The Growing Index Effect in the Corporate Bond Market [*]

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Abstract

The rapid expansion of investment funds in the corporate bond market has significantly increased index-driven bond trading. Leveraging data on actual transactions and high-frequency, minute-by-minute bond price estimates generated by machine learning algorithms, we show that this shift has fundamentally reshaped trading dynamics and liquidity conditions. Whereas bond trading was historically distributed more evenly throughout the day, it is now increasingly concentrated around specific time points, particularly index closing times. Using the Bloomberg Index closing time shift on January 14, 2021, we establish the causal effect of index tracking on bond trading and liquidity. While liquidity during other periods of the trading day has declined, liquidity at index closing time has improved, resulting in a net positive effect. However, during periods of market stress, when trading becomes one-sided, this concentration of activity diminishes the benefits of indexing and leads to higher liquidity costs.

JEL classification: G10, G11, G12, G23.

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I. Introduction

Since the Global Financial Crisis, investment funds have grown into major players in the corporate bond market. By 2024, mutual funds and exchange-traded funds (ETFs) collectively hold over 20% of the total outstanding corporate bonds (Figure 1). Unlike traditional investors such as insurance companies and pension funds, which typically follow long-term buy-and-hold strategies, investment funds operate under different constraints and employ distinct investment approaches, making them more sensitive to daily or even intraday fluctuations in bond prices. These unique characteristics, combined with their growing market presence, can exert significant influence on the dynamics of the corporate bond market.

In this paper, we examine the growing adoption of indexing as a strategy by investment funds and its impact on trading dynamics and market liquidity. In the corporate bond market, an increasing number of investment funds, including index funds and ETFs, are explicitly designed to track specific bond indices and prioritize minimizing tracking errors on a daily basis. Since these indices typically close daily pricing of corporate bonds in their constituents at predetermined times (e.g., 3:00 PM or 4:00 PM),[1] index tracking has led to heightened trading demand for constituent bonds at these specific points in time. How has the market adapted to this shift in trading demand, and how have broader market conditions influenced this evolution? More broadly, what are the implications for corporate bond market liquidity?

We analyze corporate bond indices provided by Bloomberg and leverage data from actual transactions along with high-frequency, minute-by-minute bond price estimates generated by machine learning algorithms to investigate these questions. Bloomberg is a leading index provider in the bond market, with more than 70% of passive bond funds tracking its indices in terms of total assets under management (AUM) as of 2023 (Figure 2). During the early years of our sample period, trading in investment-grade (IG) bonds eligible for Bloomberg indices (and their predecessors) was relatively evenly distributed throughout the trading day. However, as index tracking became more widely adopted in bond investments, trading activity gradually concentrated around the time when bond indices close. In 2023, over 8% of daily trading volume was executed within the one minute following the index closing time.

[1] All time points referenced in this paper are based on Eastern Standard Time unless otherwise noted.

While other structural changes in the corporate bond market, such as the increasing use of delayed Treasury spotting, have contributed to some degree of trade clustering, we find that index tracking is the primary driver of this phenomenon. On January 14, 2021, Bloomberg shifted the closing time for its bond indices from 3:00 PM to 4:00 PM, leading to an immediate migration of trades from 3:00 PM to 4:00 PM. Our analysis provides further causal evidence that index tracking drives bond trade clustering. We find that the clustering effect is notably absent in index-ineligible IG bonds and high-yield (HY) bonds, where passive funds have a much smaller market presence (Bretscher, Schmid, and Ye, 2023). Additionally, when a bond exits the index, trade clustering declines significantly, further reinforcing the role of index tracking in shaping corporate bond trading patterns.

Market conditions play a critical role in amplifying index-tracking-induced trade clustering. During periods when passive bond mutual funds and ETFs experience extreme flows, imbalanced demand from these vehicles leads to more pronounced clustering of trades around index closing time. The trade clustering around index-closing time is also more severe during periods of market stress, such as the COVID-19 bond market liquidity crisis and spikes in the VIX index, when passive investors are more likely to trade in the same direction.

Trade clustering has enhanced liquidity around index-closing time compared to other periods of the trading day. Using both actual transaction prices and machine-learning-based price estimates, we construct two alternative measures of trade-level transaction costs for customer trades. Compared to other periods during the day, transaction costs at index-closing time decrease significantly, ranging from 17% to 32% of the average transaction cost in our sample.

To establish the causal impact on liquidity, we again leverage the 2021 change in pricing convention by Bloomberg Indices. Specifically, we compare transaction costs during the five-minute window following index closing time to those observed at other times of the day and analyze how these differences evolved when Bloomberg shifted its bond index closing time from 3:00 PM to 4:00 PM. After this shift, transaction costs at the new closing time (4:00 PM) decreased, while those at the previous closing time (3:00 PM) rose, providing further evidence for the role of index tracking in shaping liquidity conditions.

What drives the liquidity benefits of trade clustering induced by index tracking? One possible explanation is that trade clustering enhances the matching of customer buy and sell orders, reducing market frictions. This, in turn, lowers search costs, mitigates dealer inventory risks, and reduces transaction costs for customers. Indeed, our findings show that following the closing time shift, the volume of inter-dealer trades, which dealers use to manage inventory imbalances from customer transactions, declined at the new closing time while increasing at the old closing time. This shift suggests that the improved matching of trades at the new index close reduced the need for liquidity provision facilitated by interdealer trading.

One could argue that the lower transaction costs observed at index closing time can be attributed to the increasing use of portfolio trading. In the corporate bond market, portfolio trading is more likely to occur around index closing, as funds rebalance their portfolios to closely align with their benchmark indices. This creates increased demand for large, coordinated trades, making portfolio trading an efficient execution method. Li, O'Hara, Rapp, and Zhou (2025) find that transaction costs for portfolio trades tend to be lower, as these trades are more diversified and easier for dealers to hedge. While portfolio trading undoubtedly contributes to the lower transaction costs at index closing, our findings suggest that the liquidity benefits of trade clustering extend beyond portfolio trades. Even after excluding portfolio trades using a conservative identification algorithm, the liquidity advantage of trade clustering remains, with only a slight reduction in magnitude.

Another possible explanation for lower transaction costs at index closing is the lower information asymmetry associated with trading at that time. Since a large share of trading around index close is conducted by passive investment funds, the risk of informed trading in a single bond may be reduced, potentially leading to lower transaction costs. However, our results provide little support for this hypothesis. In fact, the liquidity benefits of trade clustering are evident even in high-quality IG bonds (AAA or AA rated), which are unlikely to face information asymmetry. Moreover, these benefits are slightly stronger than those observed in lower-quality IG bonds (A and BBB rated).

Importantly, indexing-induced trade clustering not only redistributes liquidity within a trading day but also significantly affects overall corporate bond market liquidity. Comparing across bonds, bonds with greater trade clustering around index closing time tend to enjoy lower daily average transaction costs, despite having higher transaction costs outside index closing time. On net, index-closing trade clustering improves the overall liquidity of corporate bond trading.

Since the liquidity benefits of trade clustering at index-closing time primarily stem from offsetting diverse trading demands among customers with minimal reliance on dealer intermediation, these advantages are not consistent across all market conditions. They may be limited, or even reversed, when trading demand becomes one-sided. Indeed, our findings show that during periods of large, unbalanced bond trading, driven by substantial passive fund flows or heightened volatility (as indicated by the VIX index), the reduction in overall transaction costs diminishes significantly. During the COVID-19 pandemic, when the corporate bond market faced its first systemic shock since investment funds became major market participants, these transaction cost benefits were entirely reversed, resulting in higher transaction costs. These findings highlight the vulnerability of index-driven trade clustering under stressed market conditions.

Our paper carries important implications for financial stability. A large body of research has examined the growing role of investment funds in bond markets, particularly their potential to amplify financial system fragility.[2] These studies primarily focus on active funds, examining how they adjust their bond holdings in response to large outflows and how their liquidity management can trigger or mitigate panic-driven runs and amplify fundamental shocks. In contrast, our paper highlights the role of passive funds in shaping bond market liquidity. Although liquidity management at passive funds is generally more straightforward due to their objective of tracking bond indices, we show that, despite their passive trading approach, they can still exert significant influence on the underlying bond market. While the growth of passive investing enhances liquidity, particularly around index closing times, this improvement is not consistently robust across market conditions. During periods of market stress, when trading becomes unbalanced, index-driven trade clustering can strain liquidity and increase transaction costs.

Our paper contributes to the extensive literature on the effects of indexing and passive investment on financial markets. Prior research has examined how indexing influences asset demand and pricing dynamics.[3] More broadly, studies have explored its implications for informational efficiency (Israeli, Lee, and Sridharan 2017, Glosten, Nallareddy, and Zou 2021, Coles, Heath, and Ringgenberg 2022, Sammon 2024), volatility (Ben-David, Franzoni, and Moussawi 2018), return

[2]For example, see Chen, Goldstein, and Jiang (2010), Goldstein, Jiang, and Ng (2017), Chernenko and Sunderam (2020), Choi, Hoseinzade, Shin, and Tehranian (2020), Falato, Hortacsu, Li, and Shin (2021b), Anand, Jotikasthira, and Venkataraman (2021), Falato, Goldstein, and Hortaçsu (2021a), Haddad, Moreira, and Muir (2021), Jiang, Li, Sun, and Wang (2022), Ma, Xiao, and Zeng (2022), Chen, Du, and Sun (2024), Giannetti and Jotikasthira (2024), Giannetti, Jotikasthira, Rapp, and Waibel (2024) and Li, O'Hara, and Zhou (2024).

[3]See, for example, Shleifer (1986), Harris and Gurel (1986), Madhavan (2003), Chang, Hong, and Liskovich (2015), Baltussen, van Bekkum, and Da (2019), Greenwood and Sammon (2022), Kashyap, Kovrijnykh, Li, and Pavlova (2023), Sammon and Murray (2024), Sammon and Shim (2024),Tamburelli (2024).

comovement and systemic risk (Da and Shive 2018, Bhattacharya and O'Hara 2018, O'Hara 2020), and corporate governance (Appel, Gormley, and Keim 2016).

In the corporate bond market, several studies highlight how ETF ownership affects bond pricing and liquidity.[4] Dick-Nielsen and Rossi (2019) use index exclusions to examine periods when index trackers demand immediate execution, while Bretscher et al. (2023) show that maturity cutoffs shaping fund classifications drive passive demand shocks, influencing bond pricing and issuance. Our study extends this literature by providing a comprehensive analysis of how index tracking influences the microstructure of liquidity. Unlike prior research, which focuses on cross-bond differences driven by index investment, we examine the high-frequency trading behavior of index-tracking funds across the broader market and its implications for overall liquidity conditions.

In this regard, our study is more closely aligned with recent research on how index tracking has reshaped intraday liquidity distribution in equity markets. Jiang, Wu, and Yao (2024) find that trading by index funds has contributed to the reallocation of intraday liquidity toward market close, leading to the disappearance of the stock market's traditional U-shaped intraday trading and liquidity pattern, an effect well-documented in prior studies (see, for example, McInish and Wood 1992). Our study not only targets a different market but also diverges in several key aspects. First and foremost, the growth of index tracking in equity markets can at least be partially attributed to the increasing role of closing auctions,[5] an element absent in the corporate bond market. Instead, in the bond market, major index closing time serves as a coordination mechanism that concentrates intraday trading. This distinction allows us to leverage Bloomberg's switch in index closing time as a natural experiment to cleanly identify and quantify the impact of index tracking on bond market liquidity. Second, our results show that index tracking not only redistributes liquidity throughout the trading day but also fundamentally improves the net liquidity conditions in the corporate bond market. Finally, we highlight that this liquidity benefit is not robust across all market conditions. During periods of heightened market stress, when liquidity is most crucial, the advantages of index tracking can be entirely offset, resulting in increased liquidity costs.

