scrutiny of Decimalization, there has been rather limited regulatory scrutiny on the impact of the other market reforms, even though these regulations were implemented within the same time frame: Reg FD on October 23, 2000; Decimalization in phases ending on January 29, 2001 for New York Stock Exchange (NYSE) firms and on April 9, 2001 for NASDAQ firms; and regulations related to GARS on July 1, 2002.[2] This is problematic for two reasons. First, since identifying the consequences of each regulation is complicated by their overlapping enactments, it is difficult to attribute consequences to one particular regulation without considering the effect of the others (Leuz and Wysocki 2016). Second, although each regulation has a unique objective, it is likely that the regulations impact one other. For example, if trading spreads helped fund analyst coverage, then reducing the spreads for small companies through Decimalization can lead to a reduction in analyst coverage, which can adversely impact the informational efficiency of the market (IPO Task Force 2011). Similarly, granting investors equal access to price relevant information (Reg FD) can affect stocks' trading costs in two ways – it can reduce information asymmetry (Eleswarupu 2004), or it can reduce the flow of information to the market (Gintschel and Markov 2004; Arya et al. 2005), which in turn affects informational

[1] https://www.sec.gov/oiea/investor-alerts-bulletins/ia_ticksize.html

[2] Reg FD has been characterized as "unassailable" by the regulators (Unger 2003). In sharp contrast, empirical evidence on Reg FD has yielded dramatically mixed results [see for example, Heflin et al. (2003), Bailey et al. (2003), Eleswarupu et al. (2004), Chiyachantana et al. (2004), Sidhu et al. (2008), Gomes et al. (2007), Duarte et al. (2008) and Chen et al. (2010)]. The mixed results are likely due to the presence of concurrent events (Leuz and Wysocki 2016).

efficiency.[3]

In this study, we exploit small non-synchronicities in the regulatory implementations of Reg FD, Decimalization, and GARS to tease out confounding impacts and to examine the extent to which Decimalization adversely impacted the information environments of small cap stocks, as alleged by the recent policy initiatives, and whether other regulations played a role. Since the recent policy initiatives focus on small firms, it is important from a policy perspective to examine the impact of the regulations across size partitions. Specifically, we examine the impact of the regulations on two dimensions of stocks' information environments – informational efficiency and trading costs.[4] We consider two information events – analyst forecasts and earnings announcements. We focus on these information events because two of the regulations, Reg FD and GARS, are directly designed to impact the flow of information between management, analysts and investment banking divisions, and the third regulation, Decimalization, is alleged to have impacted stocks' information environments indirectly by impacting analyst coverage (Weild and Kim 2010; IPO Task Force Report 2011). We directly address regulators' concerns that revolve around analysts' incentives for information gathering and forecasting by examining analyst forecast informativeness and analyst coverage.

Our findings suggest that Decimalization did not adversely impact the small stocks' analyst forecast informativeness or analyst coverage (number of analyst following and forecast frequency), as alleged by the recent policy initiatives. Instead, our findings suggest that there was no decrease in analyst following post-adoption of the regulation and the frequency of analyst

[3] Eleswarupu et al. (2004) argue that equal access to firm disclosures can lead to decreased trading costs. However, if the market makers are also the analysts who had preferred access prior to Reg FD, overall information flow to the market may have been reduced because of the restricted access.

[4] Trading costs are often used to proxy for information asymmetry (Leuz and Verrechia 2000), a component of a firm's information environment (Frankel and Li 2004). Therefore, we examine stocks' trading costs in addition to their informational efficiency to capture the regulations' potential effects on stocks' information environments.

forecasts and analysts' informativeness *increased* following Decimalization for small cap stocks. Additionally, we find that Reg FD is associated with reduced analyst informativeness and following for small cap stocks.

We conduct several additional tests to confirm these findings. We exploit the prior reduction in tick size that occurred when U.S. stock exchanges reduced the minimum tick size from one-eighth to one-sixteenth of a dollar in 1997, and we examine its impact on the informativeness of analyst forecasts and on analyst coverage. In addition, Decimalization was implemented in phases on sets of pilot firms and we make use of this feature by adopting a difference-in-differences design.[5] Consistent with our main analysis, we find an increase in analyst coverage and analysts' informativeness following the adoption of fractional pricing. We find no decrease in analyst forecast informativeness for pilot firms, relative to a sample of non-pilot firms, and. Both additional analyses support our main findings that Decimalization did not adversely impact either analysts' informativeness or analyst coverage.

In additional tests where we examine earnings announcements, our results suggest that abnormal return volatility and trading spreads surrounding earnings announcements significantly *declined* following Decimalization across all size partitions. In addition, we find no significant change in abnormal trading volume for small firms following Decimalization. While the decline in spreads is the targeted outcome of Decimalization, the simultaneous decline in abnormal return volatility and no significant change in abnormal trading volume around earnings announcements suggests that Decimalization did not have an adverse impact on small stocks' informational

[5] Similar to Fang et al. (2014), we conduct these difference-in-difference tests for NYSE firms only since the time difference between the NASDAQ implementation phases was not large enough to have sufficient observations. We are unable to conduct analyst coverage or earnings announcement difference-indifference tests for the same reason since these are associated with a specific fiscal quarter's earnings and we do not have enough earnings announcements within the narrow window.

efficiency. Taken together, our findings provide evidence that is inconsistent with the claims made by Weild and Kim (2010), the IPO Task Force (2011), and the concerns in the 2012 JOBS Act.

With respect to trading costs, we find that effective spreads and abnormal return volatility significantly *increased* following the promulgation of both Reg FD and GARS for small stocks.[6] This result suggests that Reg FD and GARS likely adversely impacted small stocks' information environments. These results are consistent with the theoretical predictions in Bessembinder et al. (2014). If the analysts covering small firms in the pre-Reg FD period were also market makers in those stocks, then the communication between the small firms' management and those analysts served not only to retain the analysts' coverage but also to provide the analysts with incentives to continue market making in those stocks. After the passage of Reg FD, analysts no longer received private information and may have lost the incentive to cover the small stocks.[7] The Reg FD results in our study contrast the conclusions of Eleswarupu et al. (2004), who find that trading costs diminished across all size partitions following Reg FD. We note that their hand-collected sample comprises only certain NYSE firms and is different from the sample in the present study, which includes all NASDAQ and NYSE firms. Our results, which hold for the subsample of all NYSE firms as well, are consistent, however, with Siddhu et al. (2008).

The findings in this study have implications for the current policy debate surrounding Decimalization. Specifically, our findings suggest that Decimalization did not adversely impact small firms and speak directly to the policy initiatives of the SEC and U.S. Congress to increase tick sizes for small firms. Additionally, we provide evidence suggesting that Reg FD and GARS

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[6]We find that for small firms abnormal trading volume significantly increased following Reg FD, but significantly declined following GARS.

[7]The Reg FD result for small firms, suggesting an overall loss of information previously disclosed to and disseminated by select analysts, is also consistent with Brown et al. (2014, 19) who survey sell-side analysts and find that information conveyed in private conversations with management is extremely valuable to analysts.

may have adversely impacted small firms in terms of their information environments, with increased trading costs and declines in the stocks' informational efficiency. Thus, policy makers concerned with Decimalization's adverse impact on small firms may want to revisit these overlapping regulations instead. While prior research has examined the effect of each regulation on trading costs and informational efficiency piecemeal (Heflin et al. 2003; Francis et al. 2006; Kadan et al. 2009), it does not adequately disentangle the confounding effects of the other regulations, the notable exception being Bailey et al. (2003) who examine informational efficiency surrounding earnings announcements around Reg FD and Decimalization. However, Bailey et al. (2003) do not examine differences across size partitions, which, as outlined above, is the emphasis of the current regulatory debate.

2. REGULATIONS AND THEIR IMPACT ON TRADING COST AND INFORMATIONAL EFFICIENCY

In this section, we provide a brief description of the three regulations we examine, their implementation dates, and any current regulatory initiatives regarding the regulations. A timeline of the regulations' implementation is provided in Appendix B. Finally, we discuss the implications of the regulations for stocks' information environments and trading costs.

2.1 Regulations

2.1.1 Reg FD

On October 23, 2000, the SEC implemented Reg FD, which prohibits U.S. firms listed on American exchanges from selectively disclosing material information, unless the same information is publicly disclosed within 24 hours. The rule was intended to eliminate the practice of selective disclosure, where certain investors and analysts received material information from firms before the information became public, i.e., "level the playing field" for analysts and investors

(Francis et al. 2006). Following Reg FD's implementation, the SEC revisited the regulation in a roundtable discussion in December 2001. Despite concerns expressed by some roundtable participants that Reg FD may have decreased the level of information firms' disclose, the SEC appears to express the view that Reg FD is "unassailable" and accomplished its goal of granting equal access to information (SEC 2001, 14).

2.1.2 Decimalization

In March 1997, Congressman Michael Oxley introduced a bill directing the SEC to adopt decimal pricing for all equity securities listed on American exchanges (SEC 2012). Subsequent to the introduction of the bill, both the NYSE and the NASDAQ implemented decimal pricing in phases rather than all at once in order to provide the SEC and market participants with an adjustment period, and to impose less stress on the trading venues' computer systems (SEC 2012).

The NYSE began its phase-in of decimal pricing with seven securities on August 28, 2000, an additional 57 securities on September 24, 2000 and 94 securities on December 4, 2000, and fully implemented Decimalization for all securities on January 29, 2001. The NASDAQ began its phase-in of decimal pricing with 14 securities on March 12, 2001, an additional 197 securities on March 26, 2001 and fully implemented Decimalization for all securities on April 9, 2001.

