Market Transparency and Pricing Efficiency: Evidence from Corporate Bond Market*

Jia Chen
chen.1002@gmail.com
Guanghua School of Management
Peking University

Ruichang Lu
ruichanglu@gsm.pku.edu.cn
Guanghua School of Management
Peking University

September 1, 2016

Abstract

This paper investigates how mandatory post-trade market transparency affects pricing efficiency in the corporate bond market. Using the phase implementation of TRACE and a differences-in-differences research design, we find that higher transparency leads to a shorter return drift and a lower price delay. These effects are similar between bonds with low and high liquidity and between bonds with low and high trading activity. In addition, the increase in market transparency leads to a higher co-movement between individual bond return and bond market return. These results highlight the importance of market transparency on the information efficiency in financial markets.

*We thank Bing Han, Laura Liu, Qiao Liu, Xiong Wei, Lucy White, Liyan Yang, and Haoxiang Zhu and brown bag participants at the Guanghua School of Management and the Five-star workshop at Tsinghua PBC School of Finance.

1 Introduction

Transparency is a fundamental issue in the functioning of financial markets to which financial economics have paid substantial attention. Researchers write down models to study how transparency induced by different market structure impacts welfare, trading activity, and liquidity (Biais, 1993; Naik, Neuberger, and Viswanathan, 1999; Madhavan, 1995, 1996; Pagano and Röell, 1996). Empirical studies examine how transparency changes caused by regulatory changes in equity and bond markets affect trading and liquidity (Boehmer, Saar, and Yu, 2005; Gemmill, 1996; Bessembinder, Maxwell, and Venkataraman, 2006; Madhavan, Porter, and Weaver, 2005; Edwards, Harris, and Piwowar, 2007; Goldstein, Hotchkiss, and Sirri, 2007; Asquith, Covert, and Pathak, 2013). Laboratory experiments are used to help determine the effects of transparency changes (Bloomfield and O'Hara, 1999, 2000).

There have been disagreements on what effects market transparency has on pricing efficiency between regulators and researchers. On the one hand, a positive, beneficial view is often held by U.S regulators: transparency improves the price discovery, fairness, competitiveness, and attractiveness of U.S. markets (SEC, 1994). A number of studies support this view using different contexts: market fragmentation versus consolidation (Madhavan, 1995), auction versus dealer markets (Pagano and Röell, 1996), and experiments (Bloomfield and O'Hara, 1999). The intuition of this view is simple. Transparency helps pricing efficiency because patterns in trades allow investors to better learn information from trades and thereby set their prices more efficiently.

On the other hand, UK regulators have had concerns that increased market transparency may reduce liquidity and/or market efficiency (Franks and Schaefer, 1995). Several recent papers argue that transparency may have adverse impacts on market efficiency in the contexts of correlated asset values (Asriyan, Fuchs, and Green, 2015), investors with or without immediate liquidity needs (Bhattacharya, 2016), and liquidity traders' learning about fundamentals (Banerjee, Davis, and Gondhi, 2016). In these models, investors' incentives of collecting fundamental information can be lowered by transparency, leading to less informative prices and lower pricing efficiency.

Despite the research importance and attention, the empirical research on this topic is relatively little, partially due to the lack of data and the rarity of the regulation change event. In this paper, we offer empirical evidence on how a specific form of transparency, post-trade transparency, causally impacts pricing efficiency. Specifically, we use the implementation phases of Trade Reporting and Compliance Engine (TRACE) to examine whether disclosing trading price and volume information after the trade affects pricing efficiency. We focus on the impacts of transparency on pricing efficiency because pricing efficiency is critical for financial markets to provide accurate information for resource allocation (Fama, 1970).

TRACE implementation provides a unique setting for understanding the impacts of market transparency on pricing discovery. From 1940s to July 2002, there was no public disclosure of transaction details in the corporate bond market, where transactions happened over the counter with private negotiations.[1] In July 2002, the prices and volume information of transactions became publicly disclosed after the transactions were completed. FINRA (then NASD) required all transactions of U.S. corporate bonds by regulated market participants be reported to TRACE shortly after transaction completion. TRACE then publicly release the prices and volume information, which is known as dissemination.

The implementation of TRACE is not applied to all bonds at the same time. Although TRACE began collecting all price and volume information for all corporate bonds in July 2002, it began on that day dissemination of this information for a subset of bonds. Three other primary TRACE implementation phases (Phases 2, 3A, and 3B) followed, each including more bonds into the dissemination. FINRA assigned bonds into each phase according to bond issue size, credit quality, and previous levels of trading activity. In February 2005, all corporate bonds' price and volume information was publicly disseminated shortly after trade completion.

We take advantage of these implementation phases to conduct a difference-in-difference analysis that compares the price discovery speed of bonds subject to a change in transparency and that of the bonds that are not. This research design helps control for the confounding effects of unobserved shocks to the corporate bond markets.

We consider two primary pricing efficiency measures: bond return drift after a bond analysts' report or credit rating change and the delay with which a bond's price responds to information. We follow Gleason and Lee (2003) to define the return drift measure as 8-week sum of the absolute abnormal return ($\sum_{n=1}^{8} |AR_n|$) after a bond analyst report or rating change. We follow Hou and Moskowitz (2005) to define the price delay measure. Both these measures rely on an intuitive principle: a security price that is slow to incorporate information in market events or market index movements is less efficient than a security price that instantaneously incorporates the information. Both these measures decrease with pricing efficiency.

We find that post-trade transparency of price and volume leads to a significant increase in pricing efficiency. According to our difference-in-difference regression analysis, drift after bond analyst's reports decreases by about 50% after phase implementation in all three phases compared to pre-phase levels. Drift after credit rating change decreases by about

[1] See Biais and Green (2007) and Piwowar (2011) for detailed account of evolution of the transparency regulations in the bond market.

30% after phase implementation in phase 3A and 3B and 5% in phase 2 compared to pre-phase implementation levels . Delay decreases by about 16% for in one year after phase implementation for Phase 2 bonds, 25% for Phase 3A bonds, and 24% for Phase 3B bonds. These results are robust to using different ways of measuring delay and logarithm and logistic transformations of the drift and delay measures. These findings suggest that with higher transparency information is more quickly incorporated into bond prices, which is consistent with the conclusions of Madhavan (1995), Pagano and Röell (1996), and Bloomfield and O'Hara (1999).

Because recent papers suggest transparency can potentially lower investors' information collection incentive and reduce price informativeness (Asriyan et al., 2015; Bhattacharya, 2016; Banerjee et al., 2016), we consider the R-squared of the regression of individual bond returns on bond and stock market returns and bond portfolio returns. Previous literature suggests that this variable is negatively related to the informativeness of bond prices (Morck, Yeung, and Yu, 2000; Durnev, Morck, Yeung, and Zarowin, 2003; Durnev, Morck, and Yeung, 2004; Chun, Kim, Morck, and Yeung, 2008). We find that post-trade transparency significantly increases R-squared. A treated bond's R-squared increases by 59.6% relative to the mean of treated bonds' R-squared before phase implementation. These findings are consistent with the conjecture that transparency can lead to lower price informativeness.

Using TRACE implementation, previous studies show that higher market transparency can lead to higher liquidity (Bessembinder et al., 2006; Edwards et al., 2007; Goldstein et al., 2007) and lower trading activity (Asquith et al., 2013). These studies, however, do not examine the impact of market transparency on pricing efficiency. To understand whether the improvement of pricing efficiency can vary depending on the liquidity and trading activity characteristics of the bonds, we conduct the difference-in-difference analysis for different bond groups sorted by illiquidity and trading activity. Using Amihud as the illiquidity measure and the ratio of volume divided by issue amount as the trading activity measure, we find that the difference-in-difference estimates do not significantly differ between bonds with high and low illiquidity or bonds with high and low trading activity. Therefore, the impact of market transparency on pricing efficiency is relatively uniform across bonds with different liquidity and trading activity.

We study how higher bond market post-trade transparency impacts pricing efficiency and price informativeness of the stock market. We repeat the difference-in-difference regression analysis using the stocks corresponding to the treated bonds and the stocks corresponding to the control bonds and use as the dependent variable the delay measure and R-squared measure based on the stock prices. We find no significant improvements of pricing efficiency or price informativeness of stocks matched with the treated bonds relative to that of the stocks matched with the control bonds.

Our paper is closely related to and contributes to two strands of literature. First, it adds new empirical evidence to the literature that studies market transparency. This literature studies the effect of market transparency on pricing efficiency in a setting of laboratory experiment (Bloomfield and O'Hara, 1999, 2000) but is lack of empirical analysis using real market data. Our paper fills that void. Our paper is related to the literature that studies how implementation of TRACE impacts liquidity (Bessembinder et al., 2006; Edwards et al., 2007; Goldstein et al., 2007) and price dispersion and trading (Asquith et al., 2013). We consider pricing efficiency that this literature has not addressed.

Not only does our analysis contribute to the above literature, it is also relevant to the ongoing regulatory changes. During and after the Global Financial Crisis, the issues relating to the trading and the valuation of over-the-counter instruments during the crisis has made many people to promote greater transparency in such markets. As a result, regulatory agenda has considered implementing for these instruments trade reporting systems similar to TRACE and Transaction Reporting System (TRS). Such a system became effective for OTC swap trades in January 2013, and TRACE has expanded its coverage to including agency debentures, mortgage-backed securities, 144-A private placement, and asset backed securities in recent years. Our paper can help understand the potential impacts of these regulatory changes.

The rest of this paper is organized as follows. Section 2 reviews the related literature. Section 3 provides information on TRACE and discusses key empirical variables and the research design. Section 4 describes the data source and presents descriptive statistics. Section 5 shows the main difference-in-difference results. Section 6 concludes.

