1-1-2024

The Trading Dynamics of Corporate Bonds and Bond ETFs

Cindy Pan

THE TRADING DYNAMICS OF CORPORATE BONDS AND BOND ETFS

A Dissertation
presented in partial fulfillment of requirements
for the degree of Doctor of Philosophy
in the Department of Finance
The University of Mississippi

by

CINDY PAN

May 2024

ABSTRACT

We find trading dynamics in bond ETFs and equity ETFs to be different. Although lit trading activity in equity ETFs is greater than bond ETFs, hidden liquidity in bond ETFs is significantly higher than in equity ETFs. Dark trading volume in bond ETFs is also greater than dark trading volume in equity ETFs. Results are robust to an out-of-sample test and is not driven by a specific exchange or specific types of bond ETFs. The extensive use of hidden and dark liquidity for bond ETFs relative to equity ETFs indicates that demand for opaquely trading bond ETFs has value to traders, which may be due to no pre-trade transparency in the underlying bond markets.

We examines how corporate bonds trade as a response to corporate events that usually come to the market as a surprise. Such unscheduled corporate events include CEO turnovers, dividend changes, mergers and acquisitions (M&As), stock repurchases, seasoned equity offerings (SEOs), spin-offs, stock splits, and ticker symbol changes. Although some events resulted in an increase in corporate bond trading activity, some events did not drastically change the trading activity of their firms' bonds. Overall, bond traders react to dividend change announcements, M&A announcements, repurchase announcements, SEO announcements, and spin-off events, but not to CEO turnover events, stock splits, and stock ticker changes.

We investigate how convertible bonds trade when the option to convert the convertible bond is in-the-money. Empirical results show trading activity in convertible bonds increase when the option is in-the-money. We examine whether in-the-money convertible bonds lead to a spillover effect on a firm’s other bonds and find an increase in trading activity in those other bonds. We explore the equity market’s reactions to when convertible bonds are convertible and find increases in trading activity (lit and hidden liquidity).

DEDICATION

This dissertation is dedicated to my parents for going above and beyond to support my academic journey in every way possible. My success is owed to both of you.

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to Dr. Robert Van Ness, my dissertation chair, for his invaluable support and guidance throughout the PhD program. I would also like to extend my sincere thanks to the other members of my committee, Dr. Bonnie Van Ness, Dr. Kathleen Fuller, and Dr. Clay Dibrell for their service and contributions. I had the pleasure of working with and am grateful to the entire finance department and my fellow PhD students.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

PART 1: HIDDEN LIQUIDITY PUZZLE: BOND ETFS VERSUS EQUITY ETFS

PART 2: CORPORATE BOND TRADING AROUND UNSCHEDULED CORPORATE EVENTS

PART 1: HIDDEN LIQUIDITY PUZZLE: BOND ETFS VERSUS EQUITY ETFS

I. INTRODUCTION

This paper examines the trading activity of the two largest types of U.S.-listed exchange traded funds (ETFs), equity ETFs and bond ETFs.[1] Trading in equity and bond ETFs may differ due to differences in the underlying securities and the markets in which these securities trade. Equity markets in the U.S. allow traders to trade on either lit exchanges, where bid and ask quotes are publicly posted, with the option to hide orders by placing hidden limit orders, or away from lit exchanges in dark pools, where price quotes are not posted publicly (Bloomfield, O'Hara, and Saar, 2015; Lee and Chung, 2022). Bonds in the U.S. trade primarily in the over-the-counter (OTC) bond market, which is characterized as illiquid with no pre-trade transparency (Edwards, Harris, and Piwowar, 2007; Bessembinder, Spatt, and Venkataraman, 2020).[2] With bond markets being different from other asset classes, electronic trading in bonds has encountered barriers of entry (O'Hara and Zhou, 2021). Unlike equity markets, OTC bond markets do not allow traders to hide orders or route orders to dark pools.

Much of the research that examines ETFs primarily study equity ETFs. Ben-David, Franzoni, and Moussawi (2018) analyze equity ETFs and find that equities with higher ETF ownership have higher volatility. Huang, O'Hara and Zhong (2021) examine equity industry ETFs and find that these ETFs can help hedge risk and improve market efficiency. Box, Davis,

---

[1] See the Assets Under Management (AUM) Leaderboard of ETFs on https://etfdb.com/etfs/asset-class/.
[2] Fewer than 5% of all bonds are listed and trade on the NYSE's Automated Bond System (ABS) (Edwards, Harris, and Piwowar, 2007).

Evans, and Lynch (2021) study equity ETFs and find little evidence that equity ETFs impact returns on the underlying equities. Two studies examine short selling activity in equity ETFs (Li and Zhu, 2022; Karmaziene and Sokolovshi, 2022) and show that equity ETFs can be used to circumvent short sale constraints of underlying stocks. Converse, Levy-Yeyati, and Williams (2023) examine both bond and equity ETFs and contrast those to mutual funds.

The purpose of this study is to directly compare trading activity in bond and equity ETFs, while past literature primarily examines equity ETFs. Differences in trading between equity and bond ETFs has not been examined. As equities and bonds trade in different markets with very different trading structures, with equities trading in a more liquid and transparent market compared to bonds, we expect to see differences in the trading of the equity and bond ETFs, even though both of these ETFs trade in the equity market. This paper shows trading differences in these ETFs, that have different underlying assets trading in different markets, when both these types of ETFs trade in the same market – the equities market.

ETFs represent over 10% of the market capitalization of securities traded on U.S. exchanges accounting for more than 30% of the overall daily trading volume.[3] ETFs are attractive to investors for several reasons including lower trading costs, higher liquidity, and diversification (Ben-David, Franzoni, and Moussawi, 2017; Lettau and Madhavan, 2018). These ETF benefits are even more important to bond ETFs due to the stark contrast between the ETF market and the underlying OTC bond market. Bonds in the OTC bond market have infrequent trading and low liquidity, high transaction costs, and a lack of pre-trade price transparency (Edwards, Harris, and Piwowar, 2007). ETFs, including both equity ETFs and bond ETFs, trade

[3] See https://www.nasdaq.com/articles/global-etf-market-facts%3A-three-things-to-know-from-q1-2023

on exchanges which provide pre-trade transparency, high liquidity, and low transaction costs. The popularity of bond ETFs relative to the underlying bonds shows bond ETFs as an alternative to investing in bonds directly (Dannhauser, 2017). [4]

A feature of U.S. equity markets absent from the OTC bond market is the ability of traders to choose to provide transparent or hidden liquidity. Traders can place hidden orders, which follow price, display, and time precedence rules (Lee and Chung, 2022). Market participants embrace reduced transparency both on- and off-exchanges through placing hidden orders on exchanges and hiding orders in dark pools (Degryse, Karagiannis, Tombeur, and Wuyts, 2021). Bloomfield, O'Hara, and Saar (2015) use an experimental method to investigate traders' use of hidden orders for their trading strategies. When permitted to use hidden orders, informed and liquidity traders opt for nondisplayed orders rather than displayed orders which shows that traders value the ability to hide orders. Using a sample of Euronext-Paris stocks, Bessembinder, Panayides, and Venkataraman (2009) find hidden orders represent 44% of the sample order volume. On U.S. stock exchanges, 13% of trades execute against hidden orders and 14% of order volume is hidden (Jain and Jain, 2017).

Traders may opt to submit hidden orders or trade in dark pools for several reasons. First, submitting hidden orders or trading in dark pools can help traders avoid private information leakage, increased trading costs, and decreased liquidity due to front-running from opportunistic traders (Harris, 1996). In addition, traders might use dark pools, which have limited access, to reduce the risk of trading against informed order flow while retaining the ability to trade inside the lit market spread (Buti, Rindi, and Werner, 2022).

[4] See "4 Trends Driving ETF Growth" on https://www.blackrock.com/hk/en/ishares/insights/growth-trends.

Cox (2022) finds trade volume which executes against hidden orders on NYSE Chicago (CHX) to represents 11.07% and 2.38% of all hidden volume across lit exchanges for ETFs and stocks, respectively. The finding of higher hidden volume in ETFs is puzzling, since traders use hidden orders and trade in dark pools to hide their private information, and it is more likely that these traders have information on individual securities rather than a basket of securities. The high level of hidden volume in ETFs relative to stocks is surprising when the sample size of stocks is almost seven times the sample size of ETFs (243 stocks versus 35 ETFs). Cox does not differentiate between types of ETFs in his study and mainly focuses on the NYSE Chicago's (CHX) transition to the Pillar trading platform. Cox concludes that hidden liquidity on CHX is a result of cross trades that allows institutional brokers to execute the equity portion of trades in a multi-leg option strategy. Therefore, his findings imply that sophisticated investors use hidden orders to trade ETFs. In this study, we will examine the aggregate (across all lit exchanges) level of hidden liquidity in equity and bond ETFs and explain differences in hidden liquidity between the two types of ETFs.

We study the differences in trading activity between equity and bond ETFs and find hidden liquidity in bond ETFs to be significantly higher than in equity ETFs. [5] Given the lack of pre-trade transparency in the OTC bond markets and bonds being harder to value due to infrequent trading, bond traders are accustomed to trading bonds opaquely, which may affect how they trade bond ETFs. Therefore, when trading bond ETFs, these traders often choose a more opaque route, engaging in hidden limit order placement or routing bond ETF orders to dark

[5] Only orders that execute fully or partially against hidden orders can be identified, so hidden volume and hidden trades will refer to the executed proportion of hidden orders.

pools, which leads to increased hidden volume and hidden trades in bond ETFs relative to equity ETFs.

The remainder of the paper proceeds as follows. Section II provides a detailed review of the literature on the ETFs and trading features on exchanges and outline the development of the hypotheses. Section III describes the data and sample selection process. Section IV explains the methods used to conduct the analyses. Section V presents the empirical findings. Section VI details the robustness tests and section VII concludes.

II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Traders may choose to hide their orders due to several reasons. Yao (2017) finds informed traders using hidden limit orders to trade common stocks on NASDAQ, which suggests traders with information use hidden orders to prevent publicizing their trading intentions. Traders may use hidden orders to avoid information leakage, pick-off risk, and price impact (Harris, 1996). Traders may also simply have a preference for using hidden orders and value the option to use hidden orders (Bloomfield, O'Hara, and Saar, 2015; Bessembinder, Panayides, Venkataraman, 2009).

Hidden orders are not reserved for trading stocks but can also be used to trade ETFs. Traders with information regarding an industry or a group of similar firms may choose to trade ETFs, as opposed to the individual stocks, using hidden orders. Bond ETFs trade on equity exchanges and provide pre-trade price transparency, which is absent in the underlying bond market. Assuming bond traders trade bond ETFs rather than the individual bonds to take advantage of this transparency benefit, hidden liquidity in bond ETFs is expected to be low.

Hence, we anticipate that traders of ETFs are less likely to use hidden orders when trading bond ETFs than when trading equity ETFs.

In the U.S., off-exchange market share in 2023 increased to 43.97%.[6] Kwan, Masulis, and McInish (2015) find the opportunity to bypass limit order queues on traditional exchanges is one of the reasons for the rapid rise of dark pools. The use of dark trading venues and hidden limit order trading on exchanges can be considered substitutes (Degryse, Karagiannis, Tombeur, and Wuyts, 2021). If trading in dark pools is a substitute for hidden limit order trading on exchanges, equity ETFs will have more dark trading than bond ETFs.

H1: Hidden liquidity on exchanges, as measured by hidden volume and hidden trades, in equity ETFs is greater than in bond ETFs.

H2: Equity ETFs are traded more in dark pools than bond ETFs.

If equity ETFs have more hidden liquidity than bond ETFs, then we expect other trading differences to exist between equity and bond ETFs. Lee and Chung (2022) find that the use of hidden liquidity is associated with an increase in spreads (quoted, effective, and realized), informed trading, and trading volume and trade size. Degryse et al. (2021) find hidden-order trading on exchanges increases with stock volatility. If, as hypothesized, hidden liquidity for equity ETFs is greater than for bond ETFs, then trading metrics including trade volume, the number of trades, spread, and volatility will be higher in equity ETFs than in bond ETFs.

H3: Trading volume, the number of trades, spread, and volatility will be higher in equity ETFs than in bond ETFs.

[6] See https://www.rblt.com/market-structure-reports/let-there-be-light-us-edition-54

In today's fast-paced markets, algorithmic trading (AT) has gained popularity and is a key characteristic for high frequency trading (HFT) strategies (Menkveld, 2013). Traders engaging in AT extract information from other market participants and benefit from short-term price movements (Weller, 2018). Boehmer, Li, and Saar (2018) use the return and volatility of an index ETF as proxies to identify HFT firms engaging in short-term directional speculation strategies. Algorithmic traders are also likely to engage in pinging activities to discover hidden orders of other market participants (Lee and Chung, 2022). If, as hypothesized, hidden liquidity in equity ETFs is greater than hidden liquidity in bond ETFs, then algorithmic trading will be greater in equity ETFs relative to bond ETFs as algorithmic traders try to identify hidden orders.

H4: Algorithmic trading of equity ETFs is higher than in bond ETFs.

III. DATA AND SAMPLE

We obtain trading data on the Market Information Data Analytics System (MIDAS) from the SEC's website. Volume and trade information is identified in MIDAS along with security characteristics such as ticker symbols, trading dates, and security identifiers (whether it is a stock or ETF). Information on ETF prices, number of shares outstanding, total volume, ask price, bid price, high price, and low price are sourced from the CRSP daily security files. The sample period encompasses January 2021 to March 2022. To distinguish between equity ETFs and bond ETFs from other types of ETFs, we use the asset class list compiled on the ETF database website.[7] ETF characteristics such as fund inception year, assets under management (AUM), and

[7] See https://etfdb.com/etfs/asset-class/.

expense ratio are from the ETF database website. Dark trading data consisting of ATS Tier 1 securities are obtained from FINRA.

ETFs have to be priced at or above \$5 and trading every day in the sample period to be included in the sample. There are a total of 1,182 unique equity ETFs and bond ETFs that satisfy the filter conditions of which 962 are equity ETFs and 220 are bond ETFs. To ensure that certain characteristics are not driving the results, we create three different match samples based on price and market capitalization (Match 1), price (Match 2), and market capitalization (Match 3). Davies and Kim (2009) find that the best practice is to match firms one-to-one (without replacement) based on share price and market capitalization, therefore, Match 1 will be the main sample of interest. To obtain a matching sample based on price and market capitalization, we calculate the following score from Huang and Stoll (1996) for each bond ETF using the entire sample of equity ETFs,

$$\sum\left(\frac{x_i^B - x_i^E}{(x_i^B + x_i^E)/2}\right)^2, \qquad (1)$$

where x_i is one of the two attributes, and B and E refers to bond ETF and equity ETF, respectively. Then, for each bond ETF, we select an equity ETF with the smallest score as its match (without replacement). Match 2 and Match 3 are based on the smallest difference in the match variables. Match 1 consists of 194 matched pairs, while Match 2 and Match 3 each consist of 220 matched pairs. Table 1 reports the different type and grade classifications of the 220 bond ETFs. The classification for bond type is found on the ETF Database under FactSet Classifications for Category, and the classification for bond grade is found on the ETF Database under FactSet Classifications for Focus. The largest type of bond ETFs is corporate bond ETFs

(80 bond ETFs) with the second largest category being broad type of bond ETFs (56 bond ETFs). Most bond ETFs in the sample are investment grade (149 bond ETFs).

Hidden liquidity is proxied by *Hidden Volume (%)*, total hidden volume divided by total trade volume, and *Hidden Trades (%)*, total hidden trades divided by total trades. The four algorithmic trading proxies, the odd lot volume ratio, the trade-to-order volume ratio, the cancel-to-trade ratio, and the average trade size, are constructed following Weller (2018). According to Weller, high odd lot volume ratios and cancel-to-trade ratios indicate high levels of algorithmic trading, while high trade-to-order volume ratios and trade size indicate low levels of algorithmic trading. Spread is the difference in the closing ask and closing bid divided by the midpoint of the closing ask and closing bid. Chung and Zhang (2014) find that the CRSP-based spread is highly correlated with TAQ-based spread and provides a better approximation than other low-frequency liquidity measures. Volatility is the difference in daily high price and the daily low price. ETF age is the difference between the ETF's inception year and the year 2022 which is the last year of the sample period.

Table 2 presents the descriptive statistics on the three match specifications. Panel A of table 2 reports the trading activities and security characteristics of Match 1. Equity ETFs have more trading activity with an average number of trades of 6,682, trade volume of 1.008 million, canceled trades of 540,745, and odd lot volume of 2,447, while bond ETFs have an average number of trades of 1,930, trade volume of 0.45 million, canceled trades of 77,086, and odd lot volume of 473. From the summary statistics, there is preliminary evidence that bond ETFs have a higher hidden volume than equity ETFs, 41% versus 28%, respectively. On average, bond (equity) ETFs have an expense ratio of 0.29% (0.45%), $4.6 billion ($4.1 billion) of assets under management (AUM) and are 9.60 (11.60) years old. Panel B and panel C in table 2 present the summary statistics on Match 2 and Match 3, respectively.

To ensure good matches across the three match specifications, we conducted a t-test on the match variables. Table 3 presents the results from the t-test on the match variables for each of the three specifications. Panel A reports the t-test on Match 1, while panel B and panel C report the t-test on Match 2 and 3, respectively. The difference between the match variables across the three match specifications are insignificant which indicates good matches between bond and equity ETFs.

IV. METHODS

Instead of the traditional z-test used in testing proportion variables, we use the normalized difference method to test for differences in hidden liquidity between equity and bond ETFs (Imbens and Wooldridge, 2009). This method is recommended when the sample size is large which will make even small differences in the covariates statistically significant. We calculate the following normalized difference, Δx, for the hidden liquidity proxies, *Hidden Volume (%)* and *Hidden Trades (%)*, between bond ETFs and equity ETFs,

$$\Delta x = \frac{\bar{X}_B - \bar{X}_E}{\sqrt{S_B^2 + S_E^2}}, \tag{2}$$

where $\bar{X}_B$ and $\bar{X}_E$ are the average of one of the hidden liquidity proxies for bond ETFs and equity ETFs, respectively. S_B^2 and S_E^2 are the variance of one of the hidden liquidity proxies for bond ETFs and equity ETFs, respectively. A normalized difference above 0.25 suggests differences in the covariate distribution between the two groups.

In regression analysis, we initially use ordinary least squares (OLS) regressions and estimate the following regression:

$$Y_i = \beta_0 + \gamma X_i + \varepsilon_i \, , \qquad \textbf{(3)}$$

where i is ETFs and Y_i is one of the hidden liquidity proxies. X_i is the set of independent variables including price, market capitalization, total trade volume, spread, volatility, trade size, cancel-to-trade ratio, trade-to-order-volume ratio, the odd-lot volume ratio, expense ratio, AUM, and fund age (all in logs). All OLS regressions use the average of the variables over the sample period.

Since the difference in trading dynamics between equity and bond ETFs is one of the main interests of the paper, we regress the differences in the dependent and independent variables to identify which variables significantly determines trading dynamics between the two groups. Using the same regression specification as above, Y_i is now the difference of one of the hidden liquidity proxies between bond and equity ETFs (i.e., *Hidden Volume* (%) = *Hidden Volume*$_B$ *(%)* − *Hidden Volume*$_E$ *(%)* where B and E is for bond ETFs and equity ETFs, respectively). X_i is now the difference in the set of independent variables between the two groups (i.e., *price* = *price*$_B$ – *price*$_E$). We take the absolute value of the control variables before taking the log or the log(1+x) transformation to use in the difference regressions.

Next, we use probit regression analysis and marginal effects to examine hidden liquidity between equity and bond ETFs. The main variable of interest is the dummy variable, *Bond*, coded one for bond ETFs and zero for equity ETFs. Control variables are the same variables used in the OLS regressions (all in logs).

V. EMPIRICAL FINDINGS

HIDDEN LIQIDITY

Figures 1A to 1C present a visualization of the trading dynamics between equity ETFs and bond ETFs for each of the three match specifications. Focusing on Match 1 in Figure 1A, Panel A shows that *Hidden Volume (%)* is higher in bond ETFs than equity ETFs. Panel B shows that *Hidden Trades (%)* is also higher in bond ETFs than equity ETFs. The reverse is true for *Lit Volume (%)* and *Lit Trades (%)*, which is higher in equity ETFs than bond ETFs.

The results are consistent across Match 2 (Figure 1B) and Match 3 (Figure 1C). *Hidden Volume (%)* and *Hidden Trades (%)* in bond ETFs are higher than *Hidden Volume (%)* and *Hidden Trades (%)* in equity ETFs. The figures provide preliminary evidence that bond ETFs are traded more opaquely than equity ETFs on exchanges.

Table 4 tests the different levels of hidden and lit trading activity presented in figures 1A to 1C. Focusing on panel A (Match 1), the average *Hidden Volume (%)* and *Hidden Trades (%)* in bond ETFs are 40.8% and 40.3%, respectively. The average *Hidden Volume (%)* and *Hidden Trades (%)* in equity ETFs are 27.8% and 26.7%, respectively. The normalized difference is greater than 0.25 for *Hidden Volume (%)* and *Hidden Trades (%)* which suggests differences in the level of hidden liquidity between bond and equity ETFs with bond ETFs having higher levels of hidden liquidity.

In table 4 panel A, the average *Lit Volume (%)* and *Lit Trades (%)* in bond ETFs are 59.2% and 59.7%, respectively, while the average *Lit Volume (%)* and *Lit Trades (%)* in equity ETFs are 72.2% and 73.3%, respectively. The normalized difference score in *Lit Volume (%)* and *Lit Trades (%)* indicates higher levels of lit liquidity in equity ETFs than bond ETFs. Panels B

(Match 2) and C (Match 3) show similar levels of hidden and lit liquidity in bond and equity ETFs. Overall, results in table 4 are consistent with the figures in that bond ETFs have higher levels of hidden liquidity than equity ETFs, while equity ETFs have higher levels of lit trading activity than bond ETFs. Results are also consistent across Match 2 (panel B) and Match 3 (panel C). This leads to the rejection of hypothesis 1 which states equity ETFs have higher levels of hidden liquidity than bond ETFs.

The empirical evidence in table 4 finds that bond ETFs have more hidden liquidity compared to similarly matched equity ETFs. A possible explanation of this finding could be that bond traders are accustomed to no pre-trade transparency in the OTC bond market and trade bond ETFs in a similar manner on equity exchanges. Alternatively, traders of bond ETFs may simply have a preference for hidden orders when trading this type of security.

DARK TRADING

Due to the feature of no pre-trade transparency in dark pools, these types of off-exchanges are used as substitutes to hidden liquidity on lit exchanges (Degryse et al., 2021). Figure 2 presents graphical evidence on the levels of dark trading for bond and equity ETFs. Focusing on Match 1 in panel A (dark share quantity) and panel B (number of dark trades), it appears that dark share quantity is higher in bond ETFs than equity ETFs, but the number of dark trades between the two is not much different. The conclusions are similar for Match 2 (panels C and D) and Match 3 (panels E and F).

To further test figure 2, we use a t-test to test for differences in dark trading between bond and equity ETFs. Table 5 presents t-tests on dark trading variables between the two groups. Across the match specifications, bond ETFs have significantly higher dark trading volume.

Equity ETFs have a significantly higher number of dark trades in Match 1, but results are insignificant in Match 2 and 3 which may indicate that the number of dark trades in bond ETFs and equity ETFs are at similar levels. Consistent with dark trading being a substitute for hidden liquidity, dark trading is higher or at similar levels for bond ETFs compared with similarly matched equity ETFs. This leads to the rejection of hypothesis 2 which states that equity ETFs have more dark trading activity than bond ETFs.

TRADING DIFFERENCES

To determine factors affecting the difference in trading dynamics between equity and bond ETFs, we run OLS regressions using *Hidden Volume (%)* and *Hidden Trades (%)* as dependent variables. Tables 6 and 7 present results of the OLS regressions on the Match 1 sample for *Hidden Volume (%)* and *Hidden Trades (%)*, respectively. In Tables 6 and 7, the regression specification examining other trading variables, trade volume, spread, and volatility, while controlling for price and market capitalization is presented in columns (1) – (3). The algorithmic trading proxies of trade size, cancel-to-trade ratio, trade-to-order volume ratio, and odd lot volume ratio, while controlling for price and market capitalization, are in the specification presented in columns (4) – (6). ETF characteristics include expense ratio, AUM, and fund age while controlling for price and market capitalization are in the specification presented in columns (7) – (9). All independent variables are log-transformed. The difference regressions use the absolute value of log-transformed or log(1+x) transformed difference as the independent variables between equity ETFs and bond ETFs. Regression results for Match 2 and Match 3 are in Appendix A.

In table 6 column (1), an increase in average market capitalization and average spread will increase average *Hidden Volume (%)* in bond ETFs, while an increase in average trade volume and average volatility will decrease average *Hidden Volume (%)* in bond ETFs. When trade volume and volatility are high, bond ETFs are less likely to be traded using hidden orders but when the spread is high, hidden volume increases. For equity ETFs in column (2), an increase in average price, average market cap, and average spread will increase average *Hidden Volume (%)*, while an increase in average volatility will decrease average *Hidden Volume (%)*. High price and high market cap equity ETFs with wide spread have high hidden volume, while high volatility decrease hidden volume in equity ETFs. Column (3) in table 6 reports that spread and volatility are the main factors affecting the trading differences in *Hidden Volume (%)* between bond and equity ETFs.

Regarding algorithmic trading, columns (4) and (5) in table 6 provide mixed evidence. While higher cancel-to-trade ratio and odd-lot volume ratio indicate higher levels of AT, only cancel-to-trade ratio is significant for bond ETFs. Trade size and trade-to-order volume ratio are both significant but have conflicting signs in bond ETFs. Together, the positive cancel-to-trade ratio and negative trade size indicates high levels of AT. In equity ETFs, the cancel-to-trade ratio and odd-lot volume ratio are both positive and significant which indicate higher levels of algorithmic trading, but trade size is insignificant with trade-to-order volume ratio indicating less algorithmic trading. The difference regression in column (6) indicates only trade size and the cancel-to-trade ratio explain differences in algorithmic trading between bond and equity ETFs. Overall, there is conflicting evidence regarding the level of AT in bond and equity ETFs, but trade size and cancel-to-trade ratio is significantly different in the two types of ETFs.

Column (7) in table 6 reports that an increase in the average expense ratio, average AUM, and average fund age will decrease average *Hidden Volume (%)* in bond ETFs. This indicates that bond ETFs with high expense ratio, high AUM, and are older will have less hidden volume.

Column (8) in table 6 reports that an increase in average AUM (average fund age) will increase (decrease) average *Hidden Volume (%)* in equity ETFs. Therefore, equity ETFs with high AUM and less mature will have high hidden volume. In column (9) of table 6, results indicate that only AUM explain the differences in *Hidden Volume (%)* between bond and equity ETFs. Results in table 7 regarding *Hidden Trades (%)* in bond and equity ETFs are similar to findings in table 6 with respect to *Hidden Volume (%)*. Overall, spread volatility, trade size, cancel-to-trade ratio, and AUM explain the differences in *Hidden Volume (%)* between bond and equity ETFs, while spread, volatility, the cancel-to-trade ratio, and AUM explain the differences in *Hidden Trades (%)* between bond and equity ETFs.

Table 8 presents the results of the probit regressions and marginal effects on *Hidden Volume (%)* and *Hidden Trades (%)* for Match 1. The variable of interest is the dummy variable *Bond* coded one for bond ETF and zero for equity ETF. The marginal effects on the *Bond* dummy in column (2) show that bond ETFs lead to an increase in *Hidden Volume (%)* by 5.92%. The marginal effects on the *Bond* dummy in column (4) show that bond ETFs lead to an increase *Hidden Trades (%)* by 5.56%. These results are evident of bond ETFs having more hidden liquidity than equity ETFs. Probit regressions and marginal effects on *Hidden Volume (%)* and *Hidden Trades (%)* for Match 2 and Match 3 are in Appendix A.

VI. ROBUSTNESS

OUT-OF-SAMPLE TEST

To examine how the results hold out-of-sample, we examine the trading dynamics between bond and equity ETFs in the sample period of January 2012 to December 2012. The year 2012 is the first year the MIDAS data became available. The same matching procedure and filters are used for this sample. The Match 1 specification (match on price and market capitalization) in this sample period consists of 40 matched pairs due to less bond ETFs in the market at the time or the lack of trading as recorded in MIDAS.

Figure 3 presents the graphs of hidden and lit trading activity between the two groups across the 2012 sample period. The average *Hidden Volume (%)* (*Hidden Trades (%)*) in bond ETFs is 16.6% (15.7%). The average *Hidden Volume (%)* (*Hidden Trades (%)*) in equity ETFs is 10.5% (10.7%). The average *Lit Volume (%)* and *Lit Trades (%)* in bond ETFs are 83.4% and 84.3%, respectively, while the average *Lit Volume (%)* and *Lit Trades (%)* in equity ETFs are 89.5% and 89.3%, respectively. The normalized difference score of 0.601 and 0.526 indicates that bond ETFs have higher *Hidden Volume (%)* and *Hidden Trades (%)*, respectively, than equity ETFs.

Results remain consistent over the 2012 sample period. Bond ETFs have higher levels of hidden volume and hidden trades, while equity ETFs have higher levels of lit volume and lit trades. Interestingly, the level of hidden liquidity in bond and equity ETFs in the main sample period is over two times the level of hidden liquidity in the 2012 sample period. This indicates that hidden liquidity is more prevalent in today's modern markets and hidden orders have value to traders.

Table 9 reports the normalized difference in hidden liquidity and lit liquidity between bond and equity ETFs in 2012. Results indicate that hidden volume and hidden trades in bond ETFs are significantly higher than in equity ETFs, while lit volume and lit trades in equity ETFs are significantly higher than in bond ETFs. Overall, the results in the out-of-sample test are consistent with the main finding of the paper with bond ETFs having higher levels of hidden liquidity relative to equity ETFs.

ACROSS EXCHANGES

Lit exchanges in the U.S. compete for order flow with fifteen exchanges competing for market share in the main sample period. As a result, it would be interesting to examine whether a specific exchange or set of exchanges is driving the high levels of hidden liquidity in bond ETFs. The fifteen exchanges in MIDAS include Amex, Arca, Bats-Y, Bats-Z, Boston, CHX, Edge-A, Edge-X, IEX, MEMX, MIAX, NSX, NYSE, Nasdaq, and Phlx. Figure 4 illustrates the breakdown of hidden volume and hidden trades of bond ETFs and equity ETFs across the fifteen exchanges. Panel A and panel B depict the level of hidden liquidity in the Match 1 sample of ETFs. Panels C and D show the level of hidden liquidity in the Match 2 sample of ETFs, while panels E and F show the level of hidden liquidity in the Match 3 sample of ETFs.

Across the three match specifications in figure 4, it appears that the level of hidden liquidity in bond ETFs across exchanges are not different from the level of hidden liquidity in equity ETFs. In other words, no exchange is dominant in catering to hidden liquidity provision of bond ETFs over equity ETFs. Interestingly, Arca has the highest level of hidden liquidity in ETFs followed by Nasdaq. It seems that traders have a preference for using hidden orders to trade ETFs opaquely on Arca and Nasdaq.

To formally test the graphs in figure 4, table 10 reports the normalized difference test in hidden liquidity between bond and equity ETFs on each exchange for Match 1. Panel A reports the normalized difference test across the fifteen exchanges for Hidden Volume (%). Panel B reports the normalized difference test across the fifteen exchanges for Hidden Trades (%). There is no evidence of higher hidden liquidity in bond ETFs compared to equity ETFs on a specific exchange as no normalized difference score is above 0.25. The normalized difference tests on the levels of hidden liquidity across exchanges for Match 2 and Match 3 are in Appendix A. Overall, the high level of hidden liquidity in bond ETFs relative to equity ETFs is not driven by a certain exchange.

EXOGENOUS SHOCK ON CHX

On November 4th, 2019, the NYSE Chicago (CHX) transitioned to the Pillar trading platform.[8] Prior to the transition, no trades which executed against hidden orders are reported in the MIDAS database. In other words, when using hidden orders to trade bond and equity ETFs there is no pre-trade and post-trade price transparency (similar to trading in off-exchange venues like dark pools but on-exchange). This unique setting allows us to examine hidden liquidity on an exchange, specifically CHX, and see what occurs once hidden trades are reported.

Using this exogenous shock on CHX, we compare the level of hidden liquidity in these ETFs on CHX relative to all exchanges (including CHX) 20 days pre-transition and 20 days post-transition. To analyze differences in hidden liquidity levels in bond and equity ETFs around the transition, we examine a [-5, +5] event window. We expect to find similar results to the empirical analysis on dark pool trading activity between the two types of ETFs.

Using the last quarter of 2019 from MIDAS (October, November, and December 2019) as the sample period, we identified bond and equity ETFs in Match 1 that trade on CHX during this period to be included in the sample. From the Match 1 sample, this resulted in 63 matched pairs where the matched bond and equity ETFs both trade on CHX (126 unique ETFs). Table 11 panel A reports the t-test on the level of hidden liquidity on CHX 20 days pre-transition and 20 days post-transition to Pillar. The increase in reported hidden volume, hidden trades, and hidden trade size post-transition is significant in the sample of bond and equity ETFs that trade on CHX when

[8] See Cox (2022) for a detailed account of the Pillar trading platform.

compared to the pre-transition period when no trades executed against hidden orders are reported.[9] Hidden volume in the sample ETFs is 20,000 with hidden trade size in the order of 5,701 per trade.

In the robustness test of hidden liquidity across the fifteen exchanges, we find that hidden volume and hidden trades in the sample ETFs on CHX is minimal. Therefore, we compare hidden liquidity on CHX to all fifteen exchanges (including CHX) during the period of 20 days pre-transition and 20 days post-transition to Pillar. The hidden liquidity measures are calculated as follows:

$$Hidden\ Volume\ (\%) = \frac{CHX\ Hidden\ Volume\ ('000)}{All\ Hidden\ Volume\ ('000)}, \quad (4)$$

$$Hidden\ Trades\ (\%) = \frac{CHX\ Hidden\ Trades}{All\ Hidden\ Trades}, \quad (5)$$

$$Hidden\ Trade\ Size\ (\%) = \frac{CHX\ (Hidden\ Volume\ ('000 * 1{,}000)/Hidden\ Trades)}{All\ (Hidden\ Volume\ ('000 * 1{,}000)/Hidden\ Trades)}. \quad (6)$$

We conduct a t-test on the percentage of hidden liquidity on CHX relative to all exchanges to compare the 20 days pre-transition period to the 20 days post-transition period. Table 11 panel B shows all hidden liquidity measures to be zero in the 20 days pre-transition, since trades executed against hidden orders are not reported at the time. The average hidden liquidity level post-transition is significant in the 20 days post-transition. Hidden volume on CHX represents around 1% of total hidden volume across exchanges in the sample ETFs. Hidden trades represent around 0.01% and hidden trade size is around the magnitude of 3.76% on CHX in the sample ETFs. The results of significantly higher levels of hidden liquidity on CHX is not surprising since hidden liquidity went unreported prior to the transition to Pillar. However,

[9] Hidden Trade Size = (Hidden Volume (‘000) * 1,000)/Hidden Trades

hidden liquidity on CHX in the sample ETFs represents a small percentage of the overall level of hidden liquidity across exchanges.

Next, we are interested in the level of hidden liquidity in the sample ETFs on CHX relative to all the exchanges when we distinguish between bond and equity ETFs. To test for differences in hidden liquidity measures in bond and equity ETFs pre- and post-transition, we calculate the difference as follows:

$$Hidden\ Liquidity\ (\%) = \left(\frac{CHX\ Hidden\ in\ ETF_B\ Pre}{All\ Hidden\ in\ ETF_B\ Pre} - \frac{CHX\ Hidden\ in\ ETF_B\ Post}{All\ Hidden\ in\ ETF_B\ Post}\right) - \left(\frac{CHX\ Hidden\ in\ ETF_E\ Pre}{All\ Hidden\ in\ ETF_E\ Pre} - \frac{CHX\ Hidden\ in\ ETF_E\ Post}{All\ Hidden\ in\ ETF_E Post}\right), \quad (7)$$

where ETF_B and ETF_E represents bond ETFs and equity ETFs, respectively. *Hidden Liquidity (%)* represents hidden volume, hidden trades, or hidden trade size. Results from the t-test is presented in panel C of Table 11. All hidden liquidity proxies in panel C are insignificant which suggests that hidden liquidity levels on CHX relative to all exchanges in bond and equity ETFs 20 days post-transition are not statistically different. Hidden volume for bond (equity) ETFs on CHX represents 0.838% (1.37%) of total hidden volume in these ETFs. Hidden trades in bond (equity) ETFs on CHX represents 0.003% (0.006%) of total hidden trades in the sample ETFs across exchanges. Hidden trade size in bond (equity) ETFs on CHX represents 2.65% (4.88%) of total hidden trade size in the sample ETFs across exchanges. While hidden liquidity in the sample ETFs proxied by hidden volume and hidden trades are marginal in magnitude, average hidden trade size per order is relatively large. This suggests that traders are using hidden orders to trade large quantities of ETFs opaquely on CHX.

While a broad event window around the transition period is informative, we are interested in the different hidden liquidity levels between bond and equity ETFs on CHX only. Zoning into

CHX allows us to identify differences, if any, in hidden liquidity between bond and equity ETFs when both their hidden liquidity levels were unreported to when their hidden liquidity levels are reported. In this case, we examine the hidden liquidity proxies around a [-5, +5] event window comparing bond and equity ETFs.

Table 12 presents the results from a t-test on the differences in hidden liquidity between bond and equity ETFs around the [-5, +5] event window. Panel A shows that *Hidden Volume ('000)* from day -5 to day -1 is zero which is before the Pillar transition for reporting trades against hidden orders. The t-test on the average difference between bond and equity ETFs show that stock ETFs have significantly higher *Hidden Volume ('000)* on the event day in the magnitude of around 968,000 more than bond ETFs. While *Hidden Volume ('000)* in bond ETFs is higher than equity ETFs on day 1, equity ETFs have higher *Hidden Volume ('000)* than bond ETFs over the rest of the event window (with day 3 being insignificant). *Hidden Trades* in panel B follow a similar pattern to *Hidden Volume ('000)*. Equity ETFs have higher *Hidden Trades* than bond ETFs in days 0, 2, 3, 4, and 5, but bond ETFs have higher *Hidden Trades* than stock ETFs on day 1. *Hidden Trade Size* in panel C show a slightly different finding. *Hidden Trade Size* in bond ETFs is significantly higher than in equity ETFs on days 0, 1, and 4 while *Hidden Trade Size* in equity ETFs is significantly higher than in bond ETFs on days 2, 3, and 5.[10] The magnitude of the average *Hidden Trade Size* is nontrivial. On the day CHX transitioned to Pillar,

[10] Outside the event window, we extend the analysis in table 12 a few days after CHX's the transition to Pillar. From days +10 to +25, *Hidden Trade Size* between bond and equity ETFs is insignificant on days 10, 22, and 24. *Hidden Trade Size* in bond ETFs is significantly higher than in equity ETFs on days 11, 13, 16, 18, 20, 21, and 25. *Hidden Trade Size* in equity ETFs is significantly higher than in bond ETFs on days 12, 14, 15, 17, 19, 22, 23 and 24. Overall, *Hidden Trade Size* on CHX does not appear to be consistently higher in bond ETFs after the transition to Pillar, which may imply that traders do not favor trading one type of ETF opaquely over the other.

the average *Hidden Trade Size* in bond (equity) ETFs is 12,269 (3,053). Again, this implies that traders are using hidden orders to trade large quantities of ETFs opaquely.

Overall, after trades executed against hidden orders are reported on CHX after the transition to Pillar, the level of hidden liquidity in ETFs on CHX is significant. Equity ETFs have higher hidden volume and hidden trades on the day CHX transitioned to the Pillar trading platform compared to bond ETFs. Although this result seemingly contradicts the main findings where we found higher hidden liquidity in bond ETFs compared to equity ETFs, hidden trade size in bond ETFs is significantly higher than in stock ETFs which still shows that traders have a preference for trading bond ETFs opaquely and in large quantities. Furthermore, 20 days post-transition, the difference in the average hidden liquidity proxies in bond and equity ETFs on CHX relative to all exchanges are not significant.

BY BOND ETF TYPES

To examine if certain types of bond ETFs are driving the results, we split the bond ETF sample into bond ETFs that are considered relatively "more risky" versus "less risky" using the ETFs in the Match 1 sample. Bond ETFs that track government bonds, treasuries, and municipal bonds are less risky and broadly classified as Government Bond ETFs. For the riskier bond ETF type, all corporate bond ETFs are included in this sample named Corporate Bond ETFs. The full sample of equity ETFs in Match 1 is used for comparison. The larger sample size in equity ETFs relative to Government Bond ETFs and Corporate Bond ETFs should bias the results against finding significantly higher hidden liquidity in the two types of bond ETFs.[11]

[11] The full sample of bond ETFs in Match 1 is not used since some bond ETFs are classified as agency, broad, ABS, etc.