Upon adoption of Decimalization, exchanges switched from quoting and trading all of their listed securities in fractions to a decimal system. Besides the change to a decimal system, the arguably more important impact was the reduction in the minimum price increment, or tick size, to one cent from increments of 1/16th of a dollar ($0.0625). As discussed earlier, Decimalization has come under criticism in recent years, with several opponents arguing that Decimalization adversely impacted small firms' information environments by reducing the economic incentive for analysts to cover small firms, since spreads helped fund analysts coverage. For example, in 2013 the SEC held a roundtable to discuss the impact of Decimalization on securities markets and the possibility of introducing a pilot program to allow larger tick sizes for smaller firms (Michaels 2013). In the roundtable, former SEC director Richard Lindsey lamented the lack of academic research examining the effects of Decimalization across different firm sizes (Michaels 2013). In addition, Maureen O'Hara, chairperson of Investment Technology Group Inc. and a finance professor, characterized the association between higher trading profits to market makers and more research coverage of smaller firms "very tenuous" (Michaels 2013). Meanwhile, Congress introduced two bills, the Spread Pricing Liquidity Act and the Small Cap Liquidity Reform Act of 2013, both intending to increase the tick sizes for smaller firms. Finally, on August 26, 2014, the SEC announced a proposal for a 12-month pilot program that will allow pilot securities to be quoted at $0.05 minimum increments.

2.1.3 GARS and Related Rules

Beginning in July of 2002 with the implementation of the NYSE Rule 472 and the SEC approved National Association of Dealers (NASD) Rule 2711, and ending with the Global Analyst Research Settlement (GARS) implemented in December of 2002, American exchanges enacted a series of rules to address the conflict of interest between sell-side analysts and the investment banks that employ them. Specifically, the NYSE Rule 472 and the NASD Rule 2711 prohibit NYSE and NASD members from tying analysts' compensation to their company's investment banking transactions and from offering favorable research or ratings to a firm in order to curry future business (Chen and Chen 2009). In addition, NASD Rule 2711 requires analysts to disclose in the research report the percentage of their recommendations that are "buy," "hold," and "sell" (Chen and Chen 2009; Kadan et al. 2009).

The GARS objectives were similar to the NYSE and NASD's rules: to address the conflicts between research and investment banking divisions. As part of GARS, firms agreed to physically separate their banking and research divisions. The physical separation was meant to prohibit analysts from being compensated based on investment banking transactions; to prohibit investment bankers from having input into analysts' research; and to prohibit analysts from accompanying investment bankers on pitches to solicit business or new issues (Weild and Kim 2010). For expositional ease, throughout the remainder of the paper we refer to the period of regulations that includes the implementation of NYSE Rule 472, NASD Rule 2711 and GARS, collectively as "GARS."[8]

2.2 Impact of Regulations on Information Environments

2.2.1 Reg FD

Advocates of Reg FD believed that the regulation would improve the flow of information to markets by eliminating favored access to information. For example, proponents of Reg FD believed that it would reduce analysts' reliance on manager provided information and encourage independent research (Francis et al. 2006). On the other hand, opponents of Reg FD believed that it would reduce the flow of information to the markets by replacing information channels between managers and analysts with distinct blocks of public disclosure. As Francis et al. (2006, 272) observe, opponents argued that, "Reg FD would likely result in deteriorations of informational efficiency and accuracy; in particular, they argued that … informational efficiency …would decrease… Thus, Reg FD is an example of a rule whose intent is to shift an informational advantage (in this case, from analysts to investors generally), but whose unintended effects may extend to the amount of information in the marketplace."

[8] We also note that the GARS enactment overlapped with the promulgation of the Sarbanes-Oxley Act (SOX) and as such, it is difficult to separate out the effect of GARS from SOX. Notwithstanding this difficulty, we follow prior research (Kadan et al. 2009) in labeling our findings surrounding the GARS implementation a GARS effect.

Generally, research on Reg FD and its effect on the information environment provides mixed findings. While Gintschel and Markov (2004) find that post-Reg FD analyst informativeness declines, consistent with the regulation curtailing selective disclosure, Shane et al. (2001) and Heflin et al. (2003) find no significant change in either analyst forecast accuracy or dispersion following Reg FD, and Bailey et al. (2003) find no increase in forecast accuracy, but a significant increase in dispersion, as do Irani and Karamanou (2003). On the other hand, Agrawal et al. (2006) and Mohanram and Sunder (2006) find increases in both accuracy and dispersion following Reg FD. Finally, Gomes et al. (2007) find that after the passage of Reg FD, analyst following significantly declined for small firms, and they argue their evidence is consistent with analyst re-allocating their resources to following larger firms.

With respect to abnormal stock return volatility surrounding earnings announcements, some studies find a significant decline in stock return volatility following Reg FD (e.g. Heflin et al. 2003; Eleswarapu et al. 2004), while other studies (Bailey et al. 2003; Francis et al. 2006) find no significant difference in abnormal return volatility following the passage of Reg FD. Consistent with Reg FD negatively impacting the information environment, Bailey et al. (2003), Heflin et al. (2003) and Ahmed and Schneible (2007) find a significant increase in abnormal trading volume surrounding earnings announcements post-Reg FD, while Francis et al. (2006) find no significant change in trading volume.

Our intent is to disentangle the effect of Reg FD on small stocks' informational efficiency from the role other regulations may have played. As some existing research already suggests, Reg FD affected the information environment of small stocks by reducing private information gathering, resulting in the loss of analyst informativeness and following, and by increasing abnormal stock return volatility and abnormal trading volume. Although Bailey et al. (2003), Heflin et al. (2003), Gintschel and Markov (2004), and Francis et al. (2006) examine Reg FD's impact on public information, they do not consider the differential effect by firm size. Additionally, with the exception of Francis et al. (2006), the other studies do not consider the effect of overlapping regulations. Similarly, although Ahmed and Schneible (2007) consider the impact of Reg FD on public information for technology firms of different sizes, they do not examine the average effect on public information by firm size, nor do they examine trading costs.

2.2.2 Decimalization

To our knowledge, existing research has not examined the impact of Decimalization on analyst informativeness or coverage. Research has considered, however, the impact of Decimalization on the other information environment characteristics we consider. Ronen and Weaver (2001) argue that if Decimalization increased competition in bidding by allowing for price improvements by a penny from 6.25 cents, the variance of price changes would decline and result in a decline in stock return volatility. Specifically, Ronen and Weaver (2001) and Bailey et al. (2003) find that stock return volatility surrounding earnings announcements significantly declined following Decimalization, while Bessembinder (2003) finds that stock return volatility declined across exchanges and size partitions following Decimalization in longer-windows. However Chakravarthy et al. (2004) provide evidence that Decimalization increased stock return volatility in the short-term. With respect to abnormal trading volume around earnings announcements, Bailey et al. (2003) find no significant change post-Decimalization, although they do not examine differences across size partitions.

If Decimalization led to a decrease in analyst coverage for small and medium cap stocks, as suggested by the SEC (2012) and the IPO Task Force (2011), then we expect analyst informativeness and coverage to decline post-Decimalization. Analysts could simply reduce their efforts after Decimalization, while still issuing the same quantity of earnings forecasts. If analysts lower their efforts in gathering firm-specific information, we expect there will be less information content when they issue their earnings forecasts. Relatedly, extending the SEC (2012) and IPO Task Force (2011) argument to earnings announcements, if analyst informativeness and coverage declines then we also expect abnormal stock return volatility and abnormal trading volume around earnings announcements to increase post-Decimalization for small and medium cap stocks. If, however, Decimalization encourages more traders to enter the market at a lower cost, then increased trading can aid price discovery and lead to better informational efficiency. Under this scenario, abnormal stock return volatility and abnormal trading volume around earnings announcements would decline post-Decimalization.

2.2.3 GARS

As discussed earlier, Weild and Kim (2010) argue that GARS led to a decline in analyst coverage for small firms because the analysts who likely covered small firms were also part of the firm's investment banking team, and GARS now prohibited these analysts from following the firms. If this argument is true, then we expect to see a decline in the information environment of small firms because overall information regarding the stock is reduced. This would be consistent with the findings in Kadan et al. (2009) who find that the overall informativeness of analysts' outputs declined following GARS. Thus, we would expect a decrease in analyst informativeness and coverage, and an increase in abnormal stock return volatility and abnormal trading volume around earnings announcements for small cap stocks.

However, some research that examines GARS' effect on analyst outputs finds that, following GARS, analyst forecast recommendations were less optimistic and became more informative, evidenced by an increase in the association between analyst recommendations and future firm returns (Barber et al. 2006; Chen and Chen 2009). Such improvement in the information outputs of analysts can lead to improvements in overall informational efficiency, resulting in a decline in abnormal stock return volatility and abnormal trading volume around earnings announcements. To our knowledge, no research examines the impact of GARS on public information events like earnings announcements.

2.3 Impact of Regulations on Trading Costs

2.3.1 Reg FD

There is little research examining the impact of Reg FD on trading costs, with the exception of Eleswarapu et al. (2004). Eleswarapu et al. argue that Reg FD was intended to reduce informed trading by requiring firms to disclose information publicly or to disclose less information. They argue that, if private information is disclosed publicly as a result of Reg FD, then information asymmetry declines and trading costs would also decline. We argue, however, that it is not clear whether Reg FD will result in a decline in trading costs. If, as a result of Reg FD, firms opt to disclose less information (SEC 2001), then prices would become less informative and traders who discover the information via alternative channels gain a trading advantage. This would lead to information asymmetry regarding the stock and result in an increase in trading costs.

However, Eleswarapu et al. (2004) report evidence that, across all firm size partitions, small, medium and large, effective spreads surrounding earnings announcements declined post-Reg FD. Their finding is consistent with the argument that Reg FD reduced trading costs by requiring private information to be disclosed publicly. We note, however, that their conclusions are based on a small hand-collected sample of 300 NYSE firms. Further, their controls for the confounding impact of Decimalization are inadequate. Specifically, they treat the period prior to January 29, 2001 as pre-Decimalization, but do not exclude NYSE firms that were part of the pilot program where stocks began decimalizing in September 2000. This could lead to the finding that spreads declined for NYSE firms following Reg FD, but the result would be attributable to the pilot stocks that decimalized, not to Reg FD. Therefore, it is unclear whether their finding of a decline in trading costs can be exclusively attributed to Reg FD or whether Decimalization played a role.

2.3.2 Decimalization

Bessembinder (2003) argues that a potential mechanical relation of reducing the tick size to a penny would be a decline in both quoted and effective bid-ask spreads, leading to a reduction in trading costs. Consistent with this argument, empirical research on Decimalization generally documents a reduction in trading costs. Bacidore et al. (2003), Bessembinder (2003) and Chakravarty et al. (2003) find that, on average, both quoted and effective bid-ask spreads declined with the advent of Decimalization on both the NYSE and the NASDAQ, suggesting that the cost of trading significantly declined post-Decimalization. Further, Bessembinder (2003) documents a decline in trading costs across all sizes of firms: small, medium and large.