2 Related literature

Market transparency has received significant attention from researchers. A number of papers point out the positive effects of market transparency on the functioning of markets. Madhavan (1995) argues that fragmented markets will not become consolidated by themselves unless transparency of trade price information is required. Madhavan (1996) demonstrates that an increase in transparency of order flow information can lead to higher price informativeness but can potentially lead to higher price volatility and lower liquidity. Pagano and Röell (1996) define transparency as the extent to which market makers can observe the size and direction of the current order flow and find that greater transparency generates lower trading costs for uninformed traders on average, although not necessarily for every size of trade. Using laboratory experiments, Bloomfield and O'Hara (1999) find that trade disclosure significantly improves the informational efficiency of the markets but can cause spread to widen. They also find that quote disclosure has little effects.

A few recent theory papers discuss how market transparency might negatively impact efficiency. Asriyan, Fuchs, and Green (2015) argue that when asset values are correlated, higher market transparency does not necessarily lead to higher welfare. In a multi-period auction model, Bhattacharya (2016) shows that potential counterparties may delay their trades when there is transparency because they can monitor transaction prices and learn more before participating. As a result, investors with immediate liquidity needs suffer in terms of revenue. Banerjee, Davis, and Gondhi (2016) find that an increase in transparency can lower liquidity traders' incentives for learning about fundamentals and hence lead to lower informativeness. Goldstein and Yang (2016) and Han, Tang, and Yang (2016) both discuss the potential negative effects of public information transparency on real efficiency.

Four empirical studies have examined the change in market transparency due to TRACE phase implementation, each of which focuses on either the liquidity or trading costs. Bessembinder, Maxwell, and Venkataraman (2006) study the bonds in phase 1 using transaction data from the National Association of Insurance Commissioners. They find that the transaction costs reduce after the implementation of the phase 1 of TRACE. Edwards, Harris, and Piwowar (2007) exam the imputed transaction cost for phase 2 bonds. They find that transparent bonds have lower transaction costs. Goldstein, Hotchkiss, and Sirri (2007) use a controlled experiment of 120 BBB phase 2 bonds. Using a matching sample, they find that the transaction costs for all but the group with the smallest trade size experience a reduction. Asquith, Covert, and Pathak (2013) use the phase 1, 2, 3A, 3B of TRACE setting and find that the transparency causes a significant decrease in price dispersion for all bonds and a significant decrease in trading activity for some categories of bonds. They conclude that the mandated transparency may help some investors and dealers though a decline in price dispersion, while harming others through a reduction in trading activity.

3 Research design

3.1 TRACE

In this section, we first introduce the historical background of Trade Reporting and Compliance Engine (TRACE) and discuss why it provides an ideal setting for this research.

3.1.1 History and implementation of TRACE

The prices and volume of completed transactions became publicly disclosed when FINRA[2] launched TRACE in 2002.[3] All transactions in U.S. corporate bonds by regulated market participants were required to be reported to TRACE on a timely basis. FINRA then made this information transparent by publicly releasing it. FINRA called this disclosing process “disseminating”. TRACE covers any US dollar-denominated debt security that is depository-eligible and registered with SEC, or issued pursuant to Section 4(2) of Securities Act of 1933 and purchased or sold pursuant to Rule 144a.

When FINRA implemented TRACE on 1 July 2002, it required all transactions on TRACE-eligible securities to be reported within 75 minutes of trading. As described in Table 1, FINRA began disseminating price and volume data for trades in selected investment-grade bonds with initial issue of $1 billion or greater. We call these bonds Phase 1 bonds. The dissemination occurred immediately upon reporting for these bonds. Additionally, the 50 high-yield securities previously disseminated under FIPS were transferred to TRACE, whose trades were disseminated. We denote these bonds the FINRA50. About 520 securities had their information disseminated by the end of 2002.

After FINRA and SEC approved the expansion of TRACE beyond Phase 1, Phase 2 of TRACE was implemented on 3 March 2003, and it expanded dissemination to include smaller investment grade issues. The securities added into dissemination include those with at least $100 million par value or greater and rating of A- or higher. In addition, dissemination began on 14 April 2003 for a group of 120 investment-grade securities rated BBB. We denote these BBB bonds FINRA120. After Phase 2 was implemented, the number of disseminated bonds increased to approximatively 4,650 bonds. Meanwhile, the FINRA50 subset did not remain constant over the time period. On July 13, 2003, the FINRA50 list was updated, and the list was then updated quarterly for the next 5 quarters. We exclude FINRA50 and FINRA120 bonds from our analysis.

Finally, on 22 April 2004, after TRACE had been in effect for some bonds for almost two years, FINRA approved the expansion of TRACE to almost all bonds. The last Phase came in two parts, which FINRA designates as Phase 3A and Phase 3B. The distinction between Phase 3A and 3B is that Phase 3B bonds are eligible for delayed dissemination. Dissemination is delayed if a transaction is over $1 million and occurs in a bond that trades infrequently and is rated BB or below. In addition, dissemination is delayed for trades immediately following the offering of TRACE-eligible securities rated BBB or below. In

[2] The National Association of Security Dealers (NASD) changed its name to the FINRA in 2007.

[3] Price and volume information of corporate bonds were publicly available in 1930s and 1940s when corporate bonds were primarily traded on exchanges.

Phase 3A, effective on 1 October 2004, 9,558 new bonds started having their information about trades disseminated. In Phase 3B, effective on 7 February 2005, an additional 3016 bonds started dissemination, though sometimes with delay. According to FINRA at that point, there was "real-time dissemination of transaction and price data for 99 percent of corporate bond trades."

In an effort parallel to increase the number of bonds with disseminated trade information, FINRA reduced the time delay for reporting a transaction from 75 minutes on 1 July 2002, to 45 minutes on 1 October 2003, to 30 minutes on 1 October 2004, and to 15 minutes on 1 July 2005. On 9 January 2006, the time delay for dissemination was eliminated. Since most bond trades infrequently, our analysis uses one week as the basic unit of time. Therefore, we do not focus on changes in time to dissemination, but instead on new dissemination.

3.2 Measuring pricing efficiency in bond market

3.2.1 Individual bond, bond market, and bond portfolio returns

In this section, we discuss two different measures for the information efficiency. Our first measure is return drift after bond analysts' reports, and the second measure is a price delay measure.

Both these measures rely on bond returns, which we calculate at the weekly frequency as follows. For a bond in week t, we take all trades within the week and calculate the clean price for the week as the transaction size-weighted average of these trades. Returns are then calculated as

$$Ret_{i,t} = \ln\left(\frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t-1} + AI_{i,t-1}}\right), \tag{1}$$

where $P_{i,t}$ is the transaction size-weighted clean price[4], $AI_{i,t}$ is the accrued interest, and $C_{i,t}$ is the coupon paid in week t. Coupon rates and maturities are obtained from FISD.

The construction of the return drift and price delay measures needs bond market return and bond portfolio returns. We define corporate bond market return as the amount-outstanding weighted average of bond returns for all bonds from TRACE.[5] We follow Bessembinder, Kahle, Maxwell, and Xu (2009) to create portfolios segmented by both bond rating and time-to-maturity and calculate amount-outstanding weighted bond portfolio return. We segment bonds by Moody's six major rating categories (Aaa, Aa, A, Baa, Ba, below Ba) and three time-to-maturity categories. For investment grade bonds, the time to-maturity

[4]Bessembinder, Kahle, Maxwell, and Xu (2009) recommend calculating prices as the transaction size-weighted averages of prices because it minimizes the effects of bid-ask spread in prices. Bao and Pan (2013) and Bao, Pan, and Wang (2011) also use transaction size-weighted averages of prices.

[5]According to NASD (2005), TRACE covers 99% of corporate bonds.

cutoffs are 0 to 5 years, +5 to 10 years, and +10 years. For non-investment grade bonds, the cutoffs are 0 to 6 years, +6 to 9 years, and +9 years. These cutoffs are designed to ensure roughly equivalent terciles. Because the Aaa sample size is too small to split into three subsets based on maturity, we follow Bessembinder, Kahle, Maxwell, and Xu (2009) to split the Aaa sample into two maturity categories, 0 to 7 years and +7 years. The procedure above provides a total of seventeen matching portfolios. The portfolio return is amount-outstanding weighted return of the portfolio. We martch each bond with a portfolio by the above rating and time-to-maturity categories and follow Bessembinder, Kahle, Maxwell, and Xu (2009) to abnormal return (AR) as the difference between a bond's observed return and the matching portfolio return.

3.2.2 Return drift

Following Gleason and Lee (2003), we consider return drift after bond analyst report as measures of pricing efficiency. We use bond analyst report as the events for return drift calculation for following reasons. First, bond investors are almost exclusively institutions. The average level of investor sophistication is higher than in the equity market. Institutional investors likely have access to multiple sources of information and better understand how to utilize the bond analyst's report. Therefore, the post bond analyst report drift would be good measure of pricing of information incorporation rather than a measure of noise trading. Second, unlike quarterly earning announcement and quarterly report, the fixed income reports are issued throughout the quarter. Because of their frequency and timeliness, these reports have become a vital source of information for many users of corporate financial reports. According to Bond Market Association (BMA 2004), fixed income research analysts play an important role in informing the marketplace about particular issues or securities. These bond reports are critical in promoting market efficiency in the fixed income price discovery process. De Franco, Vasvari, and Regina (2009) find that bond analysts issue more negative reports than equity analysts and provide more information about low credit quality bonds as a result of the asymmetric demand for negative information by bond investors.

In an alternative specification, we use return drift after rating change to measure the information efficiency. Rating agencies have preferential access to information that are not public available. Because rating agencies are alternative information intermediaries with extensive reputational capital at stake, their disclosures provide potentially relevant information that can serve as an independent check on the results of bond analyst reports.