Table 13 panel A compares hidden liquidity in Government Bond ETFs and Corporate Bond ETFs. The average *Hidden Volume (%)* (*Hidden Trades (%)*) in Corporate Bond ETFs is 41.4% (40.7%). The average *Hidden Volume (%)* (*Hidden Trades (%)*) in Government Bond ETFs is 35.2% (35.9%). The normalized difference score of 0.287 indicates that Corporate Bond ETFs have higher *Hidden Volume (%)* than Government Bond ETFs, but *Hidden Trades (%)* between the two types are not much different (normalized difference score of 0.242). This result provides some evidence that "more risky" bond ETFs may be traded more opaquely than "less risky" bond ETFs.

Table 13 panel B compares hidden liquidity in Equity ETFs and Government Bond ETFs. The average *Hidden Volume (%)* (*Hidden Trades (%)*) in Equity ETFs is 27.8% (26.7%), while the average *Hidden Volume (%)* (*Hidden Trades (%)*) in Government Bond ETFs is 35.3% (35.9%). The normalized difference score of -0.300 and -0.405 indicates that Government Bond ETFs have higher *Hidden Volume (%)* and *Hidden Trades (%)*, respectively, relative to Equity ETFs. The main finding of bond ETFs having higher levels of hidden liquidity compared to equity ETFs still holds when comparing a category of relatively "less risky" bond ETFs to equity ETFs.

Table 13 panel C compares hidden liquidity in Equity ETFs and Corporate Bond ETFs. The average *Hidden Volume (%)* (*Hidden Trades (%)*) in Equity ETFs is 27.8% (26.7%), while the average *Hidden Volume (%)* (*Hidden Trades (%)*) in Corporate Bond ETFs is 41.4% (40.7%). The normalized difference score of -0.583 and -0.646 indicates that Corporate Bond ETFs have higher *Hidden Volume (%)* and *Hidden Trades (%)*, respectively, than Equity ETFs. Overall, bond ETFs have significantly higher hidden liquidity compared to equity ETFs regardless of whether the underlying bonds are relatively more or less risky.

VII. CONCLUSION

ETFs have gained interest in the literature (Ben-David, Franzoni, and Moussawi; 2018; Box, Davis, Evans, and Lynch, 2021; Huang, O'Hara and Zhong, 2021; Li and Zhu, 2022; Karmaziene and Sokolovshi, 2022). However, research on ETFs primarily focus on equity ETFs with few studies examining bond ETFs (Dannhauser, 2017; Levy-Yeyati, and Williams, 2023). In this study, we are interested in the trading dynamics between bond and equity ETFs.

We suspect different trading between equity and bond ETFs because the underlying securities trade in different markets and are structured differently with different features. Bonds trade primarily in the OTC market structure with no pre-trade price transparency and relatively less liquidity than equity markets. Equities trade on liquid lit exchanges where price quotes are publicly available but has a feature to submit hidden orders. Equities can also be traded off-exchange in dark pools where price quotes are not publicly posted. ETFs trade through the same platforms as equities, lit exchanges and dark pools. Therefore, when a type of security (bonds) have access to another market with different features (pe-trade price transparency and hidden limit orders), it is of interest on how it trades in that new market.

Empirical evidence confirms differences in trading dynamics between bond ETFs and equity ETFs. Specifically, bond ETFs have a larger percentage of hidden liquidity than comparable equity ETFs even though the percentage of lit trading activity in equity ETFs is higher than in bond ETFs. Consistent with dark trading off-exchange being a substitute for hidden liquidity on exchanges, bond ETFs have higher or similar levels of dark trading activity than equity ETFs.

The findings of higher hidden liquidity for bond ETFs relative to equity ETFs is persistent throughout the sample period and out-of-sample. Results are not driven by a specific exchange, and results are not driven by certain types of bond ETFs. Using the CHX transition to the Pillar trading platform as an exogenous shock, we find that hidden liquidity in the sample ETFs on CHX relative to all fifteen exchanges is relatively minimal. Although hidden volume and hidden trades are reportedly higher in equity ETFs around the transition period, hidden trade size in bond ETFs is significantly higher than in equity ETFs. 20 days post-transition, the difference in hidden liquidity levels in bond and equity ETFs on CHX relative to all fifteen exchanges are not significant. Overall, even though lit liquidity in bond ETFs has not caught up to the momentum of equity ETFs, hidden liquidity in bond ETFs is significantly higher than hidden liquidity in equity ETFs. Some factors that may explain the differences in hidden liquidity between these two types of ETFs include spread, volatility, trade size, cancel-to-trade ratio, and AUM.

In conclusion, it is a puzzle as to why bond ETFs have higher hidden liquidity than stock ETFs. The higher level of hidden liquidity and dark trading in bond ETFs may be a result of bond traders being accustomed to the bond market having no pre-trade transparency and trade accordingly when they trade bond ETFs rather than take advantage of the transparency offered on exchanges. Alternatively, traders of bond ETFs may simply have a preference for trading this type of security opaquely. The implication associated with this conclusion suggests that rather than providing a transparency bridge to the OTC bond market, bond ETFs are traded opaquely like the underlying security. Furthermore, this may provide some additional insight to the slow adoption of electronic trading in bonds (O'Hara and Zhou, 2021).

LIST OF REFERENCES

Bao, J., Pan, J., & Wang, J. (2011). The illiquidity of corporate bonds. *The Journal of Finance*, *66*(3), 911–946.

Ben-David, I., Franzoni, F., & Moussawi, R. (2017). Exchange-Traded Funds. *Annual Review of Financial Economics*.

Bessembinder, H., Panayides, M., & Venkataraman, K. (2009). Hidden liquidity: An analysis of order exposure strategies in electronic stock markets. *Journal of Financial Economics*, *94*(3), 361–383.

Bessembinder, H., Spatt, C., & Venkataraman, K. (2020). A survey of the microstructure of fixed-income markets. *Journal of Financial and Quantitative Analysis*, *55*(1), 1–45.

Bloomfield, R., O'Hara, M., & Saar, G. (2015). Hidden liquidity: Some new light on Dark Trading. *The Journal of Finance*, *70*(5), 2227–2274.

Boehmer, E., Li, D., & Saar, G. (2018). The competitive landscape of high-frequency trading firms. *The Review of Financial Studies*, *31*(6), 2227–2276.

Boulatov, A., & George, T. J. (2013). Hidden and displayed liquidity in securities markets with informed liquidity providers. *Review of Financial Studies*, *26*(8), 2096–2137.

Box, T., Davis, R., Evans, R., & Lynch, A. (2021). Intraday arbitrage between etfs and their underlying portfolios. *Journal of Financial Economics*, *141*(3), 1078–1095.

Buti, S., Rindi, B., & Werner, I. M. (2022). Diving into dark pools. *Financial Management*, *51*(4), 961–994.

Chung, K. H., & Zhang, H. (2014). A simple approximation of intraday spreads using daily data. *Journal of Financial Markets*, *17*, 94–120.

Converse, N., Levy-Yeyati, E., & Williams, T. (2023). How etfs amplify the global financial cycle in emerging markets. *The Review of Financial Studies*, *36*(9), 3423–3462.

Cox, J. S. (2022). The Impact of Reporting Changes on Hidden Liquidity: Evidence from the Chicago Stock Exchange. *Global Finance Journal*, *53*, 100740.

Dannhauser, C. D. (2017). The Impact of Innovation: Evidence from Corporate Bond Exchange-Traded Funds (ETFs). *Journal of Financial Economics*, *125*(3), 537–560.

Davies, R. J., & Kim, S. S. (2009). Using matched samples to test for differences in trade execution costs. *Journal of Financial Markets*, *12*(2), 173–202.

Degryse, H., de Jong, F., & Kervel, V. van. (2015). The impact of dark trading and visible fragmentation on market quality*. *Review of Finance*, *19*(4), 1587–1622.

Degryse, H., Karagiannis, N., Tombeur, G., & Wuyts, G. (2021). Two Shades of Opacity: Hidden Orders and Dark Trading. *Journal of Financial Intermediation*, *47*, 100919.

Edwards, A. K., Harris, L. E., & Piwowar, M. S. (2007). Corporate Bond Market Transaction Costs and Transparency. *The Journal of Finance*, *62*(3), 1421–1451.

Grégoire, V., & Martineau, C. (2021). How is earnings news transmitted to stock prices? *Journal of Accounting Research*, *60*(1), 261–297.

Harris, L. (1996). Does a Large Minimum Price Variation Encourage Order Exposure? (Vol. 96, No. 5). *New York Stock Exchange*.

Huang, R. D., & Stoll, H. R. (1996). Dealer versus auction markets: A paired comparison of execution costs on NASDAQ and the NYSE. *Journal of Financial Economics*, *41*(3), 313–357.

Huang, S., O'Hara, M., & Zhong, Z. (2020). Innovation and informed trading: Evidence from industry etfs. *The Review of Financial Studies*, *34*(3), 1280–1316.

Imbens, G., & Wooldridge, J. (2009). Recent developments in the econometrics of program evaluation.

Jain, A., & Jain, C. (2017). Hidden Liquidity on the U.S. Stock Exchanges. *The Journal of Trading*, *12*(3), 30–36.

Karmaziene, E., & Sokolovski, V. (2021). Short-selling equity exchange traded funds and its effect on stock market liquidity. *Journal of Financial and Quantitative Analysis*, *57*(3), 923–956.

Kwan, A., Masulis, R., & McInish, T. H. (2015). Trading rules, competition for order flow and market fragmentation. *Journal of Financial Economics*, *115*(2), 330–348.

Lee, A. J., & Chung, K. H. (2022). Hidden Liquidity, Market Quality, and Order Submission Strategies. *Journal of Financial Markets*, 100739.

Lettau, M., & Madhavan, A. (2018). Exchange-Traded Funds 101 for Economists. *Journal of Economic Perspectives*, *32*(1), 135–154.

Li, F. W., & Zhu, Q. (2022). Short selling etfs. *The Review of Asset Pricing Studies*, *12*(4), 960–998.

Menkveld, A. J. (2013). High frequency trading and the New Market Makers. *Journal of Financial Markets*, *16*(4), 712–740.

O'Hara, M., & Alex Zhou, X. (2021). The electronic evolution of corporate bond dealers. *Journal of Financial Economics*, *140*(2), 368–390.

Weller, B. M. (2018). Does algorithmic trading reduce information acquisition? *The Review of Financial Studies*, *31*(6), 2184–2226.

Yao, C. (2017). Do hidden orders contain information? evidence from cross-sectional returns and corporate events. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3024465

APPENDIX

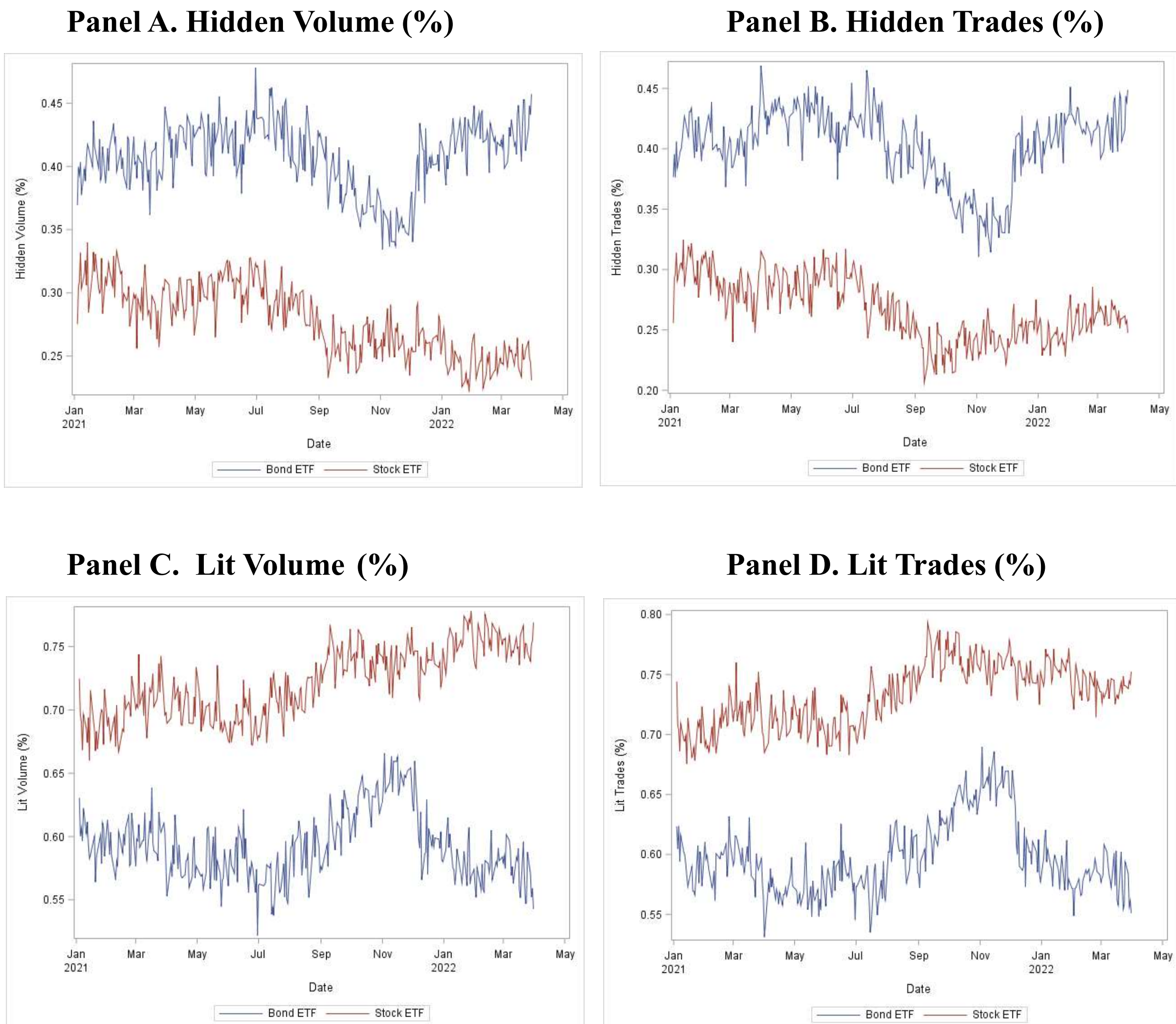
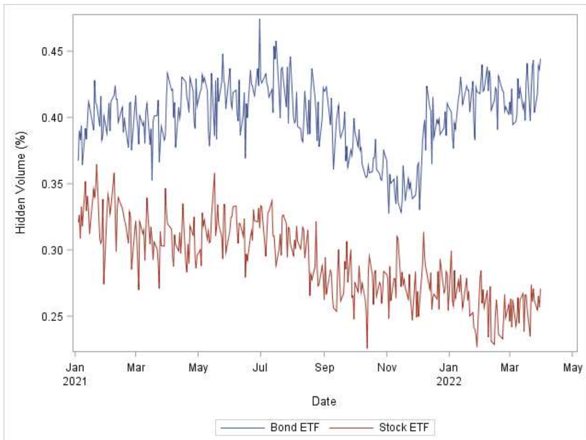


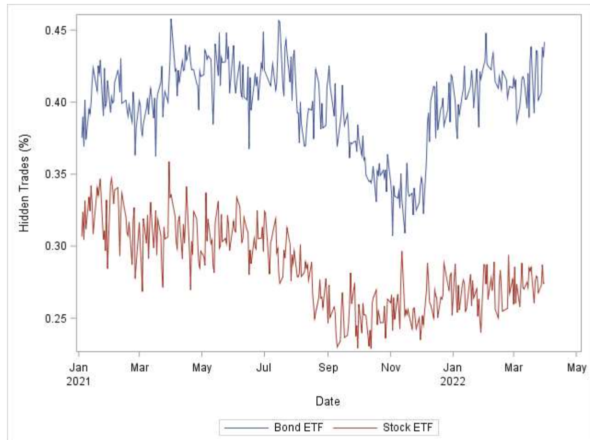
Figure 1A: Time-series of trading dynamics in Match 1 bond ETFs and equity ETFs

This figure shows the time-series of various trading dynamics between bond ETFs and equity ETFs in the sample period from January 2021 to March 2022. In panel A, the blue (red) line denotes hidden volume as a percentage of total volume for Match 1 sample of bond ETFs (equity ETFs). In panel B, the blue (red) line denotes hidden trades as a percentage of total trades for Match 1 sample of bond ETFs (equity ETFs). In panel C, the blue (red) line denotes lit volume as a percentage of total volume for Match 1 sample of bond ETFs (equity ETFs). In panel D, the blue (red) line denotes lit trades as a percentage of total trades for Match 1 sample of bond ETFs (equity ETFs).

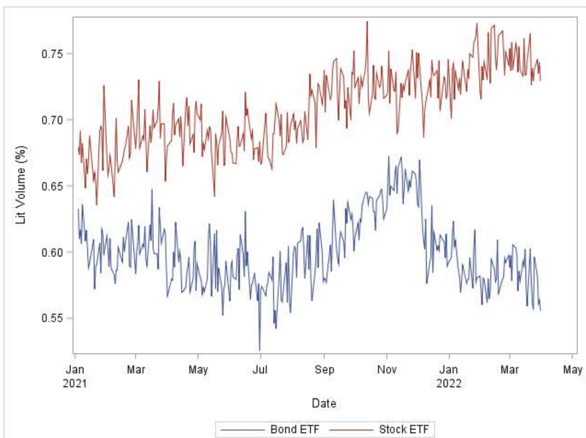
Panel A. Hidden Volume (%)



Panel B. Hidden Trades (%)



Panel C. Lit Volume (%)



Panel D. Lit Trades (%)

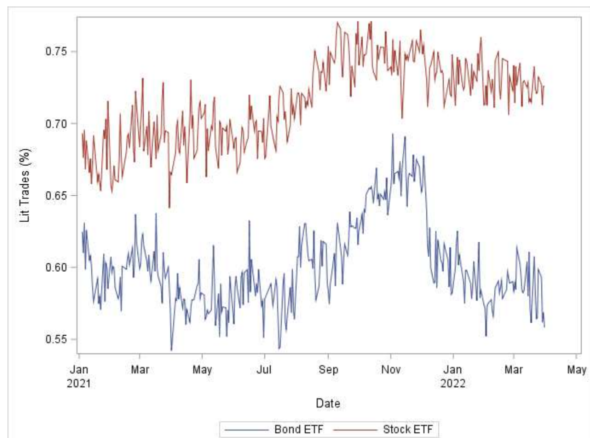
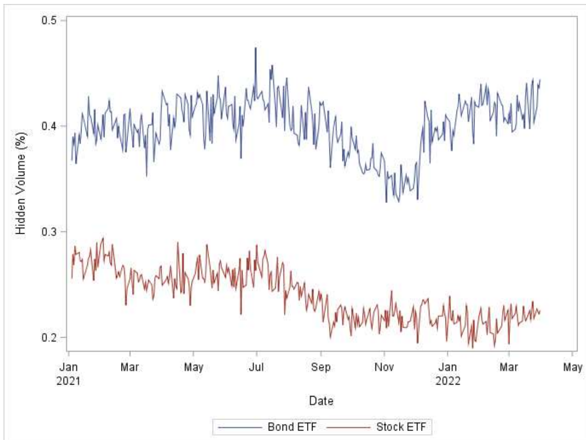


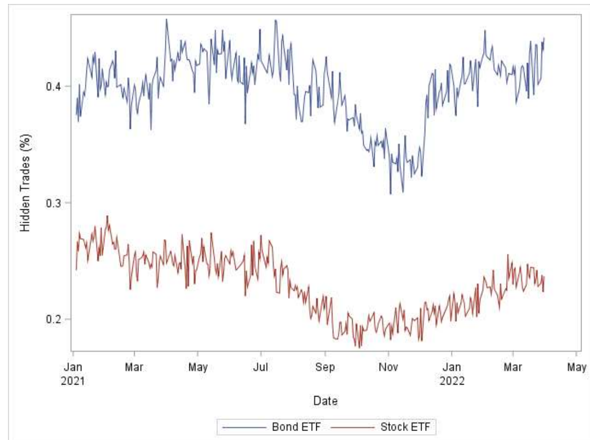
Figure 1B: Time-series of trading dynamics in Match 2 bond ETFs and equity ETFs

This figure shows the time-series of various trading dynamics between bond ETFs and equity ETFs in the sample period from January 2021 to March 2022. In panel A, the blue (red) line denotes hidden volume as a percentage of total volume for Match 2 sample of bond ETFs (equity ETFs). In panel B, the blue (red) line denotes hidden trades as a percentage of total trades for Match 2 sample of bond ETFs (equity ETFs). In panel C, the blue (red) line denotes lit volume as a percentage of total volume for Match 2 sample of bond ETFs (equity ETFs). In panel D, the blue (red) line denotes lit trades as a percentage of total trades for Match 2 sample of bond ETFs (equity ETFs).

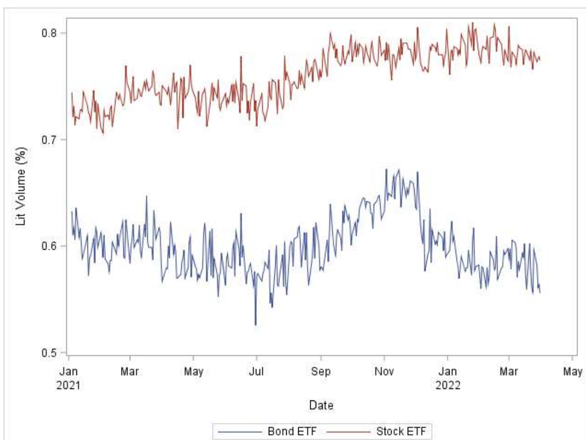
Panel A. Hidden Volume (%)



Panel B. Hidden Trades (%)



Panel C. Lit Volume (%)



Panel D. Lit Trades (%)

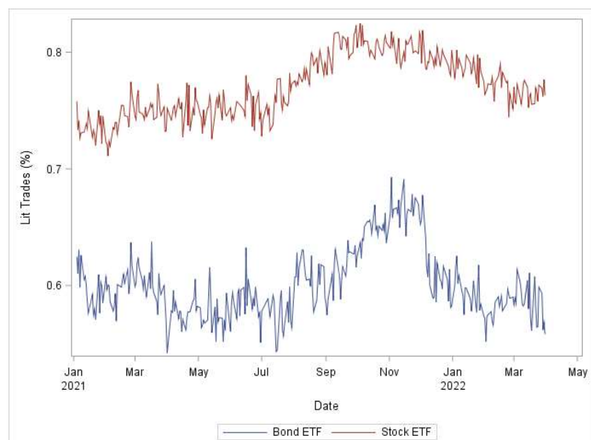
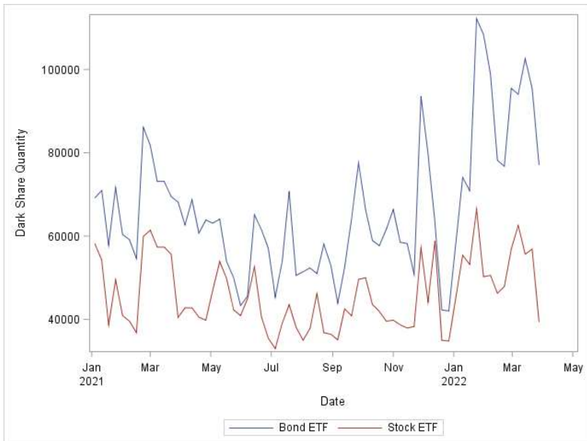


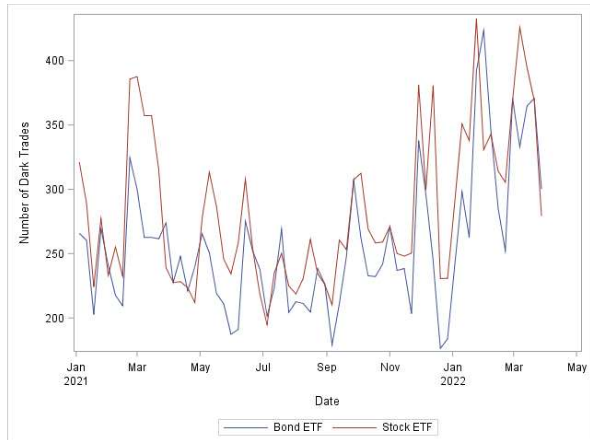
Figure 1C: Time-series of trading dynamics in Match 3 bond ETFs and equity ETFs

This figure shows the time-series of various trading dynamics between bond ETFs and equity ETFs in the sample period from January 2021 to March 2022. In panel A, the blue (red) line denotes hidden volume as a percentage of total volume for Match 3 sample of bond ETFs (equity ETFs). In panel B, the blue (red) line denotes hidden trades as a percentage of total trades for Match 3 sample of bond ETFs (equity ETFs). In panel C, the blue (red) line denotes lit volume as a percentage of total volume for Match 3 sample of bond ETFs (equity ETFs). In panel D, the blue (red) line denotes lit trades as a percentage of total trades for Match 3 sample of bond ETFs (equity ETFs).

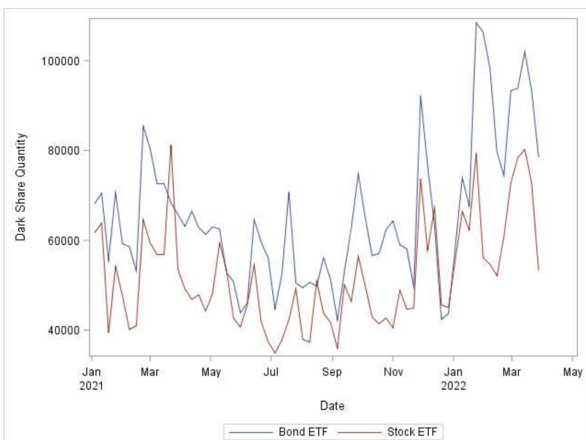
Panel A. Dark Share Quantity – Match 1



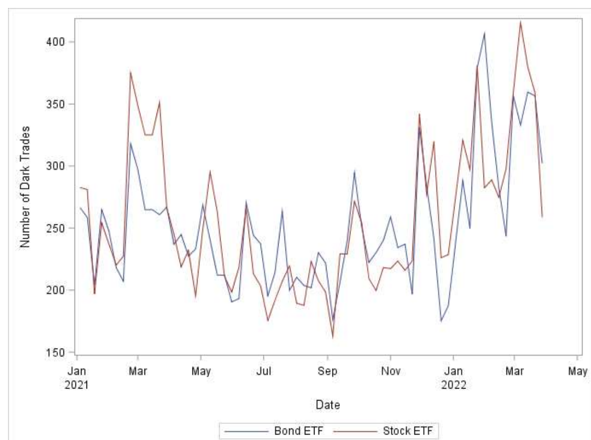
Panel B. Number of Dark Trades – Match 1



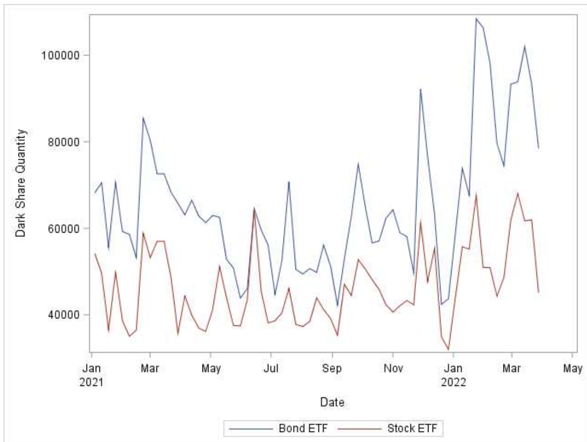
Panel C. Dark Share Quantity – Match 2



Panel D. Number of Dark Trades – Match 2



Panel E. Dark Share Quantity – Match 3



Panel F. Number of Dark Trades – Match 3

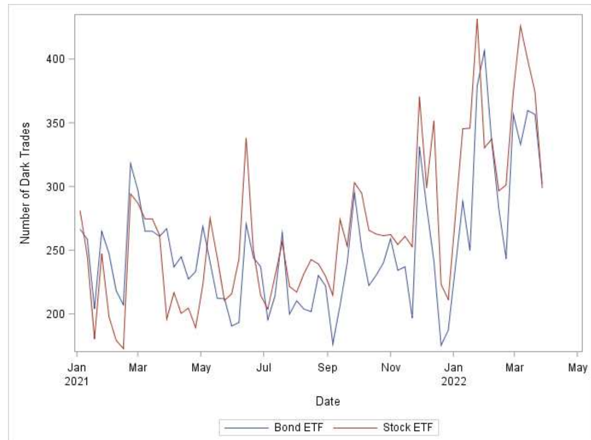
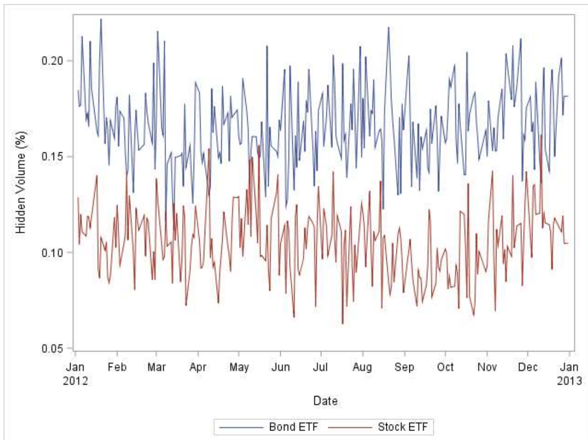


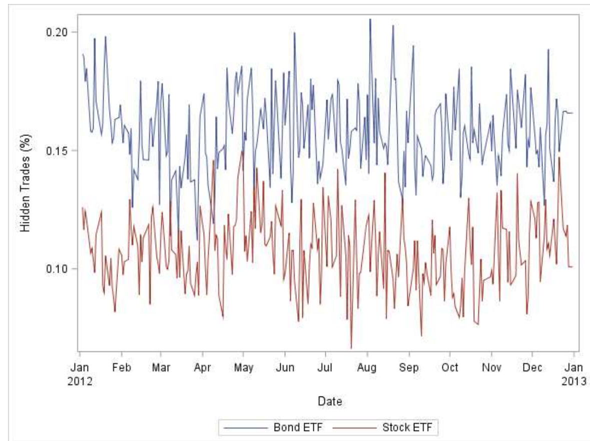
Figure 2: Time-series of dark trading activity in bond ETFs and equity ETFs

This figure shows the time-series of dark trading activity between bond ETFs and equity ETFs in the sample period from January 2021 to March 2022. In panel A, the blue (red) line denotes dark share quantity for Match 1 sample of bond ETFs (equity ETFs). In panel B, the blue (red) line denotes the number of dark trades in Match 1 sample of bond ETFs (equity ETFs). In panel C, the blue (red) line denotes dark share quantity for Match 2 sample of bond ETFs (equity ETFs). In panel D, the blue (red) line denotes the number of dark trades in Match 2 sample of bond ETFs (equity ETFs). In panel E, the blue (red) line denotes dark share quantity for Match 3 sample of bond ETFs (equity ETFs). In panel F, the blue (red) line denotes the number of dark trades in Match 3 sample of bond ETFs (equity ETFs).

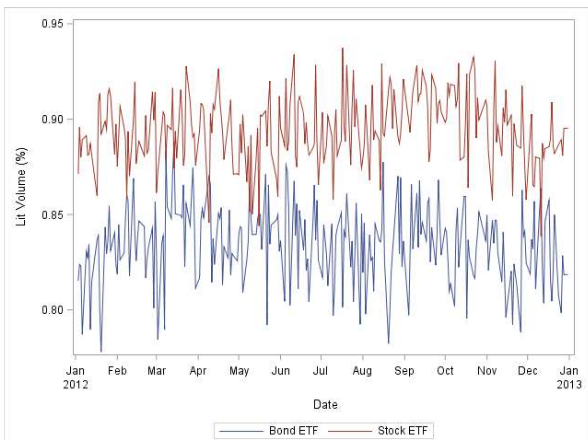
Panel A. Hidden Volume (%)



Panel B. Hidden Trades (%)



Panel C. Lit Volume (%)



Panel D. Lit Trades (%)

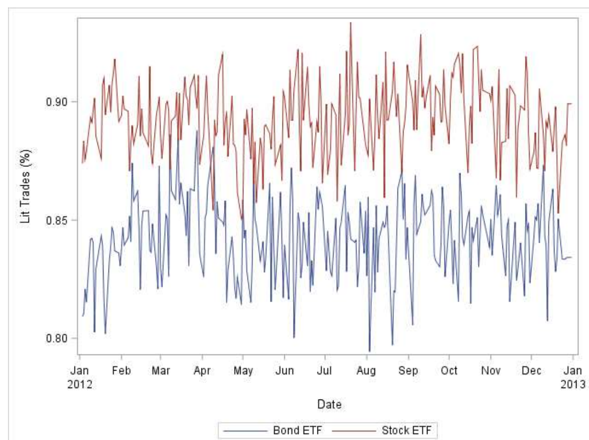
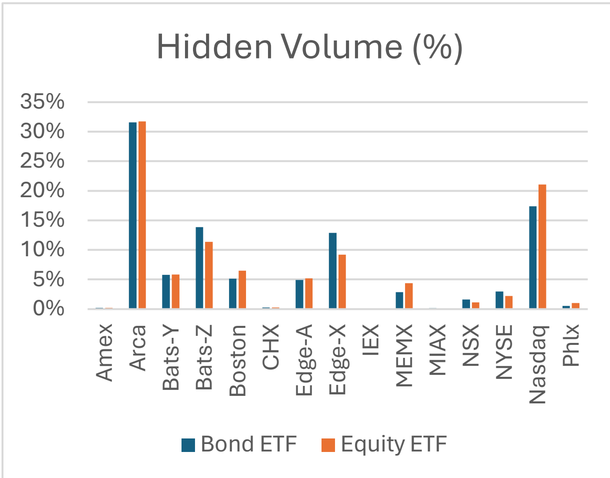


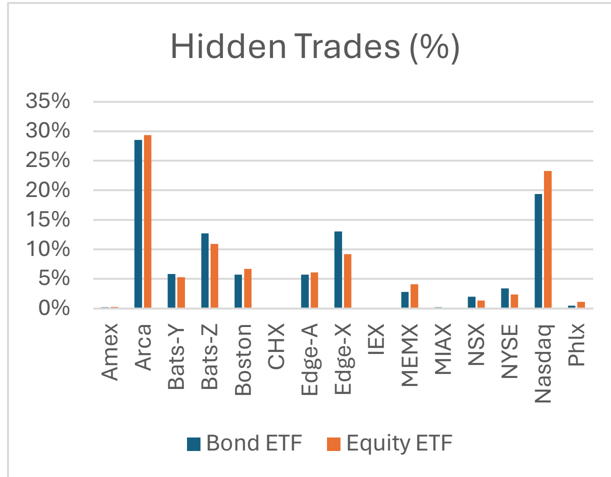
Figure 3: Time-series of trading dynamics in Match 1 bond ETFs and equity ETFs in 2012

This figure shows the time-series of various trading dynamics between bond ETFs and equity ETFs in the sample period from January 2012 to December 2012 that are matched on price and market capitalization (Match 1). In panel A, the blue (red) line denotes hidden volume as a percentage of total volume for the sample of bond ETFs (equity ETFs). In panel B, the blue (red) line denotes hidden trades as a percentage of total trades for the sample of bond ETFs (equity ETFs). In panel C, the blue (red) line denotes lit volume as a percentage of total volume for the sample of bond ETFs (equity ETFs). In panel D, the blue (red) line denotes lit trades as a percentage of total trades for the sample of bond ETFs (equity ETFs).

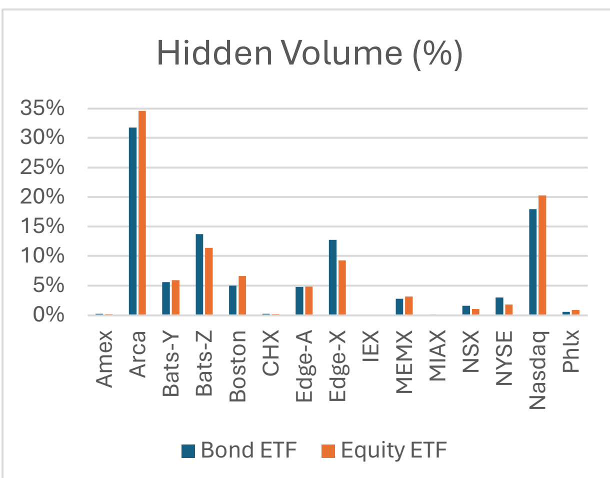
Panel A. Hidden Volume (%) – Match 1



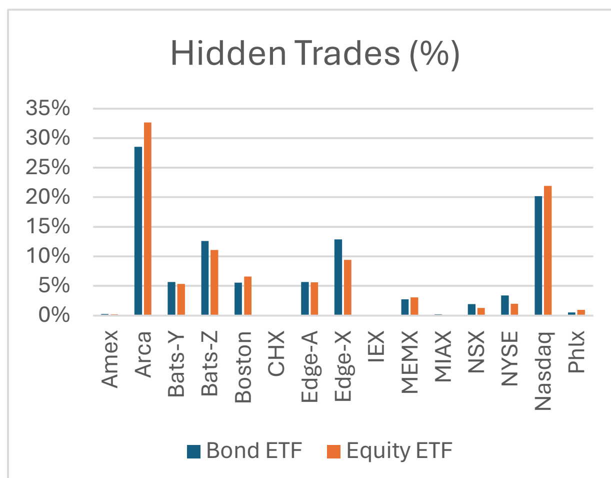
Panel B. Hidden Trades (%) – Match 1



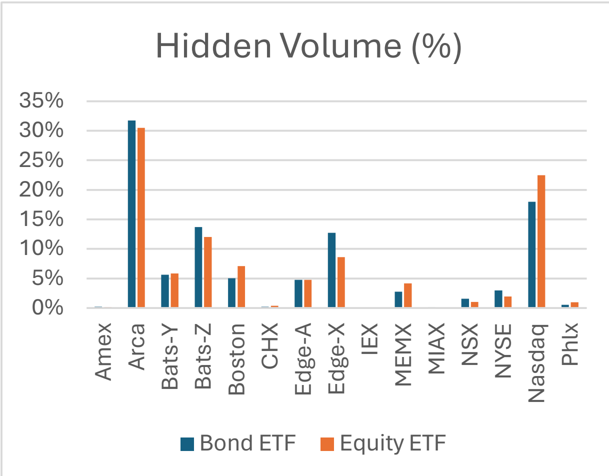
Panel C. Hidden Volume (%) – Match 2



Panel D. Hidden Trades (%) – Match 2



Panel E. Hidden Volume (%) – Match 3 **Panel F. Hidden Trades (%) – Match 3**



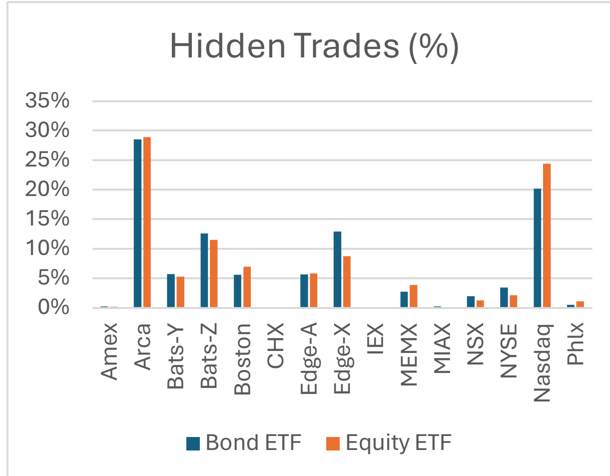


Figure 4: Hidden trading activity in bond ETFs and equity ETFs across exchanges

This figure shows the hidden trading activity between bond ETFs and equity ETFs across exchanges in the sample period from January 2021 to March 2022. In panel A, the blue (orange) bar denotes hidden volume (%) for Match 1 sample of bond ETFs (equity ETFs). In panel B, the blue (orange) bar denotes hidden trades (%) in Match 1 sample of bond ETFs (equity ETFs). In panel C, the blue (orange) bar denotes hidden volume (%) for Match 2 sample of bond ETFs (equity ETFs). In panel D, the blue (orange) bar denotes hidden trades (%) in Match 2 sample of bond ETFs (equity ETFs). In panel E, the blue (orange) bar denotes hidden volume (%) for Match 3 sample of bond ETFs (equity ETFs). In panel F, the blue (orange) bar denotes hidden trades (%) in Match 3 sample of bond ETFs (equity ETFs).

Table 1: Type of Bond ETFs

This table reports the type of bond ETFs in the full sample. Panel A reports the counts for the type of bonds held in the bond ETFs. The classification for bond type is found on the ETF Database under FactSet Classifications for Category. Panel B reports the counts for the grade of the bonds held in the bond ETFs. The classification for bond grade is found on the ETF Database under FactSet Classifications for Focus.