Bessembinder's (2003) results across size partitions notwithstanding, some recent reports still dispute the positive impact of Decimalization on trading costs, especially for small stocks (see Weild and Kim 2010). Specifically, the IPO Task Force (2011, 14) report states that "decimalization... put the economic sustainability of sell-side research departments under stress by reducing the spreads and trading commissions that formerly helped to fund research analyst coverage." The SEC (2012) report argues that as a result of the reduced profitability of covering small stocks, analyst coverage has shifted from smaller capitalization stocks towards more liquid, larger capitalization stocks. Further, the lack of analyst coverage can lead to an increase in information asymmetry around earnings announcements and potentially raise trading costs.

Whether Decimalization negatively impacted small stocks, or whether other concurrent regulations played a role, is an empirical question we investigate in this study. Although Bessembinder (2003) finds that trading costs significantly declined for small stocks, he doesn't investigate Decimalization's impact on short-window trading costs by firm size, or disentangle the effects of other overlapping regulations.

2.3.3 GARS

Weild and Kim (2010) argue that GARS led to a decline in analyst coverage for small firms because the analysts who likely covered small firms were also part of the firm's investment banking team, and GARS now prohibited these analysts from following the firms. This would result in an overall reduction of information about the stock (Kadan et al. 2009). As argued earlier, a reduction in information about the stock could lead to less informative prices and a greater trading advantage for those able to discover the information via alternative channels. This would lead to an increase in trading costs and firms' effective bid-ask spreads.

Alternatively, GARS could have improved the information outputs of analysts (Barber et al. 2006; Chen and Chen 2009), resulting in an improvement in firms' information environments and a reduction in trading costs and effective bid-ask spreads. To our knowledge, no research has examined the impact of GARS on stocks' effective bid-ask spreads.

3. SAMPLE SELECTION AND RESEARCH DESIGN

3.1 Sample Selection

To examine analyst coverage, informativeness and trading activities around earnings announcements, we begin the sample selection by including all NYSE and NASDAQ stocks with an earnings announcement date that occurs during the calendar quarters 2000Q2-2002Q4. Similar to Francis et al. (2006), we use calendar quarters instead of fiscal quarters so that we do not restrict our sample to firms with December fiscal-year ends. Prior to full implementation, both the NYSE and the NASDAQ implemented phase-in programs, where certain stocks adopted Decimalization early. In our main analysis, we eliminate the pilot stocks from our sample so that we do not contaminate our inferences. We use these firms to execute a difference-in-differences design to assess the robustness of our results, as discussed further below. Our main sample includes 21,213 firm-quarter observations. To examine analyst forecast informativeness, we obtain analysts' earnings forecasts for our sample firms over the same calendar quarters, which provides a sample of 82,207 analysts' reports.

One contribution of this paper is to explore the impact of several overlapping regulations on firms' informational efficiency and trading costs to better identify whether Decimalization negatively impacted small stocks. By exploiting the non-synchronicity of the different regulations, we attempt to separate the impact of each regulation. However, in order to rule out alternative explanations, and to provide more causal evidence on how Decimalization impacts small firms' information environments, we conduct two additional analyses that are similar to Fang et al. (2014).

First, we examine an earlier reduction in tick size that occurred on U.S. exchanges in 1997 when the minimum tick size was reduced from an eighth of a dollar to one-sixteenth (fractional pricing). Weild et al. (2012) also criticize fractional pricing, arguing that it negatively affected small firms' information environments and trading costs. The advantage of examining the impact of fractional pricing on analyst coverage and informativeness is that the regime is less subject to overlapping regulations. Thus, we repeat the analysis in the sample period between 1996Q1 and 1998Q4, using a window length similar to Kadan et al. (2009), to provide additional evidence on whether a smaller tick size negatively impacts firms' informational environment.

Second, we use the phase-in of Decimalization on a series of pilot stocks to execute a difference-in-differences research design where we examine whether Decimalization impacted the information environment of pilot firms relative to non-pilot firms (Fang, Tian and Tice 2014).[9] Before fully implementing Decimalization, the NYSE created three pilot programs and the NASDAQ created two pilot programs (please refer to Appendix B for a timeline of the pilot programs). In order to conduct the difference-in-differences design, we follow Fang, Tian and Tice (2014) and examine the Pilot firms on NYSE because NASDAQ only conducted pilot studies for two weeks before full decimalization.

3.2 Research Design

We define three variables that correspond to the periods of the three regulations. The first variable, FD, is an indicator that takes a value of one if the firm's earnings announcement occurs after the implementation of Reg FD on October 23, 2000. The second variable, DEC, is an indicator that takes a value of one for NYSE firms' earnings announcements that occur after January 29, 2001 and DEC takes a value of one if NASDAQ firms' earnings announcements occur after April 9, 2001. Finally, the third variable, GARS, is an indicator variable that takes a value of one if the firm's earnings announcement occurs after July 1, 2002.[10] The remaining sample observations are part of the pre- Reg FD period, from 2000Q2 until October 23, 2000; all three indicator variables take a value of zero for this period. In our forecast level analysis of analyst forecast informativeness, we define FD, DEC and GARS in a similar way based on the dates of analyst forecasts, instead of earnings announcement.

[9] We hand-collect the tickers of the NYSE and NASDAQ stocks that were part of the Decimalization pilot programs from newspaper articles released during the period, and matched the stock names to CRSP permnos.

[10] GARS include a series of different regulations with different implementation dates, and accordingly we use alternative dates for the GARS period to assess the robustness of our results.

We define size as the market cap of the firm at the calendar quarter-end associated with the firm's earnings announcement date. In order to create a ranking of observations by size, we pool observations across time and exchanges and rank observations by market cap into terciles – small, medium and large. We create our size partitions in this manner for two reasons. First, the current policy debate focuses on small firms. Second, the current policy initiatives specify size cut-offs irrespective of time and exchange. In all analyses, we provide results for the pooled sample first, and then we provide results for each of the size groups described above.

3.2.1 Analyst Coverage and Informativeness

The main argument against Decimalization is that it adversely impacted small firms' information environment by reducing the economic incentives of investment banks and analysts to follow small firms (SEC 2012; IPO Task Force 2011). To evaluate the legitimacy of these claims, we empirically examine whether analysts reduced their research in quantity (coverage) and quality (informativeness).

We use two measures to proxy for analyst coverage (Yu 2008). Our first proxy is *NUM_Analyst*, which is the number of analysts that issue earnings forecasts for a given firm-quarter. We obtain detailed analyst forecasts from the IBES detailed forecast file, and measure the number of analysts who issue at least one earnings forecast during the 90-day period prior to the earnings announcement. Our second proxy is *NUM_Forecast*, which is the number of earnings forecasts issued during the 90-day period prior to the earnings announcement. Since one analyst may issue multiple earnings forecasts in a given firm-quarter, we intend our second measure, *NUM_Forecast*, to capture information about the total quantity of analysts' earnings forecasts. We estimate the following model (Yu 2008):

$$NUM\_Analyst(NUM\_Forecast)_{i,t} = \alpha_0 + \alpha_1 FD_t + \alpha_2 DEC_t + \alpha_3 GARS_t + \alpha_4 LogMVE_{i,t} + \alpha_5 ROA_{i,t-1} + \alpha_6 GROWTH_{i,t} + \alpha_7 Ext\_Fin_{i,t} + \alpha_8 CF\_VOL_{i,t} + \alpha_9 QTR4_{i,t} + \varepsilon_t \quad (1)$$

Our main variables of interest are FD, DEC and GARS, which capture the incremental effects of each regulation on analyst coverage. Following Yu (2008), we control for lagged ROA, asset growth rate (*GROWTH*), external financing activity (*EXT_FIN*), and cash flow volatilities (*CF_VOL*) that may affect the number of analyst following a firm. To control the seasonal effects, we also control for QTR4, which equals to one if the quarter is the fourth fiscal quarter. Please refer to Appendix A for more detailed variable definitions.

Then we use an analyst forecast-level sample to assess whether the informativeness of analyst forecasts changed following Decimalization, while controlling for other concurrent regulations and variables that also impact analyst informativeness. We follow Frankel et al. (2006) and measure the informativeness of analysts' earnings forecasts using the absolute value of the size-adjusted cumulative abnormal return on the date of the analysts' earnings forecast (*AF_INFO*), and estimate the following model:

$$\begin{aligned} AF\_INFO_{i,t} = \; & \alpha_0 + \alpha_1 FD_t + \alpha_2 DEC_t + \alpha_3 GARS_t + \alpha_4 SIGMA_{i,t} + \alpha_5 LnVOL_{i,t} + \alpha_6 INST_{i,t} \\ & + \alpha_7 LnOwners_{i,t} + \alpha_8 MB_{i,t} + \alpha_9 LogMVE_{i,t} + \alpha_{10} NSIC_{i,t} + \alpha_{11} MMRsg_{i,t} \\ & + \alpha_{12} NSEGS_{i,t} + \alpha_{13} AccRsq_{i,t} + \alpha_{14} LnAnalys_{i,t} + \alpha_{15} GNEWS_{i,t} \\ & + \alpha_{15} QTR4_{i,t} + \varepsilon_t \qquad (2) \end{aligned}$$

Frankel et al. (2006) argue that the model above might be subject to endogeneity concerns as the determinants of forecast informativeness are likely to be affected by whether analyst forecasts are informative. Thus, we follow Frankel et al. (2006) and use a two-stage-least-squares model of simultaneous equations. We then use the fitted values, SIGMA and LnVOL, in our second stage regression of equation (2).

3.2.2 Fractional Pricing

In order to better identify Decimalization's impact on small firms' information environments, we examine an earlier reduction in the tick size initiated by U.S. stock exchanges in 1997. Even though there is less of a concern regarding overlapping regulations confounding inferences during the fractional pricing regime, the setting is similar to Decimalization in that it also reduced minimum tick size, and Weild et al. (2012) express similar concerns that fractional pricing may have hurt analysts' incentives to follow small firms. We estimate models (1) and (2), and focus on the fractional pricing regime. The variable of interest is FP, which indicates whether a firm's analyst forecast or earnings announcement occur after the implantation of fractional pricing (June 2, 1997 for NASDAQ firms, and June 24, 1997 for NYSE firms). Since fractional pricing was implanted in the middle of 1997, our sample period is between1996Q1 and 1998Q4, and includes 22,261 firm-quarters and 128,987 analyst forecasts.