Specifically, we use 8-week window after bond analyst report or rating change to measure return drift. We choose the 8-week window for two reasons. First, bond market liquidity is low. Therefore it may take time to incorporate information. Second, too short time window may mainly capture the initial reaction to the events. To better capture information diffusion instead of over- or under- reaction, we use a long enough window. Since we do not care about the direction of reaction, we do not classify the news in bond analyst report or rating change into good news or bad news. We define the Drift variable as 8-week sum of the absolute abnormal return ($\sum_{n=1}^{8} |AR_n|$) after the events (bond analyst report or rating change). In the robustness tests, we alternatively use the sum of the absolute values of weekly abnormal return as a drift measure, and the results are similar.

3.2.3 Price delay

We adopt Hou and Moskowitz's (2005 price delay measure as the second pricing efficiency measure. This measure is an estimate of how quickly prices incorporate public information in market and/or portfolio return movements. Same as for the drift measure, we calculate the price delay measure each week. Although calculation at a higher frequency, such as daily, provide more precision and perhaps more dispersion in delay, they may also introduce more confounding microstructure influences such as bid-ask bounce and non-synchronous trading.

We consider bond market portfolio return, stock market return[6], and bond portfolio return as the relevant market information to which bonds respond. Using the dissemination date as the cut-off point, we divide the sample into two parts, 1 year before dissemination and 1 year after dissemination. We then estimate a regression of each bond's weekly returns on contemporaneous and four weeks of lagged returns on the bond market, stock market, and bond portfolio before and after dissemination.

$$\begin{aligned} Ret_{i,t}^{B} = \alpha_i + & \beta_i^{BM} Ret_{BM,t} + \sum_{n=1}^{4} \delta_i^{BM,(-n)} Ret_{BM,t-n} + \\ & \beta_i^{SM} Ret_{SM,t} + \sum_{n=1}^{4} \delta_i^{SM,(-n)} Ret_{SM,t-n} + \\ & \beta_i^{BP} Ret_{BP,t} + \sum_{n=1}^{4} \delta_i^{BP,(-n)} Ret_{BP,t-n} + \epsilon_{i,t} \end{aligned} \tag{2}$$

where $Ret_{i,t}^{B}$ is the return on bond i, $Ret_{BM,t}$ is the return on the value-weighted bond market return in week t, $Ret_{SM,t}$ is value-weighted stock market return in week t, and $Ret_{BP,t}$ is the value-weighted bond portfolio return in week t. If the bond responds immediately to market news, then β_i will be significantly different from zero, but none of the $\delta_i^{(-n)}$ will differ from zero. Otherwise, $\delta_i^{(-n)}$ will differ significantly from zero. This regression identifies the delay with which a bond responds to market-wide information if expected returns are relatively

[6]Stock market return is the value-weighted CRSP market index return.

constant over weekly horizons. Our delay measure is one minus the ratio of the R^2 from above regression restricting $\delta_i^{(-n)} = 0$ for all n, over the R^2 from above regression without restriction.

$$Delay1 = 1 - \frac{R^2_{\delta(-n)=0,\ \forall n \in [1,4]}}{R^2}. \tag{3}$$

The higher this number, the more return variation is captured by lagged returns, and hence the stronger is the delay in response to new information. Because *Delay1* does not distinguish between shorter and longer lags or the precision of the estimates, we follow Hou and Moskowitz (2005) to consider two alternative measures of price delay: *Delay2* and *Delay3*.

$$Delay2 = \frac{\sum_{n=1}^{4}\left(n\left|\delta^{BM,(-n)}\right| + n\left|\delta^{SM,(-n)}\right| + n\left|\delta^{BP,(-n)}\right|\right)}{|\beta^{BM}| + |\beta^{SM}| + |\beta^{BP}| + \sum_{n=1}^{4}\left(|\delta^{BM,(-n)}| + |\delta^{SM,(-n)}| + |\delta^{BP,(-n)}|\right)} \tag{4}$$

$$Delay3 = \frac{\sum_{n=1}^{4}\left(n\left|\frac{\delta^{BM,(-n)}}{se\left(\delta^{BM,(-n)}\right)}\right| + n\left|\frac{\delta^{SM,(-n)}}{se\left(\delta^{SM,(-n)}\right)}\right| + n\left|\frac{\delta^{BP,(-n)}}{se\left(\delta^{BP,(-n)}\right)}\right|\right)}{\left|\frac{\beta^{BM}}{se(\beta^{BM})}\right| + \left|\frac{\beta^{SM}}{se(\beta^{SM})}\right| + \left|\frac{\beta^{BP}}{se(\beta^{BP})}\right| + \sum_{n=1}^{4}\left(\left|\frac{\delta^{BM,(-n)}}{se\left(\delta^{BM,(-n)}\right)}\right| + \left|\frac{\delta^{SM,(-n)}}{se\left(\delta^{SM,(-n)}\right)}\right| + \left|\frac{\delta^{BP,(-n)}}{se\left(\delta^{BP,(-n)}\right)}\right|\right)}, \tag{5}$$

where se(.) is the standard error of the coefficient estimate. When *Delay2* or *Delay3* is higher, the current bond's return has a stronger relation to the distant past public market information relative to the current public market information.

3.2.4 R-squared

In addition to price delay measures, we also consider R-squareds from regressions in Equation 2 with or without the restriction that $\delta_i^{(-n)} = 0$. We label the R-squared with the restriction R-squared1 and the one without the restriction R-squared2. R-squared1 captures how much variation in bond return can be explained by the contemporaneous bond market returns, and R-squared2 captures how much the variation in bond return can be explained by the contemporaneous and past four-week public information. These two R-squareds can measure how much bond-specific information that the bond prices contain (Morck et al., 2000; Durnev et al., 2003, 2004; Chun et al., 2008). The higher the two R-squared numbers, the less bond-specific information in the bond prices.

3.3 Difference-in-difference method

We esitmate a difference-in-difference regression to empirically test and quantify the impact of market transparency on information efficiency in bond market.

$$y_{i,t} = b_0 + b_1 Treated_i + b_2 Post_t + b_3 Treated_i \times Post_t + \epsilon_{i,t}, \tag{6}$$

where $y_{i,t}$ is the measure of information efficiency for bond i in week t, $Treated_i$ is an indicator for whether the bond changes its dissemination status and $Post_t$ is a dummy variable which equals to one in the period after the dissemination starts and zero otherwise. The coefficient b_3 on interaction term, $Treated_i \times Post_t$, captures the difference-in-difference effect. This parameter measures how the difference in information efficiency between treated bonds and control bonds changes before and after the public dissemination status of the bond changes. The detail variable description is in Appendix A.

Since the phase implementation is directly related to the rating and issue size of the bond, we define the control groups as follows in order to get a better match. We use the phase 1 bonds as the control group for the phase 2 bonds (phase 3A and 3B bonds as control group is reported in the robust test). Phase 2 bonds are used as the control group for the phase 3A and 3B bonds.[7] We do not utilize the phase 1 shock because there was no return data available before TRACE implemented. Therefore, we can not compare the pre- and post- return drift for phase 1 bonds.

4 Data and Summary Statistics

4.1 Data source

TRACE is available starting from July 1, 2002. Approximately 500 corporate bond transactions data was made public since then. To obtain information on the characteristics of each traded bond, including maturity date and bond rating, we use the Fixed Income Security Database (FISD).

The source of sell-side bond analyst report data is Investext, a provider of full-text analyst reports. In our sample, the sell-side debt report data covers the period from 2001 to 2006. The intersection of the bond pricing and debt report data is the period from July 1, 2001 (i.e. 1 year before the implementation of TRACE) to February 7, 2006 (i.e. 1 year after the dissemination of the Phase 3B bonds), because this period aligns with the implementation

[7]Although 3A bonds and 3B bonds are more comparable to each other, we do not use phase 3A bonds as the control for phase 3B bonds, because phase 3A and 3B are only 4 months apart and our test window is 1-year surround the phase start date.

of phases of TRACE. We manually collect the bond analysts' reports and code the name of the analyst and brokerage firm who issues the report, report date, name of the company the report is about, and the analysts' recommendation. We exclude reports about industry, geographic, investing/economics, and reports that are aggregated either by industry or time, which often repeat previously published information (e.g. Stickel 1995). More details on the collection of bond analyst report can be found in Appendix B.

Financial and accounting data is obtained from Compustat. Equity return data is obtained from CRSP.

4.2 Summary statistics of pricing efficiency measures

Table 2 reports the summary statistics of efficiency measures for each phase implementation. The total sample size differs across measures of information efficiency. The treatment and control groups of bonds are defined in Panel A of Table 1. There is a trade-off in choosing the time window surrounding dissemination. On the one hand, to focus on immediate effect of dissemination, we should use the short time window which is really relevant to the event; on the other hand, to have enough observation for credit report or rating change, we should use the longer time window. Generally, we use the time period between phase change as our investigation period. Details could be found in Panel B of Table 1.

Panel A of Table 2 provides summary statistics of bond report drift based on phases and treatment. The difference in bond report drift provides an independent and intuitive justification for the market transparency shocks. Three patterns emerge from this panel. First, the bonds with smaller issue size and lower rating will have larger drift in all phases. For example, drift is 0.027 for the Phase 2 bonds (treated) whereas it is 0.075 for the phase 3A and phase 3B bonds (control). This is consistent with our intuition that bonds with large issue size and high rating have better information environment and the market more quickly incorporates information into their prices. Second, bonds experience a decrease in drift after the dissemination of trading price. For example, drift is 0.028 for phase 3A treated bonds before the dissemination and is 0.015 after the dissemination. Third, the difference in pre- and post-dissemination period is relative large for treated group and small for control group. The difference for control group is roughly 0 for phase 3A and 3B. This provides some confirmation of the validity of our research design. The diff-in-diff numbers are capturing the net effect of dissemination and they are negative in phase 3A and 3B. These results indicate an beneficial impact of market transparency on pricing efficiency.