Panel A: Type	Count
ABS	5
Agency	1
Broad	56
Convertible	2
Corporate	80
Government	25
Municipal	16
Treasury	35
Total	220
Panel B: Grade	
Broad	32
High-Yield	39
Investment	149
Total	220

Table 2: Descriptive Statistics

This table reports descriptive statistics of equity and bond ETFs over the sample period from January 2021 to March 2022. Panel A reports the trading activities and security characteristics of the sample matched on price and market capitalization. Panel B reports the trading activities and security characteristics of the sample matched on price. Panel C reports the trading activities and security characteristics of the sample matched on market capitalization.

	Bond ETFs			Equity ETFs		
Variable	Mean	Median	Std. Dev	Mean	Median	Std. Dev
			Panel A: Match 1			
Price	52.78	50.52	29.58	52.79	49.09	29.68
Market Cap ('000)	3,970,471	1,050,052	7,469,574	3,967,613	1,062,371	7,522,108
Number of Trades	1,930.33	261.77	6,904.23	6,682.77	511.58	24,654.98
Trade Size	184.37	142.81	119.13	141.30	117.43	85.58
Trade Volume ('000)	449.97	45.48	52.42	1,008.92	52.42	3,257.77
Cancels	77,086.08	10,163.88	241,964.51	540,745.47	191202.05	1,360,227.90
Odd Lots	473.70	54.94	1,789.66	2,447.20	261.28	10,250.23
Hidden Volume (%)	0.41	0.41	0.15	0.28	0.23	0.19
Lit Volume (%)	0.59	0.60	0.15	0.72	0.77	0.18
Expense Ratio (%)	0.29	0.20	0.28	0.45	0.47	0.26
AUM (in millions)	4,586.56	1,278.85	8,307.80	4,102.04	980.65	8,301.20
Fund Age	9.60	9.50	4.17	11.60	11.00	6.61
Observations	194			194		
			Panel B: Match 2			
Price	52.83	50.41	30.52	52.90	50.17	30.54
Market Cap ('000)	5,048,517	1,212,169	10,830,080	3,057,820	412,703	9,754,370
Number of Trades	1,932.41	326.88	6,532.92	3,922.26	212.93	14,330.93
Trade Size	195.58	150.70	133.49	128.49	103.37	84.12
Trade Volume ('000)	466.41	49.63	1,426.166	694.106	23.578	2,665.153
Cancels	75,525.06	11,013.27	229,142.17	392,087.72	130,782.89	813,642.85
Odd Lots	471.17	65.99	1,692.71	1,575.17	111.10	6,978.67
Hidden Volume (%)	0.40	0.40	0.15	0.29	0.27	0.18
Lit Volume (%)	0.60	0.60	0.15	0.71	0.73	0.18
Expense Ratio (%)	0.30	0.20	0.29	0.56	0.49	0.77
AUM (in millions)	5,869.12	1,462.80	11,985.73	3,323.66	488.40	10,318.29
Fund Age	9.74	10.00	4.24	11.11	10.50	6.48
Observations	220			220		

Panel C: Match 3						
Price	52.83	50.41	30.52	77.00	61.07	56.01
Market Cap (‘000)	5,048,517	1,212,169	10,830,080	5,031,729	1,204,538	10,687,411
Number of Trades	1,932.41	326.88	6,532.92	7,252.23	614.57	24,396.94
Trade Size	195.58	150.70	133.49	121.83	92.73	123.29
Trade Volume (‘000)	466.41	49.63	1,426.166	1,056.10	52.91	3,959.42
Cancels	75,525.06	11,013.27	229,142.17	673,963.64	275,773.83	1,449,575.00
Odd Lots	471.17	65.99	1,692.71	3,013.28	302.57	10,436.24
Hidden Volume (%)	0.40	0.40	0.15	0.24	0.20	0.17
Lit Volume (%)	0.60	0.60	0.15	0.76	0.81	0.17
Expense Ratio (%)	0.30	0.20	0.29	0.40	0.39	0.26
AUM (in millions)	5,869.12	1,462.80	11,985.73	5,470.28	1,126.00	11,863.71
Fund Age	9.74	10.00	4.24	12.06	12.00	6.28
Observations	220			220		

Table 3: Differences in Match Variables

This table reports the t-test on the differences in the match variables based on the three different match specifications. Match 1 is the match on both price and market capitalization (panel A). Match 2 is the match on price only (panel B). Match 3 is the match on market capitalization only (panel C).

	Equity ETF	Bond ETF	Difference	t-value	p-value
Panel A: Match 1					
Price	52.79	52.78	0.01	0.03	0.97
Market Cap ('000)	3,967,613	3,970,471	-2,858	-0.07	0.95
Panel B: Match 2					
Price	52.90	52.83	0.07	0.40	0.69
Panel C: Match 3					
Market Cap ('000)	5,031,729	5,048,517	-16,788	-0.29	0.77

Table 4: Differences in Hidden and Lit Liquidity

This table reports the normalized difference test on hidden and lit liquidity. Match 1 is the match on both price and market capitalization (panel A). Match 2 is the match on price only (panel B). Match 3 is the match on market capitalization only (panel C). A normalized difference above 0.25 suggests differences in the covariate distribution between the two groups.

	Bond ETFs		Equity ETFs		Normalized Difference
	Mean	Std. Dev.	Mean	Std. Dev.	
Panel A: Match 1					
Hidden Volume (%)	40.8	14.6	27.8	18.5	0.552
Hidden Trades (%)	40.3	13.6	26.7	17.2	0.620
Lit Volume (%)	59.2	14.6	72.2	18.5	-0.552
Lit Trades (%)	59.7	13.6	73.3	17.2	-0.620
Observations	194		194		
Panel B: Match 2					
Hidden Volume (%)	40.0	14.6	29.1	17.9	0.472
Hidden Trades (%)	39.9	13.5	28.5	16.8	0.529
Lit Volume (%)	60.0	14.6	70.9	17.9	-0.472
Lit Trades (%)	60.1	13.5	71.5	16.8	-0.529
Observations	220		220		
Panel C: Match 3					
Hidden Volume (%)	40.0	14.6	24.0	16.6	0.724
Hidden Trades (%)	39.9	13.5	22.9	15.4	0.830
Lit Volume (%)	60.0	14.6	76.0	16.6	-0.724
Lit Trades (%)	60.1	13.5	77.1	15.4	-0.830
Observations	220		220		

Table 5: Differences in Dark Trading

This table reports the t-test on the differences in dark trading variables based on the three different match specifications. Match 1 is the match on both price and market capitalization (panel A). Match 2 is the match on price only (panel B). Match 3 is the match on market capitalization only (panel C). ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Bond ETFs	Equity ETFs	Difference	t-value
Panel A: Match 1				
# of Dark Trades	246.7	273.5	-26.74***	-2.75
Dark Share Quantity	63,422.5	44,895.6	1,8526.9***	8.10
Observations	194	194		
Panel B: Match 2				
# of Dark Trades	253.0	257.2	-4.2	-0.43
Dark Share Quantity	65,662.1	52,067.9	13,594.3***	5.43
Observations	220	220		
Panel C: Match 3				
# of Dark Trades	253.0	266.6	-13.6	-1.38
Dark Share Quantity	65,662.1	46,433.2	19,228.9***	8.35
Observations	220	220		

Table 6: Hidden Volume (%) OLS Regression

The table reports the OLS regression analysis to examine the determinants for the percentage of hidden volume to total trade volume between bond and equity ETFs. Match 1 is the match of bond and equity ETFs on both price and market capitalization. Variables include the ETFs' price, market capitalization ('000), total trade volume, spread, volatility, trade size, cancel-to-trade ratio, trade-to-order-volume ratio, and the odd-lot volume ratio (all in logs). The difference specifications use the absolute value of the variables before taking the log or log(1+x) transformation. T-statistics are recorded in the parentheses and asterisks ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Match 1 – Hidden Volume (%)								
	Bond ETFs (1)	Equity ETFs (2)	Difference (3)	Bond ETFs (4)	Equity ETFs (5)	Difference (6)	Bond ETFs (7)	Equity ETFs (8)	Difference (9)
Price	0.0363	0.1051***	-0.0006	-0.0841***	-0.1387***	0.0077	0.0406*	0.0089	0.0062
	(1.4354)	(2.8684)	(-0.0497)	(-3.3237)	(-4.7039)	(0.6417)	(1.9306)	(0.3720)	(0.4973)
Market Cap	0.0677***	0.0306***	0.0009	0.0404***	-0.0017	0.0141*	0.0103	-0.1007***	0.0130
	(7.1293)	(3.0863)	(0.1117)	(3.4794)	(-0.1756)	(1.8974)	(0.6261)	(-4.2810)	(1.4908)
Trade Volume	-0.0625***	-0.0109	-0.0056						
	(-7.0211)	(-1.3021)	(-0.893)						
Spread	0.1163***	0.1902***	-0.0552***						
	(5.9326)	(9.0088)	(-5.2923)						
Volatility	-0.0297**	-0.0914***	0.0501***						
	(-2.1617)	(-4.5079)	(3.4583)						
Trade Size				-0.1074**	0.0202	-0.0213*			
				(-2.3716)	(0.3252)	(-1.669)			
Cancel-to-Trade				0.0858***	0.1259***	-0.0309***			
				(4.4603)	(6.9869)	(-3.7757)			
Trade-to-Order Vol				0.0478***	0.0666***	0.0038			
				(3.7605)	(3.8229)	(0.3728)			
Odd-Lot Vol				0.0377	0.0813**	0.0018			
				(1.1572)	(2.1694)	(0.1363)			
Expense Ratio							-0.0207*	0.0056	0.0286
							(-1.8028)	(0.3297)	(0.3282)
AUM							-0.0400**	0.0488**	0.0168*
							(-2.5044)	(2.1545)	(1.7802)
ETF Age							-0.0761***	-0.0706***	0.0151
							(-3.5047)	(-3.8583)	(0.7638)
Intercept	0.3865***	0.7787***	-0.2542***	0.2596	-0.0541	0.2384**	0.5247***	1.4756***	-0.1430
	(4.0571)	(7.7909)	(-2.7794)	(0.7935)	(-0.1333)	(2.0822)	(3.9734)	(8.2238)	(-1.5991)
Observations	194	194	194	194	194	194	194	194	194
R-Squared	0.6220	0.6729	0.2200	0.3430	0.5493	0.1210	0.1837	0.3714	0.0711
F-Stat	61.8600	77.3551	10.6051	16.2738	37.9809	4.2895	8.4633	22.2191	2.8768

Table 7: Hidden Trades (%) OLS Regression

The table reports the OLS regression analysis to examine the determinants for the percentage of hidden trades to total trades between bond and equity ETFs. Match 1 is the match of bond and equity ETFs on both price and market capitalization. Variables include the ETFs' price, market capitalization ('000), total trade volume, spread, volatility, trade size, cancel-to-trade ratio, trade-to-order-volume ratio, the odd-lot volume ratio, expense ratio, AUM, and fund age (all in logs). The difference specifications use the absolute value of the variables before taking the log or log(1+x) transformation. T-statistics are recorded in the parentheses and asterisks ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Match 1 – Hidden Trades (%)								
	Bond ETFs (1)	Equity ETFs (2)	Difference (3)	Bond ETFs (4)	Equity ETFs (5)	Difference (6)	Bond ETFs (7)	Equity ETFs (8)	Difference (9)
Price	0.0786***	0.1316***	0.0004	-0.0610**	-0.1011***	0.0076	0.0206	0.0040	0.0046
	(3.2031)	(3.8641)	(0.0355)	(-2.3909)	(-3.6867)	(0.6795)	(1.0483)	(0.1809)	(0.3967)
Market Cap	0.0452***	0.0200**	0.0058	0.0278**	-0.0119	0.0164**	0.0093	-0.0873***	0.0140*
	(4.8985)	(2.1617)	(0.7741)	(2.3775)	(-1.2835)	(2.3689)	(0.6012)	(-3.9842)	(1.7324)
Trade Volume	-0.0378***	0.0032	-0.0058						
	(-4.3632)	(0.4142)	(-0.9867)						
Spread	0.1323***	0.1978***	-0.0508***						
	(6.9497)	(10.0760)	(-5.2217)						
Volatility	-0.0689***	-0.0987***	0.0402***						
	(-5.1587)	(-5.2367)	(2.9749)						
Trade Size				0.0051	0.0355	-0.0030			
				(0.1112)	(0.6148)	(-0.2519)			
Cancel-to-Trade				0.0835***	0.1271***	-0.0240***			
				(4.3085)	(7.5813)	(-3.1475)			
Trade-to-Order Vol				0.0472***	0.0768***	0.0032			
				(3.6835)	(4.7390)	(0.3409)			
Odd-Lot Vol				0.0610*	0.0676*	-0.0014			
				(1.8541)	(1.9416)	(-0.1185)			
Expense Ratio							-0.0148	0.0101	-0.0089
							(-1.3791)	(0.6370)	(-0.1114)
AUM							-0.0298**	0.0385*	0.0187**
							(-1.9935)	(1.8265)	(2.1406)
Fund Age							-0.0817***	-0.0581***	0.0053
							(-4.0204)	(-3.4107)	(0.2901)
Intercept	0.4733***	0.7999***	-0.2715***	-0.2606	-0.0926	0.1180	0.5594***	1.3432***	-0.1310
	(5.1153)	(8.6097)	(-3.1822)	(-0.7906)	(-0.2455)	(1.1037)	(4.5264)	(8.0403)	(-1.5864)
Observations	194	194	194	194	194	194	194	194	194
R-Squared	0.5880	0.6730	0.2222	0.2293	0.5488	0.1227	0.1741	0.3696	0.0937
F-Stat	53.6712	77.3919	10.7441	9.2706	37.9153	4.3572	7.9234	22.04	3.8882

Table 8: Probit Regression on Hidden Liquidity

The table reports the probit regression analysis and marginal effects to examine hidden liquidity between bond and equity ETFs. Match 1 is the match of bond and equity ETFs on both price and market capitalization. Variables include the ETFs' price, market capitalization ('000), total trade volume, spread, volatility, trade size, cancel-to-trade ratio, trade-to-order-volume ratio, the odd-lot volume ratio, expense ratio, AUM, and fund age (all in logs). Bond is a dummy variable coded one for bond ETF and zero for equity ETF. Robust standard errors are recorded in the parentheses and asterisks ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Match 1 Hidden Volume (%)		Match 1 Hidden Trades (%)	
	Probit	Marginal Effects	Probit	Marginal Effects
	(1)	(2)	(3)	(4)
Price	0.3069***	0.4216***	0.4276***	0.5825***
	(0.0571)	(0.0782)	(0.0506)	(0.0684)
Market Cap	0.1345***	0.6740***	0.0967***	0.4806***
	(0.0322)	(0.1613)	(0.0290)	(0.1440)
Trade Volume	-0.0354	-0.0546	0.0188	0.0288
	(0.0279)	(0.0431)	(0.0256)	(0.0391)
Spread	0.5724***	-1.4854***	0.5921***	-1.5235***
	(0.0401)	(0.1032)	(0.0363)	(0.0920)
Volatility	-0.2621***	0.1199***	-0.3268***	0.1482***
	(0.0355)	(0.0161)	(0.0301)	(0.0135)
Cancel-to-Trade	0.1214***	0.2404***	0.1455***	0.2856***
	(0.0294)	(0.0582)	(0.0280)	(0.0549)
Trade-to-Order Volume	0.0530**	-0.0316**	0.0527***	-0.0312***
	(0.0215)	(0.0128)	(0.0197)	(0.0116)
Odd-Lot Volume	0.0116	0.0086	-0.0414	-0.0303
	(0.0415)	(0.0306)	(0.0373)	(0.0273)
Expense Ratio	-0.0176	0.0085	-0.0014	0.0007
	(0.0214)	(0.0104)	(0.0183)	(0.0088)
AUM	0.0122	0.0310	0.0021	0.0054
	(0.0278)	(0.0706)	(0.0246)	(0.0620)
Fund Age	-0.1070***	-0.0846***	-0.1230***	-0.0964***
	(0.0298)	(0.0236)	(0.0282)	(0.0221)
Bond	0.3298***	0.0592***	0.3119***	0.0556***
	(0.0482)	(0.0087)	(0.0440)	(0.0078)
Intercept	-0.1987		-0.2119	
	(0.3884)		(0.3533)	
Observations	388	388	388	388

Table 9: Differences in Hidden and Lit Liquidity in 2012

This table reports the normalized difference test on hidden and lit liquidity for the 2012 sample period. This sample matches bond and equity ETFs on both price and market capitalization. A normalized difference above 0.25 suggests differences in the covariate distribution between the two groups.

	Bond ETFs		Equity ETFs		Normalized Difference
Variable	Mean	Std. Dev.	Mean	Std. Dev.	
Hidden Volume	16.6	7.7	10.5	6.6	0.601
(%)	15.7	7.3	10.7	6.1	0.526
Hidden Trades (%)	83.4	7.7	89.5	6.6	-0.601
Lit Volume (%)	84.3	7.3	89.3	6.1	-0.526
Lit Trades (%)	40		40		
Observations					

Table 10: Differences in Hidden Liquidity across Exchanges – Match 1

This table reports the normalized difference test on hidden liquidity between bond and equity ETFs across lit exchange in the sample period of January 2021 to March 2022. Match 1 is the match on both price and market capitalization. Panel A reports the level of hidden volume (%) on each exchange. Panel B reports the level of hidden trades (%) on each exchange. A normalized difference above 0.25 suggests differences in the covariate distribution between the two groups.

	Bond ETFs		Equity ETFs		Normalized Difference
	Mean	Std. Dev.	Mean	Std. Dev.	
Panel A: Hidden Volume (%)					
Amex	0.19	0.80	0.18	0.71	0.0036
Arca	31.59	21.45	31.75	23.48	-0.0050
Bats-Y	5.75	8.27	5.82	9.22	-0.0053
Bats-Z	13.86	13.98	11.38	12.69	0.1317
Boston	5.14	8.01	6.49	10.26	-0.1039
CHX	0.26	3.03	0.24	2.71	0.0050
Edge-A	4.89	6.99	5.18	7.40	-0.0291
Edge-X	12.87	14.27	9.18	10.99	0.2049
IEX	0.00	0.00	0.00	0.00	0.0000
MEMX	2.84	6.89	4.36	10.02	-0.1254
MIAX	0.12	1.16	0.02	0.26	0.0845
NSX	1.62	4.65	1.10	3.36	0.0919
NYSE	2.98	5.33	2.22	4.71	0.1065
Nasdaq	17.39	14.89	21.07	17.93	-0.1579
Phlx	0.52	2.03	1.02	2.97	-0.1410
Panel B: Hidden Trades (%)					
Amex	0.21	0.78	0.23	0.88	-0.0160
Arca	28.54	19.84	29.35	20.77	-0.0283
Bats-Y	5.83	7.65	5.29	7.51	0.0507
Bats-Z	12.69	12.47	10.94	11.22	0.1045
Boston	5.70	7.75	6.70	8.91	-0.0853
CHX	0.00	0.09	0.00	0.09	-0.0019
Edge-A	5.71	7.74	6.10	7.25	-0.0368
Edge-X	13.06	13.63	9.19	10.06	0.2287
IEX	0.00	0.00	0.00	0.00	0.0000
MEMX	2.80	6.20	4.08	8.41	-0.1224
MIAX	0.20	1.32	0.02	0.23	0.1350
NSX	1.97	5.01	1.36	3.34	0.1026
NYSE	3.41	5.57	2.36	4.42	0.1483
Nasdaq	19.40	15.45	23.27	17.06	-0.1682
Phlx	0.49	1.73	1.13	2.82	-0.1948

Table 11: Differences in Hidden Liquidity of CHX over All Exchanges

This table reports the t-test on the level of hidden liquidity on CHX around the transition to Pillar on November 4th, 2019. Panel A reports hidden liquidity level on CHX 20 days prior to the transition and 20 days post transition. Panel B reports hidden liquidity level on CHX relative to all fifteen exchanges (including CHX) 20 days prior to the transition and 20 days post transition. Panel C reports the difference in hidden liquidity levels in bond and equity ETFs 20 days pre- and 20 days post-transition following equation 7. ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	20 Days Pre	20 Days Post	Difference	t-stat
Panel A: CHX				
Hidden Volume (‘000)	0.00	20.02	-20.02*	-1.72
Hidden Trades	0.00	0.12	-0.12**	-2.07
Hidden Trade Size	0.00	5,701.40	-5,701.40**	-2.25
Panel B: CHX/All				
Hidden Volume (%)	0.00	1.11	-1.11***	-2.62
Hidden Trades (%)	0.00	0.01	-0.01***	-3.31
Hidden Trade Size (%)	0.00	3.76	-3.76***	-2.89
Panel C: Bond ETFs – Equity ETFs (Pre – Post of CHX/All)	Bond ETFs	Equity ETFs	Difference	t-stat
Hidden Volume (%)	0.838	1.37	-0.535	0.63
Hidden Trades (%)	0.003	0.006	-0.003	0.92
Hidden Trade Size (%)	2.65	4.88	-2.24	1.51

Table 12: Differences in Hidden Liquidity on CHX 2019

This table reports the average hidden liquidity in bond and equity ETFs on CHX around the [+5, -5] event window surrounding November 4, 2019 when CHX transitioned to the Pillar trading platform. Panel A reports the average hidden volume (‘000) in the sample ETFs. Panel B reports the average hidden trades in the sample ETFs. Panel C reports the average hidden trade size in the sample ETFs. ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Bond ETFs Mean	Equity ETFs Mean	Difference
Panel A: Hidden Volume (‘000)			
-5	0.00	0.00	0.00
-4	0.00	0.00	0.00
-3	0.00	0.00	0.00
-2	0.00	0.00	0.00
-1	0.00	0.00	0.00
0	12.27	21.94	-9.68***
1	22.17	4.12	18.04***
2	1.48	39.40	-37.92***
3	21.06	21.13	-0.07
4	15.94	23.68	-7.74***
5	2.22	18.97	-16.74***
Panel B: Hidden Trades			
-5	0.00	0.00	0.00
-4	0.00	0.00	0.00
-3	0.00	0.00	0.00
-2	0.00	0.00	0.00
-1	0.00	0.00	0.00
0	0.03	0.21	-0.17***
1	0.06	0.03	0.03***
2	0.03	0.11	-0.08***
3	0.08	0.22	-0.14***
4	0.10	0.21	-0.11***
5	0.02	0.16	-0.14***
Panel C: Hidden Trade Size			
-5	0.00	0.00	0.00
-4	0.00	0.00	0.00
-3	0.00	0.00	0.00
-2	0.00	0.00	0.00
-1	0.00	0.00	0.00
0	12,269.84	3,053.43	9,216.41***
1	14,448.41	2,061.11	12,387.30***
2	738.89	6,850.53	-6,111.64***
3	4,211.75	8,290.56	-4,078.81***
4	6,371.96	5,157.00	1,214.96*
5	2,222.22	3,856.97	-1,634.75***

Table 13: Differences in Hidden Liquidity by ETF Types

This table reports the normalized difference test on hidden and lit liquidity between different bond ETF types and equity ETFs in Match 1 in the sample period of January 2021 to March 2022. Corporate bond ETFs consists of all ETFs that hold corporate bonds and government bond ETFs consists of all ETFs that are classified as government ETFs, Treasury ETFs, and Municipal ETFs. Equity ETFs consists of the full sample of equity ETFs. Panel A compares lit and hidden liquidity in Corporate Bond ETFs and Government Bond ETFs. Panel B compares lit and hidden liquidity in Equity ETFs and Government Bond ETFs. Panel C compares lit and hidden liquidity in Equity ETFs and Corporate Bond ETFs. A normalized difference above 0.25 suggests differences in the covariate distribution between the two groups.

Panel A:

	Corporate Bond ETFs		Government Bond ETFs		Normalized Difference
Variable	Mean	Std. Dev.	Mean	Std. Dev.	
Hidden Volume (%)	41.4	14.2	35.2	16.3	0.287
Hidden Trades (%)	40.7	13.2	35.9	14.8	0.242
Lit Volume (%)	58.6	14.2	64.8	16.3	-0.287
Lit Trades (%)	59.3	13.2	64.1	14.8	-0.242
Observations	80		76		

Panel B:

	Equity ETFs		Government Bond ETFs		Normalized Difference
Variable	Mean	Std. Dev.	Mean	Std. Dev.	
Hidden Volume (%)	27.8	18.5	35.2	16.3	-0.300
Hidden Trades (%)	26.7	17.2	35.9	14.8	-0.405
Lit Volume (%)	72.2	18.5	64.8	16.3	0.300
Lit Trades (%)	73.3	17.2	64.1	14.8	0.405
Observations	194		76		

Panel C:

	Equity ETFs		Corporate Bond ETFs		Normalized Difference
Variable	Mean	Std. Dev.	Mean	Std. Dev.	
Hidden Volume (%)	27.8	18.5	41.4	14.2	-0.583
Hidden Trades (%)	26.7	17.2	40.7	13.2	-0.646
Lit Volume (%)	72.2	18.5	58.6	14.2	0.583
Lit Trades (%)	73.3	17.2	59.3	13.2	0.646
Observations	194		80		

APPENDIX A: EMPIRICAL TESTS FOR MATCH 2 AND MATCH 3 SAMPLES

Table A1: Hidden Volume (%) OLS Regression - Match 2

The table reports the OLS regression analysis to examine the determinants for the percentage of hidden volume to total trade volume between bond and equity ETFs. Match 2 is the match of bond and equity ETFs on price. Variables include the ETFs' price, market capitalization ('000), total trade volume, spread, volatility, trade size, cancel-to-trade ratio, trade-to-order-volume ratio, and the odd-lot volume ratio (all in logs). The difference specifications use the absolute value of the variables before taking the log transformation. T-statistics are recorded in the parentheses and asterisks ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Match 2 – Hidden Volume (%)								
	Bond ETFs (1)	Equity ETFs (2)	Difference (3)	Bond ETFs (4)	Equity ETFs (5)	Difference (6)	Bond ETFs (7)	Equity ETFs (8)	Difference (9)
Price	0.0159	0.0923***	-0.0046	-0.0888***	-0.1698***	-0.0023	0.0303	-0.0373	-0.0043
	(0.6990)	(2.7055)	(-0.5508)	(-3.9442)	(-5.327)	(-0.2631)	(1.6344)	(-1.6163)	(-0.4639)
Market Cap	0.0723***	0.0495***	-0.0025	0.0426***	0.0279**	0.0155*	-0.0132	-0.0352*	-0.0085
	(8.3587)	(5.5819)	(-0.2591)	(4.2138)	(2.5868)	(1.8310)	(-1.1094)	(-1.8245)	(-0.6058)
Trade Volume	-0.0671***	-0.0093	-0.0097						
	(-7.9899)	(-1.1288)	(-1.1793)						
Spread	0.1094***	0.1950***	-0.0744***						
	(5.8164)	(12.0238)	(-5.9616)						
Volatility	-0.0230*	-0.0886***	0.0438***						
	(-1.8121)	(-4.5680)	(2.8397)						
Trade Size				-0.0883**	-0.0902	-0.0542***			
				(-2.2186)	(-1.2771)	(-3.8667)			
Cancel-to-Trade				0.0952***	0.1091***	-0.0368***			
				(5.5713)	(5.5141)	(-4.0828)			
Trade-to-Order Vol				0.0520***	0.0568***	0.0001			
				(4.5096)	(3.0909)	(0.0070)			
Odd-Lot Vol				0.0490*	0.0123	-0.0026			
				(1.6549)	(0.2699)	(-0.1530)			
Expense Ratio							-0.0168	-0.0118	0.0060
							(-1.5328)	(-0.7030)	(0.0876)
AUM							-0.0165	0.0115	0.0126
							(-1.4356)	(0.6362)	(0.9257)
ETF Age							-0.0599***	-0.0459***	-0.0064
							(-3.0217)	(-2.6449)	(-0.2832)
Intercept	.3785***	.5792***	-.3191**	.0851	.4063	.3443**	0.6902***	0.9161***	0.1325
	(4.4012)	(6.3965)	(-2.0344)	(.3031)	(.8748)	(2.5375)	(6.6104)	(5.9130)	(0.8919)
Observations	220	220	220	220	220	220	220	220	220
R-Squared	0.6126	0.6353	0.1863	0.3739	0.2905	0.1432	0.1674	0.1611	0.0059
F-Stat	67.6739	74.5667	9.8023	21.1999	14.5351	5.9349	8.6046	8.2218	0.2554

Table A2: Hidden Trades (%) OLS Regression - Match 2

The table reports the OLS regression analysis to examine the determinants for the percentage of hidden trades to total trades between bond and equity ETFs. Match 2 is the match of bond and equity ETFs on price. Variables include the ETFs' price, market capitalization ('000), total trade volume, spread, volatility, trade size, cancel-to-trade ratio, trade-to-order-volume ratio, the odd-lot volume ratio, expense ratio, AUM, and fund age (all in logs). The difference specifications use the absolute value of the variables before taking the log transformation. T-statistics are recorded in the parentheses and asterisks ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Match 2 – Hidden Trades (%)								
	Bond ETFs (1)	Equity ETFs (2)	Difference (3)	Bond ETFs (4)	Equity ETFs (5)	Difference (6)	Bond ETFs (7)	Equity ETFs (8)	Difference (9)
Price	0.0649***	0.1238***	-0.0003	-0.0583**	-0.1306***	0.0017	0.0104	-0.0362*	0.0001
	(2.9618)	(3.9715)	(-0.0339)	(-2.5777)	(-4.4114)	(0.209)	(0.5978)	(-1.6808)	(0.0090)
Market Cap	0.0498***	0.0367***	0.0009	0.0277***	0.0178*	0.0152*	-0.0147	-0.0353*	-0.0068
	(5.9875)	(4.5215)	(0.1037)	(2.7255)	(1.7717)	(1.945)	(-1.3298)	(-1.9632)	(-0.5314)
Trade Volume	-0.0393***	0.0025	-0.0076						
	(-4.8575)	(0.3287)	(-0.9913)						
Spread	0.1308***	0.1961***	-0.0649***						
	(7.2261)	(13.2353)	(-5.6178)						
Volatility	-0.0668***	-0.1020***	0.0390***						
	(-5.4600)	(-5.7523)	(2.7299)						
Trade Size				0.0333	-0.0218	-0.0377***			
				(0.8319)	(-0.3322)	(-2.9058)			
Cancel-to-Trade				0.0886***	0.1082***	-0.0366***			
				(5.1621)	(5.8823)	(-4.3863)			
Trade-to-Order Vol				0.0484***	0.0594***	-0.0022			
				(4.1818)	(3.4755)	(-0.2369)			
Odd-Lot Vol				0.0747**	0.0233	-0.0031			
				(2.5115)	(0.5505)	(-0.2009)			
Expense Ratio							-0.0138	-0.0131	0.0104
							(-1.3504)	(-0.8421)	(0.1644)
AUM							-0.0063	0.0106	0.0151
							(-0.5874)	(0.6288)	(1.2156)
Fund Age							-0.0590***	-0.0399**	-0.0053
							(-3.1879)	(-2.4665)	(-0.2579)
Intercept	.4591***	.5791***	-.2958**	-.4617	.0482	.2952**	0.7162***	0.8975***	0.1058
	(5.5449)	(6.9996)	(-2.0371)	(-1.6384)	(.1117)	(2.353)	(7.3415)	(6.2168)	(0.7778)
Observations	220	220	220	220	220	220	220	220	220
R-Squared	0.578	0.6539	0.1716	0.2576	0.3035	0.1298	0.1456	0.1719	0.0102
F-Stat	58.624	80.8772	8.8639	12.3194	15.4669	5.2939	7.2942	8.8831	0.4407

Table A3: Probit Regression on Hidden Trading Activity – Match 2

The table reports the probit regression analysis and marginal effects to examine hidden trading activity between bond and equity ETFs. Match 2 is the match of bond and equity ETFs on price. Variables include the ETFs' price, market capitalization ('000), total trade volume, spread, volatility, trade size, cancel-to-trade ratio, trade-to-order-volume ratio, the odd-lot volume ratio, expense ratio, AUM, and fund age (all in logs). Bond is a dummy variable coded one for bond ETF and zero for equity ETF. Robust standard errors are recorded in the parentheses and asterisks $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Match 2 Hidden Volume (%)		Match 2 Hidden Trades (%)	
	Probit (1)	Marginal Effects (2)	Probit (3)	Marginal Effects (4)
Price	0.1961***	0.2706***	0.3267***	0.4492***
	(0.0513)	(0.0708)	(0.0475)	(0.0652)
Market Cap	0.1660***	0.8181***	0.1154***	0.5665***
	(0.0237)	(0.1167)	(0.0214)	(0.1051)
Trade Volume	-0.1024***	-0.1466***	-0.0503*	-0.0718*
	(0.0273)	(0.0391)	(0.0260)	(0.0371)
Spread	0.5227***	-1.3421***	0.5491***	-1.4047***
	(0.0403)	(0.1034)	(0.0380)	(0.0969)
Volatility	-0.1669***	0.0776***	-0.2426***	0.1124***
	(0.0336)	(0.0156)	(0.0307)	(0.0142)
Cancel-to-Trade	0.0809**	0.1671**	0.1059***	0.2179***
	(0.0321)	(0.0663)	(0.0306)	(0.0630)
Trade-to-Order Volume	0.0674***	-0.0443***	0.0591***	-0.0387***
	(0.0235)	(0.0154)	(0.0208)	(0.0136)
Odd-Lot Volume	-0.0455	-0.0351	-0.1123***	-0.0864***
	(0.0400)	(0.0309)	(0.0340)	(0.0261)
Expense Ratio	-0.0173	0.0080	-0.0108	0.0049
	(0.0189)	(0.0087)	(0.0161)	(0.0074)
AUM	0.0270	0.0661	0.0290*	0.0706*
	(0.0184)	(0.0449)	(0.0159)	(0.0388)
Fund Age	-0.0892***	-0.0703***	-0.0925***	-0.0726***
	(0.0264)	(0.0208)	(0.0230)	(0.0181)
Bond	0.3489***	0.0631***	0.3146***	0.0567***
	(0.0486)	(0.0088)	(0.0443)	(0.0080)
Intercept	0.0225		0.0937	
	(0.3610)		(0.3250)	
Observations	440	440	440	440

Table A4: Differences in Hidden Trading Activity across Exchanges – Match 2

This table reports the normalized difference test on hidden trading activity between bond and equity ETFs across lit exchange in the sample period of January 2021 to March 2022. Match 2 is the match on price. Panel A reports the level of hidden volume (%) on each exchange. Panel B reports the level of hidden trades (%) on each exchange. A normalized difference above 0.25 suggests differences in the covariate distribution between the two groups.

	Bond ETFs		Equity ETFs		Normalized Difference
	Mean	Std. Dev.	Mean	Std. Dev.	
Panel A: Hidden Volume (%)					
Amex	0.20	0.82	0.15	0.71	0.0519
Arca	31.77	21.35	34.56	26.81	-0.0815
Bats-Y	5.61	8.13	5.89	10.54	-0.0215
Bats-Z	13.69	13.66	11.40	14.66	0.1142
Boston	5.01	8.02	6.59	11.05	-0.1159
CHX	0.23	2.86	0.17	2.14	0.0165
Edge-A	4.78	6.89	4.82	8.01	-0.0034
Edge-X	12.75	14.05	9.28	12.81	0.1828
IEX	0.00	0.00	0.00	0.00	0.0000
MEMX	2.77	6.86	3.16	8.09	-0.0368
MIAX	0.12	1.30	0.01	0.22	0.0795
NSX	1.59	4.66	1.05	4.01	0.0878
NYSE	3.00	5.29	1.78	4.38	0.1767
Nasdaq	17.96	15.01	20.27	19.99	-0.0924
Phlx	0.53	2.09	0.87	3.26	-0.0878
Panel B: Hidden Trades (%)					
Amex	0.22	0.80	0.17	0.78	0.0511
Arca	28.50	19.67	32.63	24.53	-0.1315
Bats-Y	5.68	7.51	5.34	8.76	0.0296
Bats-Z	12.59	12.19	11.08	13.24	0.0840
Boston	5.56	7.71	6.60	9.55	-0.0843
CHX	0.00	0.08	0.00	0.11	-0.0124
Edge-A	5.65	7.68	5.59	7.88	0.0047
Edge-X	12.87	13.34	9.39	11.73	0.1964
IEX	0.00	0.00	0.00	0.00	0.0000
MEMX	2.72	6.09	3.07	7.19	-0.0368
MIAX	0.20	1.41	0.01	0.14	0.1346
NSX	1.93	4.95	1.28	3.83	0.1044
NYSE	3.41	5.53	1.96	4.18	0.2097
Nasdaq	20.16	15.61	21.93	19.07	-0.0721
Phlx	0.51	1.80	0.96	3.05	-0.1282

Table A5: Hidden Volume (%) OLS Regression - Match 3

The table reports the OLS regression analysis to examine the determinants for the percentage of hidden volume to total trade volume between bond and equity ETFs. Match 3 is the match of bond and equity ETFs on market capitalization. Variables include the ETFs' price, market capitalization ('000), total trade volume, spread, volatility, trade size, cancel-to-trade ratio, trade-to-order-volume ratio, and the odd-lot volume ratio (all in logs). The difference specifications use the absolute value of the variables before taking the log transformation. T-statistics are recorded in the parentheses and asterisks ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Match 3 – Hidden Volume (%)								
	Bond ETFs (1)	Equity ETFs (2)	Difference (3)	Bond ETFs (4)	Equity ETFs (5)	Difference (6)	Bond ETFs (7)	Equity ETFs (8)	Difference (9)
Price	0.0159	0.1403***	0.0078	-0.0888***	-0.1204***	0.0466***	0.0279	0.0136	0.0311***
	(0.6990)	(4.596)	(0.6293)	(-3.9442)	(-4.3935)	(3.7563)	(1.5335)	(0.7561)	(2.6681)
Market Cap	0.0723***	0.0197**	-0.0086	0.0426***	0.0075	-0.0060	-0.0153	-0.0186	-0.0002
	(8.3587)	(2.4021)	(-1.298)	(4.2138)	(0.7638)	(-0.9371)	(-1.3147)	(-0.8657)	(-0.0327)
Trade Volume	-0.0671***	0.0102	-0.0012						
	(-7.9899)	(1.4294)	(-0.1945)						
Spread	0.1094***	0.2110***	-0.0494***						
	(5.8164)	(13.1106)	(-4.5417)						
Volatility	-0.0230*	-0.1037***	0.0283**						
	(-1.8121)	(-5.6340)	(2.0453)						
Trade Size				-0.0883**	-0.0704	-0.0297**			
				(-2.2186)	(-1.2679)	(-2.1394)			
Cancel-to-Trade				0.0952***	0.1135***	-0.0343***			
				(5.5713)	(5.7867)	(-3.7499)			
Trade-to-Order Vol				0.0520***	0.0707***	0.0130			
				(4.5096)	(4.0244)	(1.4534)			
Odd-Lot Vol				0.0490*	0.0307	0.0005			
				(1.6549)	(0.8588)	(0.0400)			
Expense Ratio							-0.1815***	-0.1398**	-0.0302
							(-3.3315)	(-2.0441)	(-0.3494)
AUM							-0.0197*	-0.0221	0.0025
							(-1.7930)	(-1.1160)	(0.3015)
ETF Age							-0.0495**	-0.0712***	0.0201
							(-2.5141)	(-4.1501)	(1.0322)
Intercept	0.3785***	0.8204***	-0.1765**	0.0851	0.3492	0.4069***	0.8024***	0.8117***	0.0218
	(4.4012)	(9.5095)	(-2.0026)	(0.3031)	(0.9678)	(4.0267)	(7.4305)	(4.9963)	(0.3022)
Observations	220	220	220	220	220	220	220	220	220
R-Squared	0.6126	0.6588	0.1469	0.3739	0.3431	0.1127	0.1998	0.2711	0.0424
F-Stat	67.6739	82.6363	7.3721	21.1999	18.5388	4.5096	10.6835	15.9148	1.8934

Table A6: Hidden Trades (%) OLS Regression - Match 3

The table reports the OLS regression analysis to examine the determinants for the percentage of hidden trades to total trades between bond and equity ETFs. Match 3 is the match of bond and equity ETFs on market capitalization. Variables include the ETFs' price, market capitalization ('000), total trade volume, spread, volatility, trade size, cancel-to-trade ratio, trade-to-order-volume ratio, the odd-lot volume ratio, expense ratio, AUM, and fund age (all in logs). The difference specifications use the absolute value of the variables before taking the log transformation. T-statistics are recorded in the parentheses and asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Match 3 – Hidden Trades (%)								
	Bond ETFs (1)	Equity ETFs (2)	Difference (3)	Bond ETFs (4)	Equity ETFs (5)	Difference (6)	Bond ETFs (7)	Equity ETFs (8)	Difference (9)
Price	0.0649***	0.1468***	0.0094	-0.0583**	-0.0845***	0.0427***	0.0081	0.0134	0.0293***
	(2.9618)	(5.3298)	(0.8053)	(-2.5777)	(-3.3198)	(3.6485)	(0.4779)	(0.7918)	(2.6979)
Market Cap	0.0498***	0.0144*	-0.0029	0.0277***	0	-0.0037	-0.0167	-0.0245	0.0008
	(5.9875)	(1.9475)	(-0.4713)	(2.7255)	(-0.0003)	(-0.6202)	(-1.5312)	(-1.2171)	(0.1154)
Trade Volume	-0.0393***	0.0168***	-0.0045						
	(-4.8575)	(2.6253)	(-0.7528)						
Spread	0.1308***	0.2102***	-0.0472***						
	(7.2261)	(14.4691)	(-4.6396)						
Volatility	-0.0668***	-0.1008***	0.0231*						
	(-5.4600)	(-6.0657)	(1.7847)						
Trade Size				0.0333	-0.0129	-0.0117			
				(0.8319)	(-0.2491)	(-0.8915)			
Cancel-to-Trade				0.0886***	0.1096***	-0.0291***			
				(5.1621)	(6.0144)	(-3.3683)			
Trade-to-Order Vol				0.0484***	0.0718***	0.0104			
				(4.1818)	(4.3994)	(1.2318)			
Odd-Lot Vol				0.0747**	0.0425	-0.0019			
				(2.5115)	(1.2810)	(-.1774)			
Expense Ratio							-0.1636***	-0.1130*	-0.0424
							(-3.2126)	(-1.7642)	(-0.5273)
AUM							-0.0097	-0.0146	0.0063
							(-0.9397)	(-0.7847)	(0.8038)
Fund Age							-0.0493***	-0.0563***	0.0203
							(-2.6777)	(-3.5030)	(1.1198)
Intercept	0.4591***	0.8228***	-0.1891**	-0.4617	0.0287	0.3039***	0.8176***	0.7891***	0.0072
	(5.5449)	(10.5680)	(-2.2952)	(-1.6384)	(00.0855)	(3.1872)	(8.0987)	(5.1838)	(0.1074)
Observations	220	220	220	220	220	220	220	220	220
R-Squared	0.5780	0.6768	0.1489	0.2576	0.3402	0.0980	0.1780	0.2558	0.0539
F-Stat	58.624	89.6282	7.4897	12.3194	18.3073	3.8550	9.2665	14.7077	2.4406

Table A7: Probit Regression on Hidden Trading Activity – Match 3

The table reports the probit regression analysis and marginal effects to examine hidden trading activity between bond and equity ETFs. Match 3 is the match of bond and equity ETFs on market capitalization. Variables include the ETFs' price, market capitalization ('000), total trade volume, spread, volatility, trade size, cancel-to-trade ratio, trade-to-order-volume ratio, the odd-lot volume ratio, expense ratio, AUM, and fund age (all in logs). Bond is a dummy variable coded one for bond ETF and zero for equity ETF. Robust standard errors are recorded in the parentheses and asterisks ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Match 3 Hidden Volume (%)		Match 3 Hidden Trades (%)	
	Probit	Marginal Effects	Probit	Marginal Effects
	(1)	(2)	(3)	(4)
Price	0.2888***	0.3987***	0.4089***	0.5599***
	(0.0555)	(0.0766)	(0.0525)	(0.0719)
Market Cap	0.1502***	0.7328***	0.1046***	0.5064***
	(0.0286)	(0.1393)	(0.0257)	(0.1241)
Trade Volume	-0.0442*	-0.0656*	-0.0023	-0.0034
	(0.0243)	(0.0361)	(0.0226)	(0.0332)
Spread	0.5662***	-1.4354***	0.5933***	-1.4922***
	(0.0398)	(0.1014)	(0.0363)	(0.0911)
Volatility	-0.2220***	0.0852***	-0.2834***	0.1079***
	(0.0314)	(0.0121)	(0.0278)	(0.0106)
Cancel-to-Trade	0.0932**	0.1812**	0.1134***	0.2189***
	(0.0400)	(0.0778)	(0.0382)	(0.0737)
Trade-to-Order Volume	0.0667***	-0.0412***	0.0605***	-0.0371***
	(0.0248)	(0.0153)	(0.0230)	(0.0141)
Odd-Lot Volume	-0.0133	-0.0101	-0.0754**	-0.0566**
	(0.0347)	(0.0262)	(0.0295)	(0.0221)
Expense Ratio	-0.1992*	-0.0194*	-0.1594*	-0.0154*
	(0.1091)	(0.0106)	(0.0918)	(0.0089)
AUM	-0.0187	-0.0466	-0.0081	-0.0201
	(0.0213)	(0.0531)	(0.0182)	(0.0449)
Fund Age	-0.1142***	-0.0887***	-0.1084***	-0.0836***
	(0.0294)	(0.0229)	(0.0261)	(0.0201)
Bond	0.3794***	0.0659***	0.3523***	0.0607***
	(0.0482)	(0.0083)	(0.0429)	(0.0073)
Intercept	0.1739		0.1974	
	(0.4265)		(0.3857)	
Observations	440	440	440	440

Table A8: Differences in Hidden Trading Activity across Exchanges – Match 3

This table reports the normalized difference test on hidden trading activity between bond and equity ETFs across lit exchange in the sample period of January 2021 to March 2022. Match 3 is the match on market capitalization. Panel A reports the level of hidden volume (%) on each exchange. Panel B reports the level of hidden trades (%) on each exchange. A normalized difference above 0.25 suggests differences in the covariate distribution between the two groups.