The remainder of the paper is organized as follows. Section 2 provides institutional background

[4] See, for example, Holden and Nam (2017), Dannhauser (2017), Pan and Zeng (2020), Dannhauser and Hoseinzade (2022), Koont, Ma, Pástor, and Zeng (2022), Dannhauser and Dathan (2024), Marta (2024).

[5] See, for example, Comerton-Forde and Rindi (2022), Jegadeesh and Wu (2022), Bogousslavsky and Muravyev (2023).

on index tracking in the corporate bond market and details the sample construction. Section 3 examines the relationship between index tracking and trade clustering. Section 4 analyzes the impact of trade clustering on bond market liquidity, exploring its benefits, the underlying drivers, and the overall net effect on liquidity. Additionally, we assess the limitations of index-induced trade clustering. Finally, Section 5 concludes.

II. Institutional Background and Sample Construction

A. *Index Tracking in the Corporate Bond Market*

Prior to the Great Financial Crisis, investment funds were not major participants in the corporate bond market, collectively holding only about 7% of total outstanding bonds. However, this changed following the crisis. Partly due to increased regulation on banks, some activities in the corporate bond market shifted to non-bank intermediaries, including bond funds and ETFs (Falato, Goldstein, and Hortaçsu 2021a). As shown in Figure 1, the share of corporate bonds held by mutual funds and ETFs experienced rapid and substantial growth, exceeding 20% for the first time in 2019.

The increasing presence of investment funds in the corporate bond market has been especially evident for passive funds, particularly in the IG sector, where these funds aim to track specific bond indices. Bloomberg is a leading provider of bond indices, offering widely recognized benchmarks that are closely followed by passive funds. As shown in Figure 2, Bloomberg indices (previously managed by Lehman Brothers and then Barclays) has been the predominant fixed-income benchmarks. Although other index providers, such as ICE and S&P Global, have entered the market and gradually increased their market shares, Bloomberg remains the top player, with its indices followed by around 70% of passive funds in terms of AUM in 2023.

One of the most influential indices provided by Bloomberg is the Bloomberg U.S. Aggregate Bond Index ("The Agg"). Originally known as the Lehman Brothers Aggregate Bond Index, it served as the benchmark for the first bond ETF.[6] It was later renamed as the Barclays Capital Aggregate Bond Index after Barclays' acquisition of Lehman Brothers in 2008. Following Bloomberg's acquisition of Barclays' index business (Barclays Risk Analytics and Index Solutions) in 2016, it

[6]The Lehman Brothers' bond indices were created by Kuhn, Loeb & Co. in 1973, then acquired by Lehman Brothers in 1977. The indices have been the leading fixed-income benchmarks since their inception.

became the Bloomberg Barclays Aggregate Bond Index during a five-year co-branding period, until it was rebranded as Bloomberg Fixed Income Indices in on August 24, 2021. The Agg is a broad-based, market capitalization-weighted index representing the U.S. investment-grade, fixed-rate bond market. It includes U.S. Treasuries, corporate bonds, and other fixed income securities, such as mortgage-backed securities (MBS) and asset-backed securities (ABS). This index serves as a primary benchmark for the U.S. bond market and is commonly used by mutual funds and ETFs to gauge relative performance.

A key sub-index of The Agg is the Bloomberg U.S. Corporate Bond Index, which focuses specifically on the investment-grade, fixed-rate, taxable corporate bond market in the United States. This index includes U.S. dollar-denominated securities publicly issued by U.S. and non-U.S. industrial, utility, and financial issuers. It serves as a benchmark for corporate bond performance, helping investors evaluate credit exposure and corporate debt investments.

To be included in Bloomberg's U.S. bond indices, a corporate bond must meet several key eligibility criteria.[7] The bond must be issued by corporate entities (including industrial, financial, and utility companies) and be denominated in U.S. dollars. It must be investment-grade, with a rating of Baa3/BBB- or higher by at least two out of three major rating agencies (Moody's, S&P, or Fitch).[8] Additionally, bonds must have at least one year remaining until maturity, a minimum of $300 million outstanding, and a fixed coupon rate.[9] Convertible bonds, private placements, inflation-linked bonds, 144A bonds without registration rights to convert into public issues, and structured securities are not eligible for inclusion.

On January 14, 2021, Bloomberg made a significant change to the pricing methodology of its U.S. dollar-denominated bond indices, shifting the daily pricing snap from 3:00 PM to 4:00 PM. This adjustment was made to better align index pricing with the close of the U.S. equity markets, which also occurs at 4:00 PM, thereby providing a more synchronized reflection of market conditions across asset classes. This change has affected all bonds in Bloomberg U.S. dollar-denominated bond indices, except taxable municipal bonds.[10]

[7] All Bloomberg U.S. Corporate Bond and U.S. Credit indices share the same criteria as being subsets of the U.S. Aggregate Index. For details, see the Bloomberg Fixed Income Index Methodology.

[8] If there are only two ratings available, the lower (more conservative) one is used. The single rating is used in case it is only one available.

[9] The outstanding amount threshold has changed over time: it was $150 million to $200 million since October 2003, raised to $250 million in July 2004, and increased again to $300 million in April 2017.

[10] See the benchmark index pricing methodology in the Bloomberg Fixed Income Index Methodology for details.

The modification in index closing time may influence the intraday timing of bond transactions. Passive bond funds typically execute trades close to the time their benchmark indices close, primarily to minimize tracking error. Because bond indices value their underlying bonds at a specific time each day, passive funds align their trading schedules accordingly. This ensures that their holdings and valuations remain consistent with the prices of the index constituents. Trading at substantially different times could lead to discrepancies in bond prices due to intraday changes in interest rates, credit spreads, or liquidity conditions, thereby increasing tracking error and causing the fund to deviate from its benchmark returns.

B. Data and Sample Construction

Our primary dataset for this study comprises corporate bond transaction data from the Trade Reporting and Compliance Engine (TRACE), provided by the Financial Industry Regulatory Authority (FINRA). For the period from July 2002 to September 2023, we obtained detailed information from TRACE on each secondary market corporate bond trade, including the bond identifier, trade execution time, trade price and quantity, and a buy/sell indicator specifying whether the trade was a dealer buy or sell. We follow Dick-Nielsen (2014) in filtering out cancellations, corrections, reversals, error trades, and agency trades, and in applying the price sequence based filters (the median and the reversal filters).

We complement the TRACE data with high-frequency Composite Plus (CP+) pricing data from MarketAxess, a leading electronic trading platform for corporate bonds. The CP+ data offers minute-by-minute price estimates for both sides of the market (bid and offer) across a broad spectrum of corporate bonds eligible for most fixed income indexes. It combines TRACE data with proprietary data from MarketAxess's trading platform, incorporating completed trades, inquiry data, dealer runs, and indicative pricing. This comprehensive dataset not only reflects executed trades but also captures market sentiment through unexecuted inquiries and dealer expressions of interest.

MarketAxess generates CP+ data using a sophisticated pricing engine powered by a suite of machine learning models designed to predict bond prices in real time. The engine continuously ingests trade data, indicative pricing, and other market inputs, transforming them into a set of engineered features optimized for price prediction. These features are tailored along key dimensions such as time, trade side (bid vs. offer), trade size, and data source (e.g., trades, dealer runs, and RFQ responses). For highly liquid bonds, the pricing engine produces direct price estimates, while for less liquid bonds, prices are extrapolated relative to their more liquid counterparts. This dual approach ensures both pricing accuracy and comprehensive market coverage. The adoption of CP+ pricing data has been steadily increasing in the fixed-income finance industry. In October 2024, S&P Global Market Intelligence and MarketAxess announced a strategic data partnership designed to enhance market transparency and efficiency. At the core of this collaboration is the integration of S&P Global's Bond Reference Data into MarketAxess's suite of data products and the incorporation of MarketAxess's CP+ real-time pricing into S&P Global's Evaluated Bond Pricing services.[11]

We merge TRACE transaction data and CP+ bond pricing data with the Mergent Fixed Income Securities Database (FISD) to obtain bond characteristic information such as issuance and maturity dates, issue size, and historical credit ratings. For each bond on each trading day, we construct a composite rating based on ratings assigned by the three major agencies: S&P, Moody's, and Fitch.[12] To be included in our sample, corporate bonds must be issued by a U.S. entity in U.S. dollars and have a fixed-coupon rate. We exclude newly issued bonds (less than 0.5 years old), bonds nearing maturity (with less than 1.5 years remaining), and small issues (less than $1 million in issue size). Additionally, we exclude 144A, asset-backed, convertible, equity-linked, foreign currency, privately placed, and sinking-fund bonds. We use secondary market trades and exclude trades occur in weekends as well as U.S. holidays and early close days recommended by Securities Industry and Financial Markets Association (SIFMA). Our TRACE sample comprises 96,354,832 trades spanning July 2002 to September 2023, covering 20,878 bonds issued by 3,672 firms. Additionally, our CP+ bond pricing data includes 6,820,112,129 mid-price observations for the sample bonds from January 2020 to September 2023.

We supplement our corporate bond data with bond mutual fund data. Information on fund characteristics, quarterly holdings, and monthly flows is obtained from the Center for Research in Security Prices (CRSP) Survivorship-Bias-Free US Mutual Fund Database. Additionally, we

[11] See this press release by S&P.

[12] We assign a numeric value to each rating notch, with 21 representing AAA, 20 representing AA+, 19 representing AA, 18 representing AA-, and so forth. This numeric scale is applied consistently across all three agencies. If a bond has only one available rating, that rating becomes its composite rating. If a bond has ratings from two agencies, we use the lower (i.e., worse) rating as its composite rating. For bonds rated by all three agencies, we use the median of the three ratings. Bonds without ratings from any of these agencies are excluded from our sample.

identify each fund's benchmark using the primary prospectus benchmark data sourced from Morningstar.

III. Intra-day Clustering of Corporate Bond Trades

In this section, we document a striking pattern in the distribution of intra-day corporate bond trades between dealers and customer: bond trades increasingly cluster at specific time points through the day. The most pronounced trade clustering occurs at the daily closing time of Bloomberg bond indices, when the index provider prices the indices and underlying constituents. We further provide evidence suggesting that the growth of index investing in the bond market is a key driver of the increasing intra-day trading clustering.

A. *The Changing Landscape of Corporate Bond Intra-day Trading*

We begin by examining the distribution of intra-day dealer-customer corporate bond trading activities in IG bonds eligible for Bloomberg bond indices, using four historical snapshots.[13] About twenty year ago, when TRACE first began publishing corporate bond trade data, trading in U.S. corporate bonds was relatively uniform throughout regular business hours. As shown in Panel (a) of Figure 3, which plots the fraction of daily trades executed minute by minute, trading activities ramped up in the morning, remained relatively stable between 10:00 AM to 5:00 PM, and then tapered off toward the end of the trading day. Fast forward to 2015 (Panel (b)), a distinct clustering of trades at 3:00 PM emerged, coinciding with the index pricing time of the then Barclays bond indices. However, the magnitude of the clustering remained modest, with no more than 0.6% of the daily trading volume occurring within the minute after 3:00 PM. By 2020, as shown in Panel (c) of Figure 3, this clustering had intensified significantly, with trades at 3:00 PM accounting for 8% of daily corporate bond trading volume. Finally, On January 14, 2021, Bloomberg shifted the closing time of its bond indices from 3:00 PM to 4:00 PM. Correspondingly, as shown in Panel (d) (which plots the intra-day trade distribution for 2022), the largest daily trade cluster —about 8% of trading volume —shifted to 4:00 PM, while the 3:00 PM cluster diminished significantly.