One exception is the phase 2 control group, which has significant decrease in drift after the dissemination and the diff-in-diff number is positive in phase 2. One possible explanation is that there is strong spill-over effect from phase 2 bonds to phase 3A and 3B bonds during the phase 2 shock. We do not observe similar spill-over effect in phase 3A and 3B, because at that time the control group bonds are already subject to disclosure of trading information. In contrast, in phase 2 the control group bonds are not subject to dissemination requirement. Panel B provides the summary statistics for post-credit rating change drift and we find similar patterns as that in Panel A.

Panel C reports the summary statistics of price delay. 919 (866), 1959 (1778), and 311 (300) treated bonds have *Delay1* available before (after) the phase implementation for Phases 2, 3A, and 3B, respectively. The mean values of treated bonds' *Delay1* decrease for all three phases. Specifically, the mean of treated bonds' *Delay1* decreases by 0.156 (from 0.658 to 0.501) for Phase 2, by 0.062 (from 0.579 to 0.518) for Phase 3A, and by 0.071 (from 0.616 to 0.545) for Phase 3B. The mean of control bonds' *Delay1* decreases by 0.049 (from 0.608 to 0.560) for Phase 2 and increases by 0.084 (from 0.364 to 0.449) for Phase 3A and increases by 0.077 (from 0.377 to 0.454) for Phase 3B. These numbers show that information inefficiency measured by *Delay1* decreases for all three phases in the treated bonds, but the control bonds show more mixed results.

After examining the change in price delay for treated and control bond seperately, we calculate the difference between the treated and control bonds. These differences are -0.108 (-0.156 - (-0.049)) for Phase 2, -0.146 (-0.062 - 0.084) for Phase 3A, and -0.148 (-0.071 - 0.077) for Phase 3B. These numbers show that after phase implementation *Delay1* decreases more for the treated bonds than for the control bonds. Comparing these difference numbers to the mean price delay measures before phase implementation, we find that these numbers' economic magnitudes are large. For example, for Phase 2, -0.108 is -16.4% (-0.108/0.658) relative to the mean *Delay1* of treated bonds (0.658) and -21.6% (-0.108/0.501) relative to the mean *Delay1* of control bonds (0.501). These results indicate that the treated bonds' information efficiency improves relative to that of the control bonds.

We make boxplots of the efficiency measures in Figures 1, 2, and 3. In these boxplots, the bottom and top of the box are the first and third quartiles of the distribution, and the band inside the box is the median. The width of notches on the box represents the 95% confidence interval around the median. Hence, if notches of two boxes do not overlap with each other, then the medians significantly differ. The upper whisker extends from the top of the box to the highest value that is within 1.5 times the interquartile range of the box top, and the lower whisker is similarly defined. Observations outside of upper and lower whiskers are plotted as points, and such observations may or may not exist depending on the distribution.

We distinguish between four groups of bonds: treated bonds before and after phase implementation and control bonds before and after phase implementation. We compare the boxplots between these four groups of bonds for each phase implementation. Figure 1 shows the boxplots for drift after bond report. The median drift significantly decreases for the treated bonds after the phase implementation for all three phase implementation stages. The median drift for the control bonds decreases for Phase 2 and stays relatively the same for Phase 3A and 3B. This evidence suggests that the treated bonds' drift decreases relative to the control bonds for Phase 3A and 3B but not necessarily decreases for Phase 2.

Note that the treated bonds' interquartile range is lower than that of control bonds for Phase 2 and that the opposite is true for Phase 3A and 3B. This is because the treated bonds of Phase 2 are large, high credit rating bonds (Phase 2 bonds), and the control bonds are primarily smaller, non-investment grade bonds (Phase 3A and 3B bonds). In comparison, treated bonds of Phase 3A and 3B is smaller and have lower credit rating than the control bonds of these two phases. Figure 2 reports the boxplots for drift after credit rating change. The evidence is similar to that of Figure 1.

Figure 3 shows the boxplots for delay. The median delay significantly decreases for the treated bonds after the phase implementation for all three phase implementation stages. The median drift for the control bonds decreases for Phase 2 and increases for Phase 3A and 3B. These results suggest that the treated bonds' delay significantly decreases relative to the control bonds for all three phase implementation stages. In summary, evidence in Figures 1, 2, and 3 suggests that pricing efficiency for the treated bonds relative to control bonds after phase implementation, which is consistent with evidence in Table 2.

5 Difference-in-difference regression analysis

5.1 Return drift after bond analyst report

Table 3 presents a difference-in-difference regression result for post-bond report drift. *Drift* is the absolute value of the sum of weekly abnormal return after announcement week of bond report. *Treated* is a dummy variable equal to 1 if the bond is subject to disclosure requirement. *Post* is a dummy variable equal to 1 if it is after the phase implementation. *Treated* $\times$ *Post* is an interaction term between *Treated* and *Post*. Columns 1 to 3 reports the result for Phase 2, 3A, and 3B, respectively. We cluster the standard errors at firm level for all regressions. We are interested in the coefficient on *Treated* $\times$ *Post*, which captures the impact of the market transparency on return drift.

Three key results emerge from Table 3. First, the interaction term in first column is insignificant (0.018 with a t-statistic 1.14), which means that there is no effect on return drift after the phase 2. Phase 2 bonds are those bonds with at least $100 million par value or greater and ratings of A- or higher. These bonds are typically issued by companies with strong cash flows and good information environment. A potential explanation for the insignificant result is that these bonds are already very transparent, so the post-trade transparency increase has little impact on these bonds. Another explanation is the strong spill-over effect to the control group bonds as suggested in Table 2. The control groups bonds are not subject to disclosure requirement before and after the phase 2 shocks. However, due to the distinct feature of bond payoff function, bonds with similar cash flows and credit risk can be substitutes for bonds covered in the treatment group, and thus can serve as pricing benchmarks. Therefore, the control bonds will experience an improvement in information environment as well and lead to insignificant results in the interaction term.[8] This explanation is supported by the evidence that the *Post* is very significant and negative in phase 2 regression but insignificant in phase 3A and 3B regressions.

Second, the return drift is significantly smaller after the trading information disclosure for phase 3A bonds. It shows that, after the shock, the average return drift after bond analyst report reduces by 1.2%, comparing to that the average drift is 2.7% for phase 3A bonds before shock. Therefore, the effect on return drift of Phase 3A is both statistically significant and economically significant.

Third, the return drift reduction is even stronger for low credit rating bonds. Third column reports the results for phase 3B bonds. These bonds are the lowest rated bonds comparing to phase 1, 2, and 3A. The treatment effect is -1.9% and it is significantly larger than that in second column. The result suggests that those bond with worse information environment may benefit more from the disclosure of trading information.

To summarize, the evidence above supports the view that the better market transparency leads to quicker price discovery.

5.2 Return drift after rating changes

Table 4 presents a difference-in-difference regression result for post-bond report drift. Dependent variable is the absolute value of sum of (+1, +8) week abnormal return after announcement week of rating change. To be consistent with the test using fixed income report, we do not distinguish between upgrades and downgrades, since we care about only the magnitude of the drift. The results in Table 4 confirm our previous finding in Table 3. The price adjustment process has not changed for the phase 2 bonds, but significantly

[8]The spill-over effect would be minimal in Phase 3A and 3B, because the respective control groups are bonds already subject to dissemination of trading information before the shocks.

changed for phase 3A and 3B bonds. These evidence further supports the view that the better market transparency leads to better information efficiency.

5.3 Price delay

We report difference-in-difference regression results for price delay in Table 5. We use price delay measures as the dependent variables and cluster standard errors by firm. Panel A of this table shows results for *Delay1*. The coefficients on *Treated* × *Post* are -0.1076, -0.1461, and -0.1478, showing that price delay decreases more for the treated bonds than for the control bonds. These results confirm those in Table 2 and Figure 3 that price delay reduces after the phase change. These coefficient estimates are economically significant. The -0.1076 coefficient on *Treated* × *Post* of Phase 2 is -16.4% of the mean delay of treated bonds before phase implementation.[9] The decreases of *Delay1* for Phase 3A and 3B are 25.2% and 24.0% of the means of treated bonds' delay for the corresponding phase.

In Panel B and C, we report difference-in-difference regression results for two alternative measures of price delay: *Delay2* and *Delay3*. When the values of these two measures are higher, price delay is more severe, and information efficiency is lower. Compared to *Delay1*, *Delay2* and *Delay3* increase in value more if current bond return are more sensitive to distant lag public information. Panel B shows that the coefficients on *Treated* × *Post* are negative for Phase 2 and Phase 3A and positive for Phase 3B, and only the coefficient for Phase 3A is statistically significant. Panel C shows that the coefficient on *Treated* × *Post* are negative and statistically significant for all three phases. The results in Panel C support that dissemination has a negative effect on *Delay3*, while the results in Panel B are more mixed than those in Panel C.

To alleviate the concern that the distribution of *Delay1* is bounded between 0 and 1 and that extremely large values of *Delay2* and *Delay3* may affect the results, we replace raw *Delay1* with the logistic transformation of *Delay1* and replace *Delay2* and *Delay3* with log of *Delay2* and *Delay3* and repeat the analysis in Table 5. The results are similar. Overall, the results in Table 5 demonstrate that pricing efficiency improves after TRACE phase implementation.

5.4 Return R-squared

As we summarize in Section 2, theories suggest that the improvement of market transparency can decrease the price informativeness (Asriyan et al., 2015; Bhattacharya, 2016;

[9] Based on Table 2, the mean of *Delay1* is 0.658 for the treated Phase 2 bonds before the phase implementation.