	Bond ETFs		Equity ETFs		Normalized Difference
	Mean	Std. Dev.	Mean	Std. Dev.	
Panel A: Hidden Volume (%)					
Amex	0.20	0.82	0.15	0.73	0.0467
Arca	31.77	21.35	30.47	23.07	0.0413
Bats-Y	5.61	8.13	5.87	10.09	-0.0200
Bats-Z	13.69	13.66	12.03	14.05	0.0847
Boston	5.01	8.02	7.07	11.40	-0.1478
CHX	0.23	2.86	0.36	3.44	-0.0292
Edge-A	4.78	6.89	4.78	7.17	-0.0004
Edge-X	12.75	14.05	8.63	11.09	0.2301
IEX	0.00	0.00	0.00	0.00	0.0000
MEMX	2.77	6.86	4.19	9.96	-0.1170
MIAX	0.12	1.30	0.02	0.35	0.0716
NSX	1.59	4.66	1.04	3.29	0.0971
NYSE	3.00	5.29	1.97	4.12	0.1536
Nasdaq	17.96	15.01	22.46	19.05	-0.1855
Phlx	0.53	2.09	0.97	2.85	-0.1241
Panel B: Hidden Trades (%)					
Amex	0.22	0.80	0.17	0.74	0.0460
Arca	28.50	19.67	28.87	20.51	-0.0131
Bats-Y	5.68	7.51	5.26	8.17	0.0379
Bats-Z	12.59	12.19	11.50	12.65	0.0623
Boston	5.56	7.71	6.96	9.58	-0.1137
CHX	0.00	0.08	0.00	0.08	-0.0158
Edge-A	5.65	7.68	5.80	7.32	-0.0146
Edge-X	12.87	13.34	8.75	10.16	0.2461
IEX	0.00	0.00	0.00	0.00	0.0000
MEMX	2.72	6.09	3.84	8.26	-0.1089
MIAX	0.20	1.41	0.02	0.28	0.1265
NSX	1.93	4.95	1.24	3.26	0.1165
NYSE	3.41	5.53	2.11	3.90	0.1919
Nasdaq	20.16	15.61	24.40	18.17	-0.1770
Phlx	0.51	1.80	1.08	2.68	-0.1792

PART 2: CORPORATE BOND TRADING AROUND UNSCHEDULED CORPORATE EVENTS

I. INTRODUCTION

The over-the-counter (OTC) corporate bond market is characterized as opaque with infrequent trading (Edwards, Harris, and Piwowar, 2007). Several studies document the reduction in trading costs and improvement in liquidity after the introduction of the Trade Reporting and Compliance Engine (TRACE) in 2002 (Edwards, Harris, and Piwowar, 2007; Goldstein, Hotchkiss, and Sirri, 2007). Although post-trade price transparency was established after the introduction of TRACE, bond traders still experience a lack of publicly available price quotes in the OTC corporate bond market, which may lead to adverse selection.

As both debt and equity represent claims on firms' future cash flows, corporate events affect investors' expectations of the distribution of future cash flows. This revision of investors' expectations can materialize through trading. Studies examining the relevance of corporate events that materialize in equity trading are robust; however, few consider the effect of these events on bond trading. Information asymmetry around corporate events, particularly the unscheduled events, may contain value-relevant information to bond traders and cause reactions in the bond market, which may affect bond liquidity. I study changes in corporate bond liquidity around unscheduled corporate news events, which often come to the market as a surprise. Such unscheduled corporate events include CEO turnovers, dividend changes, mergers and acquisitions (M&As), stock repurchases, seasoned equity offerings (SEOs), spin-offs, stock splits, and ticker symbol changes.

The literature regarding bond market reactions around unanticipated corporate events centers on abnormal price reactions and returns to bondholders. Chen, Ramaya, and Wu (2020) examine wealth effects of M&A announcements on bondholders and provide evidence that acquiring firm bondholders experience significantly negative abnormal returns, while target firm bondholders experience significantly positive abnormal returns. Wei, Truong, and Do (2020) analyze unexpected dividend change announcements and find that, on average, bond prices increase and decrease in the same direction of the dividend change. Adams and Mansi (2009) investigate the impact of CEO turnover on bond prices and find that while CEO turnover events are value enhancing to stockholders, they are value decreasing to bondholders.

While bond price reactions to corporate events have been documented, competing theories and mixed evidence lead to the corporate bond market response to unscheduled corporate events being an open question. Woodley, DaDalt, and Wingender (2020) document abnormal returns and trading activity in corporate bonds around earnings announcements, which is a scheduled event. How certain unscheduled corporate events affect bond trading activity is not clear. For example, stock repurchases may appear as a firm's bullish view of its future performance as it allocates investment to its undervalued equity. But from a bondholder's perspective, excess free cash flow is being diverted away from paying down current debts, which may increase the overall risk of the firm. For SEOs, would bondholders benefit from the firm having a lower leverage ratio or will they react negatively as SEOs typically signal that a firm is overvalued? The effects of unscheduled firm events may result in different trading reactions in the corporate bond market. Using previous bond market event studies and equity market event studies as guides, bond price reactions to certain unscheduled corporate events may be indicative of how bond trading activity will react to these same events.

Using bond transaction data from TRACE over a sample period of 2012 to 2021, I find that certain unscheduled corporate events elicit reactions in the corporate bond market. Some events result in an increase in corporate bond trading activity, while some events do not drastically change the trading activity of their firms' bonds. Bond traders react to dividend change announcements, M&A announcements, repurchase announcements, SEO announcements, and spin-off events, but not to CEO turnover events, stock splits, and stock ticker changes. In a market that is opaque and illiquid, the finding of increased trading activity in corporate bonds around some of the events implies that bond traders find these events to contain value-relevant information and adjust their expectations of the firms accordingly through bond trading.

The remainder of the study proceeds as follows. Section II provides a detailed literature review of each unscheduled corporate event examined in this paper and outlines the development of the hypotheses. Section III describes the data and methodology. Section IV presents the results of the analyses, and Section V concludes.

II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

REPURCHASES

The extant literature on stock repurchases focuses on the wealth transfer hypothesis and the signaling hypothesis with mixed evidence of which of the two hypotheses dominates. Dann (1981) finds positive returns to stockholders after stock repurchase announcements, but no significant announcement returns to straight debtholders. Wansley and Fayez (1986) find that stock repurchase announcements in the case of Teledyne Corporation led to positive excess returns to common stockholders while bondholder returns were significantly negative. The results from Dann support the signaling hypothesis in that repurchases constitute a positive revelation of the firm's future prospects by management, while the results from Wansley and Fayez support the wealth redistribution hypothesis in that repurchases distribute cash to shareholders at the expense of bondholders, which increases the firm's default risk.

Maxwell and Stephens (2003) find that the signaling and wealth transfer hypotheses may not be mutually exclusive. While their findings are in line with the wealth transfer hypothesis, of positive abnormal stock price reaction and negative abnormal bond price reaction to stock repurchase announcements, the increase in total firm value supports the signaling hypothesis. As repurchases have become a popular profit distribution tool relative to dividends, Nishikawa, Prevost, and Rao (2011) find bond market reactions have changed.[12] Nishikawa, Prevost, and Rao conclude there is no evidence of wealth transfer from bondholders to stockholders, but there is a significant decrease in bond yields and positive returns to stockholders after repurchasing announcements. Bond trading activity may be dependent on whether the signaling or the wealth transfer hypothesis is dominant. If bond traders interpret repurchase announcements as positive signals, then they might buy more bonds or do not change their bond holdings. On the other hand, if bond traders believe the repurchase announcement will benefit stockholders at the expense of bondholders, trading in the event firms' corporate bonds will increase as bond traders adjust their holdings in the firm.

H1: If the signaling hypothesis (wealth transfer hypothesis) dominates, trading in corporate bonds of firms with repurchase announcements will either increase or not change (increase).

[12] See Michaely and Moin (2021) and Floyd, Li, and Skinner (2015) regarding the role of the repurchase-dividend substitution in payout policies and growth of repurchases.

MERGERS AND ACQUISITIONS

The coinsurance effect may come into play in mergers and acquisitions as risky debt benefits from a decrease in the probability of default when firms merge, leading to an increase in bondholder wealth. On the other hand, Furfin and Rosen (2011) find, on average, mergers increase default risk of the acquiring firm and conclude managerial motivations play a critical role for this outcome. Billett, King, and Mauer (2004) examine 940 mergers from 1979 to 1997 and find that target bondholders earn positive mean excess returns of 1.09% with even stronger returns for non-investment grade bonds, while acquirer bondholders experience a mean excess return of -0.17%. Chen, Ramaya, and Wu (2020) use the TRACE data to find support for both the coinsurance and wealth transfer hypotheses. Acquirer bondholders experience negative abnormal returns while target bondholders experience positive abnormal returns. Target (acquirer) bonds experience more positive (negative) returns when the target's credit rating is below the credit rating of the acquirer. Jankowitsch and Pauer (2021) also study the TRACE data and conclude that target bondholders experience positive wealth effects of around 40 bps, but acquirer bondholders suffer a loss of around 1.7 bps.

The effects of M&A announcements on bond trading activity may depend on whether the coinsurance or the wealth transfer hypothesis is at play. Using a sample from 1994 to 2006, Kedia and Zhou (2014) show an increase in pre-announcement trading activities (volume and number of trades) in corporate bonds of NAIC firms with M&As announcements. Target bonds experience higher trade frequency and volume in the three months prior to the announcement. Although Kedia and Zhou examine measures of trading activities prior to M&A announcements, their sample period spans only a few years after the implementation of TRACE in 2002 and they focus only on NAIC firms.

Based on past evidence on bond price reactions, target bondholders benefit from M&A announcements while acquirer bondholders suffer a loss. Thus, bond traders will increase their buying activity in target bonds while selling acquirer bonds. Overall trading activity in corporate bonds should increase as traders act on news announcements.

H2: Target bonds and acquirer bonds will experience an increase in trading activity around M&A announcements.

SPIN-OFFS

The spin-off literature focuses on abnormal stock price performance and shareholder value (Veld and Veld-Merkoulova, 2004; and Chemmanur and Yan, 2004). Maxwell and Rao (2003) find support for the wealth expropriation hypothesis in that bondholders suffer significantly negative abnormal returns during the month of a spin-off announcement. While the aggregate value of the firm increases, the firm's bonds are more likely to be downgraded after the spin-off and losses to bondholders tend to be more severe when the gains to stockholders are larger. Due to the lack of literature on the effects of spin-off announcements in the corporate bond market, I cannot predict if there will be any changes in bond trading activity around spin-off announcements. If traders' reactions to spin-offs are in line with the wealth expropriation hypothesis, then they are likely to increase their trading activity by selling the corporate bonds with spin-off announcements.

H3: Corporate bonds of firms with spin-off announcements will experience an increase in trading activity.

DIVIDEND CHANGES

The literature on the effect of dividend changes on firm value using the equity market setting is abundant. Nissim and Ziv (2001) find that dividend changes are predicative of the future profitability of firms, which supports the information content of dividends hypothesis.[13] Handjinicolaou and Kalay (1984) examine the effect of dividend changes in the bond market and find support for both the information content of dividends hypothesis and the wealth redistribution hypothesis.[14] There is a positive bond price response to unexpectedly large dividends and dividend increase announcements negatively affect bond market value. Their empirical evidence indicates that bond prices are not affected by dividend increase announcements but react negatively to dividend reductions, which implies that dividend announcement changes contain some information regarding firm value. Dhillon and Johnson (1994) find that bond price reactions to dividend changes are opposite to stock price reactions, which supports the wealth redistribution hypothesis.

Tsai and Wu (2015) use the TRACE data to examine 5,571 dividend announcements from 2005 to 2012. Their study finds some evidence supporting the information content and free cash flow hypotheses as opposed to the wealth transfer effect in the bond market.[15] Stock returns and premium bond returns on announcement dates are positively related to dividend changes, with unexpected dividend increases (decreases) being followed by better (worse) earnings one year later. Using TRACE data to study a similar sample size and sample period, Wei, Truong, and Do (2020) argue that the signaling or wealth transfer effect is conditional on bond types. Average

[13] The information content of dividends hypothesis state that dividend changes trigger stock returns because they convey new information about the firm's future profitability (Miller and Modigliani, 1961).
[14] The wealth redistribution hypothesis, termed by Handjinicolaou and Kalay (1984), states that dividend increase announcements negatively affect bond market value because stockholder gains can be at least partially explained by bondholder losses.
[15] Jensen's (1986) free cash flow hypothesis predicts that the distribution of dividends prevents managers from wasting resources, which benefits both stockholders and bondholders.

daily bond prices decline by -0.056% in response to dividend decrease announcements and increase 0.015% to dividend increase announcements. Dividend omission announcements result in a decline of 0.3%, but the bond market does not appear to react to dividend initiation announcements. Bonds rated A or better do not react to unexpected dividend changes as default risk is negligible, rather market reaction is concentrated in bonds along the investment grade borderline. The wealth expropriation effect is strongest among bonds with a probability of default greater than 10%, less than 12 months to maturity, and a corporate cash ratio less than one.

Based on these previous findings of bond price reactions to unexpected dividend changes and the non-mutually exclusive theories on dividends, the trading activity in corporate bonds of announcing firms is not clear. According to the information content of dividends hypothesis, if dividend increases (decreases) send a positive (negative) signal to investors, bond trading will increase (decline) as investors adjusts their expectations of the firm. According to the wealth redistribution hypothesis, if dividend increases (decreases) favor stockholders (bondholders), bond trading will decline (increase). Based on the free cash flow hypothesis, increases (decreases) in dividends benefits (costs) stockholders and bondholders, so bond trading should increase (decline).

H4: Corporate bonds of firms with dividend increase (decrease) announcements will experience an increase (decline) in trading activity based on the information content of dividends hypothesis and the free cash flow hypothesis but dividend increase (decrease) announcements will invoke a decline (increase) in trading activity based on the wealth redistribution hypothesis.

SEASONED EQUITY OFFERINGS

Eberhart and Siddique (2002) examine the effects of seasoned equity offerings (SEOs) on the long-term performance of bonds and stocks. Their results appear to be inconsistent with the efficient market hypothesis as there is a five-year positive delayed bond price response to SEOs. SEO announcements generate negative abnormal stock returns as stockholders experience a wealth transfer to bondholders, because SEOs decrease a firm's debt ratio and consequently its default risk. Eberhart and Siddique did not examine bond trading activity around SEO announcements. Given the lack of research regarding SEOs and the corporate bond market, it is not clear how an SEO might affect bond trading activity. However, I conjecture that if the wealth transfer hypothesis holds and bondholders benefit from SEOs, then trading in bonds of firms with SEO announcements will experience an increase in trading activity.

H5: Corporate bonds of firms with SEO announcements will experience an increase in trading activity.

CEO TURNOVERS

It can be argued that the direction of a firm is directly linked to its CEO. So, when a firm's CEO steps down (whether voluntarily or involuntarily), the direction of the firm may fundamentally change with the successor. On the other hand, the CEO holds only one seat on the board of directors and replacing one individual (albeit one of the most powerful individuals) is not likely to fundamentally change a firm. Weisbach (1995) finds that CEO turnover leads to reversals of poor prior decisions in the context of divesting acquisitions. Huson, Malatesta, and Parrino (2004) document positive average abnormal stock returns at turnover announcements. Clayton, Hartzell, and Rosenberg (2005) find significant increases in stock price volatility following CEO turnover.

Adams and Mansi (2009) investigate the impact of CEO turnover announcements on bondholder wealth and find support for both the wealth transfer and signaling hypotheses. CEO turnover announcements are value-enhancing to stockholders and value-decreasing to bondholders. Abnormal changes in bondholder wealth are larger for forced CEO turnover than for voluntary turnover. The documented effects of CEO turnovers on corporate policy, stock price, and bondholder wealth provide some insight on how trading activities of corporate bonds will response to CEO turnover announcements. For voluntary and involuntary CEO turnovers, bond traders will increase trading activity in the bonds of announcing firms.

H6: Corporate bonds of firms with CEO turnover announcements will experience and increase in trading activity.

STOCK SPLITS

Two well-established hypotheses that are not mutually exclusive in the stock split literature are the signaling hypothesis and the trading range hypothesis (Fama et al., 1969). Under the signaling hypothesis, managers use stock splits to convey favorable private information regarding the current value of the firm. The trading range hypothesis posits that the main motive for stock splits is to realign share prices to a preferred trading range to attract small investors as it becomes more affordable for investors to diversify their portfolios.

Since a stock split does not fundamentally change a firm, logic dictates that this event should not elicit a reaction from the market. However, the market reaction to this seemingly cosmetic corporate event is generally positive in the equity markets (Ikenberry, Rankine, and Stice, 1996; and Grinblatt, Masulis, and Titiman, 1984). Regarding the bond market reactions to stock splits, Michayluk and Zhao (2010) find that the average bond yield spreads decrease with positive bond price reactions after split announcements. This evidence indicates that bond investors also perceive a stock split as a favorable signal of the splitting firm's future prospects.

Nevertheless, the number of stock splits have continually declined since the 1980s, dropping from 800 in 1983 to 135 in 2007 and further declining after the 2008 financial crisis to 13 splits in 2009 (Minnick and Raman, 2014). With the changing landscape in trading (fractional share trading, no-commission trades, and easy-to-use trading platforms), investors can purchase shares of stock based on dollar value (with a minimum of $1), making the trading range hypothesis irrelevant. It is also suggested that attaining an extremely high stock price is an ego boost for some firms, which contradicts the signaling hypothesis.[16]

If the signaling hypothesis is still relevant to investors, bond trading will increase when a firm engages in a stock split. If the trading range hypothesis of stock splits is no longer relevant, then equity investors will not change their trading behavior around split events. Additionally, the trading range hypothesis should not affect the bond market, since one of the goals for stock splits is to lower equity prices to attract investors to trade equity. Therefore, bond trading of firms with stock splits will increase based on the signaling hypothesis. Alternatively, if bond traders think stock splits are merely cosmetic, there will be no changes in trading activity in the bond market.

H7: Corporate bonds of firms with stock split events will experience an increase in trading activity based on the signaling hypothesis or the bonds of firms with stock split events will experience no changes in trading activity if traders view stock splits as cosmetic events.

TICKER CHANGES

[16] See https://www.investopedia.com/comparing-fractional-trading-offerings-at-online-brokers-4847173

Announcements of ticker symbol changes often surprise the market. One might argue that a company name or ticker change indicates a firm's more diverse operations and or that it is seeking to position itself in a certain direction or project a certain image through a name or ticker change.[17] Kadapakkam and Misra (2007) argue that a ticker symbol change (without a simultaneous company name change), which should have no valuation consequences for a firm, has an adverse effect on trading volume and prices in the stock market. From a behavioral perspective, more likeable, easily pronounceable, and memorable ticker symbols experience higher firm values and returns in the equity markets (Xing, Anderson, and Hu, 2016; and Head, Smith, and Wilson, 2009).

Given little prior research from which to draw, the effect of a ticker change on the trading activity of corporate bonds is unknown. The trading activity of the announcing firms' bonds may depend on how the market perceives ticker changes, whether strategic brand positioning or merely cosmetic. If the ticker change symbolizes a new brand positioning of the firm and bond traders view the change as positive, then bond traders will increase buying activity. On the other hand, if the ticker change is merely cosmetic, then bond traders will not react and there will be no changes to bond trading activity.

H8: Corporate bonds of firms announcing ticker symbol changes will experience no change in trading activity if bond traders perceive the change as cosmetic or will increase trading activity if bond traders perceive the change as positive.

III. DATA AND METHODS

[17] For example, see these articles on Forbes and BBC News regarding Facebook's (FB) name and ticker change to Meta Platforms, Inc. (META): https://www.forbes.com/advisor/investing/facebook-ticker-change-meta-fb/ and https://www.bbc.com/news/technology-59083601

DATA SOURCES

Bond trade data are obtained from enhanced TRACE from January 1, 2012 to December 31, 2021. Some bond information, such as the indicators for 144A, convertible features, and investment or noninvestment grade, bond maturity date, and coupon rate, are sourced from the TRACE master file. Information on firm characteristics and financials are obtained from CRSP and Compustat.

Quarterly dividend announcements, stock split events, spin-off events, and ticker changes are from CRSP. CEO turnover events are merged from Execucomp and an open sourced database for CEO dismissals.[18] Repurchases, seasoned equity offerings, and M&As are collected from Bloomberg Financial Database.[19] Bloomberg filters include restricting the sample to public firms with country/region, index, and exchange being in North America. Event dates from Bloomberg are announcement dates of the events. Dates from CRSP and Execucomp are event dates, except for dividend changes where CRSP provides the announcement date.

SAMPLE SELECTION

The sample for all corporate events is formed by identifying all firms in the CRSP and Compustat databases excluding utilities and financial institutions (SIC codes 6000-6999 and

---

[18] Version V01312023 of the open source CEO dismissal dataset was updated on January 31, 2023 so only events up to December 31, 2021 are used in the sample. An indicator variable of 0 and 1 is used to separate the sample into voluntary and involuntary CEO turnovers, respectively.

[19] Some firm events' data downloaded from Bloomberg have Bloomberg-designated ticker symbols in the form of a seven-digit number with a letter at the end (e.g., 1897377D for Sprint Corporation, a telecommunications company that merged with T-Mobile in 2020). Bloomberg assigns numeric ticker symbols because it does not keep obsolete historic ticker symbols. If an acquirer assumes the target's ticker, then the acquirer's ticker becomes a Bloomberg-assigned ticker and vice versa. Firms with Bloomberg-assigned tickers are dropped from the sample. Bloomberg also uses the most current trading symbol for firms. A bankrupt firm trading in the OTC market will have a Q attached to the end of its ticker. This additional Q poses issues for merging with other datasets that use pre-bankruptcy ticker symbols. The Q from bankrupt firms trading in the OTC market was dropped in order to merge with other datasets. These firms are also excluded from the sample if they cannot be successfully matched.

4900-4999). A stock must have a share code of 10 or 11 to be included in the stock split and ticker change events. Following the literature on stock splits, all stock splits with a distribution code of 5523 and a stock split factor greater than or equal to 1 are included in the sample. A stock is excluded from the ticker change sample if its share class is classified as 1, B, C, D, E, H, N, S, or V. SEO announcements are all "ADDL" offerings indicated on Bloomberg excluding secondary offerings, debt offerings, or a combination of the two. More specifically, only additional primary share offerings with no other classification types are included in the SEO sample (Gao and Ritter, 2010). [20] Dividend change announcements must have a distribution code of 1232 and are restricted to increases and decreases with percentage changes greater than 10% (Wei, Truong, and Do, 2020).[21] Spin-off parent firms are identified in the CRSP distribution database using distribution codes 3762, 3763, 3764, 3862, 3863, and 3864.

The bond sample is restricted to non-convertible, non-144A bonds, maturing in 50 years or less, that have non-missing ticker and bond symbol information, and that are active during the event year.[22] A company's bond must trade once within the event window of [-5, +5] surrounding the event or announcement date with at least one trade in the estimation window of [-40, -6]. If a bond matures or is called in the estimation window, it is excluded from the sample.

VARIABLE MEASURES

[20] SEO offer type in Bloomberg may have multiple classifications associated with one event (e.g., "ADDL, Primary Share Offering, Best Efforts, Private Placement"). Classifications include primary share offering, secondary share offering, accelerated bookbuild, block, emerging growth, private placement, at the market, Rule 144A, registered direct, bought deal, VC backed, VC exit, PE backed, PE exit, QIP, and REG S.

[21] Following Handjinicolaou and Kalay (1984), the percentage change in unexpected dividends for company i at time t is defined as $\frac{D_{i,t}-D_{i,t-1}}{D_{i,t-1}}$.

[22] The crsp_bond_link on WRDS is used to determine when a bond starts and ends trading on TRACE. If a bond has the same start and end date, it is removed from the bond sample. If a bond matures before the event year, then it is removed from the sample.

The main bond trading variables include the daily average quantity traded, the daily average number of trades, and the daily average trading volume. Trade volume is the product of the daily average number of trades and the average daily trade size. Raw bond returns are calculated as the daily average holding period return using the clean price. Years to maturity is calculated as the number of years between the year of the event and the maturity year. The Buy/Sell Side variable is an indicator variable coded +1 for buys, -1 for sells, and 0 for no trade.

Control variables include firm size, sales, return on assets (ROA), and leverage. Firm size is equity market capitalization calculated using daily closing share price and shares outstanding from CRSP. Sales is the firm's annual sales in millions. ROA is defined as operating income before depreciation divided by total assets. Leverage is the sum of total debt, including current liabilities and total long-term debt, divided by stockholders' equity.

DESCRIPTIVE STATISTICS

Table 1 provides the event counts of each corporate event. Total event counts in column (1) is the total number of events over the sample period that pass the filters. The total number of firms in column (2) is the number of unique firms that experience an event or announcement. As some firms engage in a certain event more than once, the total number of firms may be less than the total number of events. The number of total bonds in column (3) include a count of unique bond symbols traded around the event window. There is more voluntary CEO turnovers compared to involuntary turnovers. There are more dividend increases relative to dividend decreases and more acquiring firms than target firms.

Table 2 reports the summary statistics for each corporate event or announcement in the sample. Panel A compares voluntary and involuntary CEO turnover events. Bonds are traded more frequently in the involuntary turnover sample with negative bond returns on average. Firms in the involuntary turnover sample tend to be smaller and more leveraged. Panel B compares dividend increase and decrease announcements. Bonds in the dividend increase sample are more active than bonds in the decrease sample. Firms in the dividend increase sample are larger with more sales, more profitable and more leverage in the dividend increase sample than firms in the decrease sample. Panel C compares the M&A sample between acquirers and targets. Acquirers are larger, more profitable, and less leveraged than targets. Panel D details the descriptive statistics on repurchases. Panel E provides the descriptive statistics on SEOs. Panel F reports the descriptives on parent firms in a spin-off event. Panel G and Panel H report the descriptives on stock splits and ticker changes, respectively.

METHODS

I first start with an 11-day event window around the event or announcement day for each corporate event. I compute abnormal trading measures of abnormal quantity traded, abnormal number of trades, and abnormal trading volume using the following equation:

$$Abnormal\ Trading\ Measure = Trading\ Measure_{i,t} - \overline{Trading\ Measure_{i}}\ , \quad (1)$$

where $Trading\ Measure_{i,t}$ is either the daily average quantity, the daily average number of trades, or daily average volume for firm *i* on day *t* and the $\overline{Trading\ Measure_{i}}$ is the average of either the daily average quantity, the daily average number of trades, or the daily average volume for firm *i* measured in a 35-day pre-event window [-40, -6]. $Abnormal\ Trading\ Measure$ is either abnormal quantity, abnormal trades, or abnormal volume.

Next, I run OLS regressions using the following equation:

$$Y_i = \beta_0 + \gamma X_i + \varepsilon_i\ , \quad (2)$$

where Y_i is the abnormal bond trading measures of firm i. X_i is the set of control variables including years to maturity, raw bond returns, buy/sell indicator where buy is +1, sell is -1, and no trade is 0, firm size, sales, ROA, leverage and dummy variables that capture the seven trading days around the event or announcement date (i.e., $Event_{t-3}$ is a dummy coded 1 for three days before day 0 and 0 otherwise, while $Event_{t+3}$ is a dummy coded 1 for three days after day 0 and 0 otherwise). Firm size, bond return, and sales are in logs and the buy/sell side indicator is log(1+side) transformed.

IV. EMPIRICAL RESULTS

UNIVARIATE ANALYSIS

Graphical depictions of the abnormal trading measures around the event window [-5, +5] are presented for each corporate event or announcement. Figures 1a and 1b show the abnormal bond trading variables for voluntary and involuntary CEO turnover events, respectively. Figure 1a shows that abnormal quantity, abnormal number of trades, and abnormal volume are mostly negative over the event window for voluntary CEO turnover events, which suggests little trading around this corporate event. Similarly for involuntary turnover events, abnormal quantity and abnormal number of trades are negative, suggesting less trading activity than normal around the event window, but abnormal volume spike in the two days prior (day -2) to an involuntary CEO turnover event. Overall, the figures 1a and 1b suggest that bond traders do not react to CEO turnover events.

Figures 2a and 2b show the effects of dividend increase and decrease announcements on corporate bond trading, respectively. Both figures show that abnormal trading measures are positive and stay abnormally high following dividend increase and decrease announcements.

Regarding dividend increase announcements, abnormal quantity increases five days prior to the event (day -5) and stays elevated over the event window. Abnormal number of trades increase three days prior to the event (day -3) and stays elevated over the event window and abnormal volume increases on the day of the event (day 0) and stays elevated for the days following the event. Regarding dividend decrease announcements, abnormal quantity peaks the day prior (day -1) and the day after the event (day +1). Abnormal number of trades peaks on day -3 and day +1. and abnormal volume peaks on day +1. The figures suggest that bond traders react to dividend changes, both increases and decreases.

Figure 3a and 3b present the announcement effects of the M&A samples for acquiring firms and target firms, respectively. There is a spike in trading activity for acquirers, but the effects are fleeting. Abnormal quantity spikes on day 0 and on day +4. Abnormal number of trades spikes on day +1 and abnormal volume peaks on day +1. For target firms, abnormal trading reaches a peak on the announcement day (day 0) and stays elevated throughout the event window. Abnormal number of trades and abnormal volume peak on day 0 for target firms. While trading activity in acquiring firm bonds slowly increase as the announcement day approaches, the increase in bond trading in target firms on announcement day were more dramatic. The figures suggest that the bond market were not aware of the target firms until the announcement day, but traders were increasingly trading acquiring firms' bonds prior to the announcement.

The trading activity in the corporate bond market around repurchase announcements are graphically presented in figure 4. Abnormal quantity and abnormal number of trades spike three days before (day -3) a repurchase announcement and before declining to a stable level in the event window. Abnormal volume shows two peaks around three days before (day -3) the announcement and two days after (day +2) the announcement with a smaller spike on day 0.

Figure 4 suggests that traders anticipate and react to repurchase announcements before the announcement takes place.

Figure 5 shows the effects of SEO announcements on bond trading activity. There appears to be a late reaction in terms of increased trading activity with SEOs. Abnormal quantity, abnormal number of trades, and abnormal volume spike two days after (day +2) an SEO announcement and trading activity appears to stay elevated through the end of the event window. Abnormal quantity starts declining from day -5 to day -1 and starts on an upward trend on day 0. Abnormal number of trades were at normal levels from day -5 to day 0 and starts increasing on day +1 before falling on day +3. Anormal volume patterns are similar to the patterns of abnormal number of trades. Overall, the bond market experiences a late reaction to SEO announcements.

Figure 6 shows the bond trading activity measures around the event window for corporate spin-off events. Abnormal quantity spikes three days prior (day -3) to a spin-off and stays elevated throughout the event window. The abnormal number of trades and abnormal volume start to increase before the event and reaches a peak two days after (day +2) the event. Overall, the figure hints at bond traders reacting to spin-off events by increasing their trading activity in the parent firms.

The trading activity in the corporate bond market around stock split events are graphically presented in figure 7. The three measures show different patterns regarding stock splits. Abnormal quantity is decreasing over the event window but spikes five days after (day +5) the event. Abnormal number of trades reaches a peak three days prior (day -3) to the stock split and becomes stable over the event window. Abnormal volume continually fluctuates between abnormally high trading volume to abnormally low trading volume over the event window. Abnormal volume peaks on day +2. Overall, it is difficult to determine the reaction to expect from bond traders regarding stock splits and figure 7 provide mixed evidence regarding the different trading metrics examined.

Figure 8 illustrates changes in trading activity in the bond market around ticker symbol change events. Abnormal quantity shows an increasing trend over the event window with peaks on the day after (day +1) and on day +4 to the ticker symbol change. Abnormal number of trades starts on an upward trend and peaks on day -1 before declining to abnormally low levels of trades. Abnormal volume shows that volume increases on the day of the ticker change with a peak on day +1 and stays elevated over the event window. Overall, bond traders seem to increase their trading activity in the bonds of firms with ticker changes.

To more formally test the figures regarding the different types of unscheduled corporate events, I conducted an event study around the event window [-5, +5]. The t-tests test whether the abnormal trading measures, abnormal quantity, abnormal number of trades, and abnormal volume, are significantly different from zero. Tables 3 to 10 present the results from the event study.

Table 3 presents the results from an 11-day event study for voluntary (Panel A) and involuntary (Panel B) CEO turnover events. In panel A, abnormal quantity and abnormal volume are significantly negative three days prior (day -3) to a voluntary CEO turnover event. Abnormal quantity indicates that quantity traded in event firms' bonds is 88,406 less than the estimation window and abnormal volume indicates that the volume in these bonds is lower by 678,939 compared to the 35 trading days prior to the event. Abnormal trades are significantly less than normal on days -2 and -1. After the event, only abnormal volume is significantly less than the estimation window on days +2, +3, and +5. The results in panel A indicate that bond traders do not react to voluntary CEO turnover events as corporate bonds of the events firms do not experience an increase in trading activity.

In panel B of table 3, abnormal volume is significantly less than normal three days prior (day -3) to an involuntary CEO turnover event. Abnormal quantity and abnormal volume decline on the day of (day 0) an involuntary CEO turnover event by 222,332 and 1,792,802, respectively. After the event, abnormal quantity is significantly below normal levels on day +2 by 166,322 and day +5 by 131,410. The significant decline in trading activity indicates that bond traders do not react to this corporate event. Overall, the bond market experiences significantly less trading activity than normal around voluntary and involuntary CEO turnover events.

An 11-day event study for dividend change events is presented in table 4. Panel A reports the results for dividend increase events, and Panel B reports the results for dividend decrease events. Abnormal quantity is significantly positive on day +1 and suggest that quantity traded on the day after the dividend increase is above normal by 55,146. While abnormal trades is significantly negative on day -4 (by 0.86), abnormal trades is positive leading up to the event and stays positive after the event. Abnormal trades on event day is 0.70 which means trades in the bonds of event firms are, on average, 0.70 above normal levels when the dividend increase went into effect. There is a greater increase in abnormal trades on day +4 (1.13) and day +5 (by 0.92). Abnormal volume is significantly negative on day -3 (704,702) and day -1 (by 672,707). Overall, two of the three trading metrics indicate that the corporate bonds of firms with a dividend increase event experienced an increase in trading. Additionally, the switch from negative to positive coefficients on the abnormal trading metrics also suggest that the bond market did not anticipate the dividend increase announcements, but bond trading increased after the event.

In panel B of table 4, there was significantly more abnormal trades five days prior (day -5) to dividend decrease events with increased trading as abnormal trades and abnormal volume on day +1 and day +2 after the event day. Abnormal trades on day -5 is 2.45 which means trades in event firms' bonds are 2.45 trades higher than the preceding 35 trading days. Abnormal trades on day +1 (day +2) is 7.43 (3.58). This suggests that trading activity in the bonds of firms with dividend decrease announcements experience significantly more trading as investors adjust their expectations of the firms.

Table 5 presents the results from an 11-day event study on M&A announcements. Panel A reports the results for acquiring firms, and Panel B reports the results for target firms. Acquiring firms experience significantly more trading activity throughout the event window. Abnormal quantity in the acquiring firms' bonds are significantly positive on days -5, -1, 0, 1, 2, 3, and +4. Abnormal quantity is largest on the announcement day (237,765). Abnormal trades is positive and significant over the entire [-5, +5] event window, while abnormal volume is significant on days 0, +1, and +2. The significant coefficients on abnormal quantity and abnormal trades before the announcement day may indicate that bond traders anticipate the M&A announcements of acquiring firms and began trading the bonds of acquiring firms prior to the announcements.