[13] We use the term "dealer-customer" trades to refer to any trade between a dealer and a customer. Unless specified otherwise, our analyses do not include interdealer trades.

These four snapshots are not coincidental; rather, they illustrate the gradual evolution of intraday trading activities in the corporate bond market over the past two decades and highlight the role of index tracking in driving this evolution. Figure 4 displays daily time-series heatmaps of the intraday trading volume fraction for each 5-minute interval from 2002 to 2023. As shown in Panel A, for index-eligible IG bonds, a distinct concentration of trading at 3:00 PM began to emerge after the Great Financial Crisis, with the fraction of trade volume executed during the subsequent 5-minute interval steadily increasing. However, immediately following Bloomberg's change in its index closing time, indicated by the red dropline, the 3:00 PM concentration quickly dissipated, and a new concentration at 4:00 PM emerged. Panels (b) and (c) provide further evidence of the impact of index tracking on the clustering of intraday bond trading. Both IG bonds that do not meet Bloomberg index eligibility (Panel (b)) and HY bonds, where passive investor presence is low (Panel (c)), do not display any marked time trend in trading clustering.

It is important to note that part of this clustering can be attributed to the increasing adoption of delayed Treasury spotting trades. In the corporate bond market, IG bonds are typically priced as a spread over a benchmark Treasury yield (e.g., the Treasury spot rate or yield curve), a process known as Treasury spotting. Instead of locking in the Treasury reference yield at the time of a corporate bond trade, dealers sometimes opt to use a yield determined later, taking advantage of greater liquidity for potentially better pricing. Indeed, as shown in Figure 3 and Figure 4, trade clustering has also emerged at other key times for delayed Treasury spotting, including 11:00 AM, 4:00 PM, and 4:30 PM.

To gauge the magnitude of the impact of index tracking on trade clustering, while distinguishing it from the effects of delayed Treasury spotting, we focus on four specific times during the day, 11:00 AM, 3:00 PM, 4:00 PM, and 4:30 PM, and plot the monthly time series of the fraction of trading volume executed within the five-minute interval following each time point. Panel (a) of Figure 5 shows that for eligible IG bonds, the combined trading volume within these intervals increased from below 5% of the total to over 17.5% by the end of our sample. More importantly, compared to delayed Treasury spotting, index tracking has resulted in much more pronounced trade clustering. Following Bloomberg's shift in index closing time from 3:00 PM to 4:00 PM, the share of trading volume in the five-minute window after 3:00 PM. dropped from 9.33% during December 2020 to 3.40% during February 2021, while the share following 4:00 PM surged from 1.28% during December

2020 to over 7.72% during February 2021 and then 9.50% during March 2021. Consistent with Figure 4, non-eligible IG bonds and HY bonds do not exhibit any marked time trend in trading clustering, with the volume within these intervals remaining stable at approximately 5% of the total trading volume throughout the observation period (see Panels (b) and (c) of Figure 5).

B. *Index Eligibility and Trade Clustering: Regression Analysis*

To formalize the above observations in a regression setting, we estimate the following equation at the bond-day level using IG bonds from our sample:

$$Index\text{-}closing\ Time\ Volume\%_{i,t} = \alpha + \beta D(Index\ Eligible)_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}, \tag{1}$$

where *Index-closing Time Volume%*$_{i,t}$ is the percentage of trading volume for bond i during day t that takes place within the 5-minute window following the Bloomberg index closing time. The Bloomberg index closing time is 3:00 PM prior to January 14, 2021, and 4:00 PM thereafter. *D(Index Eligible)*$_{i,t}$ is a dummy variable indicating whether bond i is eligible for inclusion in Bloomberg bond indices during month t. The vector $X_{i,t}$ is a set of bond characteristics. Standard errors are double-clustered at the bond and the daily level.

The regression results are displayed in Table I. In Column (1), the univariate regression shows that on average, the fraction of trading volume occurring within the five minutes following the index closing time is 5.35 percentage points higher for index-eligible IG bonds compared to other IG bonds that are not eligible for the Bloomberg indices. In Columns (2) and (3), after controlling for bond characteristics, as well as day fixed effects, index-eligible bonds continue to exhibit a higher fraction of trading volume at the index closing time— ranging from 4.217 to 4.466 percentage points. Finally, in Column (4), we focus on the most recent sample period (2020-2023) and estimate that trading clustering at index closing time is approximately 7.549 percentage points higher for index-eligible bonds compared to ineligible IG bonds. This finding corroborates the evidence in Figure 4 and highlights a significant intensification of daily bond trading clustering around index closing times over time.

We further examine changes in trading volume around index closing time by tracking the same bond as it moves in and out of the the Bloomberg indices. In Column (1) of Table II, we find that, after controlling for bond fixed effects, a higher fraction of trades – about 3.03 percentage points – are executed around the index closing time while the bond is included in the Bloomberg indices compared to when it exits. The variation of a bond's index eligibility stems from (1) some bonds being partially called by their issuers and (2) changes in the the Bloomberg indices' minimum outstanding amount threshold. In April 2017, this threshold for Treasury, government-related and corporate securities in the U.S. Aggregate Index was raised from $250mn to $300mn, leading to the exclusion of certain securities. To further leverage this eligibility change, in Column (2) of Table II, we restrict the sample to bonds with an outstanding amount within $250 million of the Bloomberg Index cutoff. Our results show that index membership is associated with a 2.039 percentage point increase in trade volume executed around index closing time.

We also analyze cases in which a bond exits the Bloomberg Index due to its remaining time to maturity falling below one year. To do so, we extend our sample to include maturing bonds, as our main sample excludes bonds with a maturity shorter than 1.5 years. The coefficient estimate in Column (3) of Table II indicates that when a bond drops out of the Index upon reaching one year of remaining maturity, the concentration of trades at index closing time decreases by 0.328 percentage points. Narrowing our focus to bonds with less than two years of remaining maturity, we find that exiting the Index is associated with a 1.394 percentage point decline in trading volume at index closing time.

To further strengthen the interpretation that indexing drives the clustering of corporate bonds, we exploit the shift in the closing time of Bloomberg indices. We focus on a six-month window around January 14, 2021 (October 14, 2020 to April 13, 2021), and estimate difference-in-differences regressions, where $D(\textit{Index Eligible})$ is interacted with a $D(\textit{Post Index-closing Time Change})$ binary variable that equals one for periods after the index closing time change on January 14, 2021. The regression specification is as follows:

$$\begin{aligned} \textit{Volume\%}_{i,t}^{\textit{5-minute window}} =& \alpha + \beta_1 D(\textit{Index Eligible})_{i,t} \\ &+ \beta_2 D(\textit{Index Eligible})_{i,t} \times D(\textit{Post Index-closing Time Change})_t \\ &+ \gamma X_{i,t} + \mu_r + \mu_t + \epsilon_{i,t}. \end{aligned} \tag{2}$$

In these regressions, the dependent variable represents the percentage of trading volume occurring within specific five-minute intervals for a given bond-day. We estimate separate regressions where the dependent variable measures trading volume concentration in the following time windows: 3:00 PM - 3:05 PM, 4:00 PM - 4:05 PM, 11:00 AM - 11:05 AM, and 4:30 PM - 4:35 PM. We include rating fixed effects (μ_r) and month fixed effects (μ_t) in the regressions. Standard errors are double-clustered at the bond and the day levels.

Column (1) of Table III reports the trading volume changes for the 3:00 PM-3:05 PM window, which was the index closing time prior to January 2021. The coefficient on $D(\textit{Index Eligible})$ is 8.975, indicating that prior to the index closing time switch, the 5-minute window around 3:00 PM accounts for nearly nine percentage points more of the daily trading volume for index-eligible bonds than for index-ineligible bonds. The coefficient on the interaction of $D(\textit{Index Eligible})$ and $D(\textit{Post Index-closing Time Change})$ is -7.047, suggesting this concentration of trading around 3:00 PM largely dissipated after Bloomberg shifted the closing time away from 3:00 PM. In Column (2) of Table III, we examine trading volume in the 4:00 PM-4:05 PM window. Before index closing time switch, there is no concentration of trading volume in this window when comparing index-eligible bonds and ineligible bonds. However, after the index closing time moved to 4:00 PM, the coefficient on the interaction term indicates a 6.949 percentage points increase in trading volume in this window. Notably, the increase in trading volume at 4:00 PM is almost the same in magnitude relative to the decrease at the 3:00 PM, providing strong evidence that both shifts are driven by a migration of index-tracking trades in response to index closing time change.

In Columns (3) and (4) of Table III, we examine changes in trading volume around the 11:00 AM-11:05 AM and 4:30 PM-4:35 PM windows, two periods where trading activity is moderately concentrated, likely due to delayed Treasury spotting trades. Importantly, we find no significant change in trading volume concentration following the shift in Bloombergs index closing time for the 11:00 AM and 4:30 PM windows, suggesting that trading in these periods is unrelated to index-driven activity. In Columns (5) to (8) of Table Table III, we further control for bond fixed effects, which absorb the coefficient of $D(\textit{Index Eligible})$.[14] Consistent with our previous findings, the coefficient on $D(\textit{Index Eligible}) \times D(\textit{Post Index-closing Time Change})$ indicates that the concentration of trading in the 3:00 PM decreases, while the concentration of trading in the 4:00 PM increases by approximately the same magnitude following the Bloomberg index closing time change.

[14] For this subsample (October 14, 2020, to April 13, 2021), we exclude a tiny fraction of bonds that change eligibility, accounting for approximately 0.5% of observations.

C. Demand for Trading and Trade Clustering

If index tracking drives trade clustering around the index closing time, we would expect this clustering to be more pronounced when demand for trading by index trackers increases. In this section, we test this hypothesis by examining the relationship between trade clustering and market conditions that heighten demand for trading among index trackers.

We begin by examining the relationship between the proportion of a bond's trading volume that occurs in the five-minute window following the index closing time and investor flows into mutual funds and ETFs. Inflows or outflows can prompt funds to trade their underlying bonds. Because these funds have explicit mandates to track indices, bonds held more heavily by funds experiencing significant flows are likely to see more concentrated trading activity at the index closing time.

To test this hypothesis, we first construct bond-month level flows from passive mutual funds and ETFs. We obtain data on monthly returns and assets of bond mutual funds and ETFs from the CRSP database and define the flows as follows:

$$Flow_{f,t} = \frac{TNA_{f,t} - TNA_{f,t-1} \times (1 + Ret_{f,t})}{TNA_{f,t-1}}, \tag{3}$$

where $TNA_{f,t}$ represents the total net assets of fund f at the end of month t, and $Ret_{f,t}$ denotes the monthly return for fund f and month t. We then follow Lou (2012) to aggregate fund flows at the bond-month level by assuming that investment funds adjust their existing bond holdings proportionally to their respective flows:

$$\textit{Flow-induced Trading}_{i,t} = \frac{\sum_{f \in \mathcal{F}} (Flow_{f,t} \times ParHolding_{f,i,t-1})}{ParTradingVol_{i,t}}, \tag{4}$$

where $\mathcal{F}$ represents the set of passive funds (mutual funds and ETFs) holding Bond i at month $t-1$.[15] The variable $ParHolding_{f,i,t-1}$ represents the par value of Bond i held by fund f in the previous month. We scale this variable by the bond's monthly par trading volume to quantify the impact of flow-induced trading demand from passive funds on the distribution of bond trades.