3.2.3 Difference-in-Differences Design: Decimalization Pilot Firms

In this section, we exploit the phase-in of Decimalization to further investigate whether Decimalization impacted small firms' information environments. We use a difference-in-differences research design to compare the change in information environment for pilot stocks with other stocks that are not in the pilot firms. Similar to Fang, Tian and Tice (2014), we focus on NYSE pilot firms. Due to the small number of pilot firms and the quarterly frequency of earnings announcement, we do not have sufficient observations to examine analyst coverage, which is related to s specific firm-quarter. However, we are able to examine informativeness of analyst earnings forecasts by estimating the following model:

$$AF\_INFO_{i,t} = \alpha_0 + \alpha_1 PILOT_i + \alpha_2 DEC\_PILOT_t + \alpha_3 FD_t + Year\&Quarter\ FE + \varepsilon_{i,t} \quad (3)$$

In equation (3), PILOT is an indicator variable if a firm's stock is in the NYSE pilot program and DEC_PILOT is an indicator variable that equals one if the earnings forecast is issued for a pilot firms after the implementation of the pilot program. We match each pilot firm with a control firm in the same industry, size decile, and market-to-book value decile. The final sample includes 1,329 observations.

3.2.4 Informational Efficiency around Earnings Announcement

We follow prior research and use abnormal return volatility and abnormal trading volume to proxy for informational efficiency (see Bailey et al. 2003; Heflin et al. 2003; Francis et al. 2006). Following Bailey et al. (2003) and similar to Heflin et al. (2003) and Francis et al. (2006), we estimate the following multivariate regression for abnormal stock return volatility:

$$Ab\_Ret\_Vol_{i,t} = \alpha_0 + \alpha_1 FD_t + \alpha_2 DEC_t + \alpha_3 GARS_t + \alpha_4 LogMVE_{i,t} + \alpha_5 ABSUE_{i,t} + \alpha_6 FDISP_{i,t} + \varepsilon_t \quad (4)$$

where abnormal stock return volatility, $Ab\_Ret\_Vol_{i,t}$ for firm *i* during earnings announcement period *t*, is calculated as the absolute value of cumulative abnormal returns over the earnings announcement windows (-1,1). Following Bailey et al. (2003), we estimate beta over the window (-200, -11) using a one-factor market model. We include variables in our estimation of equation (5) following prior research (Bailey et al. 2003; Heflin et al. 2003; Francis et al. 2006), in order to control for other factors that influence abnormal return volatility but are not related to the regulations we investigate. Specifically, we control for $FDISP_{i,t}$, or analysts' forecast dispersion, which is the standard deviation of the most recent individual analyst forecasts before the earnings announcement. Please refer to Appendix A for more detailed variable definitions.

Following Bailey et al. (2003) and similar to Heflin et al. (2003) and Francis et al. (2006), we estimate the following multivariate regression for abnormal trading volume:

$$Ab\_Volume_{i,t} = \alpha_0 + \alpha_1 FD_t + \alpha_2 DEC_t + \alpha_3 GARS_t + \alpha_4 LogMVE_{i,t} + \alpha_5 RETVOL_{i,1999} + \alpha_6 FDISP_{i,t} + \varepsilon_t \quad (5)$$

where abnormal trading volume, $Ab\_Volume_{i,t}$ for firm *i* during earnings announcement period *t*, is calculated following Bailey et al. (2003). Specifically, abnormal trading volume is the difference between average trading volume during the earnings announcement window (-1,1) and the average daily trading volume over the pre-announcement window (-200,-11), scaled by the average volume in the (-200,-11) window. Again, we include variables in our estimation of equation (6) following prior research (Bailey et al. 2003; Heflin et al. 2003; Francis et al. 2006), in order to control for other factors that influence abnormal volume but are not related to the regulations we investigate. Please refer to Appendix A for more detailed variable definitions.

If the regulatory regimes, Reg FD, Decimalization, or GARS positively impacted firms' information environments, we expect a decline in both abnormal return volatility and abnormal trading volume during the regulatory periods, suggesting a negative value for α_1 through α_3 in equations (5) and (5). On the other hand, if the regulatory regimes adversely impact firms' public information environments, then we would expect increases in abnormal return volatility and abnormal trading volume in the earnings management windows during the regulatory periods, suggesting a positive value for α_1 through α_3 in equations (5) and (6).

3.2.5 Trading Costs around Earnings Announcement

We follow prior research and use the effective bid-ask spread to proxy for trading costs (Bessembinder 2003; Ahmed and Schneible 2007; Eleswarapu et al. 2004). Similar to Eleswarapu et al. (2004), we estimate the following multivariate regression:

$$Log(1 + Eff\_Spread)_{i,t} = \alpha_0 + \alpha_1 FD_t + \alpha_2 DEC_t + \alpha_3 GARS_t + \alpha_4 ABSUE_{i,t} + \alpha_5 LogMVE_{i,t} + \alpha_6 LogVOL_{i,1999} + \alpha_7 LogRETVOL_{i,1999} + \varepsilon_t \quad (6)$$

where $Log(1 + Eff\_Spread)_{i,t}$ is one plus the log of the average effective spread for firm *i* over earnings announcement period *t*. The effective spread is calculated as the average effective spread over the three-day earnings announcement window (-1,1). We calculate the effective bid-ask spread following Corwin and Schultz (2012).[11]

We include variables in equation (4) following prior research (Ahmed and Schneible 2007; Eleswarapu et al. 2004) intended to control for factors that affect stocks' effective bid-ask spreads but are not related to the regulations we examine. Please refer to Appendix A for more detailed variable definitions. We calculate the control variables over the year 1999 to ensure that we control for the "normal" level of firms' trading volume and return volatility in the pre-regulation periods. Specifically, we intentionally avoid using contemporaneous volume and return volatility control variables in order to avoid contaminating our inferences by using windows that overlap with the different regulatory regime periods we examine.

4. RESULTS

4.1 Analyst Coverage and Informativeness

Table 1 presents the descriptive statistics for the analyst coverage sample. On average, a firm has 7 analysts and 10.5 forecasts for each quarterly earnings announcement. In Panel B, we present the mean values for each variable in equation (1) by size terciles. Panel B Table 1 shows that analyst coverage increases when firms size increases, firms become more profitable, less reliant on external finance, and have lower cash flow volatilities.

Table 2 presents the results for estimating equation (1). The dependent variable in Panel A is *NUM_Analyst*. Column 1 shows that the coefficient on DEC is 0.902, suggesting that there is an average increase of 0.902 analyst following decimalization. We presents results for different firm

[11] We thank Shane Corwin for SAS code he provides on his website to calculate the effective spread measure, "spread_0": http://www3.nd.edu/~scorwin/HILOW_Estimator_Sample_002.sas. We are comfortable with employing a low frequency measure, i.e. daily data, of effective spread as opposed to a high-frequency measure, i.e. intraday data, because prior research finds that certain low-frequency effective spread measures are highly correlated with high-frequency spread measures (Goyenko et al. 2009; Corwin and Schultz 2012).

size in column 2 to 4, and coefficients on DEC is all positive and statistically significant. This shows that decimalization has a positive impact on analyst coverage, although the economic magnitude is larger for firms of bigger size. The economic magnitude is also meaningful. For example, the number of analyst following small firms increased about 5.6% compared to the mean of 4.431.

In Table 2 Panel B, the dependent variable is *NUM_Forecast*. The results are similar to Panel A, suggesting that the number of forecasts increase after decimalization, and small firms experienced an increase 15.2% in earnings forecasts. The results do not support the claim in Weild and Kim (2010) that analysts stopped covering small firms after decimalization, but instead suggest that analyst coverage increased after Decimalization. Such a finding is also theoretically plausible since Decimalization likely increased market liquidity and trading and thus the demand for analyst research.

Table 3 presents the descriptive statistics for the analyst forecast informativeness sample. On average, analysts report are quite informative and the mean absolute abnormal returns is 3.2%. The effect is stronger for smaller firms, which has an average of 4.3% of absolute abnormal returns. To study whether analysts report informativeness decline after each regulation, we estimate equation (2) using a two-stage-least-square model following Frankel et al. (2005) and present the results in Table 4. In the whole sample, we find that Reg FD appeared to reduce the information content of analysts' report, consistent with the purpose of Reg FD and the findings documented in Gintschel and Markov (2004). The coefficient on DEC is positive and statistically significant, suggesting that decimalization increases the informativeness of earnings forecasts, inconsistent with the claim in Weild and Kim (2010). Across all the sample size, GARS seems to increase the informativeness of earnings forecasts[12]. For small firms, we see a stronger results for both Reg FD and decimalization. The results are also economically meaningful. For example, the informativeness of earnings forecasts increased by 12.8% after Decimalization for small firms, relative to the mean of 0.043. Take together the results from Table 2 and Table 4, we do not find evidence that Decimalization negatively affect analyst coverage and informativeness of analysts' forecasts.

4.2 Fractional Pricing

We repeat the analyses above in the adoption of fractional pricing in June 1997, which is less likely to be subject to the concern of overlapping regulations. Panel A and B in Table 5 show that analyst coverage increased for small and medium firms, but decreased for large firms. Table 5 Panel C shows that analyst forecasts became more informative across all the different size groups. Thus, we do not find any evidence that smaller tick size worsened small firms' information environment.

4.3 Difference-in-Difference Analysis on NYSE Pilot Firms

To establish the causal link between decimalization and changes in analysts' report informativeness, we utilize the phase-in feature of pilot stocks, and use non-pilot stocks as a control group. This difference-in-difference model enables us to examine the impact of decimalization, while holding other factors constant. We include year-quarter fixed effects in the model to control for time-serial trends. Table 6 column 1 shows that the coefficient on the interaction between DEC and PILOT is positive and statistically significant, suggesting pilots firms experience an increase of forecast informativeness after the implementation of decimalization, consistent with our finding

[12] Our results are different from Kadan et al. (2009). One notable difference is that Kadan et al. (2010) analyze the stock recommendation sample and we focus on the earnings forecasts. Indeed, when we use the stock recommendation results, we find similar results to Kadan et al. (2010).

in Table 4. In column 2 we include the control variables in equation (2) and the coefficient on DEC_PILOT becomes less significant. However, the sign of coefficient remains positive and t-stat is 1.58. In summary, we do not find a decrease of analyst forecasts informativeness for the pilot firms during the phase-in stage.