Panel B of table 5 shows that target firms experience significantly more trading activity on the day of the announcement and after the announcement day. Abnormal quantity, abnormal trades, and abnormal volume are highest on the announcement day and start to decline over the event window. The larger coefficients on the measures of trading activity for target firms indicate that traders have a larger reaction to the M&A announcements for target firms. On day 0, abnormal quantity, abnormal trades, and abnormal volume are 886,333, 27.75, and 34,250,199, respectively. Overall, traders anticipated the M&A announcements of acquiring firms and began trading prior to the announcements, but they may not have known the target firms which resulted in increased trading of target firms' bonds after the announcement was made.

Table 6 reports the results from an 11-day event study around repurchase announcements. In repurchase announcements, there appears to be increased trading (abnormal quantity and abnormal volume) three days prior to the announcement date. On day -3, abnormal quantity is 456,810 and abnormal volume is 5,093,455. Abnormal trades is significantly positive on the day of the announcement (3.37). Aside from three days before and the day of the announcement, repurchases do not cause much reaction in the corporate bond market.

Results from an 11-day event study around SEO announcements are shown in table 7. Abnormal quantity is significantly negative the day prior to the SEO announcements but is positive throughout the event window after the announcement day. This suggests that bond traders are increasing their trading in bonds of firms with SEO announcements after the announcement has been made. Abnormal trades is significantly negative on day -5 (-1.16) but is positive on day +1 (5.10) and day +4 (6.75). Abnormal volume is positive on day +1 (7,254,194) and day +4 (11,637,181). The sign change from negative to positive on the coefficients of the three trading measure may imply that traders do react to SEO announcements after they are made but do not anticipate this type of corporate event.

Table 8 presents the results from an 11-day event study around corporate spin-off events. Abnormal volume is significant and positive on the day of a spin-off and stays above normal up to three days after the event. Abnormal volume is 953,509 on day 0, 1,551,514 on day +1, and 1,587,136 on day +3. Abnormal quantity and abnormal number of trades are positive after the spin-off events but not significant. Overall, corporate spin-off events do seem to gather some attention in the corporate bond market but not much.

Table 9 reports the results from an 11-day event study for stock split events. Abnormal quantity and abnormal volume are significantly negative four days after a stock split event. On day +4, abnormal quantity is -94,746 and abnormal volume is -832,023. Abnormal trades is insignificant over the [-5, +5] event window. This suggests that stock splits do not garner much attention in the bond market.

Results from an 11-day event study for ticker symbol change events are shown in table 10. There is abnormally less trading in the bonds of firms with ticker changes the day prior to the event. Abnormal quantity (abnormal volume) is -195,757 (-1,464,111) on day -1, while abnormal trades is -1.71 on day -4. Abnormal quantity is significant and positive on day +4 (472,310) and day +5 (312,584) after ticker symbol changes. The results may indicate that ticker change events garner some attention in the bond market after the change.

MULTIVARIATE ANALYSIS

To determine if other factors affect trading activity around corporate events, I employ a multivariate regression based on equation (2). The regressions include seven dummy variables to capture the seven days around the event or announcement days (i.e., a [-3, +3] event window). All regression independent variables include the log of annual sales, log of firm size, ROA, leverage, years to maturity, log of bond return, and log of (1+buy/sell side). Tables 11 to 18 present the multivariate analysis related to each unscheduled corporate event.

Table 11 reports the coefficient estimates for the voluntary and involuntary CEO turnover samples. Columns (1) – (3) presents the results on abnormal quantity, abnormal number of trades, and abnormal volume as the dependent variables for the voluntary CEO turnover sample. Columns (4) – (6) presents the results on abnormal quantity, abnormal number of trades, and abnormal volume as the dependent variables for the involuntary CEO turnover sample. Column (1) provides evidence of increases in abnormal quantity of 172,532 on the event day for voluntary CEO turnovers. Column (6) reports significantly positive abnormal volume on the day prior to involuntary CEO turnover events (3,465,843). The buy/sell dummy is significantly negative for voluntary turnover events (abnormal trades and abnormal volume) and involuntary turnover events (abnormal quantity and abnormal volume). This suggests a negative reaction to CEO turnover events in the bond market.

Table 12 summarizes the coefficient estimates for the dividend increase and dividend decrease announcements. Columns (1) – (3) presents the coefficient estimates of the abnormal trading measures for dividend increases, and columns (4) – (6) presents the coefficient estimates of the abnormal trading measures for dividend decreases. For dividend increase announcements, only abnormal trades is positive and significant on the day prior to the announcement (1.70) with other trading measures showing no significant effects.

For dividend decrease announcements, abnormal trades is positive and significant three days prior to the announcement (11.63), while abnormal volume is positive and significant on the day 0 (4,382,577), and day +1 (2,464,903). The buy/sell dummy is significantly positive for dividend increases (abnormal quantity and abnormal volume) and significantly negative (abnormal trades) for dividend decreases which suggests a positive reaction to dividend increases (high buying activity) and a negative reaction to decreases (high selling activity). Overall, the empirical evidence suggests that dividend decrease announcements result in increased trading activity in the corporate bond market while dividend increase announcements elicit a muted reaction.

Table 13 presents the coefficient estimates from the regressions for M&A announcements. Columns (1) – (3) presents the coefficient estimates of the abnormal trading measures for acquiring firms, and columns (4) – (6) presents the coefficient estimates of the abnormal trading measures for target firms. Abnormal quantity is positive and significant on the day of M&A announcements for acquirers and all abnormal trading measures are positive and significant the day after the announcement for acquirers. Abnormal quantity is 143,382 on day 0 and 194,431 on day +1. Abnormal trades (abnormal volume) is 3.53 (7,138,830) on day +1.

For target firms, all abnormal trading measures are positive and significant on the day of and the day after the announcement. Abnormal quantity, abnormal trades, and abnormal volume on day 0 are 729,232, 56.04, and 41,710,585, respectively. On day +1, abnormal quantity, abnormal trades, and abnormal volume are 867,440, 68.38, and 40,179,837, respectively. Bond market reactions to M&A reactions appear stronger in target firms compared to acquiring firms. The buy/sell dummy is significantly positive for acquirers (abnormal quantity) and target firms (abnormal number of trades and abnormal volume) which suggests more buying activity. Overall, this suggests that bond traders react to M&A announcements by increasing their trading activity in the bonds of both acquirers and targets.

Table 14 summarizes the coefficient estimates from the regressions for repurchase announcements. All abnormal trading measures are positive and significant three days prior to the announcements. Abnormal quantity, abnormal trades, and abnormal volume are on day -3 are 431,129, 12.63, and 6,965,289, respectively. Abnormal quantity is negative and significant one day after the announcement (-283,656) but is positive and significant the next day (338,485). Abnormal volume is positive and significant on the event day (6,105,680). The buy/sell dummy is significantly negative for abnormal number of trades which might suggest a negative reaction by bond traders to repurchase announcements. Overall, bond traders appear to react to repurchase announcements prior to the announcement with some mixed reactions afterwards.

Table 15 reports regression coefficients for SEO announcements. Abnormal quantity is significantly negative two days prior to SEO announcements (-271,832), but abnormal trades and abnormal volume are significantly positive two days after SEO announcements (28.12 and 47,750,688, respectively). The results suggest that there is a delayed reaction in the bond market to SEO announcements. There is no evidence on whether SEO announcements are associated with more buying or selling activity.

Table 16 presents the regression results for parent firms with spin-off events. Abnormal quantity is significantly positive the day before spin-offs (337,583), and abnormal volume is significantly positive two days after spin-off events (3,214,237). The buy/sell indicator is significantly negative for abnormal quantity (-576,665) and abnormal volume (-3,018,474) which suggests more selling activity. Overall, bond traders show a muted response to spin-offs.

Regression coefficient estimates for firms with stock splits are shown in table 17. Abnormal quantity and abnormal volume are significantly positive the day prior to the split (646,078 and 3,213,357, respectively) but not in the days following the event. Although coefficients on the dummy variables related to abnormal trades changes signs from negative to positive after the event, the coefficients are insignificant. The buy/sell indicator is significantly negative for abnormal trades which might suggest more increased selling activity. Overall, stock splits do not seem to cause much reaction in terms of changes in bond trading activities.

Table 18 provides the regression results for firms with ticker symbol changes. Abnormal trades is positive and significant two days prior to the ticker change (4.00) and abnormal volume is positive and significant the day after the change (3,431,811). There is no evidence of significant changes in quantity related to ticker symbol changes or on whether ticker symbol changes are associated with more buying or selling activity in the bond market. Overall, ticker symbol changes do not seem to cause much reaction in the corporate bond market in terms of changes in bond trading activities.

V. CONCLUSION

Much research examining corporate events have focused on the equity markets. With the dissemination of corporate bond data through TRACE, researchers are gaining interest in how traders react to corporate events in the corporate bond market (Wei, Truong, and Do, 2020; Tsai and Wu 2015; Chen, Ramaya, and Wu, 2020; Kedia and Zhou, 2014). Most of the focus in these papers are centered on bond prices and abnormal bond returns.

Information asymmetry around corporate events, particularly the unscheduled events, may contain value-relevant information to bond traders and cause reactions in the bond market, which may affect bond liquidity. This paper seeks to examine how corporate bonds trade as a response to corporate events that usually come as a surprise to the market. Such unscheduled corporate events include CEO turnovers, dividend changes, mergers and acquisitions (M&As), stock repurchases, seasoned equity offerings (SEOs), spin-offs, stock splits, and ticker symbol changes.

Although some events experienced an increase in trading activity, as measured by the abnormal quantity traded, abnormal number of trades, and abnormal trading volume, some events did not drastically change trading activity in their firms' bonds. Overall, bond traders react to dividend change announcements, M&A announcements, repurchase announcements, SEO announcements, spin-off events, but not to CEO turnover events, stock splits, and ticker changes. The findings of changes or no changes in corporate bond trading activity around these eight unscheduled corporate events provide insight into bond trader behavior and what motivates trading in a market that is relatively illiquid and costly to transact in.

LIST OF REFERENCES

Adams, J. C., & Mansi, S. A. (2009). CEO turnover and Bondholder Wealth. *Journal of Banking & Finance*, *33*(3), 522–533.

Billett, M. T., King, T.-H. D., & Mauer, D. C. (2004). Bondholder wealth effects in mergers and acquisitions: New evidence from the 1980s and 1990s. *The Journal of Finance*, *59*(1), 107–135.

Chen, F., Ramaya, K., & Wu, W. (2020). The wealth effects of merger and acquisition announcements on bondholders: New evidence from the over-the-counter market. *Journal of Economics and Business*, *107*, 105862.

Chemmanur, T. J., & Yan, A. (2004). A theory of corporate spin-offs. *Journal of Financial Economics*, *72*(2), 259–290.

Clayton, M. C., Hartzell, J. C., & Rosenberg, J. (2005). The impact of CEO turnover on equity volatility. *The Journal of Business*, *78*(5), 1779–1808.

Dann, L. Y. (1981). Common stock repurchases. *Journal of Financial Economics*, *9*(2), 113–138.

Dhillon, U. S., & Johnson, H. (1994). The effect of dividend changes on stock and bond prices. *The Journal of Finance*, *49*(1), 281–289.

Eberhart, A. C., & Siddique, A. (2002). The long-term performance of corporate bonds (and stocks) following seasoned equity offerings. *Review of Financial Studies*, *15*(5), 1385–1406.

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The Adjustment of Stock Prices to New Information. *International Economic Review*, *10*(1), 1–21.

Gao, X., & Ritter, J. R. (2010). The marketing of seasoned equity offerings. *Journal of Financial Economics*, *97*(1), 33–52.

Gentry, R. J., Harrison, J. S., Quigley, T. J., & Boivie, S. (2021). A database of CEO turnover and dismissal in S&P 1500 firms, 2000–2018. *Strategic Management Journal*, *42*(5), 968–991.

Goldstein, M. A., Hotchkiss, E. S., & Sirri, E. R. (2006). Transparency and liquidity: A controlled experiment on corporate bonds. *Review of Financial Studies*, *20*(2), 235–273.

Grinblatt, M. S., Masulis, R. W., & Titman, S. (1984). The valuation effects of stock splits and stock dividends. *Journal of Financial Economics, 13*(4), 461-490.

Handjinicolaou, G., & Kalay, A. (1984). Wealth redistributions or changes in firm value. *Journal of Financial Economics*, *13*(1), 35–63.

Head, A., Smith, G., & Wilson, J. (2009). Would a stock by any other ticker smell as sweet? *The Quarterly Review of Economics and Finance*, *49*(2), 551–561.

Huson, M. R., Malatesta, P. H., & Parrino, R. (2004). Managerial Succession and firm performance. *Journal of Financial Economics*, *74*(2), 237–275.

Ikenberry, D. L., Rankine, G., & Stice, E. K. (1996). What do stock splits really signal? *Journal of Financial and Quantitative Analysis, 31*(3), 357.

Jankowitsch, R., & Pauer, F. (2021). The effect of credit, liquidity and rollover risk on bondholder wealth in mergers and acquisitions. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3859921

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American economic review*, *76*(2), 323-329.

Kadapakkam, P.-R., & Misra, L. (2007). What's in a nickname? price and volume effects of a pure ticker symbol change. *Journal of Financial Research*, *30*(1), 53–71.

Kedia, S., & Zhou, X. (2014). Informed trading around acquisitions: Evidence from corporate bonds. *Journal of Financial Markets*, *18*, 182–205.

Maxwell, W. F., & Rao, R. P. (2003). Do spin-offs expropriate wealth from bondholders? *The Journal of Finance*, *58*(5), 2087–2108.

Maxwell, W. F., & Stephens, C. P. (2003). The wealth effects of repurchases on bondholders. *The Journal of Finance*, *58*(2), 895–919.

Michayluk, D., & Zhao, R. (2010). Stock splits and bond yields: Isolating the signaling hypothesis. *Financial Review*, *45*(2), 375–386.

Miller, M. H., & Modigliani, F. (1961). Dividend policy, growth, and the valuation of shares. *The Journal of Business*, *34*(4), 411.

Minnick, K., & Raman, K. (2013). Why are stock splits declining? *Financial Management*, *43*(1), 29–60.

Nishikawa, T., Prevost, A. K., & Rao, R. P. (2011). Bond market reaction to stock repurchases: Is there a wealth transfer effect? *Journal of Financial Research*, *34*(3), 503–522.

Nissim, D., & Ziv, A. (2001). Dividend changes and future profitability. *The Journal of Finance*, *56*(6), 2111–2133.

Tsai, H.-J., & Wu, Y. (2015). Bond and stock market response to unexpected dividend changes. *Journal of Empirical Finance*, *30*, 1–15.

Veld, C., & Veld-Merkoulova, Y. V. (2004). Do spin-offs really create value? The European case. *Journal of Banking & Finance*, *28*(5), 1111–1135.

Wansley, J. W., & Fayez, E. (1986). Stock repurchases and Securityholder Returns: A Case Study of Teledyne. *Journal of Financial Research*, *9*(2), 179–191.

Wei, X., Truong, C., & Do, V. (2020). When are dividend increases bad for corporate bonds? *Accounting & Finance*, *60*(2), 1295–1326.

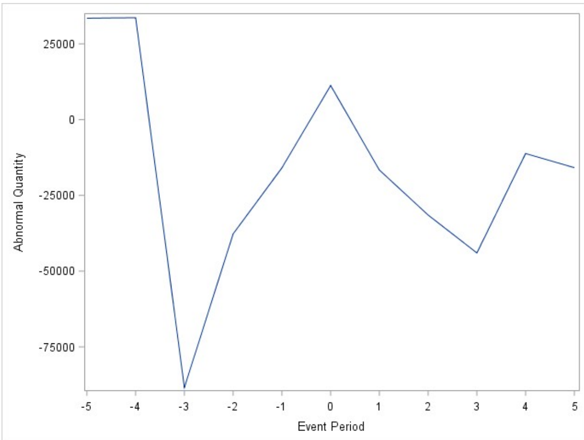
Weisbach, M. S. (1995). CEO turnover and the firm's investment decisions. *Journal of Financial Economics*, *37*(2), 159–188.

Woodley, M., DaDalt, P., & Wingender, J. R. (2020). The Price and volume response to earnings announcements in the corporate bond market. *Financial Review*, *55*(4), 669–696.

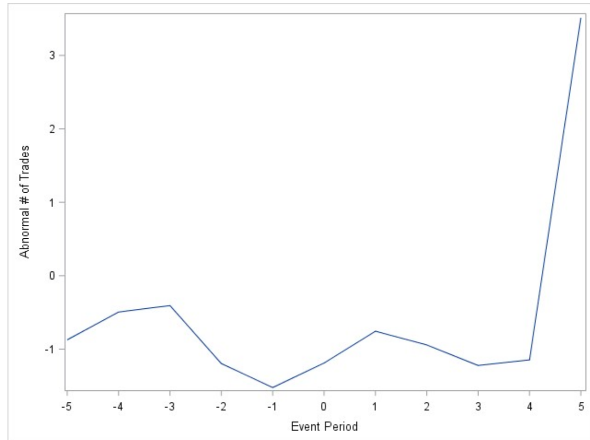
Xing, X., Anderson, R. I., & Hu, Y. (2016). What's a name worth? the impact of a likeable stock ticker symbol on firm value. *Journal of Financial Markets*, *31*, 63–80.

APPENDIX

Panel A: Abnormal Quantity



Panel B: Abnormal Number of Trades



Panel C: Abnormal Volume

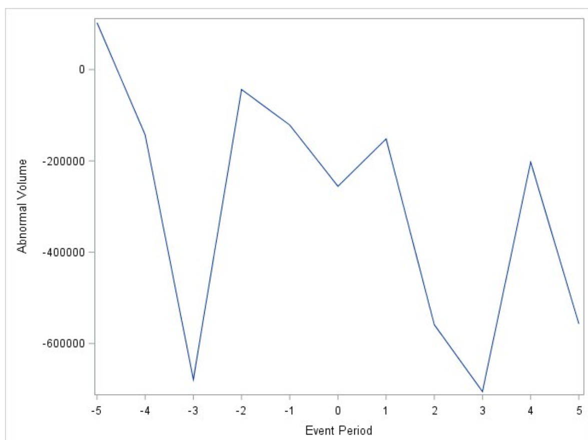
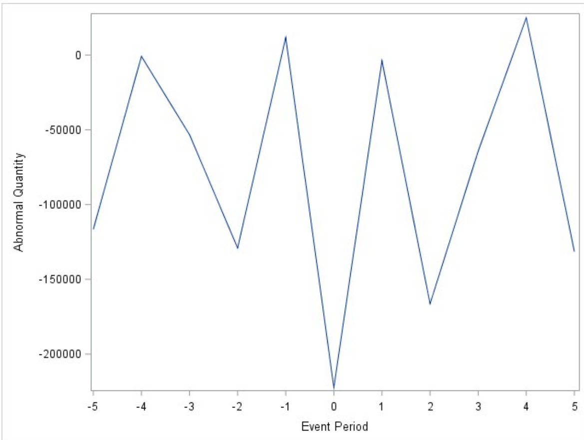


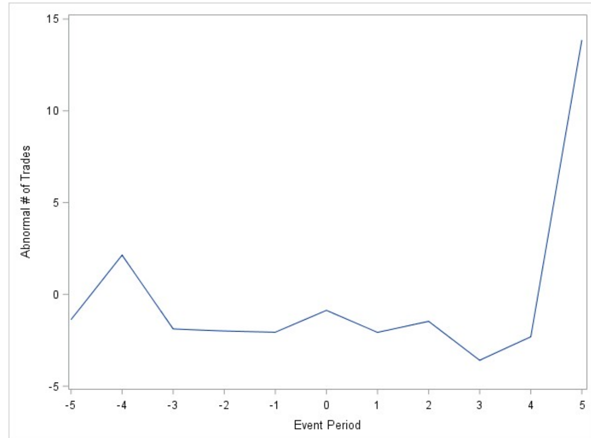
Figure 1A: Trading measures of voluntary CEO turnover sample.

This figure graphs the abnormal quantity traded (Panel A), abnormal number of trades (Panel B), and abnormal trading volume (Panel C) of bonds for firms in the voluntary CEO turnover sample between the event window of [-5, +5].

Panel A: Abnormal Quantity



Panel B: Abnormal Number of Trades



Panel C: Abnormal Volume

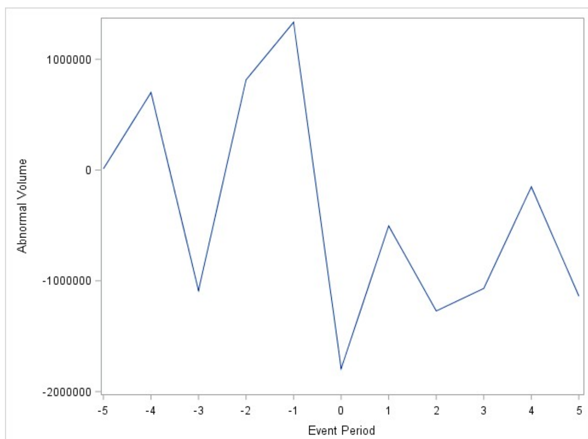
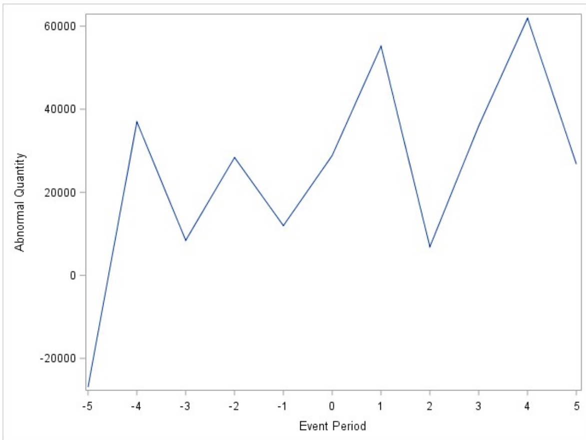


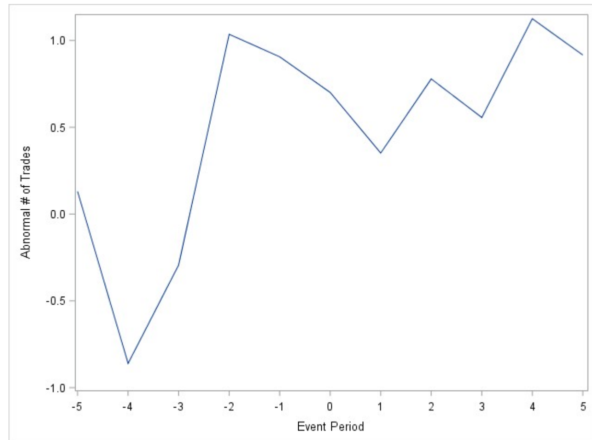
Figure 1B: Trading measures of involuntary CEO turnover sample

This figure graphs the abnormal quantity traded (Panel A), abnormal number of trades (Panel B), and abnormal trading volume (Panel C) of bonds for firms in the involuntary CEO turnover sample between the event window of [-5, +5].

Panel A: Abnormal Quantity



Panel B: Abnormal Number of Trades



Panel C: Abnormal Volume

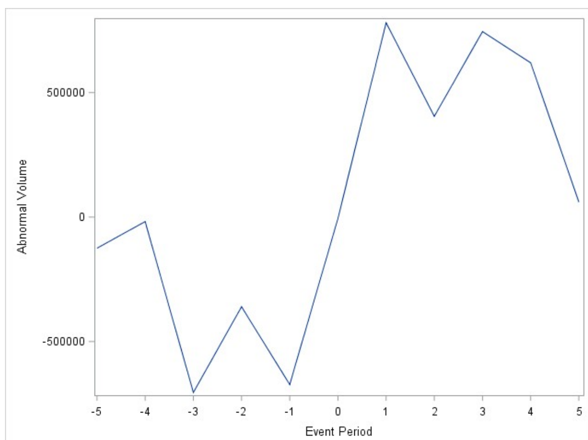
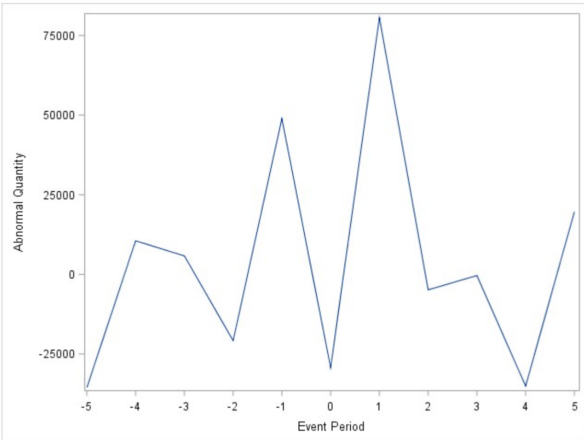


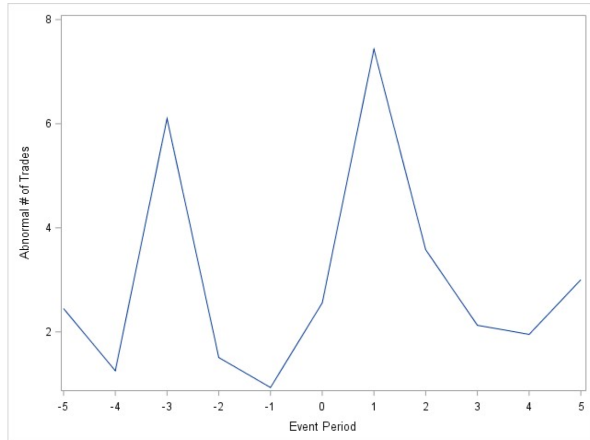
Figure 2A: Trading measures of dividend increase sample

This figure graphs the abnormal quantity traded (Panel A), abnormal number of trades (Panel B), and abnormal trading volume (Panel C) of bonds for firms in the dividend increase sample between the event window of [-5, +5].

Panel A: Abnormal Quantity



Panel B: Abnormal Number of Trades



Panel C: Abnormal Volume

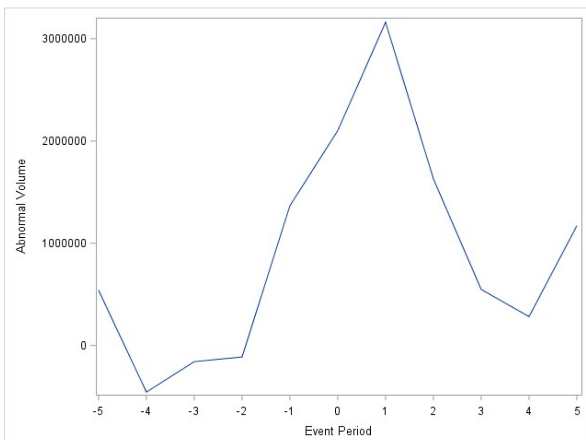
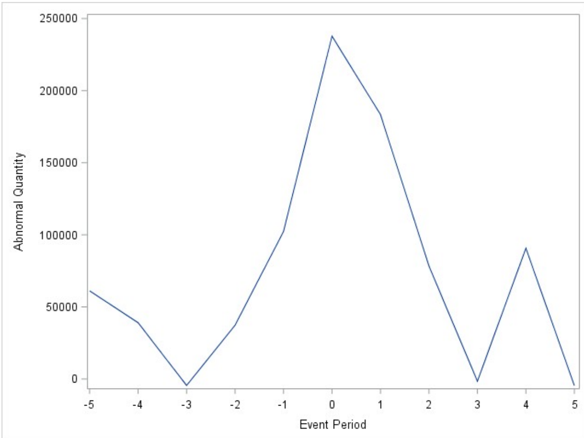


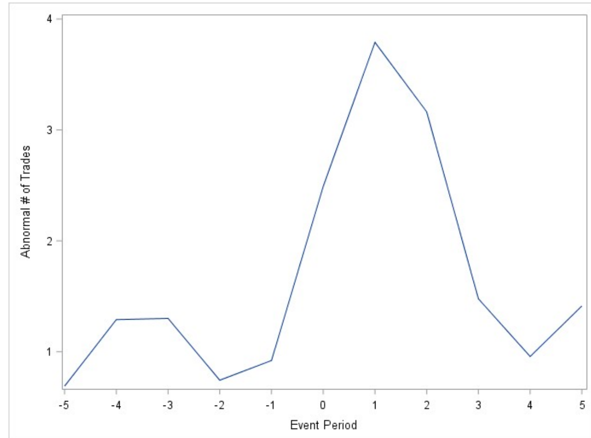
Figure 2B: Trading measures of dividend decrease sample

This figure graphs the abnormal quantity traded (Panel A), abnormal number of trades (Panel B), and abnormal trading volume (Panel C) of bonds for firms in the dividend decrease sample between the event window of [-5, +5].

Panel A: Abnormal Quantity



Panel B: Abnormal Number of Trades



Panel C: Abnormal Volume

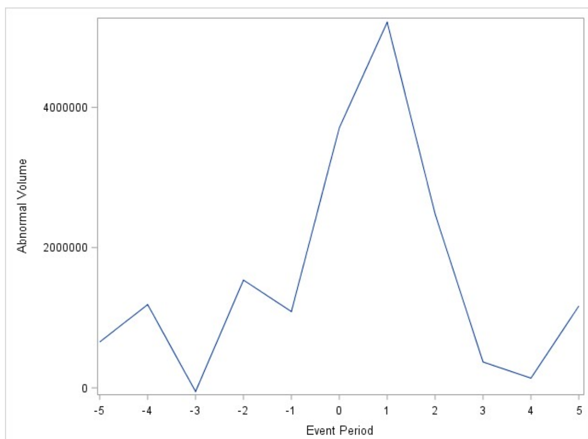
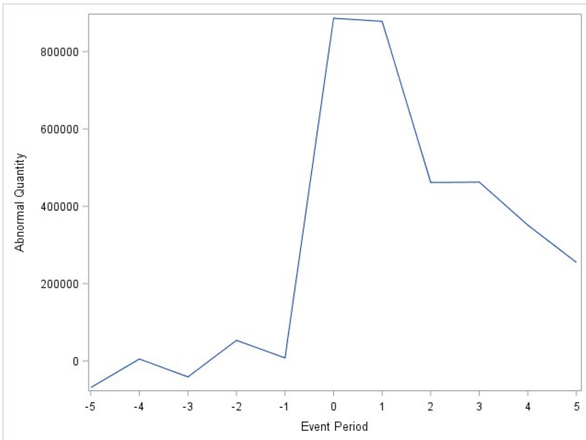


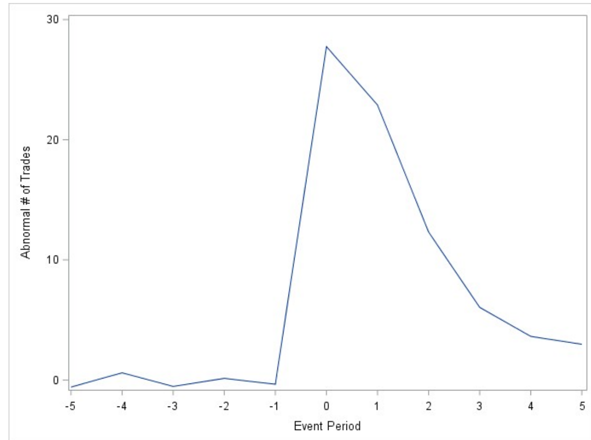
Figure 3A: Trading measures of the M&A sample of acquirers

This figure graphs the abnormal quantity traded (Panel A), abnormal number of trades (Panel B), and abnormal trading volume (Panel C) of bonds for firms in the M&A sample of acquirers between the event window of [-5, +5].

Panel A: Abnormal Quantity



Panel B: Abnormal Number of Trades



Panel C: Abnormal Volume

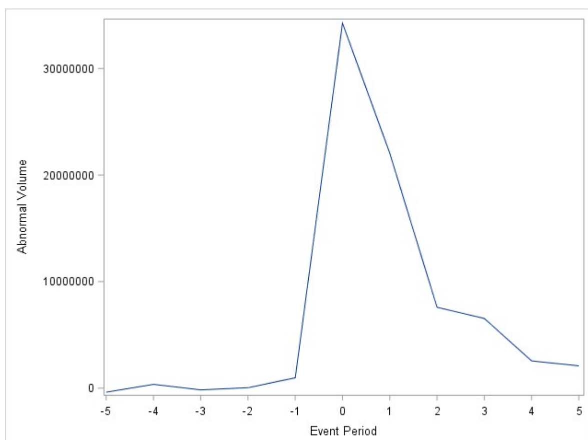
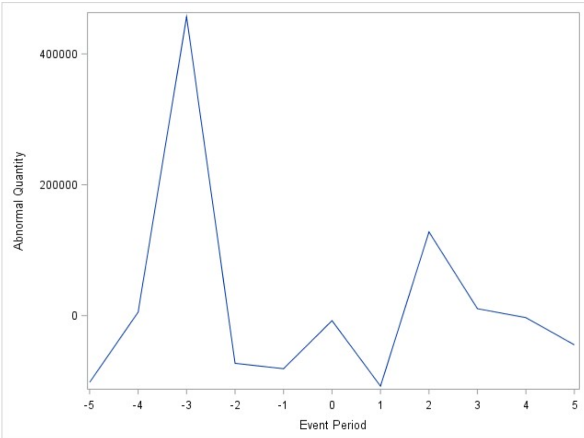


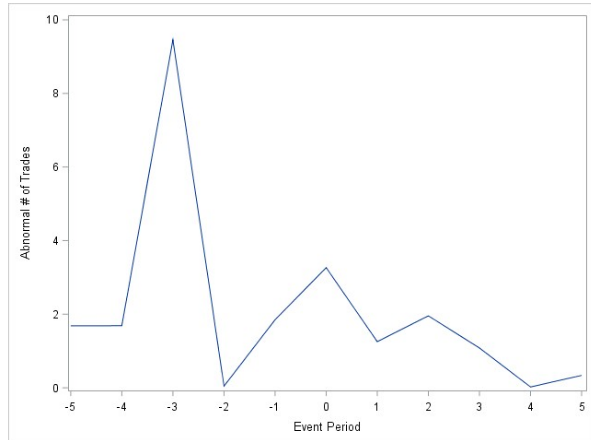
Figure 3B: Trading measures of the M&A sample of targets

This figure graphs the abnormal quantity traded (Panel A), abnormal number of trades (Panel B), and abnormal trading volume (Panel C) of bonds for firms in the M&A sample of targets between the event window of [-5, +5].

Panel A: Abnormal Quantity



Panel B: Abnormal Number of Trades



Panel C: Abnormal Volume

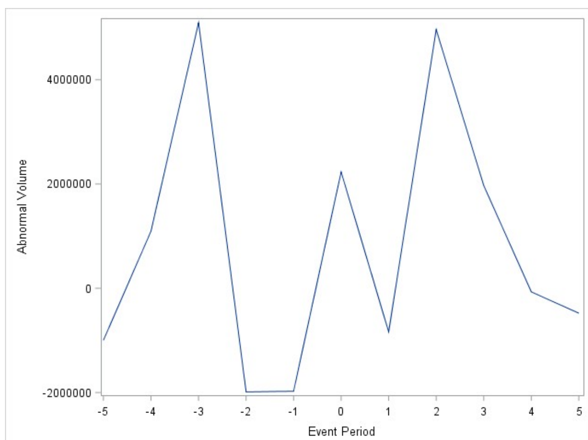
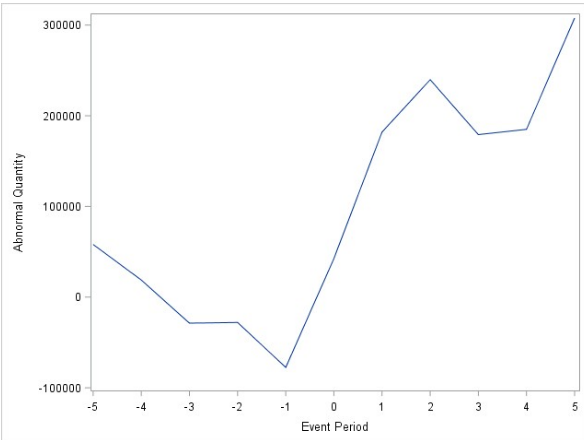


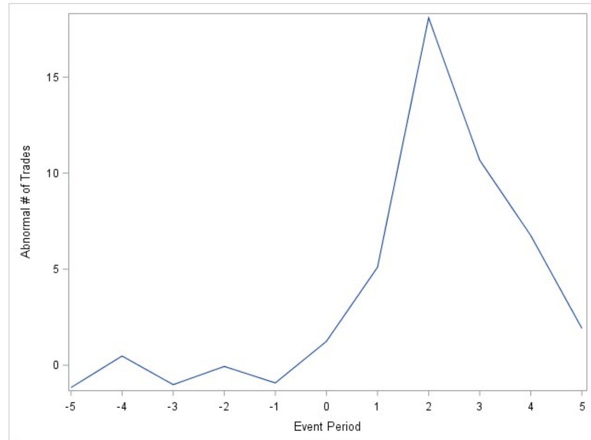
Figure 4: Trading measures of repurchase announcement sample

This figure graphs the abnormal quantity traded (Panel A), abnormal number of trades (Panel B), and abnormal trading volume (Panel C) of bonds for firms in the repurchase announcement sample between the event window of [-5, +5].

Pannel A: Abnormal Quantity



Panel B: Abnormal Number of Trades



Panel C: Abnormal Volume

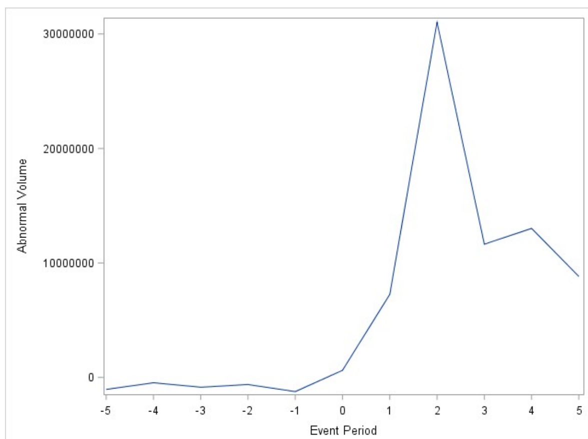
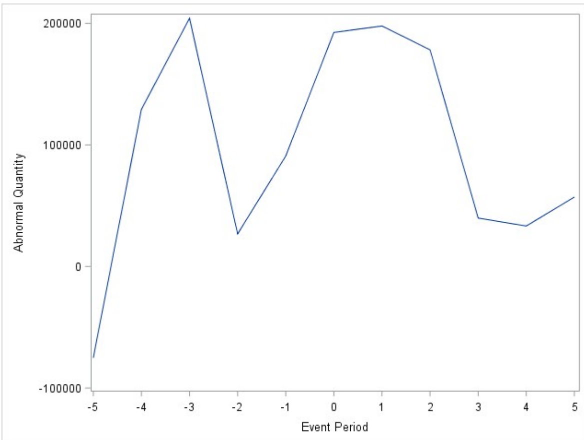


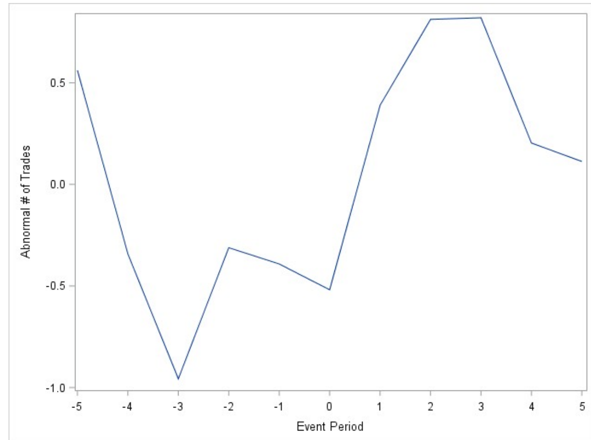
Figure 5: Trading measures of SEO announcement sample

This figure graphs the abnormal quantity traded (Panel A), abnormal number of trades (Panel B), and abnormal trading volume (Panel C) of bonds for firms in the SEO announcement sample between the event window of [-5, +5].