We define extreme flow periods for a bond ($D(\textit{Large Flow-induced Trading})_{i,t} = 1$) as periods in which *Flow-induced Trading* falls within the top or bottom 5th percentiles of our sample. We

[15] Monthly holdings are available for the majority of passive funds. We use the previous quarter-end holdings if month $t-1$ holding is not available.

then conduct the following regression analysis at the bond-day level:

$$\begin{aligned} \textit{Index-closing Time Volume\%}_{i,t} =& \alpha + \beta_1 D(\textit{Index Eligible})_{i,t} + \beta_2 D(\textit{Index Eligible})_{i,t} \times \\ & D(\textit{Large Flow-induced Trading})_{i,t} + \gamma X_{i,t} + \mu_r + \mu_t + \mu_i + \epsilon_{i,t}. \end{aligned} \tag{5}$$

Columns (1) of Table IV shows that during periods of strong inflows or outflows from passive bond funds and ETFs, the fraction of daily bond trades clustered at the index-closing time increases by an additional 0.474 percentage point, which is about 15% of the baseline estimate for $D(\textit{Index Eligible})$ at 3.011. When we further control for issuer-by-day fixed effects in Column (4), the interaction coefficient between $D(\textit{Index Eligible})$ and $D(\textit{Large Flow-induced Trading})$ becomes larger at 0.673. These results support our hypothesis that increased flow-induced trading by passive funds leads to stronger clustering of trades at index closing time.

We also analyze periods when market conditions trigger industry-wide selling by passive funds, focusing on episodes of extraordinary volatility and the COVID-19 liquidity crisis. During times of market stress, investment funds often face significant investor outflows, heightening the need to liquidate their bond holdings to meet redemptions. Given their index-tracking mandates, these funds are compelled to execute trades at the index closing time, resulting in more pronounced trade clustering during periods of market stress.

We conduct two tests to evaluate this hypothesis. First, we interact the $D(\textit{Index Eligible})$ indicator with $D(\textit{High VIX})$, a binary variable indicating calendar days when the CBOE Volatility Index (VIX) is in the highest 5% of our sample. We then estimate the following regression:

$$\begin{aligned} \textit{Index-closing Time Volume\%}_{i,t} =& \alpha + \beta_1 D(\textit{Index Eligible})_{i,t} + \beta_2 D(\textit{Index Eligible})_{i,t} \times D(\textit{High VIX})_t \\ & + \gamma X_{i,t} + \mu_r + \mu_t + \mu_i + \epsilon_{i,t}. \end{aligned} \tag{6}$$

Column (2) of Table IV reports a baseline coefficient of 2.848 for $D(\textit{Index Eligible})$, indicating that under normal conditions, index-eligible bonds exhibit a 2.848 percentage point higher concentration of trades within the five-minute window around index-closing time compared to ineligible bonds. The interaction term between $D(\textit{Index Eligible})$ and $D(\textit{High VIX})$ has a positive and significant coefficient of 2.579, suggesting that during high-volatility periods, the difference in trading concentration between eligible and ineligible bonds almost double to approximately 5.4 percentage points $(2.848 + 2.579)$.

Second, we focus on a period of significant market dislocation during the COVID-19 crisis. We replace $D(\mathit{High\ VIX})$ with $D(\mathit{COVID})$, a binary variable indicating the March 6 to March 19, 2020 period, and re-estimate Equation 6. Column (3) shows that interaction between $D(\mathit{Index\ Eligible})$ and $D(\mathit{COVID})$ has a significantly positive coefficient of 4.790. This finding indicates that during this extreme stress period, the gap in index-closing time trades between eligible and ineligible IG bonds more than doubles.

The rest of columns in Table IV repeat the analysis while additionally controlling for issuer-day fixed effects. The results remain consistent, even when comparing different bonds issued by the same company. Overall, these findings support our hypothesis, demonstrating that increased demand for trading by index trackers leads to a larger share of volume being executed around the index-closing time, highlighting the role of index tracking in driving trade clustering.

IV. The Impact of Index-Closing Trades on Bond Liquidity

The growing concentration of corporate bond trades at index-closing time raises important questions about market quality and liquidity. This section empirically evaluates how this temporal clustering of trades affects transaction costs and bond liquidity. Specifically, we analyze how trade clustering affects the intraday distribution of liquidity, explore the mechanisms driving these effects, and assess the overall net impact on bond liquidity. Additionally, we examine how market conditions affect the relationship between index trading and bond liquidity, with particular attention to the robustness of liquidity benefits during periods of market stress.

A. Index-Tracking and Intra-day Liquidity

We begin by examining trade-level transaction cost measures for trades executed around index-closing time compared to trades executed during the rest of the day. For each customer trade k in bond i on day t, we follow Hendershott and Madhavan (2015) and calculate its transaction cost as follows:

$$\mathit{Transaction\ Cost}_k = \ln\left(\frac{\mathit{Trade\ Price}_k}{\mathit{Benchmark\ Price}_v}\right) \times \mathit{Trade\ Sign}_k, \tag{7}$$

where $Trade\ Price_k$ is the transaction price for trade k. We use two sets of distinct methodologies for $Benchmark\ Price_v$. First, we utilize the price of the most recent same-day interdealer trade v executed before the customer trade k as the benchmark price.[16] $Trade\ Sign_k$ equals +1 if the customer buys from a dealer and -1 if the customer sells to a dealer in the customer trade k. We multiply *Transaction cost*$_k$ by 10,000 to express transaction costs in basis points, and winsorize the top and bottom 1% of the transaction cost distribution each day to mitigate the impact of noisy measurements and outliers.

One limitation of using the most recent inter-dealer trade price as the benchmark for estimating transaction costs in customer trades is the infrequent trading of corporate bonds. As a result, the most recent inter-dealer trade may have occurred days or even weeks before the customer trade. To mitigate this issue, we require that the inter-dealer trade must have occurred on the same day as the customer trade. While this helps reduce noise in the estimation, it does not fully address concerns about the staleness of the benchmark price. Moreover, this restriction results in missing transaction cost estimates for a significant number of customer trades when no inter-dealer trade takes place on the same day.

To overcome these limitations, we incorporate high-frequency algorithmic pricing data from MarketAxess to calculate an alternative $Benchmark\ Price_v$. This data leverages machine learning and both public and proprietary data from MarketAxess's trading platforms to generate minute-by-minute bid and ask prices for the bonds in our sample. We use the midpoint of the bid and ask prices from the minute preceding a customer trade as the benchmark price to estimate an alternative version of Hendershott and Madhavan (2015) transaction cost measure. Due to the comprehensive coverage of CP+ data, we can estimate transaction costs for nearly all customer trades in our TRACE sample. However, because the CP+ pricing engine was introduced relatively recently and required time for refinement, these estimates are only available from January 2020 onward. period, we estimate transaction costs for about 99.19% of customer trades using the CP+ midprice benchmark and about 58.73% using the interdealer price benchmark. The unconditional correlation between two measures is about 71%.

[16]Following Hendershott and Madhavan (2015), we exclude interdealer trades that match customer trades by the same bond, date, time, and quantity. Also, in untabulated results, we use an alternative version of *Transaction Cost*$_k$ by using the most recent interdealer price from the day before (Day $t-1$) to two weeks prior (Day $t-14$). Our results remain similar.

Using both transaction cost measures, we examine the within-bond-day variation in transaction cost of index-eligible bonds by estimating the following trade-level regression:

$$Transaction\ Cost_k = \alpha + \beta D(Index\text{-}closing\ Time)_t + \mu_s + \mu_d + \mu_{i,t} + \epsilon_k, \tag{8}$$

where $D(Index\text{-}closing\ Time)$ is an indicator variable for trades executed within the 5-minute window following 3:00 PM prior to January 14, 2021, and within the 5-minute window following 4:00 PM after that date. The term $\mu_{i,t}$ represents bond-day fixed effects, enabling a comparison of transaction costs for trades executed in the same bond on the same day. Additionally, We include trade size fixed effects (μ_s) and trade direction fixed effects (μ_d), as both factors have been shown to influence transaction costs.[17] Standard errors are double-clustered at the bond and the day levels.

Table V shows that trading activities clustered around the index-closing time is associated with lower transaction costs. As shown in Panel A, where transaction costs are estimated using the inter-dealer price as the benchmark, trades executed at index-closing time incur transaction costs that are 5.28 basis points lower than those executed at other times of the day (Column (1)). This difference represents about 17% of the average transaction cost of 31 basis points, and is highly statistically significant. The reduction in transaction costs at index-closing time appears to be more pronounced for customer-buy trades (Column (2)) compared to customer-sell trades (Column (3)).

Since some trade clustering also occurs at other delayed Treasury spotting times, we include an indicator variable, $D(Other\ DTS\ Time)$, to account for potential differences in liquidity at these times. Specifically, $D(Other\ DTS\ Time)$ is set to one for trades executed within the 5-minute widows following other delayed Treasury spotting times, including 11:00 AM, 3:00 PM (on or after January 14, 2021), 4:00 PM (before January 14, 2021), and 4:30 PM. Columns (4) of Table V shows that trades executed during other spotting times exhibit a moderate reduction in transaction costs of 1.24 to 1.80 basis points. However, this effect is much less pronounced than the reduction observed at index-closing time. This pattern holds for both customer-buy trades (Column (5)) and customer-sell trades (Column (6)).

The lower transaction cost at index-closing time is also evident when we use the CP+ midprice

[17] For the effect of trade size on bond transaction cost, see, for example, Schultz (2001). Consistent with the literature, trade size fixed effects are categorized into four par amount trading groups: micro (\$1–\$100,000), odd-lot (\$100,000–\$1,000,000), round-lot (\$1,000,000–\$5,000,000), and block (above \$5,000,000).

as the benchmark. The results are shown in Panel B of Table V. On average, trades executed at index closing time have transactions costs that are 7.589 basis points lower than trades executed outside of index closing time. This reduction accounts for approximately 32% of the average CP+ midpoint benchmarked transaction cost of 23 basis points. The larger reduction in transaction costs documented in Panel B, relative to those documented in Panel A, partly reflects that the CP+ results are derived from the later part of our sample period, during which index tracking has become more prominent compared to earlier periods.[18] Combined with our earlier findings on trade clustering around index-closing time, these results suggest that index tracking has shifted intra-day liquidity to the index-closing time.

To further establish the causal effect of index tracking on the redistribution of intra-day liquidity, we analyze the temporal change in transaction costs before and after Bloomberg shifted the closing time of its bond indices. As previously discussed, on January 14, 2021, Bloomberg moved the bond index closing time from 3:00 PM to 4:00 PM. We focus on a narrow window around this change – specifically, one, three, or six months before and after January 14, 2021. During this period, we examine the transaction costs of trades executed within the 3:00 PM – 3:05 PM window and the 4:00 PM – 4:05 PM window using the following difference-in-differences regression:

$$\begin{aligned} \textit{Transaction Cost}_k = {} & \alpha + \beta_1 D(15{:}00\text{-}15{:}05)_t + \beta_2 D(15{:}00\text{-}15{:}05)_t \times D(\textit{Post Index-closing Time Change}) \\ & + \gamma_1 D(16{:}00\text{-}16{:}05)_t + \gamma_2 D(16{:}00\text{-}16{:}05)_t \times D(\textit{Post Index-closing Time Change}) \\ & + \mu_s + \mu_d + \mu_{i,t} + \epsilon_k, \end{aligned} \tag{9}$$

where $D(\textit{Post Index-Closing Time Change})$ is an indicator variable that equals one for days on or after January 14, 2021. The variables $D(15{:}00\text{-}15{:}05)$ and $D(16{:}00\text{-}16{:}05)$ are indicator variables for the 5-minute windows following 3:00 PM and 4:00 PM, respectively. All other variables are defined as in Model (8), and standard errors are double-clustered at the bond and the day levels.