4.4: Informational Efficiency around Earnings Announcement

We provide additional analyses to examine informational efficiency around another information events: earnings announcements. Table 7 presents the descriptive statistics for the pooled earnings announcement sample. The sample includes 21,213 earnings announcements over the sample period, 2000Q2-2002Q4, with average market cap of $4.400 billion. The average effective spread for the pooled sample is $0.015, while abnormal return volatility is 0.109 and abnormal trading volume is 0.497. We also present the summary statistics by firm size in Panel B.

Table 8 presents the results for abnormal return volatility. We first present the results for the pooled sample, and then for each size partition. The results in Table 8 suggest that across all size partitions, abnormal return volatility significantly declined following Decimalization, and then significantly increased following GARS. The result that abnormal return volatility significantly declined following Decimalization is inconsistent with the policy claims that the regulation adversely impacted small firms' informational efficiency. In contrast, the results in Table 8 suggest that Reg FD adversely impacted stocks' abnormal return volatility for small firms, and GARS also had a negative impact across all size partitions. This result is consistent with prior studies that find a decline in the informativeness of analyst forecast revisions following Reg FD (Francis et al. 2006; Gintschel and Markov 2004) and GARS (Kadan et al. 2009).

Table 9 presents the results for abnormal trading volume. For all size partitions, Table 9 suggests that abnormal trading volume significantly increased in the Reg FD period, and decreased after the decimalization. The abnormal volumes also increased after GARS for medium and large firms. Once again the results call into question the regulatory concern surrounding Decimalization and suggest the concern should arguably surround Reg FD and GARS.

In Table 10, we present the results for trading cost. For all size partitions, we find a significant decline in effective spread following Decimalization, consistent with Bessembinder (2003), and a significant increase in effective spread following the GARS period. Thus, the multivariate results confirm our univariate findings. As discussed earlier, the decline in spreads following Decimalization is not surprising given the objective of the regulation and the findings of prior research. However, the increase in spreads following Reg FD contrasts the findings in Eleswarupu et al. (2004). The increase in spreads following GARS is a new result.

Taken together, the results in Tables 8-10 suggest that Decimalization *did not* adversely impact small firms' trading costs and informational efficiency around earnings announcements. Specifically, following Decimalization we find a significant decline in effective spread and abnormal return volatility and no significant change in abnormal trading volume for small firms. We also find an improvement in analysts' following both in quantity and quality. In contrast, our results suggest that Reg FD, and to some extent GARS, may have adversely impacted small stocks' trading costs and informational efficiency. Specifically, we find that for small firms, effective spread, abnormal return volatility and abnormal trading volume all significantly increased following Reg FD. With respect to GARS, we find that for small firms effective spread and abnormal return volatility significantly increased following GARS, while abnormal trading volume significantly declined.

4.5 Robustness Tests

In order to ensure that our results are not specific to the earnings announcement sample we employ, and for comparison with Bessembinder (2003), we re-estimate trading costs using daily firm observations over the same regulatory windows we used for the earnings announcement sample. Specifically, we use all firms' daily effective spread observations available for each regulatory regime period. The univariate results are presented in Table 2 Panel B. The daily effective spread results mirror our short-window results and are consistent with Bessembinder (2003), who documents a decrease in trading costs even for small firms following Decimalization.

In addition, we conduct several untabulated robustness analyses. First, we re-estimate our analysis using different size partitions in order to ensure that our results are not exclusive to the size partitions we employ in the main analysis. For example, we classify the lowest and highest quintiles of the sample as small and large firms respectively, and we find similar results. Second, we re-estimate the main analysis using shorter windows for the regulatory regime periods to ensure that our results are not exclusive to the windows we employ in the main analysis. Specifically, we restrict each regulatory regime period to comprise three months following the implementation dates. Our results continue to hold. Third, we restrict the sample to firms that are present in each of the regulatory regime periods to ensure that our results are not subject to survivor bias concerns. To some extent, we address this concern in our main analyses by requiring firms to have observations in 1999 in order to calculate our control variables. Nevertheless, our results are robust to this added constraint. Finally, we use different windows for the GARS regime. Specifically, Kadan et al. (2009) begin their GARS sample period in September 2002, not July 2002. We use the Kadan et al. window and our results remain virtually the same.

5. CONCLUSION

In this study, we examine whether several U.S. market regulations impacted stocks' trading costs and informational efficiency. We examine three overlapping regulations that occurred over the period 2000-2002: Reg FD, which required firms to publicly disclose price material information; Decimalization, which reduced the costs of trading; and GARS, which required separation of banks' analyst research and investment banking departments. Among these regulations, Decimalization has come under increased scrutiny in recent years. The main concern centers on whether Decimalization adversely impacted small firms' information environments (Weild and Kim 2010; SEC 2012; IPO Task Force 2011). Several policy initiatives have attempted to reverse the possible adverse impact of Decimalization on small stocks. The initiatives culminated in the SEC implementing a two-year Tick Size Pilot Program on October 3, 2016 that increases the minimum tick size for certain small cap stocks.

In contrast to the recent enhanced scrutiny of Decimalization, there has been limited regulatory scrutiny of the other market reforms, even though all regulations were enacted over the same period. We exploit non-synchronicities in regulation implementations to tease out the confounding effects the regulations. We conduct our analysis by examining analyst forecasts and earnings announcement windows because two of the regulations, Reg FD and GARS, are directly designed to impact the flow of information between management, analysts and investment banking divisions and the third regulation, Decimalization, has been alleged to have impacted informational efficiency in the market indirectly by impacting analyst coverage.

Our results suggest that that Decimalization *did not* adversely impact small firms in terms of trading costs or informational efficiency. Specifically, we find that analysts' coverage did not decline after decimalization, and analyst forecasts appear to be more informative. In addition, both abnormal return volatility and trading costs declined significantly around earnings announcements following Decimalization, across all size partitions. These findings are in direct contrast to the claims made by Weild and Kim (2010), the IPO Task Force (2011), and the concerns in the 2012 JOBS Act. In contrast, we find that, for small firms trading costs significantly increased and informational efficiency significantly declined following the promulgation of Reg FD. Further, both trading costs and abnormal return volatility significantly increased following the GARS regime across all size partitions. Since our results suggest that Reg FD and GARS, rather than Decimalization, adversely impacted small firms, we argue that policy makers concerned with small firms' access to capital may want to re-examine these regulations rather than Decimalization.

REFERENCES

Ahmed, A. S., and R. A. Schneible Jr. 2007. The impact of regulation fair disclosure on investors' prior information quality—evidence from an analysis of changes in trading volume and stock price reactions to earnings announcements. *Journal of Corporate Finance* 13 (2):282-299.

Bacidore, J., R. H. Battalio, and R. H. Jennings. 2003. Order submission strategies, liquidity supply, and trading in pennies on the New York Stock Exchange. *Journal of Financial Markets* 6 (3):337-362.

Bailey, W., H. Li, C. X. Mao, and R. Zhong. 2003. Regulation Fair Disclosure and earnings information: Market, analyst, and corporate responses. *The Journal of Finance* 58 (6):2487-2514.

Barber, B. M., R. Lehavy, M. McNichols, and B. Trueman. 2006. Buys, holds, and sells: The distribution of investment banks' stock ratings and the implications for the profitability of analysts' recommendations. *Journal of Accounting and Economics* 41 (1):87-117.

Bessembinder, H. 2003. Trade execution costs and market quality after decimalization. *Journal of Financial and Quantitative Analysis* 38 (04):747-777.

Chakravarty, S., R. A. Wood, and R. A. Van Ness. 2004. Decimals and Liquidity: A Study of the NYSE. *Journal of Financial Research* 27 (1):75-94.

Chen, C.-Y., and P. F. Chen. 2009. NASD rule 2711 and changes in analysts' independence in making stock recommendations. *The Accounting Review* 84 (4):1041-1071.

Chen, Z., S. Dhaliwal, and H. Xie. 2010. Regulation fair disclosure and the cost of equity capital. *Review of Accounting Studies* 15: 106-144.

Chiyachantana, C., C. Jiang, N. Taechapiroontong, and R. Wood. 2004. The impact of Regulation Fair Disclosure on information asymmetry and trading: An intraday analysis. *Financial Review* 39: 549-577.

Corwin, S. and P. Schultz. 2012. A simple way to estimate bid-ask spreads from daily high and low prices. *Journal of Finance* LXVII(2): 719-759.

Duarte, J., X. Han, J. Harford, and L. Young. 2008. Information Asymmetry, Information Dissemination and the Effect of Regulation FD on the Cost of Capital. *Journal of Financial Economics* 87: 24-44.

Eleswarapu, V. R., R. Thompson, and K. Venkataraman. 2004. The impact of Regulation Fair Disclosure: Trading costs and information asymmetry. *Journal of Financial and Quantitative Analysis* 39 (02):209-225.

Francis, J., D. Nanda, and X. Wang. 2006. Re-examining the effects of regulation fair disclosure using foreign listed firms to control for concurrent shocks. *Journal of Accounting and Economics* 41 (3):271-292.

Frankel, R., S. Kothari, and J. Weber. 2006. Determinants of the informativeness of analyst research. *Journal of Accounting and Economics* 41 (2):29-54.

Gintschel, A., and S. Markov. 2004. The effectiveness of Regulation FD. *Journal of Accounting and Economics* 37 (3):293-314.

Gomes, A., G. Gorton, and L. Madureira. 2007. SEC Regulation Fair Disclosure, Information, and the Cost of Capital. *Journal of Corporate Finance* 13: 300-334.

Goyenko, R., C. Holden, and C. Trzcinka. 2009. Do liquidity measures measure liquidity? *Journal of Financial Economics* 92: 153-181.

Heflin, F., K. Subramanyam, and Y. Zhang. 2003. Regulation FD and the financial information environment: Early evidence. *The Accounting Review* 78 (1):1-37.

IPO Task Force. 2011. Rebuiliding the IPO on-ramp: Putting emerging companies and the job market back on the road to growth. Working paper.