Panel A: Abnormal Quantity



Panel B: Abnormal Number of Trades



Panel C: Abnormal Volume

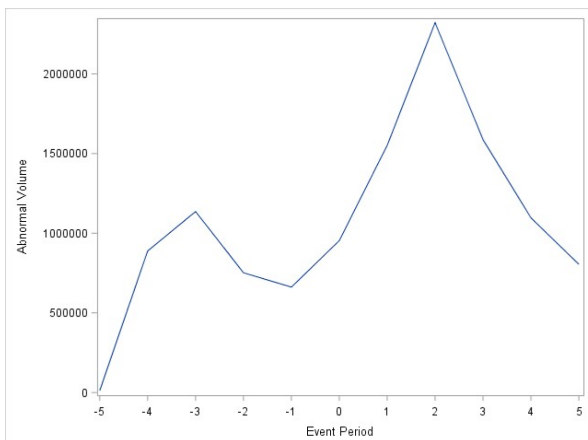
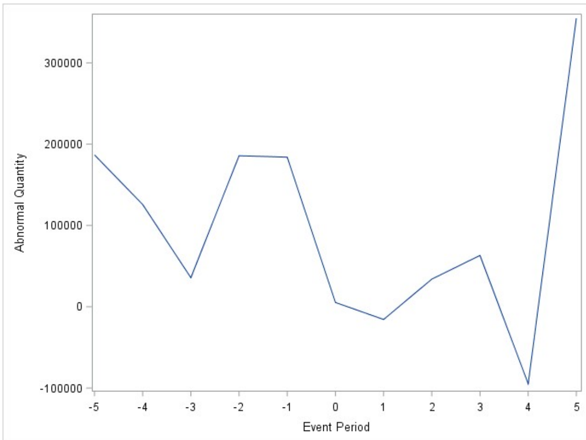


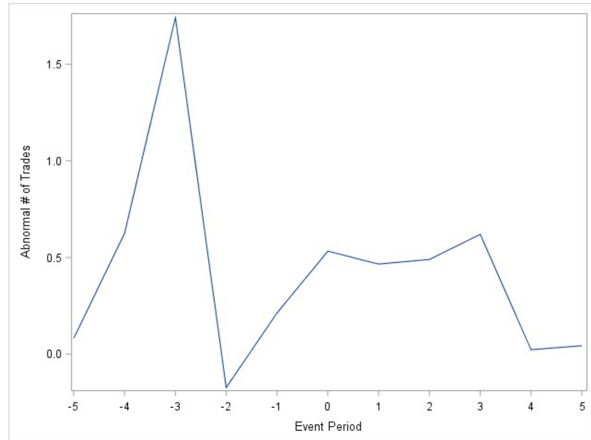
Figure 6: Trading measures of parent firms with spin-off announcements

This figure graphs the abnormal quantity traded (Panel A), abnormal number of trades (Panel B), and abnormal trading volume (Panel C) of bonds of parent firms with spin-off announcements between the event window of [-5, +5].

Panel A: Abnormal Quantity



Panel B: Abnormal Number of Trades



Panel C: Abnormal Volume

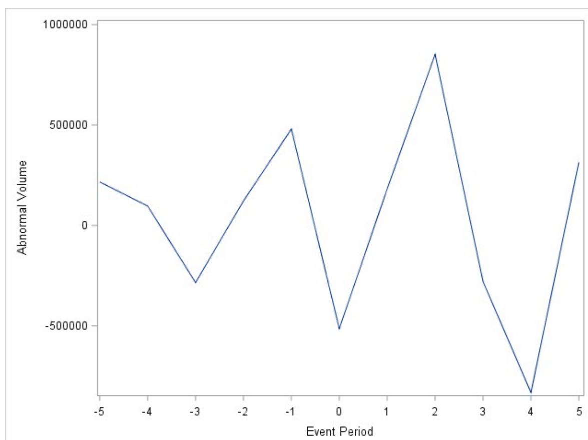
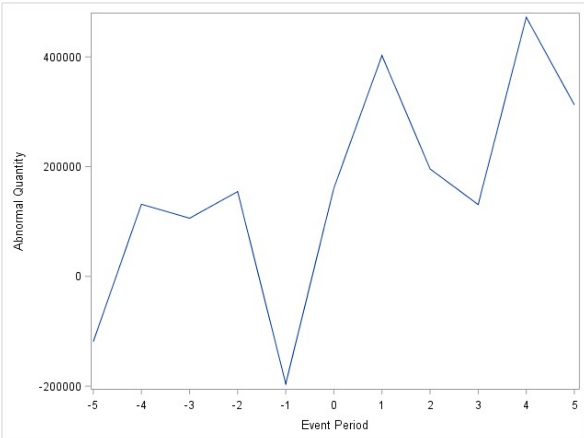


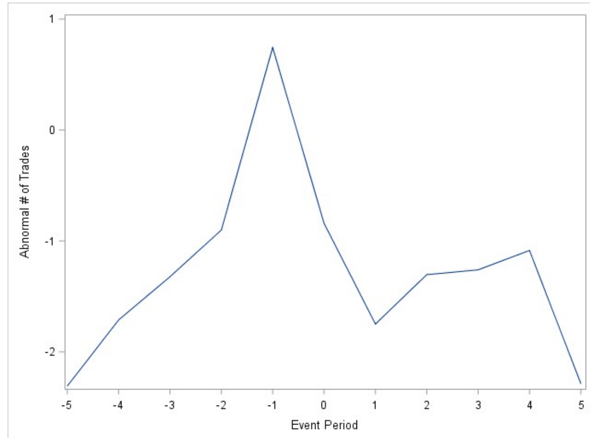
Figure 7: Trading measures of stock split events sample

This figure graphs the abnormal quantity traded (Panel A), abnormal number of trades (Panel B), and abnormal trading volume (Panel C) of bonds for firms in the of stock split events sample between the event window of [-5, +5].

Panel A: Abnormal Quantity



Panel B: Abnormal Number of Trades



Panel C: Abnormal Volume

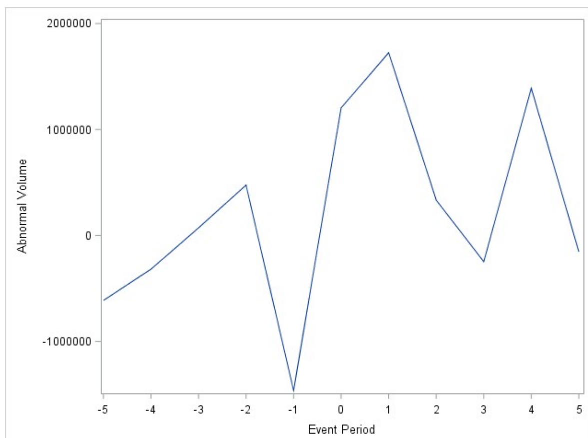


Figure 8: Trading measures of ticker symbol change sample

This figure graphs the abnormal quantity traded (Panel A), abnormal number of trades (Panel B), and abnormal trading volume (Panel C) of bonds for firms in the ticker symbol change sample between the event window of [-5, +5].

Table 1: Number of Events

This table provides the incidences of each corporate event or announcement over the sample period of January 2012 to December 2021. Total events indicate all the events that occurred over the sample period. The number of firms include all unique firms that experienced an event. Number of bonds are the unique bond symbols that traded over the event window of [-5, +5] and traded over the full estimation period of [-45, -6].

	Total Events	No. of Firms	No. of Bonds
CEO Turnover			
Voluntary	222	202	1,175
Involuntary	33	29	139
Dividend Changes			
Increase	1,353	412	3,998
Decrease	263	173	1,346
Mergers & Acquisitions			
Acquirer	250	168	2,171
Target	115	113	343
Repurchases	29	20	185
SEO	80	63	194
Spin-Offs (Parent)	82	73	394
Stock Splits	55	48	338
Ticker Changes	53	48	151

Table 2: Descriptive Statistics

This table reports the descriptive statistics for each corporate event or announcement between January 2012 to December 2021 over the [-5, +5] event window. Number of trades is the daily average number of trades. Trade size is the average daily quantity traded. Trade volume is the product of the daily average number of trades and the average daily trade size. Years to maturity is the difference between the event year and the maturity year. Raw bond return is the holding period of the bond price. Sales is the annual sales amount (in millions) sourced from Compustat. Firm size is calculated from daily closing price and shares outstanding from CRSP. ROA is defined as operating income before depreciation over total assets. Leverage is the sum of total debt in current liabilities and total long-term debt divided by stockholders' equity.

Panel A:	CEO Turnover - Voluntary				CEO Turnover - Involuntary			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Num. of Trades	11.3178	14.6393	1.5455	172.6364	15.6467	17.8293	3.0909	86.3182
Trade Volume	3,292,699.6	3,095,496.4	112,727.27	15,742,364	3,773,294.6	3,152,741.4	287,727.27	10,967,515
Trade Size	442,048.96	375,620.82	17,288.338	2,581,686.9	387,354.1	306,191.79	44,253.716	1,007,317.4
Years to Maturity	7.6761	4.8956	0	30	8.1201	6.1881	1	27
Bond Return - Raw	0.0086	0.0575	-0.1925	0.5756	0.0145	0.0426	-0.0533	0.1345
Sales	17,765.469	28,677.646	336.794	171,760	19,983.2	32,512.999	336.794	144,096.93
Firm Size	28,977,430	50,108,642	144,092.53	3.484e+08	32,659,845	69,039,789	144,092.53	3.479e+08
ROA	0.0426	0.0826	-0.2696	0.237	0.0214	0.0978	-0.1473	0.237
Leverage	1.8779	6.583	-14.3323	72.5043	0.8086	2.6156	-6.1953	7.2216
Observations	202				29			
Panel B:	**Dividend - Increase**				**Dividend - Decrease**			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Num. of Trades	21.7341	21.1592	1.7273	166.4773	23.3659	30.3272	1	170.1818
Trade Volume	8,053,467	8,972,977.6	10,727.273	76,647,727	6,477,943.5	9,064,314.1	77,090.909	72,952,159
Trade Size	528,029.91	364,028.66	2,301.9481	2,064,353.5	439,182.12	378,061.49	8,800.1337	2,094,563.3
Years to Maturity	7.7853	3.9934	0	27	7.3721	4.4051	0	29
Bond Return - Raw	0.0044	0.0375	-0.3264	0.4254	0.0068	0.2006	-0.2495	2.5222
Sales	21,819.082	454,84.82	4.648	474,259	16,355.543	32,930.265	127.135	256,762.74
Firm Size	33,271,455	76,377,917	36,760.145	9.638e+08	28,589,619	1.340e+08	98,459.637	1.672e+09
ROA	0.0755	0.0656	-0.1032	0.6276	0.0064	0.1112	-0.5189	0.2927
Leverage	1.9569	23.2767	-127.0595	432.2	0.9954	7.9196	-82.2723	33.6932
Observations	412				173			
Panel C:	**Mergers & Acquisitions - Acquirer**				**Mergers & Acquisitions - Target**			

Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Num. of Trades	8.8585	11.0954	0.0909	72.577	12.671	33.8733	0.0909	293.2727
Trade Volume	4,397,744.8	8,121,029.4	6,545.4545	58,856,945	9,442,878.2	15,218,565	909.0909	1.001e+08
Trade Size	360,652.4	319,327.14	2,409.0909	1,690,796.1	650,866.78	637,528.76	909.0909	3,374,411.8
Years to Maturity	7.7136	3.9821	1	25.5	6.9923	5.7797	0.5	46
Bond Return - Raw	0	0.0009	-0.0023	0.0069	0.001	0.0035	-0.0029	0.0298
Sales	24,090.78	46,498.898	110.922	420,714	8,726.2341	24,410.104	190.939	177,866
Firm Size	52,937,867	1.200e+08	420,360.31	1.245e+09	12,326,253	45,784,170	20,691.395	4.713e+08
ROA	0.047	0.0968	-0.6031	0.5748	-0.0104	0.2072	-1.4081	0.2446
Leverage	1.1343	7.3981	-65.4726	40.8466	3.3613	13.795	-13.3791	96.7343
Observations	168				113			

Panel D:	Repurchases			
Variable	Mean	Std. Dev.	Min	Max
Num. of Trades	10.2847	8.0782	0.0909	30.1515
Trade Volume	5,271,821	6,074,975	24,696.97	19,942,606
Trade Size	375,309.17	278,819.88	24,696.97	904,574.69
Years to Maturity	9.1092	4.361	2.1919	19.3333
Bond Return - Raw	-0.0001	0.0006	-0.0022	0.0009
Sales	10,767.576	10,087.213	626.4585	32,753
Firm Size	30,054,975	44,918,900	938,230.89	1.555e+08
ROA	0.059	0.0733	-0.1488	0.2317
Leverage	5.8197	20.6747	-41.4151	65.0457
Observations	20			

Panel E:	Seasoned Equity Offerings			
Variable	Mean	Std. Dev.	Min	Max
Num. of Trades	10.4614	16.7045	0.1818	77.1818
Trade Volume	9,419,119.7	21,273,246	41,454.546	1.434e+08
Trade Size	395,037.25	315,719.4	5,454.5455	1,401,090.9
Years to Maturity	6.51	3.9164	2	26
Bond Return - Raw	0.0006	0.0021	-0.0013	0.0134
Sales	5,140.4771	12,289.975	0.035	90,820.576
Firm Size	5,717,121.9	10,713,103	129,669.88	74,659,942
ROA	-0.0855	0.2286	-0.9848	0.1028

	Mean	Std. Dev.	Min	Max
Leverage	-1.253	20.6454	-159.9677	15.4014
Observations	63			
Panel F:	Spin-offs – Parent			
Variable	Mean	Std. Dev.	Min	Max
Num. of Trades	11.7986	12.0209	2.1818	86.6212
Trade Volume	4,562,050.4	5,220,402.9	73,454.545	29,299,636
Trade Size	570,798.8	548,553.79	18679.258	3,698,848.5
Years to Maturity	7.6272	4.8976	0	28
Bond Return - Raw	0.017	0.0583	-0.1254	0.2974
Sales	17,046.475	23,744.465	8.433	138,074
Firm Size	24,894,182	34,042,239	876,966.86	2.067e+08
ROA	0.0364	0.0856	-0.3229	0.2955
Leverage	0.6717	6.4636	-25.3556	33.6932
Observations	73			
Panel G:	Stock Splits			
Variable	Mean	Std. Dev.	Min	Max
Num. of Trades	5.2555	6.6907	0.0909	34.4545
Trade Volume	2,328,812.3	3,057,527.4	2,727.2727	15,763,545
Trade Size	413,284.18	452517.83	909.0909	2,262,954.5
Years to Maturity	7.6902	4.7911	0	22
Bond Return - Raw	0	0.0007	-0.0024	0.0028
Sales	18,181.199	39,544.227	133.887	255,884.38
Firm Size	86,390,519	2.702e+08	297,119.67	1.818e+09
ROA	0.0989	0.0658	-0.0254	0.3259
Leverage	1.066	0.9368	0	4.7166
Observations	48			
Panel H:	Ticker Change			
Variable	Mean	Std. Dev.	Min	Max
Num. of Trades	10.7161	13.4546	1.8182	63.8182
Trade Volume	4,107,892.9	3,995,245.8	138,454.55	14,057,182
Trade Size	653,145.28	844,396.6	43,250	3,856,845.5

Years to Maturity	6.7889	4.6514	0	20
Bond Return - Raw	0.0078	0.0725	-0.2433	0.2704
Sales	12,625.537	18,537.204	133.569	88,688.364
Firm Size	20,909,212	39,243,572	178,454.56	2.288e+08
ROA	0.0504	0.1008	-0.0933	0.5025
Leverage	10.6368	65.1694	-14.8259	432.2
Observations	48			

Table 3: Event Study around CEO Turnover Events

This table presents results from an 11-day event study around CEO turnover events. Panel A reports the results for voluntary CEO turnover events, and Panel B reports the results for involuntary CEO turnover events. Column (1) reports the results for abnormal trading quantity. Column (2) reports the results for abnormal number of trades. Column (3) reports the results for abnormal trading volume. The abnormal measures are computed by taking the daily measures minus the pre-event window daily average, where the pre-event window is measured from the preceding 35 trading days [-40, -6]. The *t*-tests test whether the abnormal trading measures are significantly different from zero. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Quantity (1)	Abnormal Trades (2)	Abnormal Volume (3)
Panel A: Voluntary Turnover			
t-5	33,472.63	-0.87	102,717.85
t-4	33,612.39	-0.49	-143,083.79
t-3	-88,406.74**	-0.41	-678,939.21***
t-2	-37,712.11	-1.20*	-43,587.75
t-1	-15,924.34	-1.52**	-121,472.18
Day 0	11,256.56	-1.19	-255,654.60
t+1	-16,655.79	-0.76	-151,780.43
t+2	-31,483.80	-0.94	-558,733.62*
t+3	-43,990.74	-1.22	-705,414.19**
t+4	-11,186.45	-1.15	-202,578.86
t+5	-15,848.04	3.51	-556,906.88**
Panel B: Involuntary Turnover			
t-5	-116,524.84	-1.38	11,443.75
t-4	-883.54	2.14	699,789.69
t-3	-53,257.72	-1.88	-1,087,539.13*
t-2	-129,057.02	-2.00	814,096.23
t-1	11,662.33	-2.06	1,334,069.15
Day 0	-222,332.39***	-0.87	-1,792,801.50***
t+1	-3,775.33	-2.07	-504,426.53
t+2	-166,322.21**	-1.47	-1,272,093.99
t+3	-64,332.10	-3.59	-1,068,771.31
t+4	24,930.81	-2.31	-151,657.26
t+5	-131,410.13*	13.86	-1,138,176.35*

Table 4: Event Study around Dividend Change Announcements

This table presents results from an 11-day event study around dividend change announcements. Panel A reports the results for dividend increase events, and Panel B reports the results for dividend decrease events. Column (1) reports the results for abnormal trading quantity. Column (2) reports the results for abnormal number of trades. Column (3) reports the results for abnormal trading volume. The abnormal measures are computed by taking the daily measures minus the pre-event window daily average, where the pre-event window is measured from the preceding 35 trading days [-40, -6]. The *t*-tests test whether the abnormal trading measures are significantly different from zero. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Quantity (1)	Abnormal Trades (2)	Abnormal Volume (3)
Panel A: Dividend Increases			
t-5	-26,914.96	0.13	-124,991.80
t-4	36,951.03	-0.86**	-18,103.95
t-3	8,436.70	-0.29	-704,702.01**
t-2	28,371.71	1.04	-360,096.56
t-1	11,961.82	0.91	-672,797.22*
Day 0	28,868.80	0.70*	-5,710.93
t+1	55,145.72*	0.35	780,498.81
t+2	6,873.46	0.78	404,726.39
t+3	35,967.86	0.56	744,923.49
t+4	61,911.36	1.13**	619,612.00
t+5	26,807.06	0.92*	60,343.70
Panel B: Dividend Decreases			
t-5	-35,513.83	2.45*	541,063.47
t-4	10,549.51	1.25	-454,950.57
t-3	5,792.29	6.10	-158,131.82
t-2	-20,805.51	1.51	-112,049.97
t-1	48,917.81	0.93	1,366,870.25
Day 0	-29,278.47	2.56	2,101,123.64
t+1	80,572.07	7.43***	3,161,328.26***
t+2	-4,836.11	3.58***	1,630,121.58**
t+3	-350.31	2.13*	547,982.20
t+4	-35,035.58	1.95	282,681.53
t+5	19,615.16	3.00*	1,171,206.92

Table 5: Event Study around M&A Announcements

This table presents results from an 11-day event study around M&A announcements. Panel A reports the results for acquiring firms, and Panel B reports the results for target firms. Column (1) reports the results for abnormal trading quantity. Column (2) reports the results for abnormal number of trades. Column (3) reports the results for abnormal trading volume. The abnormal measures are computed by taking the daily measures minus the pre-event window daily average, where the pre-event window is measured from the preceding 35 trading days [-40, -6]. The *t*-tests test whether the abnormal trading measures are significantly different from zero. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Quantity (1)	Abnormal Trades (2)	Abnormal Volume (3)
Panel A: Acquiring Firms			
t-5	61,091.43*	0.69*	653,663.34
t-4	39,040.96	1.29***	1,187,931.11
t-3	-4,519.21	1.30***	-53,122.55
t-2	37,318.80	0.74*	1,536,976.09
t-1	102,366.85*	0.92**	1,087,584.00
Day 0	237,764.79***	2.49***	3,708,356.57***
t+1	183,373.11***	3.79***	5,214,229.01***
t+2	78,315.00**	3.16***	2,478,169.40**
t+3	-1,565.29	1.48***	368,439.89
t+4	90,719.72*	0.96***	138,730.87
t+5	-4,623.30	1.41***	1,168,134.67
Panel B: Target Firms			
t-5	-69,070.97	-0.59	-372,769.26
t-4	4,925.48	0.60	355,940.32
t-3	-41,405.32	-0.53	-158,231.30
t-2	53,084.00	0.14	42,330.04
t-1	7,659.80	-0.35	978,124.73
Day 0	886,332.94***	27.75**	34,250,198.68***
t+1	878,143.44***	22.89**	22,046,474.63***
t+2	461,601.36***	12.31**	7,588,571.09***
t+3	462,508.57***	6.05**	6,545,797.05***
t+4	351,160.56***	3.63**	2,560,310.98***
t+5	254,911.11***	2.98**	2,096,113.84***

Table 6: Event Study around Repurchase Announcements

This table presents results from an 11-day event study around repurchase announcements. Column (1) reports the results for abnormal trading quantity. Column (2) reports the results for abnormal number of trades. Column (3) reports the results for abnormal trading volume. The abnormal measures are computed by taking the daily measures minus the pre-event window daily average, where the pre-event window is measured from the preceding 35 trading days [-40, -6]. The *t*-tests test whether the abnormal trading measures are significantly different from zero. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Quantity (1)	Abnormal Trades (2)	Abnormal Volume (3)
t-5	-101,903.16	1.68	-997,233.32
t-4	5,240.30	1.69	1,093,871.69
t-3	456,809.90*	9.46	5,093,454.58*
t-2	-72,966.48	0.05	-1,987,007.12
t-1	-81,085.80	1.85	-1,974,959.89
Day 0	-7,657.80	3.27*	2,233,059.74
t+1	-107,683.13	1.25	-837,686.67
t+2	127,926.95	1.95	4,963,204.74
t+3	10,605.13	1.08	1,968,226.90
t+4	-3,103.18	0.02	-69,346.27
t+5	-44,660.15	0.34	-478,588.80

Table 7: Event Study around SEO Announcements

This table presents results from an 11-day event study around SEO announcements. Column (1) reports the results for abnormal trading quantity. Column (2) reports the results for abnormal number of trades. Column (3) reports the results for abnormal trading volume. The abnormal measures are computed by taking the daily measures minus the pre-event window daily average, where the pre-event window is measured from the preceding 35 trading days [-40, -6]. The *t*-tests test whether the abnormal trading measures are significantly different from zero. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Quantity (1)	Abnormal Trades (2)	Abnormal Volume (3)
t-5	58,085.48	-1.16*	-1,046,450.02
t-4	18,845.01	0.48	-464,196.84
t-3	-28,768.59	-1.01	-853,224.58
t-2	-27,936.45	-0.06	-616,875.35
t-1	-77,541.96*	-0.92	-1,236,193.05
Day 0	42,451.00	1.25	624,208.53
t+1	182,020.81***	5.10***	7,254,194.33**
t+2	239,754.12***	18.09	31,027,669.77
t+3	179,214.01**	10.67	11,637,180.69*
t+4	184,995.91*	6.75*	13,018,600.33
t+5	307,821.96*	1.92	8,816,341.32

Table 8: Event Study around Spin-off Events

This table presents results from an 11-day event study around spin-off events. Column (1) reports the results for abnormal trading quantity. Column (2) reports the results for abnormal number of trades. Column (3) reports the results for abnormal trading volume. The abnormal measures are computed by taking the daily measures minus the pre-event window daily average, where the pre-event window is measured from the preceding 35 trading days [-40, -6]. The *t*-tests test whether the abnormal trading measures are significantly different from zero. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Quantity (1)	Abnormal Trades (2)	Abnormal Volume (3)
t-5	-75,106.50	0.56	12,689.18
t-4	129,272.44	-0.34	888,421.62
t-3	204,242.22	-0.96	1,136,161.43
t-2	26,813.37	-0.31	751,713.89
t-1	90,895.07	-0.39	661,784.75
Day 0	192,598.93	-0.52	953,508.92*
t+1	197,874.50	0.39	1,551,514.42*
t+2	178,240.73	0.81	2,320,996.74
t+3	39,833.13	0.82	1,587,136.08*
t+4	33,303.55	0.20	1,096,482.28
t+5	57,097.16	0.11	804,886.83

Table 9: Event Study around Stock Split Events

This table presents results from an 11-day event study around stock split events. Column (1) reports the results for abnormal trading quantity. Column (2) reports the results for abnormal number of trades. Column (3) reports the results for abnormal trading volume. The abnormal measures are computed by taking the daily measures minus the pre-event window daily average, where the pre-event window is measured from the preceding 35 trading days [-40, -6]. The *t*-tests test whether the abnormal trading measures are significantly different from zero. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Quantity (1)	Abnormal Trades (2)	Abnormal Volume (3)
t-5	186,816.86	0.08	216,684.31
t-4	125,734.04	0.62	96,322.84
t-3	35,690.06	1.74	-284,433.33
t-2	185,710.87	-0.17	122,166.57
t-1	183,971.38	0.21	480,321.29
Day 0	5,252.82	0.53	-514,634.08
t+1	-15,684.44	0.47	181,730.24
t+2	33,987.91	0.49	851,618.21
t+3	63,069.33	0.62	-279,478.57
t+4	-94,745.75*	0.02	-832,023.27**
t+5	354,895.12	0.04	313,893.82

Table 10: Event Study around Ticker Change Events

This table presents results from an 11-day event study around ticker change events. Column (1) reports the results for abnormal trading quantity. Column (2) reports the results for abnormal number of trades. Column (3) reports the results for abnormal trading volume. The abnormal measures are computed by taking the daily measures minus the pre-event window daily average, where the pre-event window is measured from the preceding 35 trading days [-40, -6]. The *t*-tests test whether the abnormal trading measures are significantly different from zero. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Quantity (1)	Abnormal Trades (2)	Abnormal Volume (3)
t-5	-118,920.83	-2.31	-612,853.58
t-4	131,504.62	-1.71*	-318,030.81
t-3	106,046.93	-1.32	72,039.30
t-2	154,540.86	-0.90	475,643.89
t-1	-195,757.15***	0.74	-1,464,110.82**
Day 0	160,761.65	-0.84	1,203,906.09
t+1	402,455.34	-1.75	1,724,184.47
t+2	195,799.70	-1.30	334,121.45
t+3	130,883.26	-1.26	-247,486.83
t+4	472,310.05*	-1.09	1,390,365.45
t+5	312,583.96*	-2.29	-153,853.87

Table 11: OLS Regression – CEO Turnover Events

This table reports the regression results from equation (2). The dependent variables are the abnormal trading measures. Seven dummy variables are included to capture the seven days around the event day. Other independent variables include annual sales, firm size, ROA, leverage, years to maturity, raw bond return, and a buy/sell indicator representing the side of a trade where buy is +1, sell is -1, and no trade is 0. Firm size, bond return, and sales are in logs and the buy/sell side indicator is log(1+side) transformed. The t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Voluntary Turnover			Involuntary Turnover		
	(1) Abnormal Quantity	(2) Abnormal Trades	(3) Abnormal Volume	(4) Abnormal Quantity	(5) Abnormal Trades	(6) Abnormal Volume
$Event_{t-3}$	-38,001.74	-3.19	-317,649.53	113,822.10	-10.18	-1,207,427.74
	(-0.57)	(-1.08)	(-0.54)	(1.02)	(-1.02)	(-0.82)
$Event_{t-2}$	-36,358.48	-2.89	476,894.70	-59,093.73	-8.76	1,074,499.53
	(-0.57)	(-1.02)	(0.85)	(-0.51)	(-0.86)	(0.71)
$Event_{t-1}$	9,135.85	-3.08	681,790.14	48,878.53	-10.66	3,465,843.26**
	(0.14)	(-1.06)	(1.18)	(0.41)	(-1.01)	(2.20)
Event Day	172,531.94**	-2.03	235,047.87	-67,008.86	-2.37	-968,750.79
	(2.54)	(-0.67)	(0.39)	(-0.53)	(-0.21)	(-0.58)
$Event_{t+1}$	-40,846.06	-0.35	95,139.64	178,152.37	-1.51	1,332,719.31
	(-0.60)	(-0.12)	(0.16)	(1.31)	(-0.12)	(0.74)
$Event_{t+2}$	15,451.78	-1.29	-173,445.60	35,181.56	-6.78	485,348.46
	(0.23)	(-0.43)	(-0.29)	(0.31)	(-0.67)	(0.32)
$Event_{t+3}$	484.20	-2.22	-460,007.75	81,880.78	-5.66	650,644.08
	(0.01)	(-0.74)	(-0.77)	(0.75)	(-0.58)	(0.45)
Sales	11,547.78	-0.24	-8,338.63	110,690.93***	1.60	270,681.69
	(0.52)	(-0.24)	(-0.04)	(2.65)	(0.43)	(0.49)
Firm Size	-26,488.61	-0.44	-319,046.76*	-46,229.67	-4.94	-81,815.91
	(-1.42)	(-0.53)	(-1.94)	(-1.35)	(-1.62)	(-0.18)
ROA	-43,688.24	4.87	-2,092,540.01	-211,700.94	42.48	-8,369,245.68*
	(-0.20)	(0.51)	(-1.11)	(-0.64)	(1.43)	(-1.90)
Leverage	-568.85	0.02	19,786.52	-35,945.92*	-2.15	63,591.71
	(-0.26)	(0.17)	(1.03)	(-1.98)	(-1.33)	(0.26)
Years to Maturity	8,193.79*	-0.19	25,451.02	6,373.94	-0.22	51,634.97
	(1.85)	(-0.97)	(0.65)	(1.16)	(-0.45)	(0.71)
Bond Return	-9,327.21	-0.77	-258,259.93***	6,447.46	-4.11*	239,770.10
	(-0.84)	(-1.57)	(-2.66)	(0.27)	(-1.91)	(0.75)
Buy/Sell Side	-3,627.00	-6.51**	-879,989.86*	-205,151.00**	-8.35	-2,438,523.47*
	(-0.06)	(-2.57)	(-1.76)	(-2.14)	(-0.98)	(-1.92)
Constant	171,395.93	7.38	3,268,418.16*	-335,847.91	54.59*	-823,669.69
	(0.89)	(0.86)	(1.92)	(-1.05)	(1.92)	(-0.20)
Observations	1,149	1,149	1,149	162	162	162
R-squared	0.01	0.01	0.02	0.14	0.07	0.09

Table 12: OLS Regression – Dividend Change Announcements

This table reports the regression results from equation (2). The dependent variables are the abnormal trading measures. Seven dummy variables are included to capture the seven days around the event day. Other independent variables include annual sales, firm size, ROA, leverage, years to maturity, raw bond return, and a buy/sell indicator representing the side of a trade where buy is +1, sell is -1, and no trade is 0. Firm size, bond return, and sales are in logs and the buy/sell side indicator is log(1+side) transformed. The t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Dividend Increases			Dividend Decreases		
	(1) Abnormal Quantity	(2) Abnormal Trades	(3) Abnormal Volume	(4) Abnormal Quantity	(5) Abnormal Trades	(6) Abnormal Volume
$Event_{t-3}$	-38,330.28	-0.53	-919,136.02	60,342.58	11.63**	771,371.51
	(-0.77)	(-0.67)	(-1.32)	(0.62)	(2.25)	(0.51)
$Event_{t-2}$	-10,364.49	0.82	-629,348.34	79,044.30	0.10	376,401.14
	(-0.21)	(1.02)	(-0.89)	(0.85)	(0.02)	(0.26)
$Event_{t-1}$	-44,222.18	1.70**	-1,035,710.12	42,598.37	0.45	1,195,734.41
	(-0.90)	(2.14)	(-1.49)	(0.44)	(0.09)	(0.79)
Event Day	29,031.20	0.27	-405,465.08	69,166.28	3.22	4,382,576.58***
	(0.58)	(0.34)	(-0.58)	(0.70)	(0.61)	(2.85)
$Event_{t+1}$	36,811.70	-0.08	783,808.32	114,727.45	3.30	2,464,902.84*
	(0.75)	(-0.10)	(1.14)	(1.19)	(0.64)	(1.65)
$Event_{t+2}$	-9,972.88	0.14	672,110.00	-29,043.03	1.96	1,548,871.40
	(-0.20)	(0.18)	(0.95)	(-0.30)	(0.38)	(1.04)
$Event_{t+3}$	5,453.37	-0.19	851,647.76	35,912.27	0.08	-745,848.84
	(0.11)	(-0.24)	(1.21)	(0.36)	(0.01)	(-0.48)
Sales	-1,522.26	-0.67***	55,852.40	-9,170.11	0.31	-459,315.71
	(-0.10)	(-2.74)	(0.26)	(-0.35)	(0.22)	(-1.15)
Firm Size	-7,926.79	0.16	56,649.15	18,939.41	-2.36*	-107,174.33
	(-0.50)	(0.65)	(0.26)	(0.77)	(-1.79)	(-0.28)
ROA	62,346.79	0.75	3,273,252.65	-479,312.31*	10.08	-14,174,064.96***
	(0.29)	(0.22)	(1.09)	(-1.87)	(0.74)	(-3.57)
Leverage	-220.44	0.00	-8,724.81	5,114.50**	0.02	84,695.11**
	(-0.44)	(0.46)	(-1.25)	(2.12)	(0.14)	(2.27)
Years to Maturity	5,414.99	-0.01	-78,286.21	279.40	-0.12	103,001.54
	(1.48)	(-0.24)	(-1.53)	(0.05)	(-0.36)	(1.08)
Bond Return	15,196.42	-0.26*	252,791.93*	29,168.31*	0.63	-428,197.10
	(1.63)	(-1.73)	(1.93)	(1.69)	(0.69)	(-1.60)
Buy/Sell Side	237,774.78***	-0.99	1,342,472.77*	56,957.88	-12.16***	-94,241.32
	(4.57)	(-1.19)	(1.83)	(0.67)	(-2.69)	(-0.07)
Constant	214,435.76	2.30	679,697.94	-80,634.33	39.46**	3,342,772.84
	(1.17)	(0.78)	(0.26)	(-0.28)	(2.56)	(0.75)
Observations	2,430	2,430	2,430	835	835	835
R-squared	0.01	0.01	0.01	0.02	0.03	0.04

Table 13: OLS Regression – M&A Announcements

This table reports the regression results from equation (2). The dependent variables are the abnormal trading measures. Seven dummy variables are included to capture the seven days around the event day. Other independent variables include annual sales, firm size, ROA, leverage, years to maturity, raw bond return, and a buy/sell indicator representing the side of a trade where buy is +1, sell is -1, and no trade is 0. Firm size, bond return, and sales are in logs and the buy/sell side indicator is log(1+side) transformed. The t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Acquiring Firms			Target Firms		
	(1) Abnormal Quantity	(2) Abnormal Trades	(3) Abnormal Volume	(4) Abnormal Quantity	(5) Abnormal Trades	(6) Abnormal Volume
$Event_{t-3}$	-84,158.80	-0.76	-1,550,134.85	-149,872.74	-1.18	-455,845.20
	(-1.23)	(-0.81)	(-0.68)	(-0.58)	(-0.04)	(-0.04)
$Event_{t-2}$	-63,730.80	-0.45	930,330.51	-53,638.68	-1.68	-902,205.14
	(-0.94)	(-0.48)	(0.41)	(-0.19)	(-0.05)	(-0.08)
$Event_{t-1}$	36,016.85	-0.45	713,716.33	-142,381.37	9.05	1,474,601.47
	(0.52)	(-0.47)	(0.31)	(-0.53)	(0.31)	(0.13)
Event Day	143,382.34*	0.08	490,425.65	729,231.70***	56.04**	41,710,584.64***
	(1.76)	(0.07)	(0.18)	(3.24)	(2.28)	(4.46)
$Event_{t+1}$	194,430.50***	3.53***	7,138,830.43***	867,440.44***	68.38**	40,179,836.79***
	(2.94)	(3.85)	(3.24)	(3.45)	(2.49)	(3.85)
$Event_{t+2}$	100,715.84	2.02*	2,313,665.56	232,888.89	22.66	9,577,383.79
	(1.33)	(1.93)	(0.92)	(0.96)	(0.86)	(0.95)
$Event_{t+3}$	-24,970.28	-0.11	-1,167,740.84	554,315.55*	-5.25	1,502,713.46
	(-0.35)	(-0.11)	(-0.49)	(1.97)	(-0.17)	(0.13)
Sales	-50,601.30**	-0.38	-2,221,142.60***	-129,033.22	15.02	1,939,795.04
	(-2.13)	(-1.16)	(-2.81)	(-1.49)	(1.59)	(0.54)
Firm Size	32,188.66	0.21	1,618,609.32**	-28,582.69	-2.95	1,599,747.62
	(1.41)	(0.66)	(2.12)	(-0.43)	(-0.40)	(0.58)
ROA	-295,989.51	-5.11*	-3,043,509.22	307,288.75	-55.35	-21,227,581.75
	(-1.48)	(-1.84)	(-0.46)	(0.66)	(-1.09)	(-1.10)
Leverage	-1,993.53	-0.01	-28,801.70	10,759.09**	0.28	73,760.71
	(-0.74)	(-0.14)	(-0.32)	(2.18)	(0.52)	(0.36)
Years to Maturity	-2,382.85	0.19***	350,967.52**	26,036.17*	-1.46	-904,648.13
	(-0.47)	(2.63)	(2.07)	(1.72)	(-0.89)	(-1.44)
Bond Return	32,284.43***	-0.41**	-26,118.51	-59,621.68	-8.65**	-3,665,193.42**
	(2.66)	(-2.43)	(-0.06)	(-1.61)	(-2.14)	(-2.39)
Buy/Sell Side	156,282.61*	-0.62	14,578.33	320,321.50	78.52***	21,987,340.21**
	(1.95)	(-0.56)	(0.01)	(1.20)	(2.69)	(1.98)
Constant	329,640.64	-2.66	-7,459,724.34	921,654.78	-134.18*	-61,400,042.96**
	(1.40)	(-0.82)	(-0.95)	(1.24)	(-1.66)	(-2.00)
Observations	775	775	775	236	236	236
R-squared	0.06	0.05	0.04	0.19	0.12	0.19

Table 14: OLS Regression – Repurchase Announcements

This table reports the regression results from equation (2). The dependent variables are the abnormal trading measures. Seven dummy variables are included to capture the seven days around the event day. Other independent variables include annual sales, firm size, ROA, leverage, years to maturity, raw bond return, and a buy/sell indicator representing the side of a trade where buy is +1, sell is -1, and no trade is 0. Firm size, bond return, and sales are in logs and the buy/sell side indicator is log(1+side) transformed. The t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	(1) Abnormal Quantity	(2) Abnormal Trades	(3) Abnormal Volume
$Event_{t-3}$	431,129.28***	12.63***	6,965,288.64**
	(3.11)	(3.22)	(2.64)
$Event_{t-2}$	-130,178.45	-0.13	195,244.72
	(-0.73)	(-0.03)	(0.06)
$Event_{t-1}$	-124,432.97	3.96	-2,964,364.74
	(-0.85)	(0.96)	(-1.07)
Event Day	74,755.78	6.02	6,105,680.19*
	(0.42)	(1.20)	(1.81)
$Event_{t+1}$	-283,656.39*	0.99	-3,339,427.22
	(-1.86)	(0.23)	(-1.15)
$Event_{t+2}$	338,485.27**	-2.48	-1,138,323.21
	(2.10)	(-0.54)	(-0.37)
$Event_{t+3}$	73,064.81	-3.07	405,174.07
	(0.43)	(-0.64)	(0.13)
Sales	-130,533.70*	2.20	-40,836.20
	(-1.71)	(1.02)	(-0.03)
Firm Size	263,388.80***	-0.89	860,276.49
	(4.24)	(-0.51)	(0.73)
ROA	-425,606.82	3.16	-21,097,058.76*
	(-0.72)	(0.19)	(-1.87)
Leverage	-3,248.92	0.09	36,986.33
	(-1.27)	(1.29)	(0.76)
Years to Maturity	-85,871.98***	-0.63	-112,207.65
	(-5.70)	(-1.47)	(-0.39)
Bond Return	33,988.60	0.07	-22,681.80
	(1.08)	(0.07)	(-0.04)
Buy/Sell Side	-282,283.34	-20.95***	-3,290,218.10
	(-1.26)	(-3.31)	(-0.77)
Constant	-2111564.62***	0.62	-12,384,661.59
	(-3.78)	(0.04)	(-1.16)
Observations	94	94	94
R-squared	0.43	0.26	0.24