The results in Table VI provide strong support for the causal impact of index tracking on the redistribution of intra-day bond liquidity. The change in Bloomberg's index closing time significantly influenced transaction costs during the 5-minute windows surrounding 3:00 PM and 4:00 PM. In the narrowest window of one-month before and after the index time change (Column (1) of

[18] Although the sample period for the tests in Panel B is less than four years – significantly shorter than that for Panel A – the number of observations remains comparable. This reflects the greater availability of the transaction cost measure when using the CP+ midprice as the benchmark.

Panel A), the analysis reveals that prior to the time change, trades executed between 3:00 PM and 3:05 PM incurred transaction costs that were 5.129 basis points lower than trades executed at other times of the day. In contrast, trades executed between 4:00 PM and 4:05 PM showed no statistically significant difference in transaction costs, as indicated by the insignificant γ_1 coefficient.

After the index closing time moved to 4:00 PM on January 14, 2021, this pattern reversed. Trades executed during the 4:00 PM window began to benefit from lower transaction costs, with a reduction of 5.509 basis points compared to other times of the day, mirroring the liquidity advantage previously observed in the 3:00 PM window. At the same time, transaction costs for trades in the 3:00 PM window increased by 2.675 basis points, partially eroding the liquidity benefit that this time slot had previously offered. Columns (2) and (3), which examine slightly longer windows around the index time change, show consistent results both qualitatively and quantitatively. Panel B presents consistent findings using the CP+ midprice as the benchmark for estimating transaction costs, with the magnitude of the liquidity shift comparable to that observed in Panel A.[19] Together, these findings underscore that the timing of the index closing plays a critical role in driving lower transaction costs for trades executed within the associated time windows.

Figure 6 provides corroborative graphical evidence that index-tracking leads to lower transaction costs.[20] The upper panels show the binned-scatter plot of transaction costs for trades executed between 2:45 PM and 3:15 PM. Prior to January 14, 2021, when 3:00 PM is the closing time for the Bloomberg Index (Panel (a)), trades executed at 3:00 PM or shortly afterwards have transaction costs that are significantly lower than trades that are executed slightly before the index closing time. After January 14, 2021 when the index closing time moved away from 3:00 PM, the difference in transaction cost before and after 3:00 PM tightened significantly.

The lower panels of Figure 6 plot the average transaction cost of trades executed between 3:45 PM and 4:15 PM. Panel (c) shows that before January 14, 2021, transaction costs are relatively similar before and after 4:00 PM. Following the shift of index closing time to 4:00 PM, Panel (d) reveals an immediate and distinct discontinuity, with transaction costs dropping significantly for trades executed at the new closing time. This sharp contrast in trading patterns provides additional

[19] Since both panels focus on time periods during which transaction costs can be estimated using both benchmarks, the substantially larger sample size in Panel B again reflects the greater availability of the CP+ midprice as a benchmark.

[20] The plots are based on transaction costs estimated using the interdealer price as the benchmark. Estimates based on the CP+ midprice present a similar picture.

support for our hypothesis that index-driven trade concentration generates liquidity improvements during the closing window.

B. Economic Drivers of Liquidity Benefits at Index-closing Times

What drives the enhanced liquidity at index-closing time? In this section, we explore several potential economic mechanisms through which transaction costs are reduced at index-closing time compared to other periods during the day.

First, the index-closing time acts as a coordination mechanism for trades among institutions aiming to minimize tracking error. This alignment leads to a concentration of customer buy and sell orders at the index-closing time. Theoretical studies (e.g., Duffie, Gârleanu, and Pedersen 2005, 2007, and Üslü 2019) have emphasized the role of search frictions and associated dealer inventory risks in influencing corporate bond liquidity and pricing. When trades executed at index-closing time are relatively balanced, this temporal clustering facilitates dealers' inventory management by allowing them to offset customer buys with customer sells, thereby reducing their search costs. Consequently, it reduces both the need for hedging inventory risks and the demand for balance sheet space and funding. These efficiency gains can ultimately translate into lower transaction costs for customers and contribute to improved bond liquidity.

To empirically examine the order coordination mechanism, we analyze how the relationship between interdealer trades and dealer-customer trades evolves across different time windows throughout the day. Access to and participation in the interdealer market is critical for dealers to manage inventory risks arising from customer trades (e.g., Hollifield, Neklyudov, and Spatt 2017). If index-tracking driven trades at index closing time enhance liquidity through the order coordination mechanism, we would expect a reduced need for interdealer trades. Specifically, dealers would require fewer interdealer transactions to facilitate their customer trades during this period.

To test this hypothesis, we define the *Interdealer-customer ratio* (ICR) as the ratio of interdealer trade volume to customer trade volume in index-eligible bonds. We calculate this ratio separately for trades executed during the 3:00 PM – 3:05 PM window and the 4:00 PM – 4:05 PM window. Figure 7 illustrates the ICR for both time windows throughout our sample period. From 2014 onward, the ICR for the 3:00 PM – 3:05 PM window consistently remains below that of the 4:00 PM – 4:05 PM window. For example, in 2017, interdealer trading volume represented less than 10%

of customer trading volume during the five-minute window around the then-prevailing index-closing time of 3:00 PM. In contrast, the ICR approached 25% for the five-minute window around 4:00 PM.

This pattern shifts dramatically in 2021 following Bloomberg's change in index-closing time from 3:00 PM to 4:00 PM. The ICR for the 3:00 PM – 3:05 PM window surges above 30% before stabilizing around 20%. Meanwhile, the ratio for the 4:00 PM – 4:05 PM window declines substantially to 10%-15%, aligning with the pre-switch levels observed in the 3:00 PM window. These findings support the order coordination mechanism by demonstrating that the shift in index-closing time led to an immediate change in the volume of interdealer trading relative to dealer-customer trading. This change likely contributed to the lower transaction costs experienced by customers.

A second possible economic mechanism behind the improved liquidity at index-closing time is portfolio trading. Portfolio trading involves trading a basket of corporate bonds – sometimes exceeding 100 issues – as a single, all-or-none transaction. It has been increasingly adopted by investment funds as a means to rebalanced their portfolios and trade in response to investor flows. Li et al. (2025) show that portfolio trading incurs lower translation costs since it reduces risks for dealers' intermediation, both through diversification across a large number of bonds and hedging via ETFs. If passive funds trade in portfolios when tracking index, the lower transaction costs observed at index closing time could be attributed to the benefits of portfolio trading.

To examine the portfolio trading mechanism, we adopt a conservative version of FINRA's approach and define a portfolio trade as a group of transactions involving at least 25 unique bonds executed simultaneously. We exclude these trades from our sample and re-estimate Equation 8 using both transaction cost measures.[21] Results are presented in Table VII. Column (1) of Panel A shows that for transactions unlikely to be part of portfolio trading, those executed within the 5-minute window around the index-closing time continue to demonstrate lower transaction costs. Compared to the full sample results reported in Column (4) of Table V Panel A, the reduction in transaction costs at the index-closing time is only modestly smaller (4.158 basis points vs. 5.355 basis points). These results indicate that while portfolio trading may have contributed to lower

[21] Our conservative approach to constructing the sample allows us to focus on a subset of trades that are unlikely to be part of portfolio trades.

transaction costs at the index-closing time, it does not fully account for the observed effect. Our findings also suggest that the liquidity improvements at index-closing time extend beyond passive funds engaged in portfolio trading, potentially benefiting the broader investment community.

Lastly, we examine whether the lower transaction costs at index-closing time are driven by reduced information asymmetry. Index-tracking investment funds are typically less likely to possess private information about individual bonds, as their trading decisions are primarily motivated by index-tracking objectives. As a result, dealers face lower adverse selection risks when providing liquidity to these trades, allowing them to offer more competitive pricing. This information selection mechanism suggests that the concentration of relatively uninformed index-tracking trades at closing time contributes to the observed liquidity improvements.

To test this mechanism, we divide our sample into two groups: corporate bonds rated AAA to AA and those rated A to BBB. Since high-quality IG bonds, particularly those with AAA or AA ratings, generally have very low default risk and are less likely to be subject to information asymmetry, the information asymmetry hypothesis would predict minimal liquidity improvement at index-closing time for these bonds.

We re-estimate Equation 8 for each of the two subsamples, with the results presented in Columns (2) and (3) of Table VII Panel A. Contrary to the information selection hypothesis, we find that even AAA and AA rated bonds exhibit significantly lower transaction costs at index-closing time compared to other periods during the day. Moreover, the magnitude of transaction cost reduction for high-quality bonds is slightly greater than that observed for A and BBB rated bonds, which are more likely to be affected by information asymmetry. These findings challenge the notion that reduced information asymmetry drives liquidity improvements at index-closing time. Again, our results remain robust when using the CP+ midprice as the benchmark for estimating transaction costs (see Panel B). Overall, our findings support the order coordination mechanism through which trade clustering enhances liquidity at index-closing time.

C. The Net Effect of Trade Clustering on Corporate Bond Liquidity

Our analysis thus far demonstrates that trades executed at index-closing time incur lower transaction costs compared to those executed during other periods for the same bond. However, the broader question of how trade clustering affects overall liquidity conditions in the corporate bond market remains open. Specifically, does temporal clustering merely shift liquidity from regular trading hours to index-closing time, or does it produce a meaningful net impact on overall bond liquidity?

To address this question, we estimate liquidity at the bond-day level and relate it to the degree of trade clustering at the index-closing time. Specifically, for each bond-day, we aggregate trade-level transaction costs by calculating the trade size-weighted average. We then regress the daily average transaction cost on the fraction of the total daily trading volume executed at index-closing time:

$$Transaction\ Cost_{i,t} = \alpha + \beta Index\text{-}closing\ Time\ Volume\%_{i,t} + \gamma X_{i,t} + \mu_t + \mu_r + \mu_i + \epsilon_{i,t}, \quad (10)$$

where *Index-closing Time Volume%* represents the proportion of daily trade volume occurring within the 5-minute window following the index-closing time, and $X_{i,t}$ is a vector of bond characteristics. Additionally, We include day fixed effects (μ_t), rating fixed effects (μ_r), and bond fixed effects (μ_i). The standard errors are double-clustered at the bond and the day levels.

Table VIII presents results using both transaction cost measures, and shows that on average, trade clustering at index-closing time improves overall corporate bond liquidity. In Column (1) of Panel A, the coefficient β on *Index-closing Time Volume%* is -9.512, suggesting that bonds with a higher fraction of trades executed at index-closing time tend to experience lower average transaction costs at the daily level. In terms of economic significance, an one-standard-deviation increase in index-closing trading volume corresponds to 2.27 basis point reduction in average daily transaction costs, representing approximately 8% of the sample's average daily transaction cost.