Banerjee et al., 2016). The previous literature suggests that R-squareds from a regression of individual bond returns on market stock and bond returns and bond portfolio returns can be related to how much bond-specific information the bond prices contain. We consider two R-squared measures (R-squared1 and R-squared2) based on Equation 2. R-squared1 is based on the regression with restriction that $\delta_i^{(-n)} = 0$, and R-squared2 is based on the regression without the restriction. According to previous literature, both these R-squareds can be negatively related to the amount of bond-specific information in bond prices (Morck et al., 2000; Durnev et al., 2003, 2004; Chun et al., 2008). In this section, we study how these two R-squareds change around phase implementation and whether the treated bonds behave differently than the control bonds.

Table 6 reports difference-in-difference regression estimates for R-squareds for all three phases. We use raw R-squareds as the dependent variable in the difference-in-difference regressions, and standard errors are clustered by firm.[10] Panel A reports the difference-in-difference regression results for R-squared1. The coefficients on $Treated \times Post$ are 0.0983, 0.1280, and 0.1051 for Phase 2, Phase 3A, and Phase 3B, respectively, and these estimates are statistically significant. Hence, R-squared1 increases more for treated bonds than for control bonds for all three phases.

The economic magnitudes of these estimates are large. For instance, the 0.0983 coefficient on $Treated \times Post$ of Phase 2 is 42.8% of the mean of R-squared1 (0.2298) for the treated Phase 2 bonds before the phase implementation. The coefficients on $Treated \times Post$ of Phase 3A and 3B are 59.6% and 45.2% of the corresponding means of R-squared1 for treated bonds before the phase implementation. Panel B shows similar results for R-squared2 with those in Panel A.

In summary, results in Table 6 suggests that after phase implementation individual bonds' prices comove more with market bond prices and are consistent with the interpretation that less bond specific information is contained in bond prices after phase implementation.

5.5 Difference-in-difference regression estimates by ex-ante bond characteristics

We study whether the difference-in-difference estimates differ between different groups of treated bonds grouped by ex-ante bond characteristics. We assign treated bonds into groups according to illiquidity and trading activity. Specifically, we calculate medians of bond characteristics across treated bonds before phase implementation and consider treated bonds above the median and those below the median. We use Amihud as the illiquidity

[10]The results are robust to using logistic transformation of R-squared as the dependent variable.

measure and the ratio of volume divided by issue amount as the trading activity measure. For the bond report drift and rating change drift, we measure illiquidity and trading activity using the average of daily illiquidity and trading activity during the week before the bond report or the rating change. For the delay measure, we measure illiquidity and trading activity using the average of daily illiquidity and trading activity one year before the phase implementation. We then estimate a regression as follows.

$$\begin{aligned} y_{i,t} =& b_0 + b_1 Treated_i + b_2 Post_t + b_3 HighGroup_i + b_4 Treated_i \times Post_t + \\ & b_3 Treated_i \times Post_t \times HighGroup_i + \epsilon_{i,t}, \end{aligned} \tag{7}$$

where the dependent variable $y_{i,t}$ is the measure of information efficiency for bond i in week t, $Treated_i$ is an indicator for whether the bond changes its dissemination status and $Post_t$ is a dummy variable that equals to one in the period after the dissemination starts and zero otherwise. $HighGroup_i$ is a dummy variable that is one for treated bonds with high characteristics values and zero for treated bonds with low characteristics values. The coefficient b_3 on interaction term $Treated_i \times Post_t$ captures the difference-in-difference effect for treated bonds with low characteristics, and the coefficient b_4 on the triple interaction term $Treated_i \times Post_t \times HighGroup_i$ captures the difference in the difference-in-difference effect between treated bonds with high and low characteristics values.[11]

Table 7 reports difference-in-difference regression results for bond groups. We highlight coefficients on $Treated_i \times Post_t$ and $Treated_i \times Post_t \times HighGroup_i$. In Panel A, the coefficients on $Treated_i \times Post_t$ show that the difference-in-difference effects on drift after bond reports for treated bonds with low Amihud values are positive for Phase 2 and negative for Phase 3A and 3B. These results are similar to those in Table 3. The coefficients on $Treated_i \times Post_t \times HighGroup_i$ demonstrate that for Phase 2 bonds the difference-in-difference effect is higher for treated bonds with high Amihud values than treated bonds with low Amihud values, while for Phase 3A and 3B the difference-in-difference effects are lower for the former group of bonds than the latter group. These coefficients, however, are not statistically significant. Hence, we conclude that the difference-in-difference effects are similar between treated bonds with high and low Amihud values. The results in Panel A show that the difference-in-difference effects are similar between treated bonds with high trading activity and low trading activity.

Panel B shows that the results for drift after rating change are similar to those in Panel A. We do not find significant difference between liquidity subgroups (trading activity sub-

[11] We omit second-order interaction term $Treated_i \times HighGroup_i$ because it is colinear with $HighGroup_i$ and omit $Post_t \times HighGroup_i$ because it is colinear with $Treated_i \times Post_t \times HighGroup_i$.

groups). Instead of overall insignificant result in Table 4, there is some evidence that the impact of dissemination on phase 2 bonds only show up in liquid bonds.

Panel C demonstrates the results for the Delay measure. The coefficient estimates for Amihud show that the coefficients on $Treated_i \times Post_t$ are negative and significant for all three phases, which is consistent with the results in Table 5. The coefficients on $Treated_i \times Post_t \times HighGroup_i$ are negative for all three phases but are not statistically significant. The coefficients estimates for trading activity again show that the coefficients on $Treated_i \times Post_t$ are negative and significant but the coefficients on $Treated_i \times Post_t \times HighGroup_i$ are not significantly different from zero.

5.6 Spillover to stock market

In this section, we test whether there is spillover effect of increased market transparency from bond market to stock market. If market transparency changes the pricing efficiency in bond market, it is possible that the corresponding stocks will be affected by it as well because investors can observe the price in bond market and adjust their valuation accordingly. To capture the potential impact of bond market transparency in the stock market, we consider delay measure and R-squared measure based on stock prices.

Specifically, we regress individual stock return on contemporaneous stock market return and lagged stock market returns up to four weeks. Similar to the definition in Equation 3, the stock delay measure is defined as one minue the ratio of R-squared from the regression without lagged market returns and the R-squared from the regression with lagged market returns. The R-squared measure is the R-squared from the regression with lagged market returns.

First and second column report the result for the treated stocks in phase 1. Third and fourth column report the result for the treated stocks in phase 2. Fifth and sixth column report the result for the treated stocks in phase 3A. Seventh and eighth column report the result for the treated stocks in phase 3B. In all specifications, we do not find any significant impact of bond market transparency on stock market. An potential explanation for this finding is that the stock market is much more liquid and transparent than bond market, and hence the impact of the increased post-trade transparency will have little impact on the stock market.

6 Conclusion

Issues related to market transparency are hotly debated by researchers and policy makers. Although previous literature has shown the potential benefits and drawbacks of increased market transparency in general, few empirical studies specifically focus on the impact of market transparency on pricing efficiency. This paper examines the causal effects of post-trade market transparency on pricing efficiency using the implementation of TRACE and a difference-in-difference research design. We find that mandated post-trade market transparency in the corporate bond market increases the pricing efficiency of individual bonds. No sample of bonds in any phases experience an decrease in pricing efficiency and phase 3A and 3B bonds experience a large and significant increase. This finding is robust across different measures of pricing efficiency. Subgroup analysis indicates that there is little variation between groups of bonds with different levels of liquidity and trading activity before phase implementation. Also, the increase in market transparency may lead to higher co-movement between bond return and market return. The results suggest the important impact of increasing post-trade market transparency on information efficiency and lend some support to the recent reform in derivative markets.

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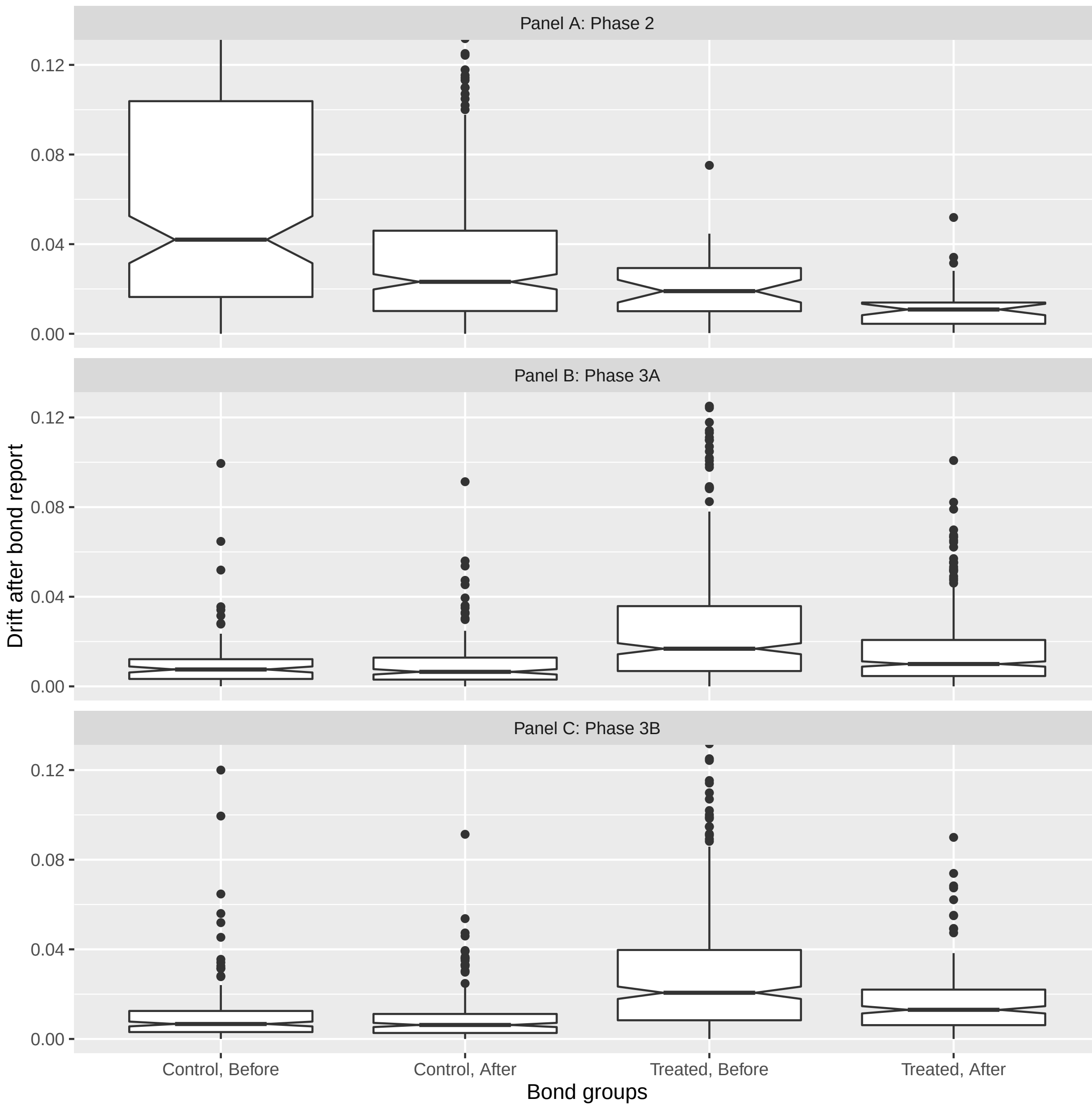