Kadan, O., L. Madureira, R. Wang, and T. Zach. 2009. Conflicts of interest and stock recommendations: The effects of the global settlement and related regulations. *Review of Financial Studies* 22 (10):4189-4217.

Lang, M., and R. Lundholm. 1993. Cross-sectional determinants of analyst ratings of corporate disclosures. *Journal of Accounting Research* 31 (2):246-271.

Leuz, C., and R. E. Verrecchia. 2000. The economic consequences of increased disclosure. *Journal of Accounting Research*:91-124.

Leuz, C. and P. Wysocki. 2016. The Economics of Disclosure and Financial Reporting Regulation: Evidence and Suggestions for Future Research. *Working paper*.

Michaels, D. 2013. SEC favors pilot to vary tick sizes for small stocks. *Bloomberg*

Ronen, T., and D. G. Weaver. 2001. 'Teenies' anyone? *Journal of Financial Markets* 4 (3):231-260.

Securities and Exchange Commission (SEC). 2001. Special Study: Regulation Fair Disclosure Revisited

Securities and Exchange Commission (SEC). 2012. The SEC report to Congress on decimalization.

Unger, L. 2003. Special study: regulation fair disclosure revisited. US Securities and Exchange Commission (2003).

Weild, D., and E. Kim. 2010. Market structure is causing the IPO crisis—and more. *Capital Market Series, Grant Thornton*.

Weild, D., E. Kim, and L. Newport. 2012. The trouble with small tick sizes. *Capital Market Series, Grant Thornton*.

Yu, F. 2008. Analyst coverage and earnings management. *Journal of Financial Economics* 88 (2):245-271.

Appendix A
Variable Definitions

Variable	Definition
Num_Analyst	The number of analysts who issue quarterly earnings forecasts within 90 days before earnings announcement dates
Num_Forecast	The number of earnings forecasts issued within 90 days before earnings announcement dates
LogMVE	Natural Log of market value of equity at the quarter end.
GROWTH	Growth rate of assets: the change of assets scaled by lagged assets.
EXT_FIN	External financing activities: the sum of net cash received from equity and debt issuance scaled by total assets.
ROA_{t-1}	Lagged return on assets, where return on assets is calculated by net income divided by total assets.
CF_VOL	Cash flow volatility: the standard deviations of cash flows of a firm in the entire sample period (2000Q2 to 2002Q4) with at least five quarters of operating cash flows, scaled by lagged assets.
FD	An indicator variable that equals 1 if the earnings announcement date or the daily observation occurs after the implementation of Regulation FD (10/23/2000), and 0 otherwise.
DEC	An indicator variable that equals 1 if the earnings announcement date or the daily observation occurs after decimalization (NYSE: 1/19/2001; NASDAQ: 4/9/2001), and 0 otherwise.
GARS	An indicator variable that equals 1 if the earnings announcement date or daily observation occurs after GARS (7/1/2002), and 0 otherwise.
FP	An indicator variable that equals 1 if the earnings announcement date or the analyst forecast date occurs after fractional pricing, and 0 otherwise.
QTR4	An indicator variable that equals 1 if a quarter is the fourth fiscal quarter.
AF_INFO	The absolute size-adjusted stock return on the date when an analyst issues earnings forecast
SIGMA (Fitted Value)	SIGMA is the daily return variance for 90 days before each analyst's report date. Following Frankel et al. (2006), we rank quarterly the sample firms according to return volatility and assign firms to three portfolios. We then use return volatility portfolio ranks as instruments to proxy for the level of volatility. SIGMA (Fitted Value) is the fitted value from the first-stage regression.
LnVOL (Fitted Value)	LnVOL is the natural log of average daily trading volume for 90 days before each analyst's report date. Following Frankel et al. (2006), we rank quarterly the sample firms according to average daily trading volume and assign firms to three portfolios. We then use return volatility portfolio ranks as instruments to proxy for the level of average trading volume. LnVOL (Fitted Value) is the fitted value from the first-stage regression.
INST	Institutional holdings: the percentage of shares held by institutions in a

	given year.
LnOwners	Natural log of the number of shareholders in a given year.
MB	Market-to-book ratio at the quarter end.
NSIC	The number of firms in a firm's four digit industry classification in a quarter (CRSP four digit SIC code) divided by the total number of firms on CRSP in the same quarter.
MMRsq	R^2 from firm's market-model regression in a quarter using daily returns.
NSEGS	The number of industry segments of the firm.
AccRsq	Following Frankel et al. (2006), AccRsq is a measure of the price earnings association which is derived from the fitted residuals from a pooled cross-sectional regression of prices on the book values of shareholders' equity and earnings.
LnAnalyst	Natural log of the number of analysts following the firm.
GNEWS	An indicator variable equal to one if buy-and-hold return during the quarter is positive.
PILOT	An indicator variable that equals one if a firm was in the NYSE pilot program
DEC_PILOT	An indicator variable that equals one if an analyst report is issued for a pilot firm after Decimalization pilot date, zero otherwise.
Eff_Spread	Average of the "spread_0" measure calculated following Corwin and Schultz (2012). The average of the "spread_0" measure over the three-day earnings announcement window, and for the long-window sample it is the average of the "spread_0" measure over the regulatory regime periods.
Ab_Ret_Vol	Abnormal return volatilities around earnings announcement window (-1,1), where abnormal returns are based on one-factor market model estimated over (-200,-11).
Ab_Volume	Abnormal volume around earnings announcement window (-1,1), where abnormal volume is based on the firm's average volume estimated over (-200,-11).
MVE	Market value of equity at the quarter end.
$RETVOL_{1999}$	The standard deviation of stock returns over the calendar year 1999.
VOL_{1999}	Average trading volume calculated over the calendar year 1999.
FDISP	Analyst forecast dispersions: standard deviation of analysts' quarterly earnings forecasts in I/B/E/S detailed files.
ABSUE	The absolute value of the difference between actual earnings and the most recent consensus analyst forecast, scaled by stock price at the quarter end.

Appendix B
Regulations Timeline

DATE	EVENT
8/28/2000	First pilot program of 7 securities for NYSE Decimalization begins. (We eliminate these stocks in our main analysis.)
9/25/2000	Second pilot program of 57 securities for NYSE Decimalization begins. (We eliminate these stocks in our main analysis.)
10/23/2000	Regulation Fair Disclosure becomes effective.
12/9/2000	Third pilot program of 94 securities for NYSE Decimalization begins. (We eliminate these stocks in our main analysis.)
1/29/2001	NYSE adopts full Decimalization.
3/12/2001	First pilot program of 15 securities for NASDAQ Decimalization begins. (We eliminate these stocks in our main analysis.)
3/26/2001	Second pilot program of 177 securities for NASDAQ Decimalization begins. (We eliminate these stocks in our main analysis.)
4/9/2001	NASDAQ adopts full Decimalization.
7/01/2002	GARS regulations become effective.

Table 1
Sample Descriptive Statistics on Analyst Coverage

This table presents the descriptive statistics for analyst coverage for firm-quarters between 2000Q2 and 2002Q4. Panel A reports descriptive statistics for the whole sample, and Panels B reports descriptive statistics by firm size. All variables are defined in Appendix A, and all continuous variables are winsorized at the 1% and 99% level.

Panel A: Sample Descriptive Statistics.

	N	Mean	Median	St. Dev.
Num_Analyst	16422	7.071	5.000	5.393
Num_Forecast	16422	10.530	7.000	10.660
LogMVE	16422	13.930	13.810	1.658
ROA_{t-1}	16422	0.000	0.009	0.051
GROWTH	16422	0.042	0.009	0.177
EXT_FIN	16422	0.033	0.004	0.117
CF_VOL	16422	0.053	0.043	0.039

Panel B: Descriptive Statistics by Firm Size.

	Small firms N = 5469	Medium firms N=5465	Large firms N=5488
	Mean	Mean	Mean
Num_Analyst	4.431	6.254	10.520
Num_Forecast	6.286	9.293	15.980
LogMVE	12.180	13.820	15.770
ROA_{t-1}	-0.016	0.004	0.012
GROWTH	0.018	0.054	0.053
EXT_FIN	0.043	0.034	0.022
CF_VOL	0.059	0.054	0.047

Table 2

The Impact of Reg FD, Decimalization and GARS on Analyst Coverage

This table reports the effect of Reg FD, Decimalization and GARS on analyst coverage. The results for the pooled sample are presented in the first column, followed by results of different firm size. The sample period is 2000Q2 to 2002Q4. The dependent variable in Panel A is *Num_Analyst*, which is the number of analysts who issued at least one earnings forecasts within 90 days before earnings announcement dates. The dependent variable in Panel B is *Num_Forecast*, which is the total number of earnings forecasts issued within 90 days before earnings announcement dates. All variables are defined in Appendix A, and all continuous variables are winsorized at the 1% and 99% level. Robust t-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: The Impact of Reg FD, Decimalization and GARS on the Number of Analysts Issuing Earnings Forecasts

	Full	**Small**	**Medium**	**Large**
	(1)	(2)	(3)	(4)
FD	**0.248****	0.173	0.174	0.0120
	(2.01)	(1.50)	(0.91)	(0.04)
DEC	**0.902*****	**0.286****	**0.737*****	**2.045*****
	(7.67)	(2.54)	(4.05)	(7.22)
GARS	0.0210	**0.411*****	-0.164	-0.298
	(0.21)	(3.67)	(-1.01)	(-1.25)
LogMVE	1.783***	0.787***	2.260***	2.088***
	(67.91)	(14.77)	(15.33)	(25.34)
ROA_{t-1}	-7.605***	-6.089***	-5.249***	-12.900***
	(-9.52)	(-7.59)	(-3.52)	(-4.37)
GROWTH	-1.525***	-0.828***	-1.256***	-1.624***
	(-7.00)	(-2.88)	(-3.72)	(-3.28)
EXT_FIN	-0.493	0.595*	-0.907*	-2.237***
	(-1.61)	(1.88)	(-1.83)	(-2.69)
CF_VOL	3.738***	-4.051***	3.494**	16.157***
	(4.02)	(-4.68)	(2.03)	(5.94)
QTR4	-0.686***	-0.430***	-0.912***	-0.734***
	(-6.05)	(-3.86)	(-5.66)	(-2.73)
Constant	-18.547***	-5.378***	-25.487***	-24.005***
	(-49.68)	(-8.21)	(-12.56)	(-18.17)
Observations	16422	5469	5465	5488
Adjusted R^2	0.288	0.06	0.062	0.137