To control for potential heterogeneity in credit risks or differences in information about bond fundamentals, Column (2) of Panel A introduces issuer-by-day fixed effects. This approach allows for comparisons of daily transaction costs among multiple bonds issued by the same company, isolating the effect of trade clustering on bond liquidity. The estimated coefficient in Column (2) remains nearly unchanged at -9.495, reinforcing the conclusion that the observed liquidity improvement associated with index-closing trade clustering is unlikely to be driven primarily by bond-specific fundamentals or issuer-related factors.

Our analysis also finds that while index-tracking-induced clustering improves overall bond liquidity, it does so at the cost of reduced liquidity during other periods of the trading day. In Columns (3) and (4) of Panel A, we re-estimate Equation 10 using bond-day level transaction costs for trades executed *outside* of the index-closing window as the dependent variable. The results show a significant positive association between *Index-closing Time Volume%* and transaction costs for trades outside of the index-closing time. This finding suggests that while temporal clustering of trades at index-closing time enhances liquidity during this specific window, it adversely affects liquidity at other times of the day. However, the negative impact on liquidity outside the index-closing window is not substantial enough to offset the stronger positive liquidity effect at index-closing time. As a result, the net effect remains an overall improvement in average daily bond liquidity. Panel B of Table VIII provides supportive evidence, showing that our results hold when using transaction costs estimated with the CP+ benchmark. Moreover, the liquidity improvement attributable to index-closing time is even more pronounced in economic magnitude.

D. The Limitations of Index-Tracking Induced Clustering

It is important to note that the order coordination mechanism, through which index-tracking-induced trade clustering enhances liquidity, relies on the assumption that customer buy and sell demand remains largely balanced. On days when trading in specific bonds or the broader bond market becomes one-sided, clustering of trades in the same direction can heighten dealers' challenges in finding counterparties to offload positions. This imbalance, in turn, may diminish the liquidity benefits typically associated with index-tracking-induced trade clustering.

To assess the potential impact of trade imbalances on the liquidity benefits of index-tracking-induced clustering, we estimate the following bond-day level regression:

$$\begin{aligned} \textit{Transaction Cost}_{i,t} = \alpha &+ \beta_1 \textit{Index-closing Time Volume\%}_{i,t} \\ &+ \beta_2 \textit{Index-closing Time Volume\%}_{i,t} \times D\textit{(High Trade Imbalance)}_{i,t} \\ &+ \gamma X_{i,t} + \mu_t + \mu_r + \mu_i + \epsilon_{i,t}. \end{aligned} \tag{11}$$

We employ three distinct measures to identify periods with high trade imbalance, as captured by the indicator variable *D(High Trade Imbalance)*. First, similar to Equation (5), we construct an indicator, *D*(*Large flow-induced trading*), which identify bond-months where the inflows or outflows of passive mutual funds and ETFs holding the bond, normalized by the bond's outstanding amount, are in the highest or lowest 5th percentile of our sample distribution. These indicators capture periods of extreme imbalances in flow-driven trading demand from investment funds. Second, we use *D(High VIX)*, a binary variable that identifies trading days when the VIX index is in the highest 5th percentile within our sample period. This measure reflects heightened market volatility often associated with increased trade imbalances. Third, we define *D(COVID)* to indicate the period of March 6 to March 19, 2021, which corresponds to the peak of bond market dislocation during the COVID-19 pandemic. All the other variables are defined as in Equation 10. Transaction costs are estimated using either the interdealer price or the CP+ midprice as the benchmark, with the results presented in Table IX.

Column (1) of Panel A shows that when passive funds and ETFs holding a bond experience large flows, the liquidity benefits of trade clustering are reduced. The coefficient on *Index-closing Time Volume%* is significantly negative at -10.108, indicating that bonds with a large proportion of trades executed at index-closing time tend to exhibit lower average transaction costs for their daily trades under normal market conditions. However, the coefficient for the interaction of *Index-closing Time Volume%* and *D*(*Large flow-induced trading*) is positive at 3.408 and highly significant. These findings suggest that for bonds held by funds experiencing large flows, the resulting unbalanced trading demand diminishes the overall liquidity benefits of trade clustering.

When such unbalanced trading needs become market-wide, the liquidity benefits of trade clustering not only disappear but can also transform into illiquidity costs. In Column (2), using *D*(*High VIX*) as a proxy for *High Trade Imbalance*, the coefficient of the interaction term increases to 9.982. This fully offset the -10.417 coefficient of *Index-closing Time Volume%*, resulting in a non-significant impact of *Index-closing Time Volume%* on bond liquidity during high-VIX periods. In Column (3) when we interaction *Index-closing Time Volume%* with *D*(*COVID*), the coefficient of the interaction term rises sharply to 27.441. This shift turns the coefficient of *Index Closing Volume%* from -9.688 into 17.753 during the COVID period, suggesting that at the peak of the COVID crisis, higher trade clustering at index-closing time led to a deterioration in liquidity. This deterioration is evident both at index-closing time and during other periods of the trading day (Panel (a) of Figure 8), with the decline in liquidity at index-closing time surpassing that of other periods at the peak of the crisis (Panel (b)).

Our results remain robust after incorporating issuer-date fixed effects to account for potential impacts of bond fundamentals on liquidity (Columns (4) to (6)). Additionally, the findings show little changes when using transaction costs estimated with the CP+ benchmark (Panel B). Overall, our findings indicate that the liquidity benefits from trade clustering induced by index tracking are not consistent across market conditions. These benefits may disappear or even reserve during times of market stress.

V. Conclusion

Index tracking, an investment strategy adopted by a growing number of investment funds in the corporate bond market, has transformed bond trading dynamics and liquidity conditions. This paper demonstrates that the increasing presence of index-tracking funds has led to significant trade clustering around index closing times, fundamentally altering the intraday distribution of liquidity. Using Bloomberg's index closing time adjustment on January 14, 2021, we establish a causal link between index tracking and corporate bond trading patterns, showing that trading activity shifts in direct response to changes in index pricing conventions.

More importantly, we find that trade clustering has enhanced overall liquidity conditions in the corporate bond market. However, this liquidity benefit is not uniform across all market conditions. During periods of market stress, when trade demand becomes one-sided, the liquidity advantage of trade clustering weakens, and in extreme cases, reverses. These results suggest that while index tracking enhances liquidity under normal conditions, its stabilizing effect weakens precisely when liquidity is most needed.

Beyond its immediate effects on trading dynamics and liquidity, our study raises broader questions about the evolving structure of the corporate bond market and the optimal market design for ensuring liquidity resilience. Historically, corporate bond market liquidity has adapted to shifts in the composition of market participants. Biais and Green (2019) document that in the 20th century, liquidity migrated from exchanges to the OTC market as institutional investors and dealers became more dominant, favoring decentralized trading mechanisms over centralized platforms. More recently, O'Hara and Zhou (2025) discuss the declining role of dealers as primary liquidity providers, alongside the rise of electronic trading platforms as alternative venues for investors to source liquidity. Meanwhile, the growth of investment funds has increased demand for liquidity.

As our study shows, the rise of index tracking has further concentrated trading activity at specific times of the day, highlighting the role of index-driven trading in shaping the microstructure of liquidity. As passive investing continues to expand, will index tracking fundamentally alter the structure of the corporate bond market? More importantly, can new trading mechanisms be designed to mitigate liquidity risks associated with excessive trade clustering, particularly during periods of financial instability? Our study provides an initial exploration of this evolving landscape and lays the foundation for future research on the long-term implications of index-driven trading for the optimal design of the corporate bond market.

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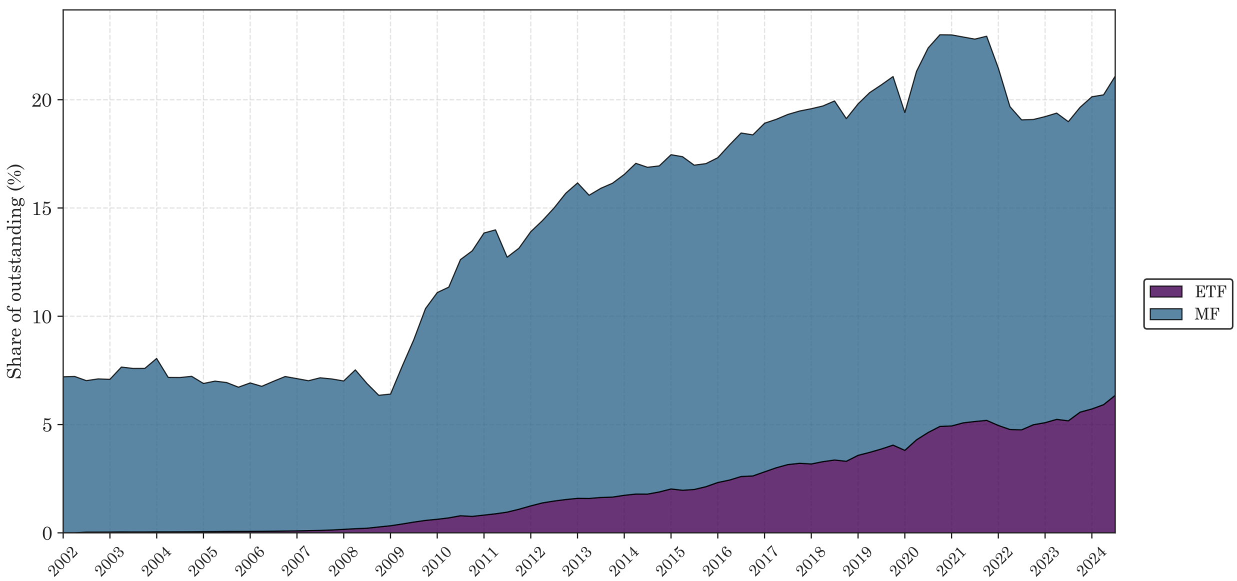


Figure 1: **Share of corporate bonds held by mutual funds and ETFs**

This figure presents the quarterly share of outstanding corporate bond amounts held by mutual funds and ETFs from Q1 2002 to Q3 2024. The data were sourced from the Federal Reserve Economic Data (FRED), provided by the Federal Reserve Bank of St. Louis.

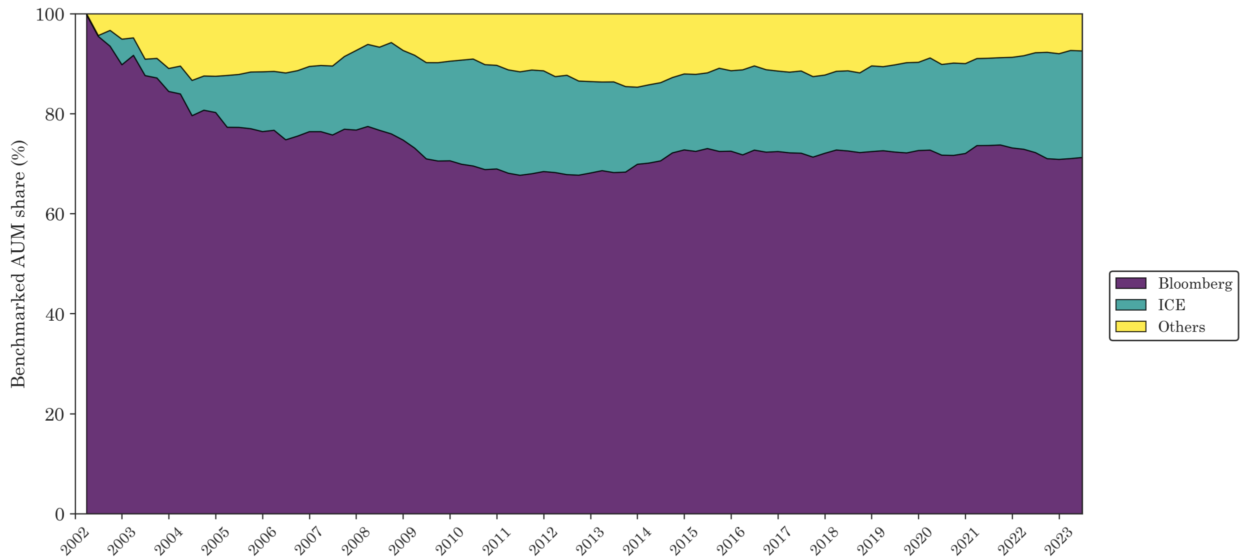


Figure 2: **Market shares of passive funds tracking each benchmark**

This figure illustrates the market value shares of passive funds that track each benchmark. We categorize passive fixed-income mutual funds and ETFs into three groups based on their primary benchmark: Bloomberg (including Bloomberg Barclays, Barclays, and Lehman indices), ICE (including ICE Bank of America indices), and all others. Benchmark classifications and quarterly fund AUM data are sourced from Morningstar. The sample period covers quarterly data from Q1 2002 to Q2 2023.