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Figure 1: Post-bond report Drift before and after TRACE phase implementation

This figure shows box-plots of delay before and after each phase implementation. For the treated bonds (Treated=1) and control bonds (Treated=0), we plot box-plots of delay for before the phase implementation (Post=0) and after (Post=1). Hence, we have four box-plots for each phase. Note that the notches represent 95% confidence interval around median. If the ranges between notches of two box-plots do not overlap, then the medians significantly differ.

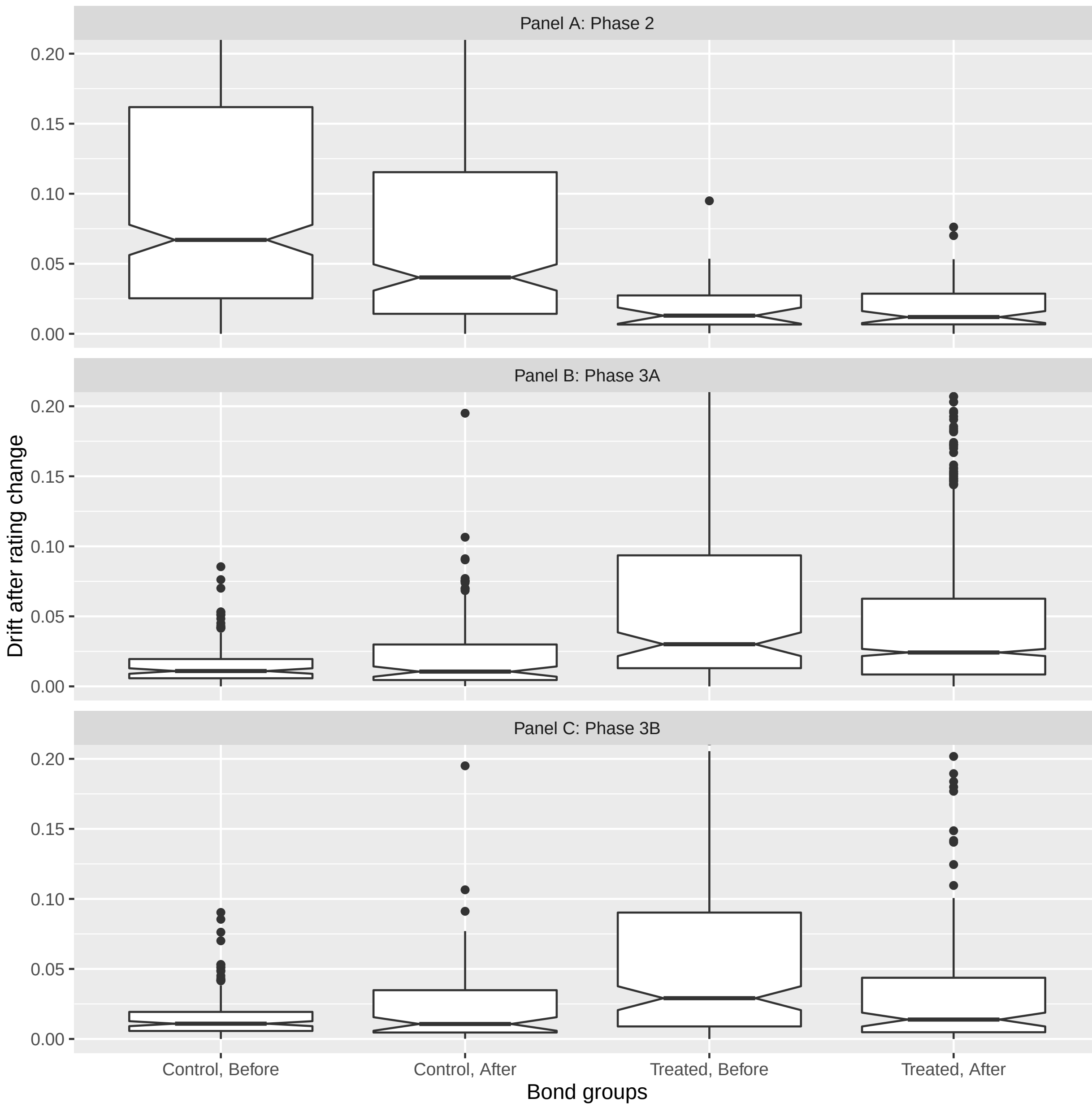

Figure 2: Post-rating change Drift before and after TRACE phase implementation

This figure shows box-plots of delay before and after each phase implementation. For the treated bonds (Treated=1) and control bonds (Treated=0), we plot box-plots of delay for before the phase implementation (Post=0) and after (Post=1). Hence, we have four box-plots for each phase. Note that the notches represent 95% confidence interval around median. If the ranges between notches of two box-plots do not overlap, then the medians significantly differ.

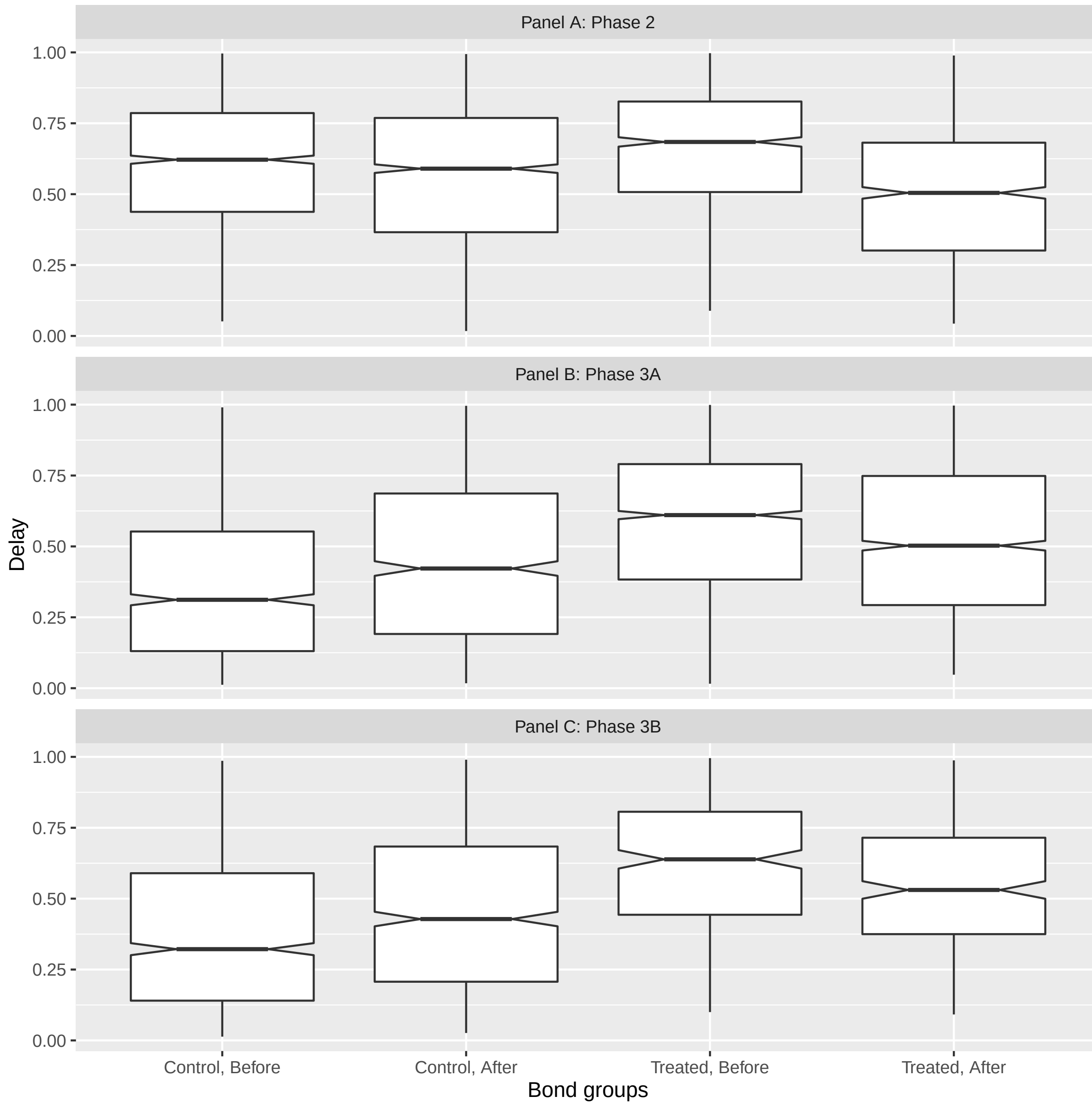

Figure 3: Delay before and after TRACE phase implementation

This figure shows box-plots of delay before and after each phase implementation. For the treated bonds (Treated=1) and control bonds (Treated=0), we plot box-plots of delay for before the phase implementation (Post=0) and after (Post=1). Hence, we have four box-plots for each phase. Note that the notches represent 95% confidence interval around median. If the ranges between notches of two box-plots do not overlap, then the medians significantly differ.