Table 15: OLS Regression – SEO Announcements

This table reports the regression results from equation (2). The dependent variables are the abnormal trading measures. Seven dummy variables are included to capture the seven days around the event day. Other independent variables include annual sales, firm size, ROA, leverage, years to maturity, raw bond return, and a buy/sell indicator representing the side of a trade where buy is +1, sell is -1, and no trade is 0. Firm size, bond return, and sales are in logs and the buy/sell side indicator is log(1+side) transformed. The t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	Abnormal Quantity	Abnormal Trades	Abnormal Volume
$Event_{t-3}$	-91,318.71	-4.41	-12,800,883.20
	(-0.65)	(-0.40)	(-0.54)
$Event_{t-2}$	-271,831.72*	-4.88	-12,912,019.86
	(-1.87)	(-0.43)	(-0.53)
$Event_{t-1}$	-185,997.01	-3.32	-11,895,316.58
	(-1.31)	(-0.30)	(-0.50)
Event Day	-110,546.24	-2.35	-13,633,518.11
	(-0.84)	(-0.23)	(-0.61)
$Event_{t+1}$	74,793.45	1.75	1,551,663.25
	(0.56)	(0.17)	(0.07)
$Event_{t+2}$	172,772.05	28.12***	47,750,688.27**
	(1.29)	(2.67)	(2.12)
$Event_{t+3}$	78,070.81	-2.67	-14,149,819.05
	(0.57)	(-0.25)	(-0.61)
Sales	-39,814.62	-2.68	-4,317,911.57
	(-1.38)	(-1.18)	(-0.89)
Firm Size	3,915.07	2.67	4,895,921.36
	(0.12)	(1.06)	(0.91)
ROA	-396,030.22*	4.77	-7,727,474.34
	(-1.82)	(0.28)	(-0.21)
Leverage	395.86	-0.02	-57,033.45
	(0.21)	(-0.16)	(-0.18)
Years to Maturity	4,379.10	-0.12	-117,806.17
	(0.48)	(-0.17)	(-0.08)
Bond Return	10,857.43	-3.61**	-8,219,255.31**
	(0.47)	(-1.97)	(-2.10)
Buy/Sell Side	103,042.99	1.00	-660,509.38
	(0.83)	(0.10)	(-0.03)
Constant	495,821.16	-40.82	-88,954,078.35
	(1.13)	(-1.18)	(-1.20)
Observations	267	267	267
R-squared	0.10	0.06	0.05

Table 16: OLS Regression – Spin-Off Events

This table reports the regression results from equation (2). The dependent variables are the abnormal trading measures. Seven dummy variables are included to capture the seven days around the event day. Other independent variables include annual sales, firm size, ROA, leverage, years to maturity, raw bond return, and a buy/sell indicator representing the side of a trade where buy is +1, sell is -1, and no trade is 0. Firm size, bond return, and sales are in logs and the buy/sell side indicator is log(1+side) transformed. The t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	(1) Abnormal Quantity	(2) Abnormal Trades	(3) Abnormal Volume
$Event_{t-3}$	118,373.03	-0.09	259,326.29
	(0.70)	(-0.10)	(0.18)
$Event_{t-2}$	46,429.00	0.19	-158,470.17
	(0.27)	(0.22)	(-0.11)
$Event_{t-1}$	337,582.79**	-0.30	1,236,929.33
	(2.00)	(-0.34)	(0.86)
Event Day	-4,975.61	-0.33	172,015.88
	(-0.03)	(-0.37)	(0.12)
$Event_{t+1}$	212,050.29	0.56	1,374,299.35
	(1.20)	(0.61)	(0.91)
$Event_{t+2}$	150,319.83	1.04	3,214,236.90**
	(0.85)	(1.12)	(2.13)
$Event_{t+3}$	4,082.27	-0.08	567,439.54
	(0.02)	(-0.09)	(0.38)
Sales	-32,642.51	0.20	-492,026.87
	(-0.78)	(0.92)	(-1.38)
Firm Size	32,501.97	-0.49**	-83,394.10
	(0.72)	(-2.09)	(-0.22)
ROA	212,345.29	-1.95	167,923.83
	(0.40)	(-0.71)	(0.04)
Leverage	11,530.37*	0.12***	93,576.80*
	(1.84)	(3.66)	(1.75)
Years to Maturity	-20,814.27**	0.03	-42,427.18
	(-2.04)	(0.52)	(-0.49)
Bond Return	15,549.71	-0.08	188,642.08
	(0.52)	(-0.54)	(0.74)
Buy/Sell Side	-576,664.62***	-1.25	-3,018,473.65*
	(-3.09)	(-1.29)	(-1.89)
Constant	-17,147.33	5.54*	7,405,499.81
	(-0.03)	(1.77)	(1.44)
Observations	401	401	401
R-squared	0.06	0.07	0.05

Table 17: OLS Regression – Stock Split Events

This table reports the regression results from equation (2). The dependent variables are the abnormal trading measures. Seven dummy variables are included to capture the seven days around the event day. Other independent variables include annual sales, firm size, ROA, leverage, years to maturity, raw bond return, and a buy/sell indicator representing the side of a trade where buy is +1, sell is -1, and no trade is 0. Firm size, bond return, and sales are in logs and the buy/sell side indicator is log(1+side) transformed. The t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	(1) Abnormal Quantity	(2) Abnormal Trades	(3) Abnormal Volume
$Event_{t-3}$	124,081.27	-0.31	-85,305.26
	(0.44)	(-0.32)	(-0.08)
$Event_{t-2}$	56,255.48	-0.77	906,650.44
	(0.21)	(-0.83)	(0.91)
$Event_{t-1}$	646,077.73**	0.41	3,213,357.14***
	(2.09)	(0.39)	(2.77)
Event Day	-113,563.05	1.42	-643,279.47
	(-0.40)	(1.45)	(-0.60)
$Event_{t+1}$	-222,062.62	1.17	-340,959.90
	(-0.73)	(1.10)	(-0.30)
$Event_{t+2}$	-108,971.00	0.94	-334,768.68
	(-0.37)	(0.93)	(-0.31)
$Event_{t+3}$	-234,959.86	-0.74	-1,864,012.90
	(-0.76)	(-0.69)	(-1.61)
Sales	-12,729.02	0.04	-240,563.92
	(-0.10)	(0.09)	(-0.49)
Firm Size	-1,874.57	0.05	177,568.47
	(-0.02)	(0.13)	(0.47)
ROA	-975,897.74	4.21	-9507542.09*
	(-0.66)	(0.82)	(-1.71)
Leverage	-105,898.47	0.04	-148,152.36
	(-1.18)	(0.14)	(-0.44)
Years to Maturity	-18,492.55	-0.05	-133,242.73**
	(-1.24)	(-1.01)	(-2.37)
Bond Return	-26,697.33	-0.06	-37,101.17
	(-0.60)	(-0.39)	(-0.22)
Buy/Sell Side	15,241.07	-2.17*	-881,571.62
	(0.05)	(-1.89)	(-0.71)
Constant	464,893.87	-1.29	1,008,083.32
	(0.41)	(-0.33)	(0.23)
Observations	191	191	191
R-squared	0.06	0.07	0.13

Table 18: OLS Regression – Ticker Change Events

This table reports the regression results from equation (2). The dependent variables are the abnormal trading measures. Seven dummy variables are included to capture the seven days around the event day. Other independent variables include annual sales, firm size, ROA, leverage, years to maturity, raw bond return, and a buy/sell indicator representing the side of a trade where buy is +1, sell is -1, and no trade is 0. Firm size, bond return, and sales are in logs and the buy/sell side indicator is log(1+side) transformed. The t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	(1) Abnormal Quantity	(2) Abnormal Trades	(3) Abnormal Volume
$Event_{t-3}$	-376,153.08	3.70	-582,067.63
	(-1.44)	(1.60)	(-0.35)
$Event_{t-2}$	184,876.11	4.00*	2,046,984.79
	(0.70)	(1.72)	(1.24)
$Event_{t-1}$	-213,403.53	2.38	-153,698.26
	(-0.82)	(1.03)	(-0.09)
Event Day	-149,188.14	3.36	726,323.69
	(-0.56)	(1.44)	(0.44)
$Event_{t+1}$	378,807.79	0.40	3,431,811.47**
	(1.44)	(0.17)	(2.07)
$Event_{t+2}$	55,380.84	2.02	1,183,126.53
	(0.21)	(0.88)	(0.73)
$Event_{t+3}$	161,935.95	1.08	1,449,566.74
	(0.61)	(0.46)	(0.87)
Sales	98,606.67	0.15	58,476.10
	(1.12)	(0.20)	(0.11)
Firm Size	17,344.80	0.15	216,724.02
	(0.21)	(0.20)	(0.42)
ROA	-456,994.63	26.51***	-16,146,653.02**
	(-0.43)	(2.82)	(-2.42)
Leverage	385.00	-0.01	20,556.83**
	(0.28)	(-0.98)	(2.40)
Years to Maturity	-4,526.04	0.23	74,802.60
	(-0.27)	(1.54)	(0.70)
Bond Return	43,625.00	-0.18	439,660.58*
	(1.07)	(-0.50)	(1.73)
Buy/Sell Side	82,901.47	2.22	-1,312,468.87
	(0.35)	(1.07)	(-0.89)
Constant	-747,845.57	-12.06	-3,031,645.97
	(-0.79)	(-1.43)	(-0.51)
Observations	255	255	255
R-squared	0.05	0.10	0.08

PART 3: CONVERTIBLE BOND TRADING

I. INTRODUCTION

A sizable portion of the corporate bond market consists of bonds that are convertible. While convertible bond issuance in the United States has decline from $41.6 billion in 2018 to $2.8 billion in 2023, average daily trading volume in convertible bonds has increased from $1.3 billion to $2 billion.[23] Globally, convertible bond issuance totals $74.1 billion in 2023.[24] Convertible bonds are hybrid securities incorporating features of debt, equity, and options. Investors enjoy the limited downside risk of convertible bonds while holding the option to convert the bond into the issuing company's stock and benefit from the equity upside. Therefore, as convertible bonds approach in-the-money status, these bonds may experience an increase in trading activity as demand for them increases.[25]

Research on convertible bonds often center around convertible bond calls (Ingersoll, 1977b; Cowan, Nayar, and Singh, 1993), convertible arbitrage (Choi, Getmansky, and Tookes, 2009; Ammann, Kind, and Seiz, 2010), or pricing of convertible bonds (Ammann, Kind, and Wilde, 2003; Batten, Khaw, and Young, 2018). As corporate bond transactions data became available through the Trade Reporting and Compliance Engine (TRACE), research in the over-the-counter (OTC) corporate bond market expanded. Edwards, Harris, and Piwowar (2007) and Goldstein, Hotchkiss, and Sirri (2007) find that increased post-trade price transparency after the

---

[23] See https://www.sifma.org/resources/research/us-fixed-income-securities-statistics/

[24] See https://dealogic.com/insight/ecm-highlights-fy22/

[25] The conversion option is in-the-money when the conversion value of the common stock to be received in the conversion exchange equals or exceeds the conversion price.

introduction of TRACE led to a decline in transaction costs for traded bonds. The literature on dealer behaviors, relationship trading, types of dealers, and how they provide liquidity are abundant (Hendershott and Madhavan, 2015; Goldstein and Hotchkiss, 2020; Hendershott, Li, Livdan, and Schurhoff, 2020; and O'Hara and Zhou, 2021). However, the majority of these corporate bond research filters out convertibles due to the option-like conversion feature.

Bessembinder, Spatt, and Venkataraman (2020) survey the literature that studies fixed-income trading, and there was no mention of convertible bonds. In the Chinese market, Chen, Xu, and Wang (2023) find that convertible bond trading contains information and positively predicts future stock returns. Dutordoir, Lewis, Seward, and Veld (2014) review the corporate finance literature on convertible bond financing and find that empirical studies on convertible debt issuance focus on testing the "Big Four" theoretical models.

The big four theoretical models on convertible bond issuance include Green (1984), Brennan and Kraus (1987), Brennan and Schwartz (1988), Mayers (1998), and Stein (1992). Green models convertibles as a funding instrument that reduces bondholder-stockholder conflicts of interest as convertibles mitigates shareholders' incentives to engage in high-risk, negative net present value projects as cash flows will be shared with convertible bondholders. Mayers focuses on convertibles as a tool to reduce agency problems between managers and stockholders as convertibles can overcome overinvestment problems by redeeming bonds and returning cash to bondholders. Convertibles can be a tool to reduce adverse selection costs resulting from asymmetric information between managers and outside investors when these two types of stakeholders disagree on the risk of the firm (Brennan and Kraus, 1987; and Brennan and Schwartz, 1988). Another group of adverse selection models builds on asymmetric information regarding firm value, rather than firm risk (Stein, 1992). The backdoor-equity model of Stein proposes that firms use convertibles as a way to obtain delayed equity financing. Overall, the studies on convertible bonds have provided insights into convertible bond issuance decisions, convertible bond design, and market participants' reactions to convertible debt issuances.

While most empirical studies on convertible bonds focus on the big four theoretical models, some papers argue that convertibles are issued as a response to investor demand considerations (de Jong, Duca, and Dutordoir, 2013). This rationale states that firms may opportunistically issue convertible bonds when there is heightened investor demand in convertibles as demand may be driven by the payoff patterns (i.e., which may be more valuable in times of heightened investor risk aversion) or by irrational investor hypes (Dutordoir, Lewis, Seward, and Veld, 2014). Therefore, trading patterns in convertible bonds may be informative of trader behavior or demand for convertibles.

Easley, O'Hara, and Srinivas (1998) develop an asymmetric information model where informed traders may trade in options or equity markets. The paper confirms that changes in stock prices lead option volumes as a result of increased hedge-related trading in options. The paper additionally finds that option volumes lead to stock price changes as option markets serve as a venue for information-based trading. Pan and Poteshman (2006) find that option trading volume contains information about future stock prices. In convertibles, increases in stock prices to in-the-money status may lead convertible bond trading volume or information-induced trading in convertible bonds may increase stock prices to be in-the-money.

Trading in the options market concentrates in at-the-money (ATM) options (Blasco, Corredor, and Santamaria, 2010). Using net trade options volume ratio as a proxy for informed options trading, Heng and Leung (2023) report that the average net trade options volume (buyer-initiated volume minus seller-initiated volume) ratio is highest for deep in-the-money (ITM) options followed by out-of-the-money (OTM) options and ATM options. Mohil, Nayyar, and Patro (2020) examines option strategies used by informed trades around mergers and acquisitions (M&As) and find that ATM calls have the highest volume. As options that are ATM experience increased trading, I examine if convertible bonds, which have option characteristics, will exhibit a similar pattern when they are in-the-money.

With very little that is known about the trading patterns of convertible bonds, this paper seeks to explore how convertible bonds trade when the option to convert is in-the-money. In a market that experience sparse trading and a unique security with features of debt, equity, and options, it is interesting to examine changes in trading behavior when a particular feature suddenly outweighs the others. Additionally, I examine changes in the trading of the non-convertible bonds of the firms' with in-the-money convertible bonds and how those firms' equity trade during the event window when the convertibles are in-the-money.

The remainder of the paper proceeds as follows. Section II provides a detailed review of the literature on the corporate bond market focusing on convertible bonds and outline the development of the hypotheses. Section III describes the data and methodology. Section IV presents the results of the analyses, and Section V concludes.

II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The corporate bond market is characterized as illiquid and costlier to transact in relative to the stock market (Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018; Goldstein and Hotchkiss, 2020). As a convertible bond becomes in-the-money, it starts trading like a stock. In other words, the convertible bond becomes linked to the firm's equity with bond trading patterns following stock trading patterns. When the option to convert the bond to stock has a greater payoff than holding the bond until maturity, demand for the bond should increase as investors try to capture the benefit of the conversion option. When in-the-money convertible bonds are more actively-traded, dealers are less exposed to inventory risk and experience reduced search costs which might result in larger trades and lower transaction costs to the benefit of institutional investors (Goldstein and Hotchkiss, 2020).[26] Even though post-trade transparency in the bond market has increased after public dissemination through TRACE, pre-trade transparency remains nonexistent (Bessembinder, Spatt, and Venkataraman, 2020).[27] While pre-trade transparency in the bond market has not been established, in-the-money convertible bonds provide investors with a glimpse of the demand for these bonds based on their equity performance.

H1: When the convertible option is in-the-money, demand for the convertible bond will increase resulting in higher trading activity.

As convertible bonds approach in-the-money status or are in-the-money, this should indicate that the stock is performing well in that the future performance of the firm is on an upward trend. If the in-the-money status of convertible bonds relates to future performance, I anticipate there will be spillover effects to the firm's other bonds. Demand for the convertible bonds should also increase demand for the firm's other bonds as investors anticipate better future performance.

H2: In-the-money convertible bonds lead to increased trading activity in the firm's other bonds.

[26] In the bond market, large trades may reflect investors waiting for relevant and material information and then quickly acting on it in large trades (Ronen and Zhou, 2013). In the equity market, large trades are exposed to adverse selection and information leakage so using large trade sizes as identification for institutional investors in the bond market is not subject to the same scrutiny as in the equity markets.

[27] Quotations are distributed only to some market participants (Bessembinder, Spatt, and Venkataraman, 2020).

The extant literature has mixed results of whether a lead-lag relationship exists between the stock and bond market. Tolikas (2018) finds that stock returns only lead the returns of high-yield bonds and that the stock market is more efficient relative to the bond market by incorporating information at a faster rate. On the other hand, Ronen and Zhou (2013) find that the majority of price discovery for the bonds with the highest institutional trade volume immediately after an earnings announcement occurs before the equity market opens.

Downing, Underwood, and Xing (2009) find that stock returns lead bond returns for convertible bonds in all rating classes but only those rated BBB and high-yield grade for nonconvertible bonds. The return predictability of convertible bonds depends on the extent to which the option is in-the-money. As the credit quality of the convertible bonds improve, they become more equity-like because the conversion option goes more into the money when firms' prospects improves (Downing, Underwood, and Xing, 2009). The findings of Batten, Khaw, and Young (2018) suggest that equity-like convertible bonds are more attractive to investors, such as hedge funds, because of the higher value of the conversion option.[28]

In the case of convertible bonds, the equity performance determines the value of the option. If the stock price continues on an upward trend leading the convertible bond deeper in-the-money, this may indicate that investors are adjusting their valuation of the stock upwards until its new intrinsic value is realized. Downing, Underwood, and Xing (2009) find that stock returns predict returns of convertible bonds because the convertible option is highly sensitive to firm-specific information.

[28] Hedge funds are one of the most common acquirers of convertible bonds purchasing 70% to 80% of convertible debt offerings (Choi, Getmansky, and Tookes, 2009).

Institutional investors typically hold both bonds and stocks in their portfolios, so I expect that they are actively trading in both debt and equity markets (Holden, Mao, Nam, 2018; Chang and Yu, 2010). In this situation, equity volume and trade size should increase due to more trading activity. On the other hand, in-the-money convertible bonds may lead to a downward demand curve for stocks (Harris and Gurel, 1986). While it is possible that demand will shift from stocks to the convertible bonds, another reason why the equity market might experience increased trading might be due to high-frequency traders trading along with informed institutional investors (Van Kervel and Menkveld, 2019).

If informed traders are incorporating new information into their trades, they might prefer to engage in hidden limit order trading, rather than lit trading, to avoid information leakage.[29] In this case, hidden liquidity in the stocks of firms with convertible bonds that are in-the-money should increase. If traders, informed or liquidity, simply prefer hidden orders, then hidden liquidity will increase as equity trading increases.

H3: Demand for firms with in-the-money convertible bonds will lead to increased equity trading.

H4: Hidden liquidity in firms with convertible bonds that are approaching or are in-the-money will increase.

Underwood (2009) finds that during high volatility periods, the effect of buying and selling pressure in Treasuries and returns on equities are stronger. When the stock market experience illiquidity shocks, the bond market will experience a decrease in illiquidity which is

[29] Equity exchanges are also referred to as lit exchanges where price quotes are publicly displayed. Hidden limit order trading refers to trading on lit exchanges when traders place hidden limit orders where price quotes are not publicly displayed (Bloomfield, O'Hara, and Saar, 2015).

consistent with flight-to-quality or flight-to-liquidity (Goyenko and Ukhov, 2009). During a crisis, illiquidity in the stock market will sever market integration as in-the-money convertibles fall out of the money.

Demand for convertibles may increase as investors' risk aversion increase in times of market uncertainty (de Jong, Duca, and Dutordoir, 2013). To examine option reversal when in-the-money convertible bonds fall out of the money due to cross-asset volatility, the COVID-19 pandemic is used as an exogenous shock. Increased volatility during the start of the COVID-19 pandemic may increase the demand for convertible bonds even if they are out-of-the money as investors retreat to relatively safer investments. As demand for these bonds increases, the bond market becomes more liquid than the stock market, which might contribute to bond prices incorporating information at a faster rate than stock prices.

H5: Demand will increase for convertible bonds during the uncertainty period due to the COVID-19 pandemic.

III. DATA AND METHODS

DATA SOURCES

Bond transaction data are obtained from enhanced TRACE from January 1, 2015 to December 31, 2022. Bond characteristics are sourced from the TRACE master file such as the indicators for 144A, convertible features, and investment or noninvestment grade, bond maturity date, and coupon rate. Information regarding features of convertible bonds like conversion price, conversion start date, issue amount, and type of convertible bond are obtained from Bloomberg

Financial Database. Information on firm characteristics and financials are obtained from CRSP and Compustat.

SAMPLE SELECTION

The sample only examines convertible bonds designated with the convertible indicator on the TRACE master file. The sample excludes 144A bonds, issues denominated in foreign currency, bonds with callable and putable conversion features, bonds of financial and utility firms (SIC 6000-6999 and 4900-4999), and firms that are not designated with share code 10 or 11. I follow Dick-Nielsen (2009) to remove duplicate, canceled, corrected, reversed, and commission trades from TRACE. A bond must have at least 10 trades in the sample period with maturity of at least one year and less than 50 years left to be included for analyses.

The convertible bonds must stay in-the-money for at least five days and trade every day in an estimation window of [-30, -6]. This ensures that the convertible bonds are relatively more liquid and have enough trading activity prior to being in-the-money to compare with its trading activity after becoming in-the-money. The first time a convertible bond stays in-the-money for at least five days is used as the event where the first of the five days is used as event day. Figure 1 provides a visual timeline of the convertible status of two hypothetical convertible bonds, CV Bond A and CV Bond B.

While CV Bond A went in-the-money for the first time on April 5th, it fell out-of-the-money on April 8th, which is less than the minimum required five days, so April 5th is not used as the event day for CV Bond A. However, on May 15th, CV Bond A went in-the-money a second time and fell out-of-the-money on May 25th,which is longer than the minimum five days, so May 15th is used as the event day for CV Bond A. While CV Bond A went in-the-money a third time on

June 10th and stayed in-the-money until August 11th, this period is not used as the event window, since I am interested in the trading patterns of convertible bonds when they first get in-the-money with a long enough event window. Similarly, the first time CV Bond B goes in-the-money for at least five days, the event day is the first day of the period that it is in-the-money.

Table 1 reports the sample selection process. The convertible bonds are identified based on the convertible flag indication in the TRACE Master File, which contains matured and active convertible bonds, and merged with enhanced TRACE. After following the standard TRACE filters, there are 4,163 convertible bonds identified in TRACE. To identify when the convertible bonds are in-the-money, I need its conversion price, which is not provided in TRACE. I identified convertible bonds in Bloomberg with a conversion price to merge with the transaction data in TRACE. The Bloomberg sample only includes active convertible bonds in the sample period (not matured or defaulted). The convertible bond sample from Bloomberg consist of 582 convertible bonds after excluding convertible bonds denominated in foreign currency and with callable and putable conversion features. Merging TRACE and Bloomberg resulted in a sample size of 298 convertible bonds. After excluding 7 bonds with less than ten trades in the sample period, 148 bonds that did not stay in-the-money for at least five days over the entire sample period, and 96 bonds that did not have the full [-30, -6] estimation window, the final sample includes 47 convertible bonds from 41 issuing firms.

Table 2 reports the descriptive statistics over a [-5, +5] event window for the convertible bonds that went in-the-money. The average number of trades for in-the-money convertible bonds over the 11-day window is 4.93 trades. These bonds have, on average, 4.80 years to maturity and an average issue amount of $412,347,000. The average stock price for these firms with in-the-money convertible bonds is $63.91.

While it is important to limit the convertible bond sample to the bonds that stay in-the-money for at least 5 days for the analyses, it is informative to examine how often the convertible bonds become convertible. Since the option to convert is dependent on the stock price movement relative to the conversion price, the convertible bond may fall in- and out-of-the-money multiple times. Table 3 reports the number of times the sample convertible bonds went in-the-money. The greatest number of times a convertible bond became in-the-money is 23 times over the sample period which suggests volatile stock prices. Five bonds went in-the-money once and stayed in the money over the entire sample period which implies the increase in stock price lead these bonds deep in-the-money or the stock price of these firms were not volatile. Eight bonds experience fluctuations in the convertible option seven times over the sample period.

I suspect that earnings announcements might be pushing stock prices to new highs causing convertible bonds to go in-the-money. Therefore, I expect most of the convertible bonds to go in-the-money around earnings season in January, April, July, or October. Table 4 reports the number of convertible bonds that went in-the-money during a particular month over the sample period. July and November appear to have the greatest number of convertible bonds go in-the-money. Although July having one of the most convertible bonds go in-the-money aligns with our expectations of earnings announcements pushing stock prices pass conversion prices, November having the greatest number of in-the-money convertible bonds is surprising. Taking a closer look at what kind of information event that may have caused a firm's stock price to increase, Table 5 reports the types of information event that may have cause the convertible bonds to go in-the-money. Earnings Announcements include news related to quarterly earnings announcements, earnings estimates from the firm or analysts, or news regarding when the firm is set to announce earnings. Macroeconomic news include news related to how the overall economy is related to the firm's operations. Firm-specific news include news related to mergers and acquisitions, partnerships, patent issuances, government contracts, CEO turnover, new product releases, etc. Analyst forecasts include news regarding analyst upgrades of stock price targets, earnings targets, EPS targets, or future forecasts. Unknown include firms with no tangible news that might affect stock prices. Firm-specific news and analyst forecasts appear to be the dominant types of information event that occurs on the day a convertible bond goes in-the-money. In unreported analyses, combining the information provided in Table 4 and Table 5 show that the main type of event that resulted in a convertible bond to go in-the-money is firm-specific announcements for July. In November, the two dominant events that resulted in a convertible bond to go in-the-money is firm-specific announcements and analyst forecasts.

METHODS

I first start with an 11-day event study around the event of when the convertible bond goes in-the-money (stock price >= conversion price). I compute abnormal trading measures of abnormal quantity traded, abnormal number of trades, and abnormal trading volume using the following equation:

$$Abnormal\ Trading\ Measure = Trading\ Measure_{i,t} - \overline{Trading\ Measure_{i}}\ , \quad (1)$$

where $Trading\ Measure_{i,t}$ is either the daily average quantity, the daily average number of trades, or daily average volume for firm *i* on day *t* and the $\overline{Trading\ Measure_{i}}$ is the average of either the daily average quantity, the daily average number of trades, or the daily average volume for firm *i* measured in a 25-day estimation window [-30, -6]. $Abnormal\ Trading\ Measure$ is either abnormal quantity, abnormal number of trades, or abnormal volume.

Next, I run OLS regressions using the following equation:

$$Y_i = \beta_0 + \gamma X_i + \varepsilon_i \,, \tag{2}$$

where Y_i are the abnormal bond trading measures of firm i. X_i is the set of control variables including years to maturity, issue amount, buy/sell side indicator (representing the side of a trade where side is +1 for buys, -1 for sells, and 0 for no trade), firm size, sales, ROA, leverage and dummy variables that capture the seven trading days around the event date (i.e., Event_{t-3} is a dummy coded 1 for three days before day 0 and 0 otherwise, while Event_{t+3} is a dummy coded 1 for three days after day 0 and 0 otherwise). Firm size, sales, and bond issue amount are in logs and the buy/sell side variable is log(1+side) transformed.

IV. EMPIRICAL FINDINGS

Figure 2 provides a graphical representation of the abnormal trading metrics related to when the convertible bonds become in-the-money on day 0 over the window of [-5, +5]. Panel A shows that abnormal quantity peaks at day -1 and remains elevated over the event window. Panel B (panel C) shows that the abnormal number of trades (abnormal volume) peaks at day 0 and falls back to normal levels over the event window.

The 11-day event study around in-the-money convertible bonds is reported in Table 6. Column (1) reports the results for abnormal trading quantity. Column (2) reports the results for abnormal number of trades and Column (3) reports the results for abnormal trading volume. The t-test in Table 6 shows that only the abnormal number of trades and abnormal volume are positively significant on day 0. The 4.23 coefficient on abnormal trades on day 0 indicates that the first day the convertible bond went in-the-money, there was around 4 more trades than the previous 25 days. The 9,693,890.21 coefficient on abnormal volume on day 0 indicates that the first day the convertible bond went in-the-money, there was around 9.7 million more trade volume than the previous 25 days. Overall, trading interest in in-the-money convertible bonds increases on the day the bonds go in-the-money.

To control for some firm and bond characteristics, Table 7 reports the OLS regression results where seven dummy variables are included to capture the seven days around the event day. Regression results in Table 7 report similar findings as the t-test. Abnormal trades and abnormal volume are positively significant on event day after controlling for firm and bond characteristics. Firm sales is positively related to abnormal trades and abnormal volume, while ROA is negatively related to abnormal trades and abnormal volume. Overall, trading activity for convertible bonds increase when the convertible option is in-the-money, supporting hypothesis 1 which states that demand for in-the-money convertible bonds will increase resulting in higher trading activity.

To see if demand for other bonds of the firms with in-the-money convertible bonds change after the convertible bonds go in-the-money, I test for spillover effects using a sample of the firms' non-convertible bonds. After using the transaction filtering process as the convertible bonds, Table 8 reports the descriptive statistics for the sample of non-convertible bonds issued by the same firms with in-the-money convertible bonds during the sample period. This sample consists of 80 unique non-convertible bonds from 18 issuing firms. The average number of trades in the non-convertible bonds over the [-5, +5] event window of when the firm's convertible bonds went in-the-money is 1.33 trades. The average volume in the non-convertible bonds is 802,521 with a minimum of zero trading volume and a maximum of over 8,000,000. The average stock price for this sample of firms is $54.41.

Figure 3 presents some graphical evidence of increased trading activity of the firms' non-convertible bonds when their convertible bonds go in-the-money. Panel A shows that abnormal quantity starts on an upward trend from day -3 to day 0. Then, there is a sharp decrease on day +1, but abnormal quantity starts to dramatically increase on day +2 before leveling off through day +5. Panel B shows that abnormal trades spikes around day -1 and day 0 before a steep decline on day +1 before increasing again on day +2. Panel C shows that abnormal volume reaches a peak on day 0 before falling around average levels and spiking once more on day +2. Overall, the trading metrics over the event window indicates an increase in trading activity in non-convertible bonds of firms when their convertible bonds go in-the-money.

To test for spillover effects related to hypothesis 2, Table 9 reports the t-test during an 11-day event study where day 0 is the day the firms' convertible bonds become in-the-money and tests the significance of changes in trading activity related to the firms' non-convertible bonds. Column 1 reports a negatively significant effect on abnormal quantity on day -4 which indicates a decrease in trading activity related to non-convertible bonds in the four days before convertible bonds go in-the-money. Column 2 reports a significant increase in abnormal trades on days -1, 0, and +2 which indicate increased trading activity in the non-convertible bonds of firms with in-the-money convertible bonds. However, the negative and significant coefficient on day +1 indicates that trading in non-convertible bonds of firms with convertible bonds decreased the day after the convertible bonds go in-the-money. Column 3 reports a significant decrease in abnormal volume on day -4 and +1. This indicates a decrease in trading volume in non-convertible bonds four days prior and one day after the firms' convertible bonds go in-the-money. The mixed results on the trading metrics over the event windows warrants a closer look at whether trading activity changed for the non-convertible bonds of firms with convertible bonds that went in-the-money.

To further test for spillover effects in non-convertible bonds, regression results controlling for firm and bond characteristics are reported in Table 10. After controlling for the independent variables, all three abnormal trading metrics have a positive and significant coefficient on event day. On event day, abnormal quantity is 166,319 which means quantity traded in non-convertible bonds increased by 166,319 compared to the estimation window. The 1.27 coefficient on abnormal trades on event day indicates that the first day the convertible bond went in-the-money, there was around 1 more trade in the non-convertible bonds than the previous 25 days. The coefficient of 2,225,700 on abnormal volume indicates an increase in volume on event day relative to the estimation window. Abnormal trades was 1.31 trades higher the day prior to the event compared to the estimation window. ROA is negatively related to all trading metrics. Overall, regression results indicate that trading activity increased in the firms' non-convertible bonds. These findings provide support to hypothesis 2 in that trading activity increased in non-convertible bonds of firms with in-the-money convertible bonds.

To test trading activity in the equity market, I examine the firms with convertible bonds around the [-5, +5] when the convertible bonds go in-the-money. I am interested in the trading activity in the firms' stock, so I examine total trade volume, total trades, and canceled trades. Table 11 provides descriptive statistics related to the equity market for the firms with convertible bonds that went in-the-money. The average stock price for the firms is $63.92 with average sales of $2.29 million. The sample firms have an ROA of -7% and leverage of 50%. The average total volume is 1.96 million and the average total trade is 12,310. The average canceled trades is 142,530.

Figure 4 presents graphical evidence of increased trading activity in the stocks of firms with in-the-money convertible bonds. Panel A shows that abnormal lit volume starts to increase on day t-1 and peaks on the day convertible bonds go in-the-money. Abnormal lit volume declines to normal levels on day +4 and day +5. Panel B shows that abnormal hidden volume peaks on day 0 and declines to normal levels over the event window.[30] Panel C shows that abnormal canceled trades are above normal levels throughout the event window and peaks on day 0. Figure 4 provides initial evidence of increased trading activity in the equity market related to firms with convertible bonds that went in-the-money.

To formally tests the graphical evidence found in Figure 4, I use an 11-day event study. Table 12 reports the results from the analysis. Across the abnormal trading metrics, the coefficients on day 0 is positive and significant. Column (1) reports abnormal total volume and column (2) reports abnormal total trades. Abnormal total volume increased by 1.53 million on event day relative to the estimation period and abnormal total trades increased by 9,324 on event day relative to the estimation period. I separate total volume and trades into its lit and hidden portions to identify where the liquidity is stemming from. Column (3) reports abnormal lit volume and column (4) reports abnormal lit trades. Column (5) reports abnormal hidden volume and column (6) reports abnormal hidden trades. Abnormal lit volume increased by 1.29 million on event day relative to the estimation period and abnormal lit trades increased by 6,860 on event day relative to the estimation period. Abnormal hidden volume increased by 234,000, and abnormal hidden trades increased by 2,464 on event day relative to the estimation period. As another measure of trading activity, I examine canceled trades. Column (7) reports the abnormal canceled trades around the event window. Abnormal canceled trades reached 66,075 on day 0. The increased

[30] Abnormal lit trades and abnormal hidden trades show similar patterns to abnormal lit volume (Panel A) and abnormal hidden volume (Panel B), respectively, and are not reported.

level of trading activity extended after day 0 with some metrics staying above average through day 4. Overall, the results from the event study are consistent with the graphical evidence.

To further test the results in Figure 4, I use an OLS regression controlling for firm and bond characteristics. Regression results are reported in Table 13. All trading metrics are positive and significant on event day with increased trading up to two days after the event. Column (1) reports the results for abnormal total volume and column (2) reports the results for abnormal total trades. Abnormal total volume increased by 1.54 million and abnormal total trades increased by 7,752 on event day after accounting for control variables. Columns (3) and (4) report the results for abnormal lit volume and abnormal lit trades, respectively. Abnormal lit volume increased by 1.29 million and abnormal lit trades increased by 5,655 on event day after accounting for control variables. Columns (5) and (6) report the results for abnormal hidden volume and abnormal hidden trades, respectively. Abnormal hidden volume increased by 239,000, and abnormal hidden trades increased by 2,096 on event day after accounting for control variables. Most of the increase in trading activity is driven by lit trading activity which lasts up to two days post event, while hidden trading activity only increases on event day. Column (7) report the regression results for abnormal canceled trades. Abnormal canceled trades increased by 45,267 on event day after accounting for control variables. Overall, all abnormal trading metrics are positive and significant on day 0 supporting hypothesis 3 and hypothesis 4 in that equity trading increases around the day the convertible bonds go in-the-money.

During the start of the COVID-19 pandemic, investors may engage in flight-to-safety and switch from equity trading to bond trading (Goyenko and Ukhov, 2009). Although investors may prefer safe corporate bonds during this period of uncertainty, they may still want to capture any upside reward associated with equity. Through convertible bonds, investors can limit their downside risk while holding the option to convert the bonds into stocks. To test hypothesis 5 regarding the COVID-19 effects, February 24, 2020 to March 20, 2020 is used as the event window (Cox and Woods, 2023). The dummy variable Covid is coded 1 for days within the event window and 0 for days in the estimation window of [-30, -1]. The convertible bonds in this sample are filtered similarly as the main convertible bond sample except they were not required to be in-the-money for any amount of time. The reasoning for excluding the in-the-money status requirement is because I am interested in investors' preferences for convertible bonds during a period of market stress regardless of whether the convertible option is in-the-money or not.

The filters resulted in 52 unique convertible bonds from 48 issuing firms. Table 14 provide descriptive statistics of the convertible bonds and the issuing firms during the Covid event window. The average number of trades in the convertible bonds is 5.38 with a volume of 5.9 million. These convertible bonds has an average maturity of 4.43 years. The issuing firms' average stock price is $80.37 with annual sales of $3.6 million. These firms have an average ROA of -7% and are leveraged around 70%.

Controlling for bond and firm characteristics, Table 15 presents the regression results related to trading activity in convertible bonds around the Covid period. The dummy variable Covid is the main variable of interest. Covid, in columns 1 and 2, indicates an increased amount of quantity traded in convertible bonds during the market uncertainty period at the start of the pandemic. Firm size is positively related to quantity traded. The number of trades and volume in convertible bonds are insignificant. The mixed results from the trading metrics provide inconclusive evidence regarding trading activity around the start of the COVID-19 pandemic. Overall, the empirical results do not support hypothesis 5 and suggest no flight-to-quality during the start of the pandemic.

V. CONCLUSION

While a sizeable part of the corporate bond market is made up of convertible bonds, research on the trading of convertible bonds is scarce. Past literature mainly focuses on convertible bond issuances, design decisions, convertible arbitrage, convertible calls. I investigate the trading activity around convertible bonds when the convertible option becomes in-the-money. Empirical results show that trading activity in convertible bonds increase when the option is in-the-money. In a market that is illiquid with relatively higher transactions costs, the increased trading activity in in-the-money convertibles show that investor demand in these convertibles increases around the time when the conversion option is valuable.

When convertible bonds are in-the-money, this indicates that the stock price of the firm has exceeded the conversion price which implies an increase in the firm's equity valuation. When the firm is performing well or valued higher by investors, the securities related to the firm will increase in demand. I examine whether in-the-money convertible bonds lead to a spillover effect on a firm's other bonds. The results from this analysis indicate that trading activity increased in non-convertible bonds of firms with in-the-money convertible bonds which confirms a spillover effect.

Since the conversion price is dependent on the stock price of the firm, I expect increased trading in the equity market when the convertible bond becomes convertible. I explore the equity market's reactions to when convertible bonds are in-the-money and find increases in trading activity and hidden liquidity. Total volume and total trades (comprising of lit and hidden volume and trades) and canceled trades all increased on the day the convertible bonds go in-the-money.

During times of market stress, such as the COVID-19 pandemic, investors engage in flight-to-safety and invest in safer assets. Through convertible bonds, investors can limit their downside risk while holding the option to convert the bonds into stocks. Using the start of the COVID-19 pandemic as a natural experiment, I test whether the pandemic led to an increase in trading in convertible bonds. The empirical findings did not support the flight-to-quality hypothesis as the pandemic did not result in increased trading in convertible bonds.

LIST OF REFERENCES

Ammann, M., Kind, A., & Seiz, R. (2010). What drives the performance of convertible-bond funds? *Journal of Banking & Finance*, *34*(11), 2600–2613.

Ammann, M., Kind, A., & Wilde, C. (2003). Are convertible bonds underpriced? an analysis of the French market. *Journal of Banking & Finance*, *27*(4), 635–653.

Batten, J. A., Khaw, K. L.-H., & Young, M. R. (2018). Pricing convertible bonds. *Journal of Banking & Finance*, *92*, 216–236.

Bessembinder, H., Jacobsen, S., Maxwell, W., & Venkataraman, K. (2018). Capital commitment and illiquidity in corporate bonds. *The Journal of Finance*, *73*(4), 1615–1661.

Bessembinder, H., Spatt, C., & Venkataraman, K. (2020). A survey of the microstructure of fixed-income markets. *Journal of Financial and Quantitative Analysis*, *55*(1), 1–45.

Blasco, N., Corredor, P., & Santamaría, R. (2010). Does informed trading occur in the options market? some revealing clues. *Accounting & Finance*, *50*(3), 555–579.

Bloomfield, R., O'Hara, M., & Saar, G. (2015). Hidden liquidity: Some new light on Dark Trading. *The Journal of Finance*, *70*(5), 2227–2274.

Chang, C., & Yu, X. (2010). Informational efficiency and liquidity premium as the determinants of capital structure. *Journal of Financial and Quantitative Analysis*, *45*(2), 401–440.

Chen, Z., Xu, Y., & Wang, Y. (2023). Can convertible bond trading predict stock returns? evidence from China. *Pacific-Basin Finance Journal*, *79*, 102026.

Choi, D., Getmansky, M., & Tookes, H. (2008). Convertible bond arbitrage, liquidity externalities, and stock prices. *Journal of Financial Economics*.