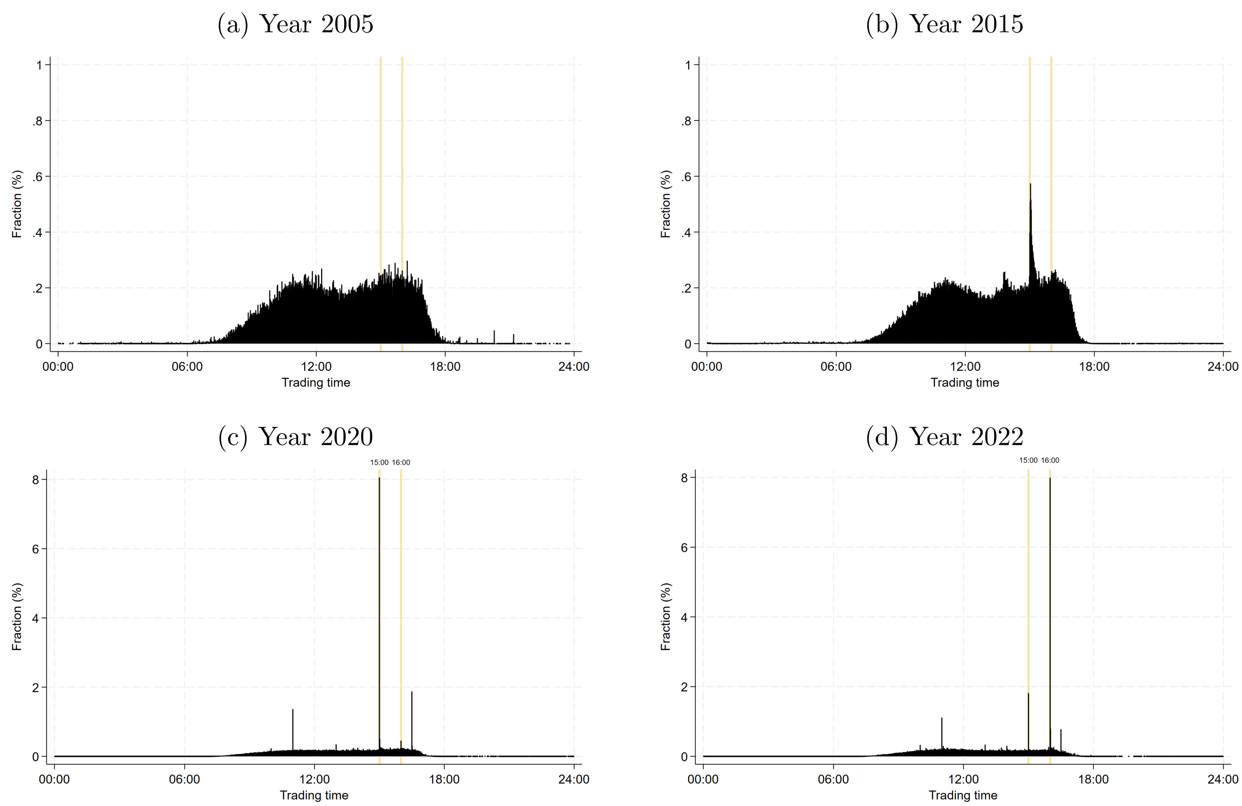
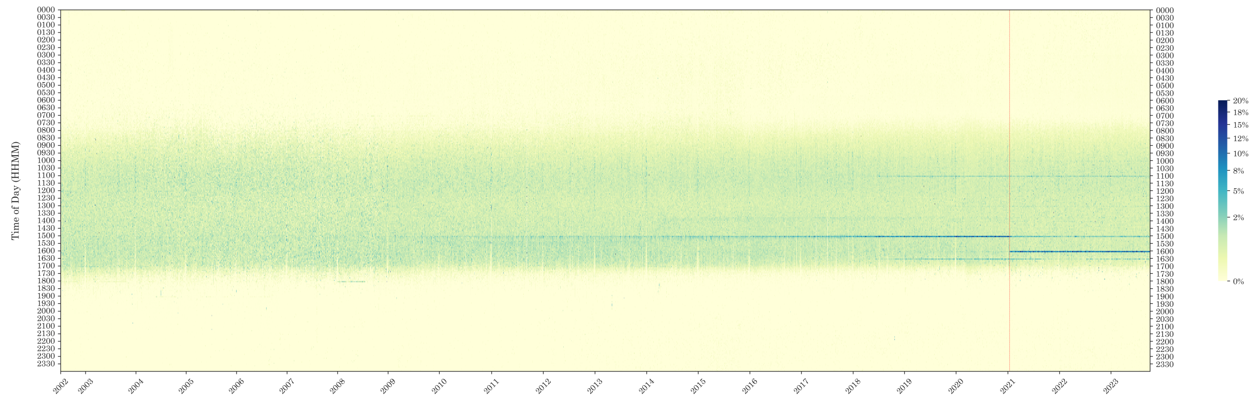


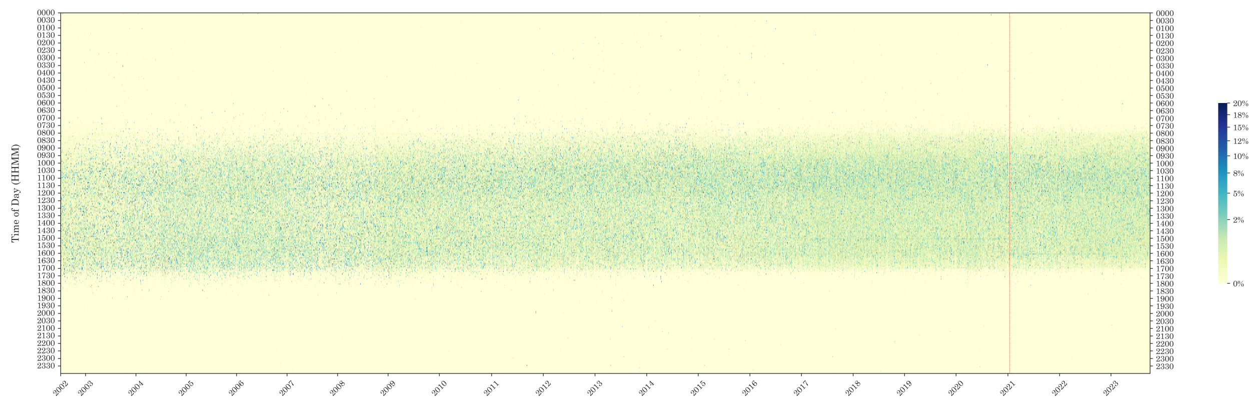
Figure 3: **Intraday distribution of trading volume**

The figure presents histograms of intraday trading volume distribution, where each bin represents the fraction of total daily customer volume executed per minute. The intraday fraction is calculated as the total customer volume per minute divided by the total customer volume for the day. The histograms display the average intraday fraction per minute for the years 2005, 2015, 2020, and 2022, shown in Panels (a) through (d). The x-axis represents time in minutes from 00:00 to 24:00, while the y-axis indicates the volume fraction (%). Two yellow vertical bars highlight the 15:00 and 16:00 time marks.

(a) Index-eligible investment grade bonds



(b) Non-eligible investment grade bonds



(c) High yield bonds

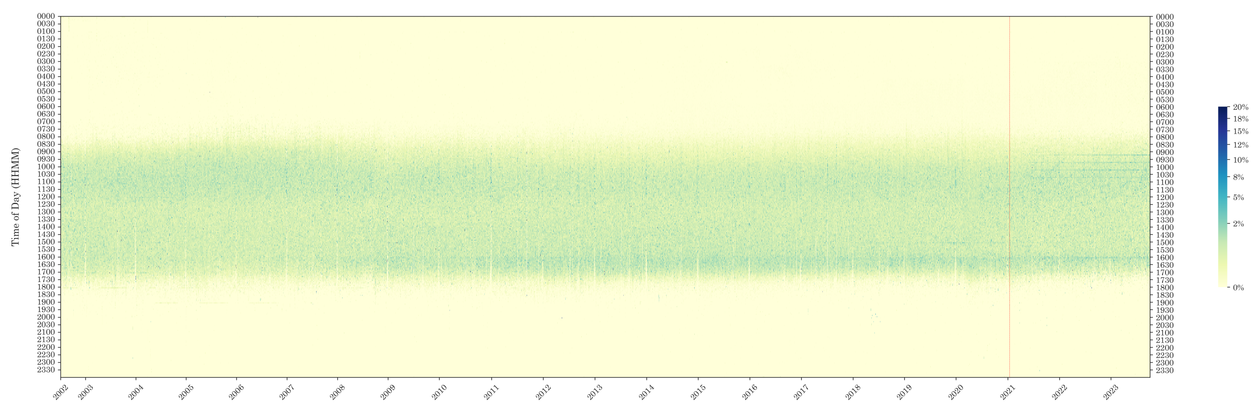
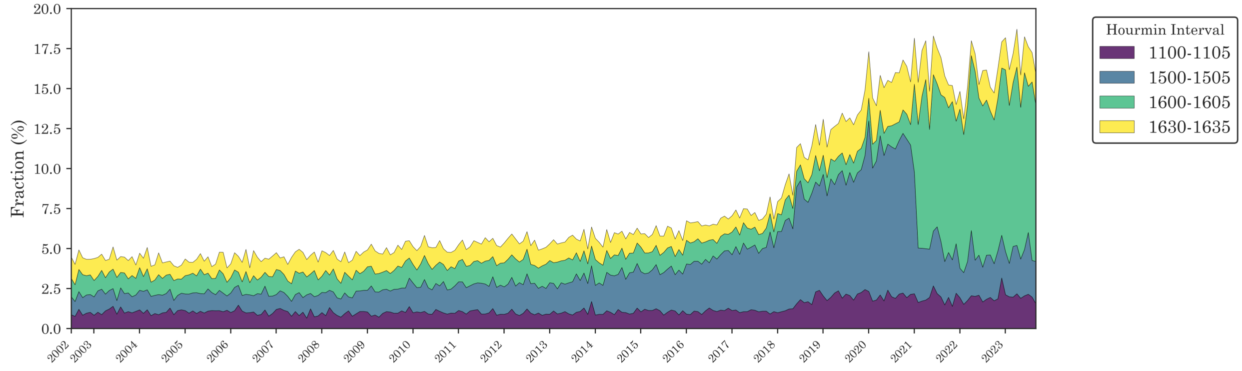