Table 1: Description of TRACE phases

Sample	Date	Treated Group	Control Group
Panel A: Phases description			
Phase 1	1 July 2002	Investment Grade TRACEeligible bonds having an initial issue of $1 billion or greater	N.A.
Phase 2	3 March 2003	All Investment Grade TRACEeligible bonds of at least $100 million par value (original issue size) or greater rated A or higher; and 50 Non-Investment Grade bonds	Phase 3A & 3B
Phase 3A	1 October 2004	All bonds that are not eligible for delayed dissemination (bonds with rating of BBB or higher)	Phase 1 & 2
Phase 3B	7 February 2005	All bonds potentially subject to delayed dissemination (bonds with ratings BB+ or lower)	Phase 1 & 2
Excluded other regulatory changes			
FINRA50	1 July 2002	50 NonInvestment Grade (HighYield) bonds disseminated under Fixed Income Pricing System (FIPS). First day is 1 July 2002, last day is 14 July 2004	N.A
FINRA120	14 April 2003	120 Investment Grade TRACEeligible bonds rated BBB	N.A

Table 2: Summary statistics

Panel A: Drift after credit report

		Treated		Control		
		Num. obs.	Mean	Num. obs.	Mean	Diff. in Diff
Phase 2	Before	36	0.027	160	0.075	
Phase 2	After	35	0.012	271	0.043	
Difference			-0.015		-0.032	0.017
Phase 3A	Before	210	0.028	107	0.010	
Phase 3A	After	315	0.015	166	0.010	
Difference			-0.013		-0.000	-0.013
Phase 3B	Before	173	0.036	135	0.011	
Phase 3B	After	107	0.016	138	0.010	
Difference			-0.020		-0.001	-0.019

Panel B: Drift after credit rating change

		Treated		Control		
		Num. obs.	Mean	Num. obs.	Mean	Diff. in Diff
Phase 2	Before	32	0.020	399	0.110	
Phase 2	After	66	0.019	296	0.086	
Difference			-0.001		-0.024	0.023
Phase 3A	Before	227	0.074	123	0.016	
Phase 3A	After	1110	0.046	119	0.022	
Difference			-0.028		0.006	-0.034
Phase 3B	Before	227	0.075	145	0.016	
Phase 3B	After	155	0.048	97	0.024	
Difference			-0.027		-0.005	-0.022

Panel C: Key statistics of Delay

		Treated		Control		
		Num. obs.	Mean	Num. obs.	Mean	Diff. in Diff
Phase 2	Before	919	0.658	1441	0.608	
Phase 2	After	866	0.501	1769	0.560	
Difference			-0.156		-0.049	-0.108
Phase 3A	Before	1959	0.579	1178	0.364	
Phase 3A	After	1778	0.518	923	0.449	
Difference			-0.062		0.084	-0.146
Phase 3B	Before	311	0.616	1118	0.377	
Phase 3B	After	300	0.545	863	0.454	
Difference			-0.071		0.077	-0.148

Table 3: **Drift after bond credit report**

Dependent variable:	Phase 2 Drift	Phase 3A Drift	Phase 3B Drift
Post	-0.033	-0.00025	-0.0012
	(-4.77)	(-0.16)	(-0.80)
Treated	-0.048	0.017	0.026
	(-5.00)	(5.55)	(5.87)
Treated × Post	0.018	-0.012	-0.019
	(1.77)	(-4.06)	(-4.14)
Constant	0.075	0.010	0.011
	(11.3)	(7.60)	(8.55)
Num. obs.	502	798	553
Adj. R-squared	0.089	0.070	0.118

This table reports the difference-in-difference estimates for the post bond report drift. *Drift* is the absolute value of sum of (+1, +8) week abnormal return after announcement week of bond report. *Post* is a dummy variable equal to 1 if it is after the phase implementation. *Treated* is a dummy variable equal to 1 if the bond is subject to disclosure requirement. *Treated x Post* is the interaction term between *Post* and *Treated*. The details on phases change can be found in Table 1. The numbers in parentheses are t-statistics. Standard errors are clustered at firm level.

Table 4: Drift after rating change

Dependent variable:	Phase 2 Drift	Phase 3A Drift	Phase 3B Drift
Post	-0.022	0.0062	0.0076
	(-1.81)	(1.31)	(1.43)
Treated	-0.091	0.058	0.059
	(-9.13)	(5.67)	(6.66)
Treated × Post	0.022	-0.035	-0.035
	(1.63)	(-2.98)	(-2.15)
Constant	0.11	0.016	0.016
	(12.5)	(8.08)	(8.94)
Num. obs.	783	1579	624
Adj. R-squared	0.067	0.053	0.088

This table reports the difference-in-difference estimates for the post rating change (Moody's) drift. *Drift* is the absolute value of sum of (+1, +8) week abnormal return after announcement week of bond report. *Post* is a dummy variable equal to 1 if it is after the phase implementation. *Treated* is a dummy variable equal to 1 if the bond is subject to disclosure requirement. *Treated x Post* is the interaction term between *Post* and *Treated*. The details on phases change can be found in Table 1. The numbers in parentheses are t-statistics. Standard errors are clustered at firm level.

Table 5: **Price Delay by Phases**

Panel A: DID estimates for Delay1	Phase 2	Phase 3A	Phase 3B
Dependent variable:	Delay1	Delay1	Delay1
Treated	0.0494	0.2151	0.2391
	(3.92)	(6.96)	(13.49)
Post	-0.0488	0.0845	0.0769
	(-2.57)	(9.48)	(8.63)
Treated × Post	-0.1076	-0.1461	-0.1478
	(-5.05)	(-3.10)	(-7.94)
Constant	0.6083	0.3642	0.3773
	(56.88)	(35.73)	(34.49)
Observations	4,995	5,838	2,592
Adj. R-squared	4.4	8.6	8.8

Panel B: DID estimates for the log of Delay2	Phase 2	Phase 3A	Phase 3B
Dependent variable:	Delay2	Delay2	Delay2
Treated	-0.0290	0.2660	0.1829
	(-1.64)	(12.00)	(6.85)
Post	0.0200	0.0714	-0.0420
	(1.05)	(4.53)	(-2.15)
Treated × Post	-0.0153	-0.1628	0.0149
	(-0.60)	(-3.27)	(0.43)
Constant	1.8831	0.3642	0.3773
	(141.11)	(35.73)	(34.49)
Num. obs.	4,995	5,838	2,592
Adj. R-squared	0.2	5.1	3.3

Panel C: DID estimates for the log of Delay3	Phase 2	Phase 3A	Phase 3B
Dependent variable:	Delay3	Delay3	Delay3
Treated	0.0349	0.1583	0.1255
	(2.22)	(6.89)	(5.64)
Post	-0.0154	0.0302	-0.0122
	(-1.02)	(2.22)	(-0.80)
Treated × Post	-0.0845	-0.0865	-0.0604
	(-3.96)	(-1.76)	(-2.15)
Constant	1.8975	1.7484	1.8168
	(163.77)	(144.99)	(144.61)
Num. obs.	4,995	5,838	2,592
Adj. R-squared	0.7	2.9	1.5

This table reports the summary of key statistics and difference-in-difference estimates for the price delay measures. Panels A, B, and C report the difference-in-difference estimates for *Delay1*, and the log of *Delay2* and *Delay3*. The delay measures, *Delay1*, *Delay2*, and *Delay3*, are defined in Equations 3, 4, 5, respectively. The numbers in parentheses are t-statistics based on standard errors clustered by firm.

Table 6: **Difference-in-difference estimates: R-squareds**

Panel A: DID estimates for R-squared1	Phase 2	Phase 3A	Phase 3B
Treated	-0.0540	-0.1799	-0.1515
	(-5.45)	(-7.44)	(-10.11)
Post	0.0341	-0.0827	-0.0691
	(2.07)	(-12.18)	(-9.43)
Treated × Post	0.0983	0.1280	0.1051
	(5.40)	(3.44)	(7.47)
Constant	0.2838	0.4213	0.4015
	(34.73)	(41.45)	(38.74)
Num. obs.	5,167	5,972	2,668
Adj. R-squared	4.3	8.9	5.5

Panel B: DID estimates for R-squared2	Phase 2	Phase 3A	Phase 3B
Treated	-0.0552	-0.0827	0.0158
	(-6.44)	(-6.93)	(1.18)
Post	-0.0146	-0.0516	-0.0391
	(-1.30)	(-8.22)	(-5.53)
Treated × Post	0.0638	0.0751	0.0216
	(5.55)	(3.25)	(1.34)
Constant	0.7086	0.6268	0.6089
	(89.78)	(85.53)	(83.25)
Num. obs.	4,995	5,838	2,592
Adj. R-squared	1.9	2.3	1.1

This table reports the summary of key statistics and difference-in-difference estimates for *R-squared1* and *R-squared2*. Panel A and B report the difference-in-difference estimates for the logistic transformation of *R-squared1* and *R-squared1*. *R-squared1* is based on Equation 2 without the restriction that $\delta_i^{(-n)} = 0$ and *R-squared2* is based on the Equation 2 with the restriction. The numbers in parentheses in Panels C and D are t-statistics based on standard errors clustered by firm.