Table 2 - Continued

Panel B: The Impact of Reg FD, Decimalization and GARS on the Number of Earnings Forecasts

	Full	**Small**	**Medium**	**Large**
	(1)	(2)	(3)	(4)
FD	0.424	0.0780	0.0850	0.395
	(1.62)	(0.36)	(0.22)	(0.61)
DEC	**2.084*****	**0.956*****	**1.778*****	**4.058*****
	(7.77)	(4.17)	(4.46)	(6.04)
GARS	-0.279	**0.468****	-0.417	**-1.046****
	(-1.36)	(2.35)	(-1.22)	(-2.15)
LogMVE	2.805***	1.122***	3.896***	3.190***
	(48.79)	(11.86)	(12.73)	(17.77)
ROA_{t-1}	-8.234***	-4.945***	-3.243	-22.039***
	(-5.52)	(-4.09)	(-1.36)	(-3.52)
GROWTH	-2.798***	-1.208**	-2.111***	-4.361***
	(-6.96)	(-2.20)	(-3.37)	(-4.56)
EXT_FIN	-1.476**	1.256**	-2.845***	-3.156*
	(-2.37)	(2.10)	(-2.77)	(-1.79)
CF_VOL	9.078***	-5.677***	11.812***	30.230***
	(4.83)	(-3.70)	(3.11)	(5.57)
QTR4	4.472***	2.715***	3.367***	7.197***
	(13.88)	(8.69)	(7.39)	(9.40)
Constant	-31.059***	-8.296***	-46.543***	-38.798***
	(-37.70)	(-7.08)	(-11.01)	(-13.49)
Observations	16422	5469	5465	5488
Adjusted R^2	0.206	0.061	0.057	0.113

Table 3
Sample Descriptive Statistics of Analyst Forecast Informativeness
The table below presents the descriptive statistics for the sample of analysts' earnings forecasts. The sample includes analyst earnings forecasts for firm-quarters between 2000Q2 to 2002Q4. Panel A reports descriptive statistics for the whole sample, and Panels B reports descriptive statistics by firm size. All variables are defined in Appendix A, and all continuous variables are winsorized at the 1% and 99% level.

Panel A: Sample Descriptive Statistics of Analyst Forecasts

	N	Mean	Median	St. Dev.
AF_INFO	81951	0.032	0.019	0.039
SIGMA	81951	0.002	0.001	0.002
LnVOL	81951	17.350	17.360	1.620
INST	81951	0.581	0.609	0.219
LnOwners	81951	1.476	1.456	2.301
MB	81951	3.441	2.382	3.831
LogMVE	81951	14.400	14.270	1.912
NSIC	81951	0.008	0.004	0.010
MMRsq	81951	0.204	0.159	0.175
NSEGS	81951	3.045	3.000	2.287
AccRsq	81951	5.015	5.771	3.112
LnAnalyst	81951	1.809	1.946	0.898
GNEWS	81951	0.254	0.000	0.435

Panel B: Descriptive Statistics by Size

	Small firms N = 27268	Medium firms N=27291	Large firms N=27392
	Mean	Mean	Mean
Analyst_INFO	0.043	0.029	0.023
SIGMA	0.003	0.002	0.001
LnVOL	16.110	17.300	18.750
INST	0.497	0.635	0.619
LnOwners	-0.037	1.210	3.408
MB	2.488	3.441	4.488
LogMVE	12.420	14.380	16.600
NSIC	0.010	0.007	0.007
MMRsq	0.143	0.231	0.244
NSEGS	1.953	3.030	4.258
AccRsq	4.410	5.166	5.524
LnAnalyst	1.201	1.868	2.415
GNEWS	0.209	0.295	0.262

Table 4
The Impact of Reg FD, Decimalization and GARS on Analyst Forecast Informativeness
This table reports the effect of Reg FD, Decimalization and GARS on analyst earnings forecast informativeness. The dependent variable is the absolute abnormal return on the day of an analyst's earnings forecast. All variables are defined in Appendix A, and all continuous variables are winsorized at the 1% and 99% level. Robust t-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Full	**Small**	**Medium**	**Large**
	(1)	(2)	(3)	(4)
FD	**-0.0012****	**-0.0028*****	-0.0003	0.0007
	(-2.53)	(-2.58)	(-0.43)	(1.13)
DEC	**0.0039*****	**0.0055*****	**0.0034*****	**-0.0011***
	(7.48)	(5.06)	(4.18)	(-1.79)
GARS	**0.0041*****	**0.0028*****	**0.0051*****	**0.0036*****
	(10.88)	(3.38)	(8.01)	(7.71)
SIGMA (Fitted Value)	10.1978***	9.6567***	9.8326***	8.7549***
	(43.42)	(24.96)	(29.67)	(22.61)
LnVOL (Fitted Value)	-0.0032***	-0.0029***	-0.0026***	-0.0003
	(-8.89)	(-4.05)	(-5.50)	(-0.53)
INST	0.0067***	0.0094***	0.0064***	-0.0009
	(8.67)	(6.22)	(5.17)	(-0.83)
LnOwners	0.0001	-0.0003*	0.0004***	-0.00004
	(0.91)	(-1.83)	(2.88)	(-0.41)
MB	-0.0001***	-0.0002	-0.0001*	-0.00005
	(-3.49)	(-1.60)	(-1.83)	(-0.92)
LogMVE	0.0021***	0.0021***	0.0013**	0.00003
	(6.88)	(3.21)	(2.13)	(0.08)
NSIC	-0.1082***	-0.0261	-0.2026***	-0.0976***
	(-7.10)	(-0.95)	(-7.50)	(-4.57)
MMRsq	-0.0215***	-0.0261***	-0.0233***	-0.0160***
	(-24.63)	(-9.77)	(-16.35)	(-15.76)
NSEGS	0.00003	0.0003	-0.0002	0.00002
	(0.55)	(1.61)	(-1.63)	(0.32)
AccRsq	0.0002***	0.0002***	0.0002**	0.0005***
	(5.47)	(2.59)	(2.14)	(4.42)
LnAnalyst	0.0005***	0.0007	0.0004	-0.00003
	(2.58)	(1.46)	(1.30)	(-0.11)
GNEWS	-0.0015***	-0.00110	-0.0014***	-0.0015***
	(-4.57)	(-1.40)	(-2.76)	(-3.95)
QTR4	-0.0001	-0.0004	0.0003	-0.0004
	(-0.50)	(-0.67)	(0.55)	(-1.01)
Constant	0.0335***	0.0289***	0.0359***	0.0193***
	(15.44)	(4.47)	(5.61)	(5.03)
Observations	81951	27268	27291	27392
Adjusted R^2	0.1441	0.0987	0.1237	0.1416

Table 5
The Impact of the 1997 Fractional Pricing on Analyst Coverage and Forecast Informativeness

This table reports the effect of 1997 Fractional Pricing on analyst coverage and forecast informativeness. The sample period is 1996Q1 to 1998Q4. All variables are defined in Appendix A, and all continuous variables are winsorized at 1% and 99% level. Robust t-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: The Impact of Fractional Pricing on the Number of Analysts Issuing Earnings Forecasts

	Full	**Small**	**Medium**	**Large**
	(1)	(2)	(3)	(4)
FP	0.0430	**0.175*** **	**0.189*** **	**-0.280** **
	(0.87)	(4.12)	(2.77)	(-2.43)
LogMVE	1.759***	0.644***	1.595***	2.587***
	(87.40)	(19.98)	(18.72)	(39.41)
ROA_{t-1}	-3.267***	0.241	-4.668***	-5.981**
	(-4.83)	(0.51)	(-4.58)	(-2.37)
GROWTH	-1.341***	-0.610***	-0.977***	-1.742***
	(-8.12)	(-4.43)	(-4.59)	(-3.57)
EXT_FIN	-0.368*	0.472***	0.386	-0.565
	(-1.73)	(2.67)	(1.28)	(-0.74)
CF_VOL	3.835***	-2.830***	-0.339	17.843***
	(5.82)	(-6.84)	(-0.41)	(8.63)
QTR4	0.597***	0.178***	0.375***	1.136***
	(9.42)	(3.47)	(4.56)	(7.74)
Constant	-18.188***	-4.066***	-16.485***	-31.366***
	(-65.30)	(-10.80)	(-14.48)	(-30.45)
Observations	22261	6467	7766	7731
Adjusted R^2	0.371	0.062	0.053	0.216

Table 5 - Continued

Panel B: The Impact of Fractional Pricing on the Number of Earnings Forecasts.