Cowan, A. R., Nayar, N., & Singh, A. K. (1993). Calls of out-of-the-money convertible bonds. *Financial Management*, *22*(4), 106.

Cox, J., & Woods, D. (2023). Covid-19 and Market Structure Dynamics. *Journal of Banking & Finance*, *147*, 106362.

Dick-Nielsen, J. (2009). Liquidity biases in trace. *The Journal of Fixed Income*, *19*(2), 43–55.

de Jong, A., Duca, E., & Dutordoir, M. (2013). Do Convertible Bond Issuers Cater to Investor Demand? *Financial Management*, *42*(1), 41–78.

Downing, C., Underwood, S., & Xing, Y. (2009). The relative informational efficiency of stocks and bonds: An intraday analysis. *Journal of Financial and Quantitative Analysis*, *44*(5), 1081–1102.

Dutordoir, M., Lewis, C., Seward, J., & Veld, C. (2014). What we do and do not know about convertible bond financing. *Journal of Corporate Finance*, *24*, 3–20.

Edwards, A. K., Harris, L. E., & Piwowar, M. S. (2007). Corporate Bond Market Transaction Costs and Transparency. *The Journal of Finance*, *62*(3), 1421–1451.

Easley, D., O'Hara, M., & Srinivas, P. S. (1998). Option volume and stock prices: Evidence on where informed traders trade. *The Journal of Finance*, *53*(2), 431–465.

Goldstein, M. A., & Hotchkiss, E. S. (2020). Providing liquidity in an illiquid market: Dealer Behavior in US corporate bonds. *Journal of Financial Economics*, *135*(1), 16–40.

Goldstein, M. A., Hotchkiss, E. S., & Sirri, E. R. (2006). Transparency and liquidity: A controlled experiment on corporate bonds. *Review of Financial Studies*, *20*(2), 235–273.

Goyenko, R. Y., & Ukhov, A. D. (2009). Stock and bond market liquidity: A long-run empirical analysis. *Journal of Financial and Quantitative Analysis*, *44*(1), 189–212.

Harris, L., & Gurel, E. (1986). Price and volume effects associated with changes in the S&P 500 list: New evidence for the existence of price pressures. *The Journal of Finance*, *41*(4), 815.

Hendershott, T., & Madhavan, A. (2015). Click or call? auction versus search in the over-the-counter market. *The Journal of Finance*, *70*(1), 419–447.

Hendershott, T., Li, D., Livdan, D., & Schurhoff, N. (2019). Relationship trading in over-the-counter markets. *The Journal of Finance*, *75*(2), 683–734.

Heng, Z. Y., & Leung, H. (2023). The role of option-based information on Stocktwits, options trading volume, and stock returns. *Journal of Futures Markets*, *43*(8), 1091–1125.

Holden, C. W., Mao, Y., & Nam, J. (2018). Price discovery in the stock, OTC corporate bond, and NYSE Corporate Bond Markets. *SSRN Electronic Journal*.

Ingersoll, J. (1977b). An examination of corporate call policies on convertible securities. *The Journal of Finance*, *32*(2), 463–478.

Mohil, S., Nayyar, R., & Patro, A. (2020). When is informed trading more prevalent?—an examination of options trading around Indian M&A announcements. *Journal of Futures Markets*, *40*(6), 1011–1029.

O'Hara, M., & Alex Zhou, X. (2021). The electronic evolution of corporate bond dealers. *Journal of Financial Economics*, *140*(2), 368–390.

Pan, J., & Poteshman, A. M. (2006). The information in option volume for future stock prices. *Review of Financial Studies*, *19*(3), 871–908. https://doi.org/10.1093/rfs/hhj024

Ronen, T., & Zhou, X. (2013). Trade and information in the corporate bond market. *Journal of Financial Markets*, *16*(1), 61–103.

Tolikas, K. (2018). The lead-lag relation between the stock and the bond markets. *The European Journal of Finance*, *24*(10), 849–866. https://doi.org/10.1080/1351847x.2017.1340320

Underwood, S. (2009). The cross-market information content of stock and bond order flow. *Journal of Financial Markets*, *12*(2), 268–289.

Van Kervel, V., & Menkveld, A. J. (2019). High-frequency trading around large institutional orders. *The Journal of Finance*, *74*(3), 1091–1137.

APPENDIX

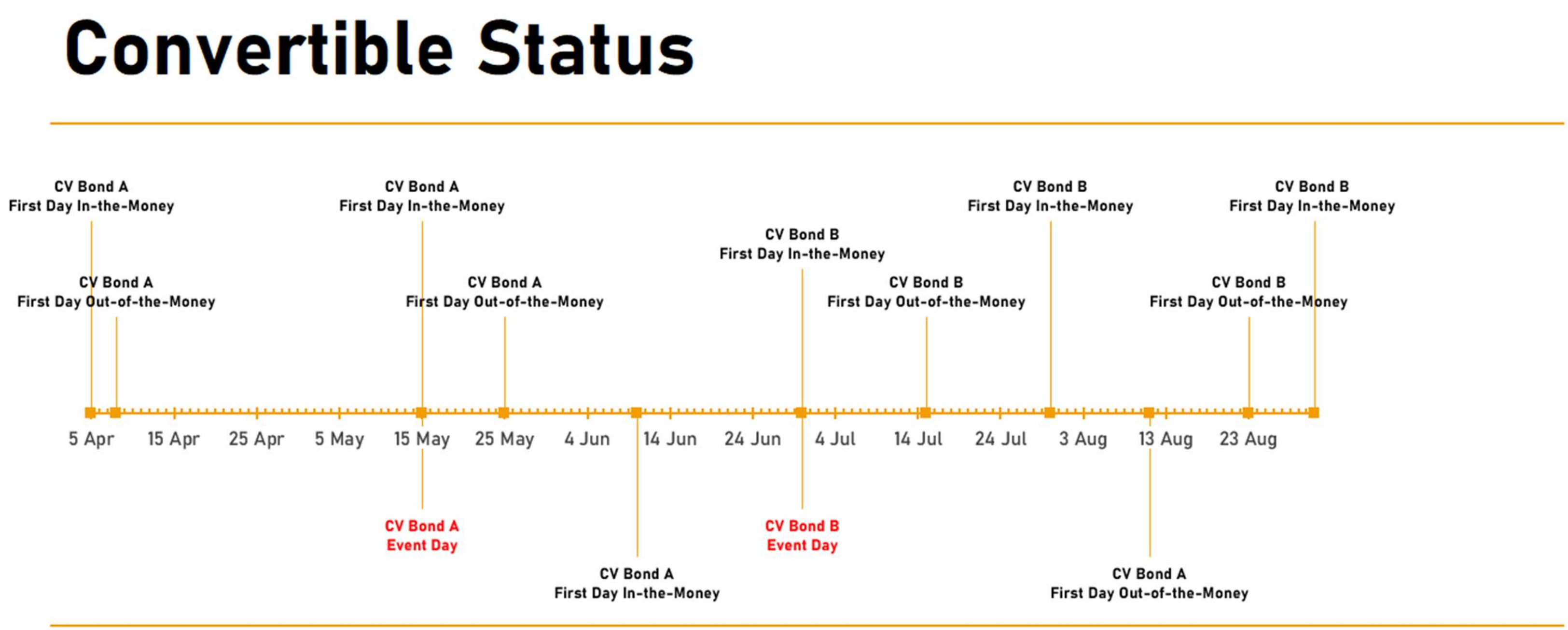
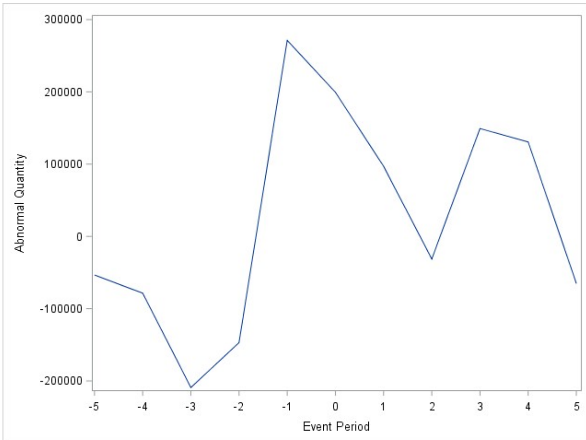


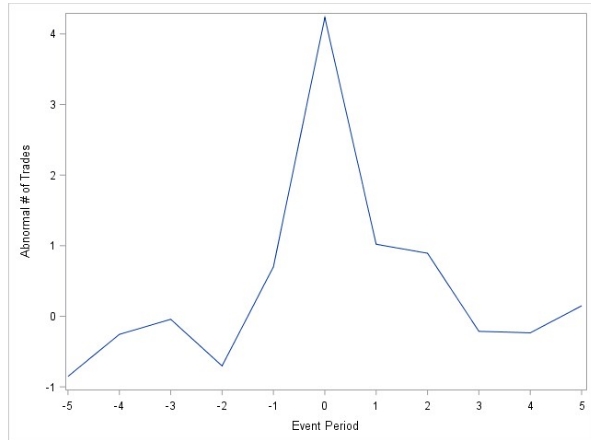
Figure 1: Timeline of Convertible Status

This figure depicts what event window is used when convertible bonds go in- and out-of-the-money throughout the sample period. CV Bond A is a hypothetical convertible bond named A and CV Bond B is a hypothetical convertible bond named B. Event Day denotes the first day the convertible bond goes in-the-money and stays in-the-money for at least 5 days.

Panel A: Abnormal Quantity



Panel B: Abnormal Number of Trades



Panel C: Abnormal Volume

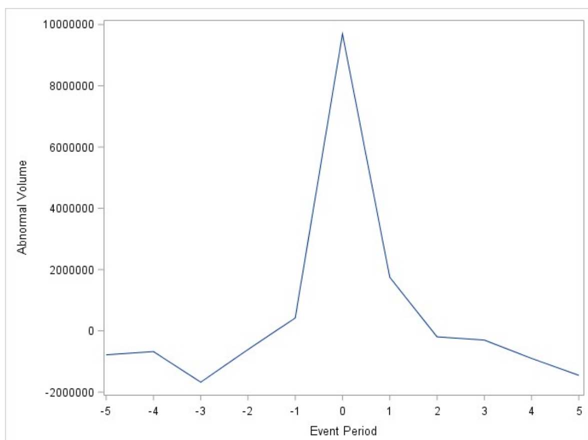


Figure 2: Trading measures of in-the-money convertible bonds

This figure graphs the abnormal quantity traded (Panel A), abnormal number of trades (Panel B), and abnormal trading volume (Panel C) of convertible bonds that went in-the-money between the event window of [-5, +5].

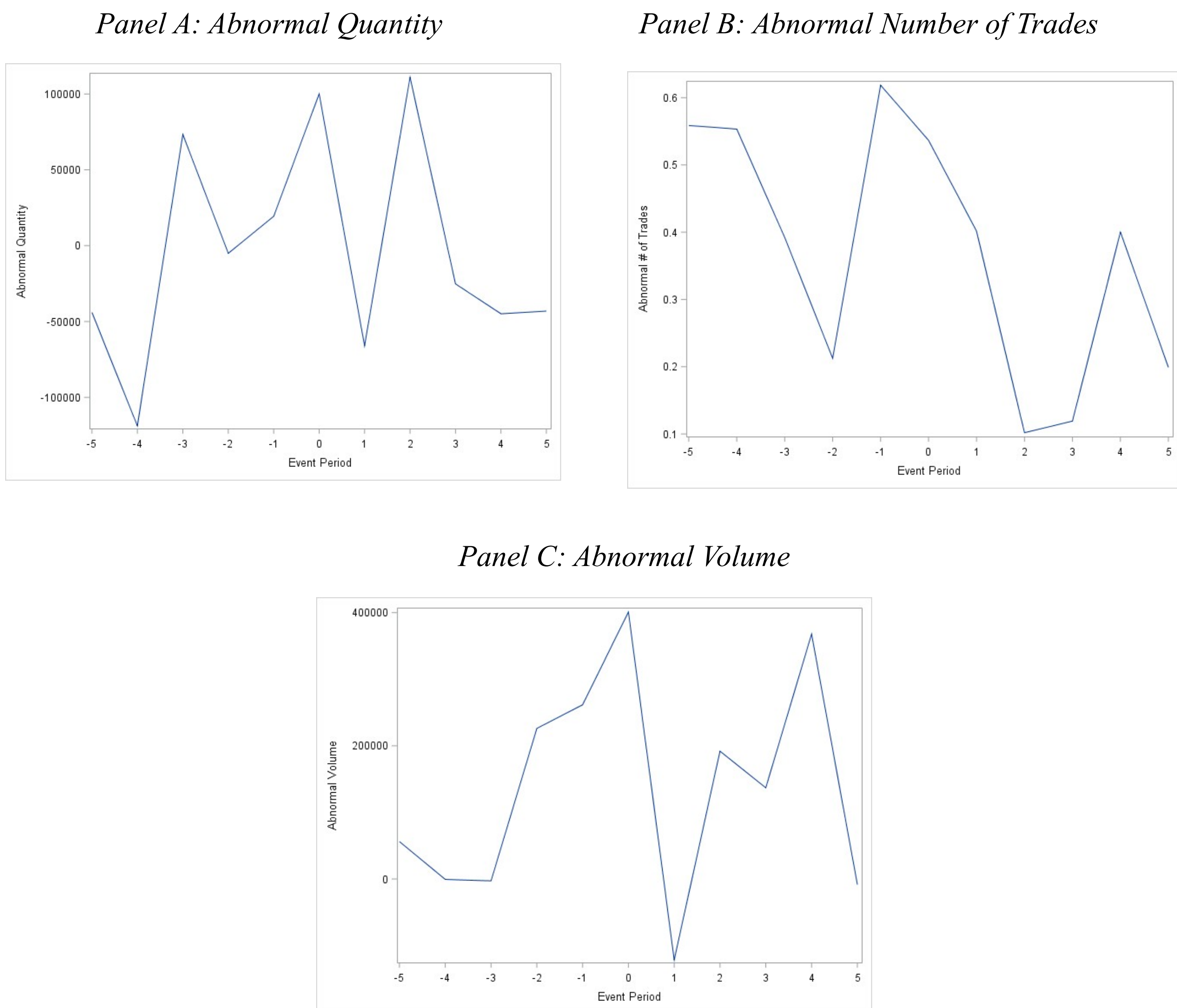
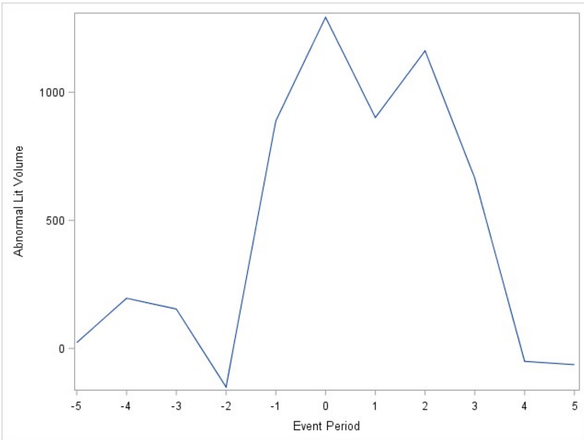


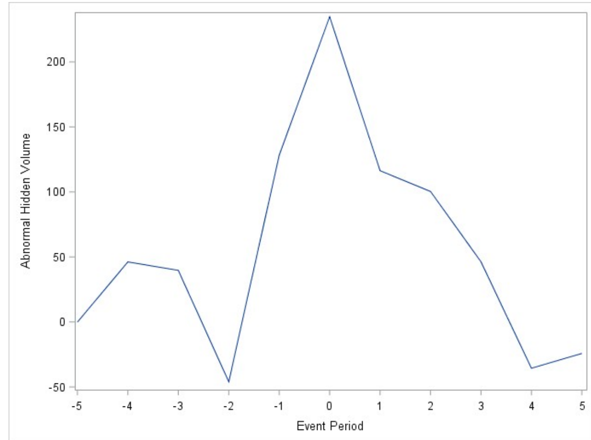
Figure 3: Trading measures of non-convertible bonds

This figure graphs the abnormal quantity traded (Panel A), abnormal number of trades (Panel B), and abnormal trading volume (Panel C) of non-convertible bonds of firms with in-the-money convertible bonds (spillover effects) during the event window of [-5, +5].

Panel A: Abnormal Lit Volume



Panel B: Abnormal Hidden Volume



Panel C: Abnormal Canceled Trades

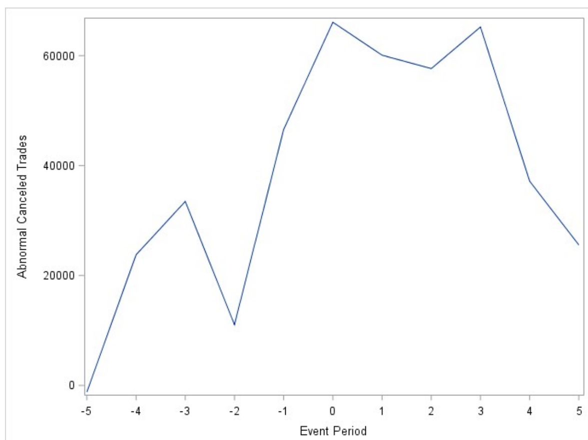


Figure 4: Trading measures of equity market

This figure graphs the abnormal lit volume (Panel A), abnormal hidden volume (Panel B), and abnormal canceled trades (Panel C) of the equity trading of firms with convertible bonds that went in-the-money during the event window of [-5, +5].

Table 1: Sample Selection

This table reports the sample selection process.

	No. of Bonds
After Standard TRACE Filters	4,163
Sample from Bloomberg	582
Matched in TRACE and Bloomberg	298
Less Than 10 Trades	7
Did Not Stayed In-the-Money for at Least 5 Days	148
No Full Estimation Window	96
Total Bonds	47

Table 2: Descriptive Statistics

This table reports the descriptive statistics for convertible bonds that became in-the-money between January 2015 to December 2022 over the [-5, +5] event window. Number of trades is the daily average number of trades. Trade size is the average daily quantity traded. Trade volume is the product of the daily average number of trades and the average daily trade size. Years to maturity is the difference between the event year and the maturity year. The issue amount is the bond issuance amount in thousands. Price is the issuing firm's closing stock price from CRSP. Sales is the annual sales amount (in millions) sourced from Compustat. Firm size is calculated from daily closing price and shares outstanding from CRSP. ROA is defined as operating income before depreciation over total assets. Leverage is the sum of total debt in current liabilities and total long-term debt divided by stockholders' equity.

Variable	Mean	Std. Dev.	Min	Max
Number of Trades	4.93	5.92	0.27	23.00
Volume	5,290,898	7,134,021	292,909	32,540,545
Trade Size	804,378	494,346	136,909	2,080,197
Years to Maturity	4.80	1.41	3.00	10.00
Issue Amount ('000)	412,347	244,926	115,500	1,150,000
Stock Price	63.91	63.62	4.73	289.47
Sale	2,286.78	3,573.00	36.91	17,337.00
Firm Size	6,310,700	7,956,083	826,879	39,210,799
ROA	-0.07	0.19	-0.53	0.47
Leverage	0.50	3.53	-12.80	10.62
Observations	41			

Table 3: Number of Times a Convertible Bond went In-the-Money

This table reports the number of times a convertible bond went in-the-money during the sample period of January 2015 to December 2022.

Frequency	No. of Bonds
1	5
2	4
3	3
4	3
5	3
6	4
7	8
8	5
9	1
11	2
12	1
13	2
14	1
15	1
19	1
21	1
23	2
Total	47

Table 4: Month of Occurrence

This table reports the number of convertible bonds that went in-the-money in each month during the sample period of January 2015 to December 2022.

Month	No. of Bonds
January	4
February	1
March	2
April	4
May	1
June	2
July	8
August	3
September	2
October	6
November	9
December	5
Total	47

Table 5: Types of Information Event

This table reports the types of information event that resulted in a convertible bond to be in-the-money. Earnings Announcements include news related to quarterly earnings announcements, earnings estimates from the firm or analysts, or news regarding when the firm is set to announce earnings. Macroeconomic news include news related to how the overall economy is related to the firm's operations. Firm-specific news include news related to mergers and acquisitions, partnerships, patent issuances, government contracts, CEO turnover, new product releases, etc. Analyst forecasts include news regarding analyst upgrades of stock price targets, earnings targets, EPS targets, or future forecasts. Unknown include firms with no tangible news that might affect stock price.

	No. of Bonds
Earnings Announcements	7
Macroeconomic News	1
Firm-Specific News	20
Analyst Forecasts	18
Unknown	1
Total	47

Table 6: Event Study of Trading Metrics

This table presents results from an 11-day event study around in-the-money convertible bonds. Column (1) reports the results for abnormal trading quantity. Column (2) reports the results for abnormal number of trades. Column (3) reports the results for abnormal trading volume. The abnormal measures are computed by taking the daily measures minus the estimation window daily average, where the estimation window is measured from the preceding 25 trading days [-30, -6]. The *t*-tests test whether the abnormal trading measures are significantly different from zero. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Quantity	Abnormal Trades	Abnormal Volume
	(1)	(2)	(3)
t-5	-53,370.75	-0.85	-782,045.96
t-4	-78,552.08	-0.26	-676,897.02
t-3	-209,085.35	-0.04	-1,677,088.51*
t-2	-146,871.12	-0.70	-609,662.98
t-1	271,171.61	0.70	420,464.68
Day 0	199,421.13	4.23***	9,693,890.21**
t+1	96,976.25	1.02	1,746,911.49
t+2	-31,300.32	0.89	-196,705.53
t+3	149,227.28	-0.21	-301,024.68
t+4	130,703.30	-0.23	-900,918.30
t+5	-65,193.76	0.15	-1,452,024.68

Table 7: OLS Regression of Trading Metrics

This table reports the regression results. The dependent variables are the abnormal trading measures. Seven dummy variables are included to capture the seven days around the event day. Other independent variables include the log of bond issue amount, log of annual sales, log of firm size, ROA, leverage, years to maturity, and a buy/sell indicator (1+side log-transformed) representing the side of a trade where side is +1 for buys, -1 for sells, and 0 for no trade. The t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1) Abnormal Quantity	(2) Abnormal Trades	(3) Abnormal Volume
$Event_{t-3}$	-219,518.21	0.29	-770,946.79
	(-1.07)	(0.31)	(-0.42)
$Event_{t-2}$	-121,657.11	-0.31	509,811.47
	(-0.59)	(-0.33)	(0.27)
$Event_{t-1}$	321,243.41	1.20	1,711,861.18
	(1.57)	(1.30)	(0.93)
Event Day	177,232.04	4.77***	11,105,857.55***
	(0.88)	(5.21)	(6.10)
$Event_{t+1}$	92,823.48	1.27	2,467,957.28
	(0.47)	(1.41)	(1.37)
$Event_{t+2}$	-40,515.68	1.04	375,325.84
	(-0.20)	(1.13)	(0.20)
$Event_{t+3}$	124,434.91	0.10	503,968.17
	(0.61)	(0.11)	(0.27)
Issue Amount	-311,919.66*	-0.01	-1,449,401.61
	(-1.82)	(-0.01)	(-0.94)
Sale	47,459.99	0.72***	1,643,292.77***
	(0.81)	(2.73)	(3.12)
Firm Size	144,511.18	-0.16	558,269.85
	(1.57)	(-0.38)	(0.67)
ROA	-464,004.55	-2.83**	-4,878,195.73*
	(-1.47)	(-1.97)	(-1.71)
Leverage	18,427.93	-0.01	169,945.71
	(0.90)	(-0.14)	(0.92)
Years to Maturity	-82,786.10*	0.16	-320,803.41
	(-1.84)	(0.79)	(-0.79)
Buy/Sell Side	-136,037.80	-2.33***	-3,872,864.46**
	(-0.74)	(-2.80)	(-2.33)
Constant	1,856,276.66	-3.32	-291,108.42
	(1.35)	(-0.53)	(-0.02)
Observations	480	480	480
R-squared	0.04	0.10	0.12

Table 8: Descriptive Statistics – Spillover Effects

This table reports the descriptive statistics for the non-convertible bonds of firms with convertible bonds that became in-the-money between January 2015 to December 2022 over the [-5, +5] event window. Number of trades is the daily average number of trades. Trade size is the average daily quantity traded. Trade volume is the product of the daily average number of trades and the average daily trade size. Years to maturity is the difference between the event year and the maturity year. Price is the issuing firm's closing stock price from CRSP. Sales is the annual sales amount (in millions) sourced from Compustat. Firm size is calculated from daily closing price and shares outstanding from CRSP. ROA is defined as operating income before depreciation over total assets. Leverage is the sum of total debt in current liabilities and total long-term debt divided by stockholders' equity.

Variable	Mean	Std. Dev.	Min	Max
Number of Trades	1.3262	3.6117	0	12.0909
Volume	802,521.51	2,280,952.6	0	8,443,754.5
Quantity	53,756.611	127,210.69	0	384,601.28
Years to Maturity	2.419	2.0114	1	6.6667
Stock Price	54.4119	42.4398	6.3882	125.2945
Sale	2,536.9619	4,036.5826	252.002	17337
Size	6,228,203.3	7,142,077.7	826,878.58	23,842,534
ROA	-0.0508	.2203	-0.4891	0.4689
Leverage	-0.3989	4.7613	-12.8044	10.6245
Observations	18			

Table 9: Event Study – Spillover Effects

This table presents results from an 11-day event study around the non-convertible bonds of firms with in-the-money convertible bonds. Column (1) reports the results for abnormal trading quantity. Column (2) reports the results for abnormal number of trades. Column (3) reports the results for abnormal trading volume. The abnormal measures are computed by taking the daily measures minus the estimation window daily average, where the estimation window is measured from the preceding 25 trading days [-30, -6]. The *t*-tests test whether the abnormal trading measures are significantly different from zero. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Quantity (1)	Abnormal Trades (2)	Abnormal Volume (3)
t-5	-43,995.97	-0.19	295,241.14
t-4	-118,852.37***	0.30	-606,658.68**
t-3	73,341.25	-0.06	-53,491.52
t-2	-5,053.18	0.28	-174,157.45
t-1	19,350.19	1.30*	426,451.41
Day 0	100,097.39	1.27**	2,036,901.14
t+1	-66,022.48	-0.58**	-398,482.38**
t+2	111,091.90	0.89**	652,125.13
t+3	-25,186.75	-0.15	-336,236.94
t+4	-44,894.14	-0.28	14,401.87
t+5	-43,120.93	0.05	-422,874.92

Table 10: OLS Regression – Spillover Effects

This table reports the regression results testing spillover effects on the trading of non-convertible bonds from firms with in-the-money convertible bonds. The dependent variables are the abnormal trading measures. Seven dummy variables are included to capture the seven days around the event day. Other independent variables include log of annual sales, log of firm size, ROA, leverage, years to maturity, and a buy/sell indicator (1+side log-transformed) representing the side of a trade where side is +1 for buys, -1 for sells, and 0 for no trade. The t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1) Abnormal Quantity	(2) Abnormal Trades	(3) Abnormal Volume
$Event_{t-3}$	99,982.88	-0.05	106,874.76
	(1.08)	(-0.08)	(0.13)
$Event_{t-2}$	45,825.49	0.38	-30,980.84
	(0.50)	(0.59)	(-0.04)
$Event_{t-1}$	70,399.02	1.31**	568,820.48
	(0.77)	(2.02)	(0.72)
Event Day	166,319.16*	1.27*	2,225,700.82***
	(1.82)	(1.95)	(2.82)
$Event_{t+1}$	-1,842.34	-0.60	-297,437.28
	(-0.02)	(-0.92)	(-0.37)
$Event_{t+2}$	130,057.52	0.85	672,739.06
	(1.42)	(1.30)	(0.85)
$Event_{t+3}$	30,796.24	-0.18	-234,792.44
	(0.34)	(-0.27)	(-0.30)
Sale	-23,954.07	-0.08	-185,911.27
	(-0.79)	(-0.38)	(-0.71)
Firm Size	24,057.47	0.16	566,698.57
	(0.56)	(0.52)	(1.54)
ROA	-162,211.84	-2.71*	-3,480,564.20*
	(-0.73)	(-1.72)	(-1.81)
Leverage	2,991.73	0.03	177,689.24**
	(0.36)	(0.49)	(2.47)
Years to Maturity	6,837.23	0.04	92,649.97
	(0.90)	(0.67)	(1.41)
Buy/Sell Side	-231,489.76	-1.11	-2,002,831.98
	(-1.46)	(-0.99)	(-1.46)
Constant	-261,154.39	-2.08	-7,476,310.62
	(-0.45)	(-0.50)	(-1.48)
Observations	789	789	789
R-squared	0.0118	0.0200	0.0312

Table 11: Descriptive Statistics – Equity Market

This table reports the descriptive statistics in the equity market for firms with convertible bonds that became in-the-money between January 2015 to December 2022 over the [-5, +5] event window. Price is the closing price from CRSP. Sales is the annual sales amount (in millions) sourced from Compustat. Firm size is calculated from daily closing price and shares outstanding from CRSP. ROA is defined as operating income before depreciation over total assets. Leverage is the sum of total debt in current liabilities and total long-term debt divided by stockholders' equity. Total Volume ('000) and Total Trades are calculated as the sum of lit and hidden volume and lit and hidden trades, respectively, from MIDAS.

Variable	Mean	Std. Dev.	Min	Max
Price	63.92	63.62	4.73	289.47
Sale (millions)	2,286.78	3,573.00	36.91	17,337.00
Firm Size	6,310.95	7,955.94	826.88	39,210.80
ROA	-0.07	0.19	-0.53	0.47
Leverage	0.50	3.53	-12.80	10.62
Total Volume ('000)	1,956.8194	5,641.8529	18.9544	32,874.451
Total Trades	12,309.87	17,581.798	1,368.88	105,907.04
Canceled Trades	142,530.18	186,476.47	20,959.68	1,122,612.00
Observations	41			

Table 12: Event Study – Equity Market

This table presents results from an 11-day event study on equity trading of firms with convertible bonds that went in-the-money during the sample period. Column (1) reports the results for abnormal total volume (in '000). Column (2) reports the results for abnormal total trades. Column (3) reports the results for abnormal lit volume (in '000). Column (4) reports the results for abnormal lit trades. Column (5) reports the results for abnormal hidden volume (in '000). Column (6) reports the results for abnormal hidden trades. Column (7) reports the results for abnormal canceled trades. The abnormal measures are computed by taking the daily measures minus the estimation window daily average, where the estimation window is measured from the preceding 25 trading days [-30, -6]. The *t*-tests test whether the abnormal trading measures are significantly different from zero. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Total Volume (1)	Abnormal Total Trades (2)	Abnormal Lit Volume (3)	Abnormal Lit Trades (4)	Abnormal Hidden Volume (5)	Abnormal Hidden Trades (6)	Abnormal Canceled Trades (7)
t-5	22.77	-60.20	22.85	12.47	-0.08	-72.67	-1,201.19
t-4	241.92*	3,591.69*	195.73**	2,538.93**	46.19	1,052.76	23,762.48*
t-3	193.29	3,679.17**	153.64	2,690.34**	39.66	988.83	33,483.63***
t-2	-196.77	944.30	-150.81	861.71	-45.96	82.59	11,056.96
t-1	1,016.42	4,652.19	888.19	3,730.34	128.23	921.85	46,579.05
Day 0	1,527.51*	9,324.30***	1,292.78*	6,860.19***	234.73**	2,464.11***	66,075.46***
t+1	1,017.42*	5,801.84**	901.09*	4,604.27*	116.33**	1,197.56**	60,082.31*
t+2	1,262.15	5,849.08**	1,161.82	4,833.91*	100.33	1,015.17**	57,645.05**
t+3	709.84*	4,810.45*	663.56*	4,126.82*	46.28	683.63*	65,212.68*
t+4	-86.19	1,540.40	-50.60	1,290.14*	-35.59	250.26	37,143.66**
t+5	-87.79	1,204.99	-63.60	1,053.77	-24.19	151.22	25,553.46

Table 13: OLS Regression – Equity Market

This table presents the regression results in the equity market for firms with convertible bonds that went in-the-money during the sample period. Column (1) reports the results for abnormal total volume. Column (2) reports the results for abnormal total trades. Column (3) reports the results for abnormal lit volume. Column (4) reports the results for abnormal lit trades. Column (5) reports the results for abnormal hidden volume. Column (6) reports the results for abnormal hidden trades. Column (7) reports the results for abnormal canceled trades. The abnormal measures are computed by taking the daily measures minus the estimation window daily average, where the estimation window is measured from the preceding 25 trading days [-30, -6]. The t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Total Volume (1)	Abnormal Total Trades (2)	Abnormal Lit Volume (3)	Abnormal Lit Trades (4)	Abnormal Hidden Volume (5)	Abnormal Hidden Trades (6)	Abnormal Canceled Trades (7)
$Event_{t-3}$	166.75	2,175.08	122.48	1,486.07	44.27	689.02	12,131.09
	(0.29)	(0.92)	(0.24)	(0.78)	(0.60)	(1.17)	(0.50)
$Event_{t-2}$	-224.20	-617.08	-180.81	-358.75	-43.39	-258.33	-10,436.31
	(-0.38)	(-0.26)	(-0.35)	(-0.19)	(-0.59)	(-0.44)	(-0.43)
$Event_{t-1}$	1,019.05*	3,159.97	884.70*	2,574.81	134.35*	585.16	25,938.96
	(1.75)	(1.33)	(1.70)	(1.36)	(1.83)	(0.99)	(1.06)
Event Day	1,534.12***	7,752.46***	1,294.21**	5,655.93***	239.91***	2,096.53***	45,267.67*
	(2.63)	(3.26)	(2.49)	(2.98)	(3.26)	(3.56)	(1.85)
$Event_{t+1}$	1,018.65*	4,194.13*	899.27*	3,396.85*	119.38	797.29	39,540.62
	(1.74)	(1.77)	(1.73)	(1.79)	(1.62)	(1.35)	(1.62)
$Event_{t+2}$	1,268.53**	4,279.56*	1,165.39**	3,655.50*	103.14	624.07	37,086.83
	(2.17)	(1.80)	(2.24)	(1.92)	(1.40)	(1.06)	(1.52)
$Event_{t+3}$	710.95	3,214.66	663.00	2,937.92	47.95	276.74	45,088.26*
	(1.22)	(1.35)	(1.27)	(1.55)	(0.65)	(0.47)	(1.84)
Price	-6.98**	0.40	-6.98**	-10.22	-0.00	10.62***	-145.67
	(-2.24)	(0.03)	(-2.52)	(-1.01)	(-0.01)	(3.38)	(-1.12)
Sale	340.09**	3,032.01***	321.91**	2,593.89***	18.18	438.13***	39,842.62***
	(2.03)	(4.45)	(2.16)	(4.77)	(0.86)	(2.60)	(5.69)
Firm Size	287.61	1,185.26	256.52	935.31	31.10	249.94	6,319.43
	(1.27)	(1.28)	(1.27)	(1.27)	(1.09)	(1.09)	(0.66)
ROA	-1,140.86	-13,630.65***	-969.06	-10,794.03***	-171.79	-2,836.62***	-121,102.75***
	(-1.24)	(-3.64)	(-1.18)	(-3.60)	(-1.48)	(-3.05)	(-3.14)
Leverage	48.05	-93.81	42.09	-96.06	5.97	2.24	-1,841.19
	(0.93)	(-0.45)	(0.91)	(-0.57)	(0.92)	(0.04)	(-0.85)
Constant	-6,324.21**	-38,405.57***	-5,705.96**	-30,971.83***	-618.25	-7,433.74**	-347,527.63***
	(-2.10)	(-3.14)	(-2.13)	(-3.16)	(-1.63)	(-2.45)	(-2.76)
Observations	495	495	495	495	495	495	495
R-squared	0.06	0.11	0.06	0.11	0.04	0.11	0.12

Table 14: Descriptive Statistics – Covid Period

This table reports the descriptive statistics of convertible bonds around the Covid period of February 28, 2020 to March 20, 2020. Number of trades is the daily average number of trades. Trade size is the average daily quantity traded. Trade volume is the product of the daily average number of trades and the average daily trade size. Years to maturity is the difference between the event year and the maturity year. The issue amount is the size of the bond issue (in thousands). Price is the issuing firm's closing stock price from CRSP. Sales is the annual sales amount (in millions) sourced from Compustat. Firm size is calculated from daily closing price and shares outstanding from CRSP (in thousands). ROA is defined as operating income before depreciation over total assets. Leverage is the sum of total debt in current liabilities and total long-term debt divided by stockholders' equity.

Variable	Mean	Std. Dev.	Min	Max
Number of Trades	5.38	5.80	0	25.98
Volume	5,940,781	10,364,957	0	68,392,260
Quantity	759,827	517,116.39	0	2,392,231.8
Years to Maturity	4.43	0.86	3.00	6.00
Issue Amount ('000)	495,866	449,512	69,000	2,000,000
Price	80.37	114.00	1.60	654.41
Sale	3,634.43	6,452.99	55.83	31,536.00
Size ('000)	10,883.86	21,274.61	306.92	119,495.17
ROA	-0.07	0.22	-0.76	0.28
Leverage	0.70	1.39	-3.45	4.04
Observations	48			

Table 15: Trading Activity around Covid Period

This table reports the regression results of trading activity around the market uncertainty period surrounding Covid-19. Covid is a dummy variable equal to 1 from February 24, 2020 to March 20, 2020 and 0 for the [-30, -1] window prior to February 24, 2020. Independent variables include the log of annual sales, log of firm size, ROA, leverage, years to maturity, and a buy/sell indicator (1+side log-transformed) representing the side of a trade where side is +1 for buys, -1 for sells, and 0 for no trade. The t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

	Quantity Traded	Quantity Traded	Number of Trades	Number of Trades	Volume	Volume
	(1)	(2)	(3)	(4)	(5)	(6)
Covid	287,258.26***	386,886.64***	-0.17	0.51	701,045.82	1,362,694.56
	(3.50)	(3.12)	(-0.44)	(0.93)	(1.07)	(1.41)
Sales		27,213.75		0.82***		2,546,257.59***
		(0.40)		(2.73)		(4.81)
Firm Size		200,952.84***		2.28***		3,127,778.67***
		(3.31)		(8.58)		(6.64)
ROA		78,151.94		-1.56		-9,662,387.57***
		(0.19)		(-0.88)		(-3.07)
Leverage		-57,932.92		-0.06		-453,409.29
		(-1.38)		(-0.32)		(-1.39)
Years to Maturity		16,058.50		-0.12		-524,727.06
		(0.32)		(-0.53)		(-1.33)
Buy/Sell Side		-157,172.95		-9.97***		-4,804,786.34***
		(-0.81)		(-11.66)		(-3.18)
Constant	614,632.68***	-2,516,916.50***	4.20***	-34.21***	4,861,210.05***	-56,772,193.62***
	(11.85)	(-3.36)	(17.22)	(-10.40)	(11.73)	(-9.76)
Observations	3,150	1,951	3,150	1,951	3,150	1,951
R-squared	0.0005	0.0196	0.0001	0.1599	0.0004	0.1031

VITA

Cindy Pan

Education

University of Mississippi Oxford, MS

Ph.D. in Finance *2020 - 2024 (Expected)*

University of Mississippi Oxford, MS

Master of Business Administration *2019 - 2020*

University of Mississippi Oxford, MS

Bachelor of Business Administration in Finance and Banking and Finance *2017 - 2019*

Research Interests

Market Microstructure, Bond Trading, Corporate Finance, Security Trading

Working Papers

“Hidden Liquidity Puzzle: Bond ETFs versus Stock ETFs” (*Job Market Paper*)
Presentations: SFA 2023, EFA 2024

“Corporate Bond Trading around Unscheduled Corporate Events”

Presentation: EFA 2024

“Convertible Bond Trading”

“Re-Exploring the Bond and Equity ETF Hidden Liquidity Puzzle: An Intraday Analysis”

Teaching Experience

Course Instructor

University of Mississippi

- FIN 331: Business Finance I
  - Spring 2024
  - Fall 2023 (3.84/5.00)
  - Fall 2022 (3.80/5.00)
  - Summer 2022 (4.33/5.00)
- FIN 338: Intermediate Financial Management
  - Summer 2023 (5.00/5.00)

Teaching Assistant

University of Mississippi

- FIN 533: Security Analysis and Portfolio Management (Fall 2020, Spring 2020, Fall 2021)
- FIN 338: Intermediate Financial Management (Fall 2021, Spring 2022, Fall 2022, Spring 2023, Fall 2023, Spring 2024)
- FIN 461: Financial Statement Analysis (Fall 2023, Spring 2024)
- GB 330: Essentials of Finance (Fall 2022, Spring 2023, Fall 2023, Spring 2024)

Professional Service

Referee:

Journal of Banking and Finance 2022, 2023, 2024

Discussant:

FMA 2023, SFA 2023, EFA 2024

Experience

The Financial Review

Assistant to the Editors Nov. 2021 – Apr. 2024

The University of Mississippi, School of Business Administration

Doctoral Graduate Assistant Aug. 2020 – May 2024