Table 7: **Difference-in-difference estimates for bond groups**

Panel A: Drift after bond report	Phase 2	Phase 3A	Phase 3B
	Bond groups sorted by Amihud		
Treated ×Post	0.017	-0.01	-0.016
	(2.06)	(-1.81)	(-2.48)
Treated × Post × High Amihud	0.0012	-0.0033	-0.0044
	(0.11)	(-0.49)	(-0.52)
	Bond groups sorted by trading activity		
Treated × Post	0.016	-0.017	-0.021
	(1.19)	(-3.90)	(-2.93)
Treated × Post × High Trading	0.0038	0.0088	0.0029
	(0.29)	(1.60)	(0.35)

Panel B: Drift after rating change	Phase 2	Phase 3A	Phase 3B
	Bond groups sorted by Amihud		
Treated × Post	0.03	-0.051	-0.056
	(2.29)	(-3.81)	(-1.94)
Treated × Post × High Amihud	-0.014	0.024	0.026
	(-2.35)	(1.66)	(1.01)
	Bond groups sorted by trading activity		
Treated × Post	0.02	-0.022	-0.049
	(1.32)	(-1.12)	(-3.66)
Treated × Post × High Trading	0.0043	-0.018	0.025
	(0.51)	(-0.87)	(1.01)

Panel C: Delay	Phase 2	Phase 3A	Phase 3B
	Bond groups sorted by Amihud		
Treated × Post	-0.0570	-0.1126	-0.1087
	(-2.03)	(-4.73)	(-3.84)
Treated × Post × High Amihud	-0.0329	-0.0524	-0.0056
	(-1.27)	(-0.92)	(-0.15)
	Bond groups sorted by trading activity		
Treated × Post	-0.0707	-0.1769	-0.1344
	(-3.43)	(-2.15)	(-5.17)
Treated × Post × High Trading	-0.0189	0.0859	0.0506
	(-0.98)	(1.22)	(1.44)

This table reports the difference-in-difference estimates for different bonds grouped by ex-ante bond characteristics before phase implementation. The bond groups include bonds with high or low trading activity and bonds with high or low illiquidity. We use sample median numbers as cutoffs to define high and low groups for trading activity and use *Amihud* to measure illiquidity. The numbers in parentheses are t-statistics.

Table 8: Test of spill-over effect to stock market

	Phase 1		Phase 2		Phase 3A		Phase 3B	
	Delay1	R-squared	Delay1	R-squared	Delay1	R-squared	Delay1	R-squared
Treated	-0.21	-1.50	-0.21	-1.32	0.086	0.71	0.19	1.29
	(-5.76)	(-6.43)	(-9.07)	(-8.85)	(4.81)	(5.51)	(8.56)	(9.32)
Post	-0.046	-0.28	-0.13	0.15	0.014	-0.37	0.090	0.081
	(-3.49)	(-3.29)	(-10.2)	(1.86)	(0.68)	(-2.45)	(3.74)	(0.54)
Treated × Post	-0.010	-0.25	0.080	0.31	0.020	0.13	-0.018	-0.17
	(-0.20)	(-0.77)	(2.50)	(1.49)	(0.77)	(0.72)	(-0.59)	(-0.86)
Constant	0.40	0.71	0.37	0.51	0.15	-0.24	0.17	-0.67
	(43.4)	(12.1)	(42.0)	(8.90)	(9.96)	(-2.22)	(10.2)	(-6.33)
Num. obs.	1869	1861	1804	1800	1196	1193	860	856
Adj. R-squared	0.041	0.055	0.104	0.066	0.048	0.063	0.153	0.148

This table reports the difference-in-difference estimates for the spill-over effect to stock market. The sample is the companies whose bonds are subject to disclosure requirement in different phases. *Delay1* is the delay measure based on stock prices. *R-squared* is the R-squared from a regression of individual stock returns on contemporaneous and lag stock market returns and industry returns. *Post* is a dummy variable equal to 1 if it is after the phase implementation. *Treated* is a dummy variable equal to 1 if the bond of the company is subject to disclosure requirement. $Treated \times Post$ is the interaction term between *Treated* and *Post*. The details of phases change can be found in Table 1. The details of delay measure and R-squared measure can be found in Appendix. The numbers in parentheses are t-statistics.

Appendices

A Definitions of Variables

Variable	Description
Bond market return	The amount-outstanding weighted average of bond returns for all bonds from TRACE.
Stock market return	The value-weighted CRSP market index return.
Bond portfolio return	The portfolio return is amount-outstanding weighted return of the portfolio. We follow Bessembinder, Kahle, Maxwell, and Xu (2009) to create portfolios segmented by both bond rating and time-to-maturity and calculate amount-outstanding weighted bond portfolio return. We segment bonds by Moody's six major rating categories (Aaa, Aa, A, Baa, Ba, below Ba) and three time-to-maturity categories. For investment grade bonds, the time to-maturity cutoffs are 0 to 5 years, +5 to 10 years, and +10 years. For non-investment grade bonds, the cutoffs are 0 to 6 years, +6 to 9 years, and +9 years. These cutoffs are designed to ensure roughly equivalent terciles. Because the Aaa sample size is too small to split into three subsets based on maturity, we follow Bessembinder, Kahle, Maxwell, and Xu (2009) to split the Aaa sample into two maturity categories, 0 to 7 years and +7 years. The procedure above provides a total of seventeen matching portfolios.
Abnormal return	Individual bond return minus the return of the corresponding bond portfolio.
Drift	We define the Drift variable as 8-week sum of the absolute abnormal bond return ($\sum_{n=1}^{8} \|AR_n\|$) after the events (bond analyst report or rating change).
Delay1	We follow Hou and Moskowitz (2005) to define *Delay1* in Equation 3. We estimate a regression of each bond's weekly returns on contemporaneous and four weeks of lagged returns on bond market, stock market, and bond portfolio. *Delay1* is one minus the ratio of R^2 from the previous regression restricting all coefficients on lagged terms to be zero and the R^2 from the previous regression without the restriction.

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Variable	Description
Delay2	We follow Hou and Moskowitz (2005) to define *Delay1* in Equation 4. We estimate a regression of each bond's weekly returns on contemporaneous and four weeks of lagged returns on bond market, stock market, and bond portfolio. *Delay2* is the ratio of the sum of scaled absolute coefficients from the previous regression restricting all coefficients on lagged terms to be zero and sum of absolute coefficients from the previous regression without the restriction.
Delay3	We follow Hou and Moskowitz (2005) to define *Delay1* in Equation 5. We estimate a regression of each bond's weekly returns on contemporaneous and four weeks of lagged returns on bond market, stock market, and bond portfolio. *Delay3* is the ratio of the sum of scaled absolute t-stat from the previous regression restricting all coefficients on lagged terms to be zero and the sum of absolute t-stat from the previous regression without the restriction.
Bond return	We define bond return according to Equation 1
Ret_{BM}	Bond market return is the amount-outstanding weighted average of all bond returns from TRACE.
Ret_{SM}	Stock market return is the value-weighted stock index return from CRSP.
Ret_{BP}	Bond portfolio return is the amount-outstanding weighted average of all bond returns in a portfolio. We follow Bessembinder, Kahle, Maxwell, and Xu (2009) to create portfolios segmented by both bond rating and time-to-maturity. We segment bonds by Moody's six major rating categories (Aaa, Aa, A, Baa, Ba, below Ba) and three time-to-maturity categories. For investment grade bonds, the time to-maturity cutoffs are 0 to 5 years, +5 to 10 years, and +10 years. For non-investment grade bonds, the cutoffs are 0 to 6 years, +6 to 9 years, and +9 years. We split the Aaa sample into two maturity categories, 0 to 7 years and +7 years. These cutoffs are designed to ensure roughly equivalent terciles. The procedure above provides a total of seventeen matching portfolios.

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Variable	Description
Amihud	The price impact of a trade per unit traded. We first calculate the daily price impact using transactions within each day and then use the mean of daily values over a certain period of time. It is similarly defined and calculated as in Dick-Nielsen, Feldhutter, and Lando (2012)
Trading activity	Volume divided by issue amount. We first calculate the daily trading activity using transactions within each day and then use the mean of trading activity over a certain period of time.

B Bond Analyst Report

We code a company list from the Compustat-CRSP database, then search and download all their fixed income reports and its summary containing information of title, page, and date according to their company name from the Thomson One Investext database manually. A few company names cannot be found in the database and we recognize it by adding a variable of report_id1=0. These company probably have not had any records in the database. In addition, many firms may not have any fixed income reports although they can be matched with the database, which we identify by report_id1=1. We then identify those firms which have fixed income reports by report_id1=2. We have a few problems when searching the company name in the database since the company name in the Compustat-CRSP list cannot be exactly same with the name recorded by Thomson one database:

The first problem is that when we type in a specific company name, there may be more than one result coming out from the database. In this case, we download all of these results and identified them by report_id1=M, report_id2=N, report_id3=P,report_id4=N. Because the number of these firms is very small, we first delete these firms and then check the robustness by adding them again.

The second problem is that we can have two firm names that are nearly the same but slightly differ (probably because a firm changes its name, and the database identifies it by adding phases like old into the old name). In this case, we download both names and then separate them by the date of report, or manually clean the records by searching on the internet.

The third problem is that some company name in our list may not be exactly same as those in Thomsonone Database, Many firms in both list may use some abbreviations as their name like “INC”, “CORP”, “LTD” which may mean “incorporated”, “corporation”, “limited”, accordingly. In this case, we match these abbreviations as much as possible. Sometimes we confirm this matching by looking at those reports title listed in the searching screening after we submit the searching command.

Finally, according to the firm list which contains 17,882 firms (gvkeys), we find 50,175 fixed income reports. All these reports can be recognized by unique gvkey_report_id, report_id is a unique id for each report given by Thomsonone Database. However, there might be many duplicate reports among these 50,175 reports for some reason.