	Full	**Small**	**Medium**	**Large**
	(1)	(2)	(3)	(4)
FP	0.0280	**0.340*****	**0.353*****	**-0.627****
	(0.26)	(4.01)	(2.63)	(-2.39)
LogMVE	2.767***	0.906***	2.385***	3.909***
	(61.87)	(13.86)	(13.98)	(25.67)
ROA_{t-1}	-5.813***	2.151**	-7.846***	-12.471**
	(-4.38)	(2.32)	(-4.30)	(-2.44)
GROWTH	-2.853***	-1.302***	-2.426***	-4.419***
	(-8.13)	(-4.56)	(-5.50)	(-4.14)
EXT_FIN	-0.783*	1.227***	1.338**	-1.185
	(-1.66)	(3.20)	(2.05)	(-0.68)
CF_VOL	5.432***	-4.720***	1.774	24.972***
	(4.07)	(-5.52)	(1.10)	(5.84)
QTR4	5.204***	2.824***	3.942***	8.393***
	(30.67)	(22.50)	(19.37)	(20.55)
Constant	-29.993***	-6.212***	-25.804***	-48.429***
	(-48.87)	(-8.09)	(-11.30)	(-20.36)
Observations	22261	6467	7766	7731
Adjusted R^2	0.279	0.141	0.104	0.181

Table 5 - Continued

Panel C: The Impact of Fractional Pricing on Analyst Forecast Informativeness

	Full	**Small**	**Medium**	**Large**
	(1)	(2)	(3)	(4)
FP	**0.0014*** **	**0.0016*** **	**0.0015*** **	**0.0008*** **
	(11.04)	(5.58)	(6.72)	(5.21)
SIGMA (Fitted Value)	14.9270***	15.4764***	13.9767***	12.5399***
	(50.89)	(29.19)	(30.71)	(27.22)
LnVOL (Fitted Value)	-0.0020***	-0.0041***	-0.0008***	0.0005**
	(-11.11)	(-10.24)	(-3.25)	(2.42)
INST	0.0037***	0.0062***	0.0013**	0.0012***
	(10.09)	(7.84)	(2.47)	(2.87)
LnOwners	0.00003	0.0003***	0.0001	-0.0003***
	(0.81)	(2.76)	(0.75)	(-4.97)
MB	-0.0001***	-0.0002***	-0.0001	-0.00002
	(-3.92)	(-4.11)	(-1.59)	(-1.02)
LogMVE	0.0012***	0.0026***	-0.0005	-0.0002
	(7.39)	(6.41)	(-1.55)	(-1.28)
NSIC	-0.0731***	-0.0444***	-0.0971***	-0.0310**
	(-8.45)	(-2.61)	(-7.00)	(-2.56)
MMRsq	-0.0043***	0.00130	-0.0016*	-0.0041***
	(-7.70)	(0.70)	(-1.69)	(-7.71)
NSEGS	-0.0003***	-0.0002	-0.0002**	-0.0001***
	(-6.05)	(-1.30)	(-2.55)	(-2.88)
AccRsq	-0.0001***	0.000	-0.000100	-0.0003***
	(-2.76)	(0.03)	(-0.99)	(-6.36)
LnAnalyst	0.0012***	0.0015***	0.0007***	0.0007***
	(10.77)	(6.42)	(3.83)	(5.00)
GNEWS	-0.0004***	-0.0009***	-0.0002	-0.0004***
	(-3.30)	(-2.73)	(-0.71)	(-3.02)
QTR4	-0.0005***	-0.0007**	-0.0005**	-0.00003
	(-3.13)	(-2.11)	(-2.16)	(-0.21)
Constant	0.0223***	0.0334***	0.0284***	0.0034*
	(19.33)	(10.92)	(8.79)	(1.65)
Observations	128987	42951	42919	43117
Adjusted R^2	0.1537	0.0774	0.1277	0.1331

Table 6

Difference-in-Difference Analysis on NYSE Pilot Firms: Analyst Forecast Informativeness

This table reports the Difference-in-Difference test of Decimalization on analyst earning forecasts informativeness. The dependent variable is the absolute abnormal return on the day of analyst's earnings forecast. DEC_PILOT is an indicator variable equaling one if an analyst forecasts is issued for a pilot firm after Decimalization pilot date, zero otherwise. Each pilot firm is matched with a control firm by same industry, size decile, and market-to-book value decile. All variables are defined in Appendix A, and all continuous variables are winsorized at the 1% and 99% level. Robust t-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	NYSE Pilot Firms	**NYSE Pilot Firms**
PILOT	-0.0011	-0.0001
	(-0.92)	(1.69)
DEC_PILOT	**0.005*** **	0.003
	(2.58)	(1.58)
FD	-0.003	-0.003
	(-1.12)	(-1.31)
Constant	0.021***	0.034
	(18.24)	(1.69)
Year-by-Quarter Fixed Effect	Yes	Yes
Controls	No	Yes
Observations	1329	1329
Adjusted R^2	0.01	0.03

Table 7
Sample Descriptive Statistics for Earnings Announcements
This table presents the descriptive statistics for the earnings announcements between 2000Q2 to 2002Q4. Panel A reports descriptive statistics for the whole sample, while Panels B reports descriptive statistics by firm size. All variables are defined in Appendix A, and all continuous variables are winsorized at the 1% and 99% level.

Panel A: Sample Descriptive Statistics for Earnings Announcements

	N	Mean	Median	St. Dev.
Eff_Spread	21213	0.015	0.011	0.014
Ab_Ret_Vol	21213	0.109	0.081	0.091
Ab_Volume	21213	0.497	0.194	1.152
MVE	21213	4400	790	12000
VOL_{1999}	21213	0.546	0.222	0.924
$RETVOL_{1999}$	21213	0.038	0.033	0.019
FDISP	21213	0.089	0.017	0.216
ABSUE	21213	0.009	0.001	0.026

Panel B: Descriptive statistics by Firm Size

	Small firms N = 7071	Medium firms N=7071	Large firms N=7071
	Mean	Mean	Mean
Eff_Spread	0.019	0.014	0.012
Ab_Ret_Vol	0.132	0.106	0.088
Ab_Volume	0.352	0.576	0.562
MVE	180	860	12,000
VOL_{1999}	0.219	0.305	1.113
$RETVOL_{1999}$	0.046	0.037	0.03
FDISP	0.072	0.087	0.109
ABSUS	0.018	0.006	0.004

Table 8

The Impact of Reg FD, Decimalization and GARS on Abnormal Return Volatilities around Earnings Announcements

The table below presents the results from analyzing abnormal return volatilities around earnings announcements. The results for the pooled sample are presented first, followed by results of different firm size. The sample period is 2000Q2 to 2002Q4. All variables are defined in Appendix A, and all continuous variables are winsorized at the 1% and 99% level. Robust t-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Full	**Small**	**Medium**	**Large**
	(1)	(2)	(3)	(4)
FD	**0.009*** **	**0.025*** **	0.00300	-0.00200
	(4.10)	(6.08)	(0.73)	(-0.71)
DEC	**-0.034*** **	**-0.038*** **	**-0.033*** **	**-0.031*** **
	(-17.17)	(-9.74)	(-9.38)	(-10.95)
GARS	**0.020*** **	**0.026*** **	**0.014*** **	**0.020*** **
	(11.99)	(7.73)	(4.91)	(8.37)
ABSUE	0.689***	0.724***	0.473***	0.531***
	(26.19)	(19.30)	(6.49)	(6.40)
LogMVE	-0.008***	-0.010***	-0.011***	-0.005***
	(-22.65)	(-5.80)	(-4.21)	(-6.44)
FDISP	-0.055***	-0.059***	-0.044***	-0.062***
	(-14.61)	(-6.75)	(-6.41)	(-11.66)
QTR4	0.00200	-0.012***	0.00400	0.020***
	(0.69)	(-2.73)	(1.00)	(5.59)
Constant	0.230***	0.239***	0.267***	0.185***
	(44.73)	(11.85)	(7.79)	(15.08)
Observations	21213	7071	7071	7071
Adjusted R^2	0.102	0.094	0.036	0.067

Table 9

The Impact of Reg FD, Decimalization and GARS on Abnormal Trading Volume around Earnings Announcements

The table below presents the results from analyzing abnormal trading volume around earnings announcements. The results for the pooled sample are presented first, followed by results of different firm size. The sample period is 2000Q2 to 2002Q4. All variables are defined in Appendix A, and all continuous variables are winsorized at the 1% and 99% level. Robust t-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Full	**Small**	**Medium**	**Large**
	(1)	(2)	(3)	(4)
FD	**0.367*** **	**0.469*** **	**0.469*** **	**0.239*** **
	(9.89)	(5.99)	(7.68)	(5.01)
DEC	**-0.208*** **	**-0.209*** **	**-0.222*** **	**-0.213*** **
	(-6.01)	(-2.87)	(-3.93)	(-4.77)
GARS	**0.145*** **	0.0120	**0.096** **	**0.361*** **
	(5.06)	(0.19)	(2.09)	(9.86)
ABSUE	0.047***	0.082***	0.0510	-0.00400
	(7.27)	(2.77)	(1.25)	(-0.33)
LogMVE	-0.183***	-0.00400	-0.0840	-0.251***
	(-2.94)	(-0.03)	(-0.82)	(-3.33)
FDISP	1.442**	-3.274***	4.303***	9.048***
	(2.41)	(-2.91)	(4.43)	(9.47)
$RETVOL_{1999}$	0.0270	-0.0290	-0.0260	0.0810
	(0.68)	(-0.36)	(-0.39)	(1.44)
QTR4	-0.315***	-0.618*	-0.458	0.283
	(-3.11)	(-1.68)	(-0.82)	(1.42)
Constant	0.367***	0.469***	0.469***	0.239***
	(9.89)	(5.99)	(7.68)	(5.01)
Observations	21213	7071	7071	7071
Adjusted R^2	0.009	0.007	0.013	0.03

Table 10
The Impact of Reg FD, Decimalization and GARS on Effective Spread around Earnings Announcements
The table below presents the results from analyzing effective spread around earnings announcements. The results for the pooled sample are presented first, followed by results of different firm size. The sample period is 2000Q2 to 2002Q4. The dependent variable is *log(1+Eff_Spread)*. All variables are defined in Appendix A, and all continuous variables are winsorized at the 1% and 99% level. Robust t-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Full	**Small**	**Medium**	**Large**
	(1)	(2)	(3)	(4)
FD	**0.001***	**0.002*****	0.0004	**-0.001*****
	(1.80)	(3.06)	(0.80)	(-2.61)
DEC	**-0.004*****	**-0.005*****	**-0.003*****	**-0.002*****
	(-11.86)	(-7.99)	(-6.54)	(-4.65)
GARS	**0.004*****	**0.004*****	**0.004*****	**0.004*****
	(16.20)	(8.13)	(9.46)	(12.34)
ABSUE	0.050***	0.038***	0.033***	0.00800
	(12.90)	(6.59)	(3.54)	(0.77)
LogMVE	-0.001***	-0.004***	-0.001	-0.0001
	(-16.83)	(-13.06)	(-1.40)	(-0.82)
$LogVOL_{1999}$	0.001***	0.002***	0.001***	0.0002
	(15.22)	(10.58)	(5.81)	(1.38)
$LogRETVOL_{1999}$	0.008***	0.008***	0.009***	0.010***
	(32.89)	(13.63)	(21.35)	(27.77)
QTR4	-0.001***	-0.002***	-0.001*	0.0003
	(-5.11)	(-3.43)	(-1.86)	(0.74)
Constant	0.046***	0.063***	0.040***	0.047***
	(40.59)	(15.61)	(8.31)	(21.62)
Observations	21213	7071	7071	7071
Adjusted R^2	0.199	0.186	0.146	0.166