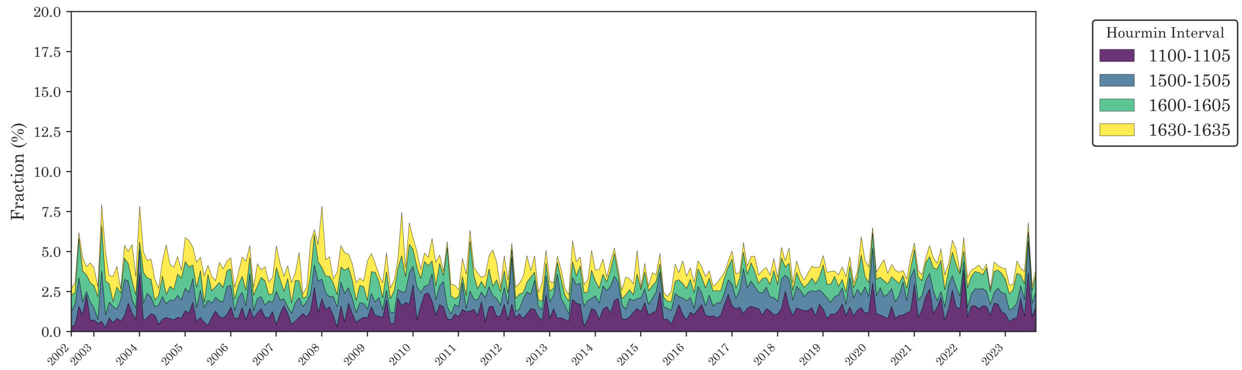
Figure 4: **Time-series heatmaps of intraday trading volume distribution**

This figure presents daily time-series heatmaps of intraday trading volume fractions for each 5-minute interval. The y-axis represents the time of day in 5-minute increments, while the x-axis spans calendar dates from July 2002 to September 2023. Panels (a), (b), and (c) display the heatmaps for Bloomberg index-eligible investment-grade bonds, non-eligible investment-grade bonds, and high-yield bonds, respectively. A vertical red line marks January 14, 2021.

(a) Index-eligible investment-grade bonds



(b) Non-eligible investment-grade bonds



(c) High-yield bonds

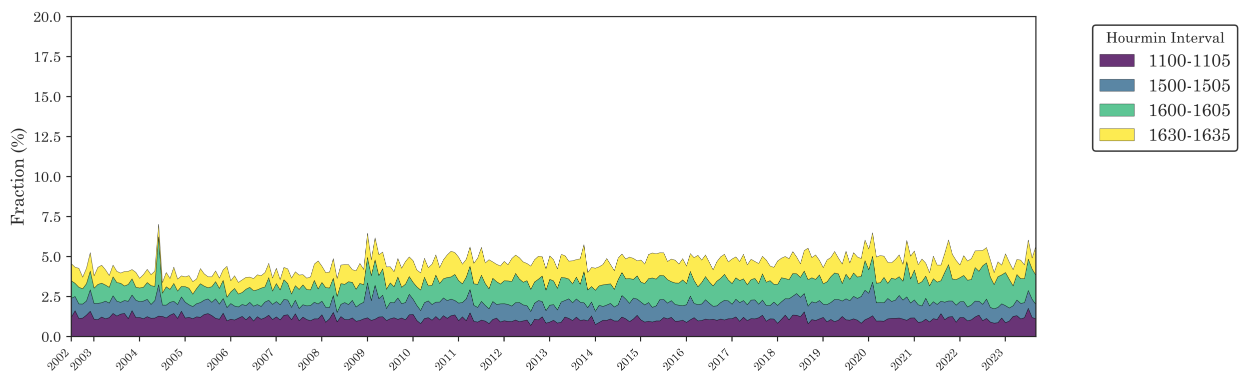


Figure 5: **Intraday trading volume distribution at index closing time and other delayed Treasury spotting times**

This figure presents the monthly time series of intraday trading volume fractions during the 5-minute intervals at 11:00, 15:00, 16:00, and 16:30. The y-axis represents the trading volume fraction (%), while the x-axis spans calendar dates from July 2002 to September 2023. Panels (a), (b), and (c) display the trends for index-eligible investment-grade bonds, non-eligible investment-grade bonds, and high-yield bonds, respectively.

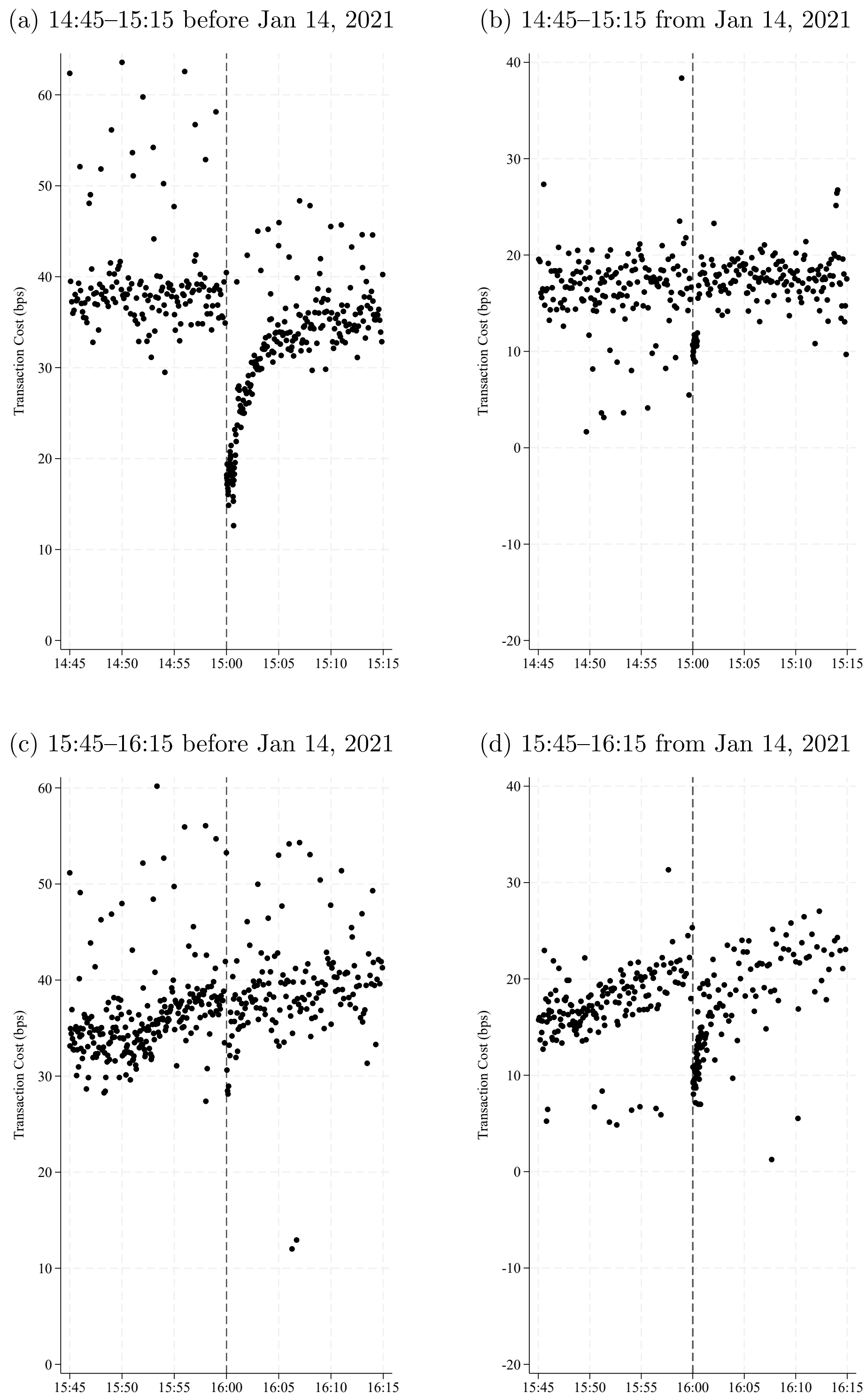


Figure 6: **Transaction costs during the 30-minute period around the Bloomberg index-closing time**

This figure presents binned scatter plots following Cattaneo, Crump, Farrell, and Feng (2024) to visualize trends in average transaction costs during 30 minutes around 15:00 and 16:00, before and after the pricing time shift on January 14, 2021. The transaction cost is calculated by using interdealer price benchmark following the approach of Hendershott and Madhavan (2015).

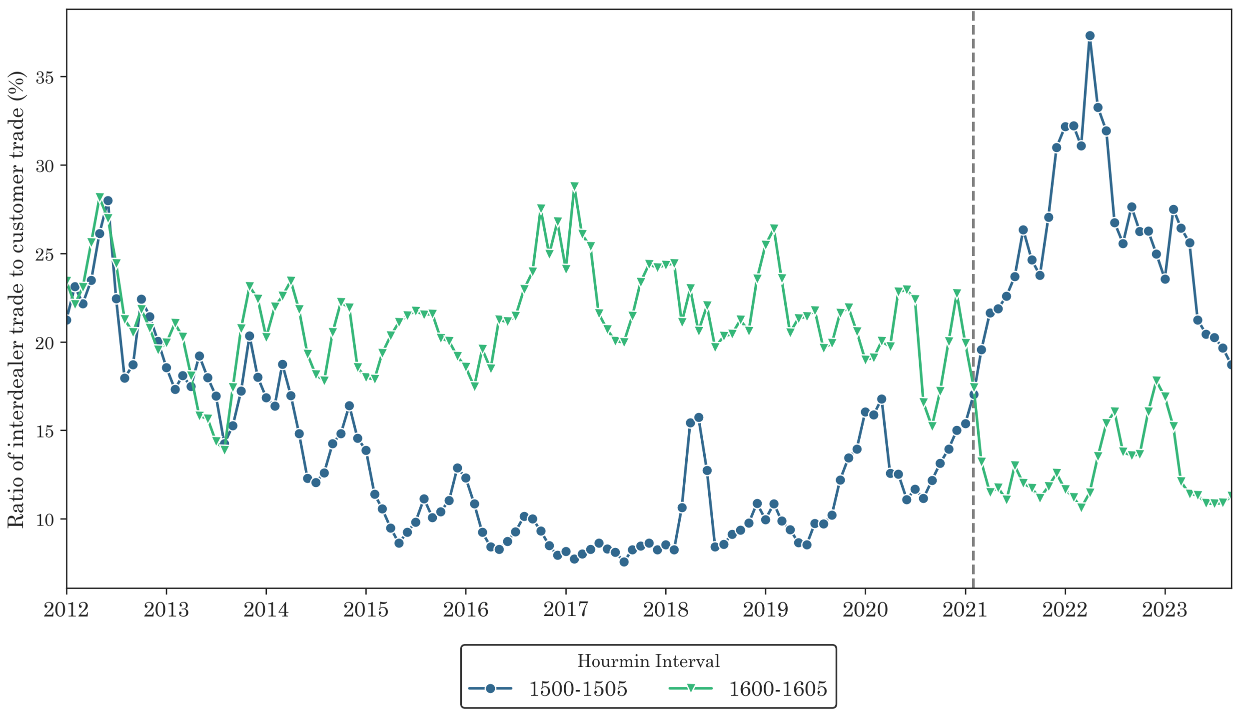
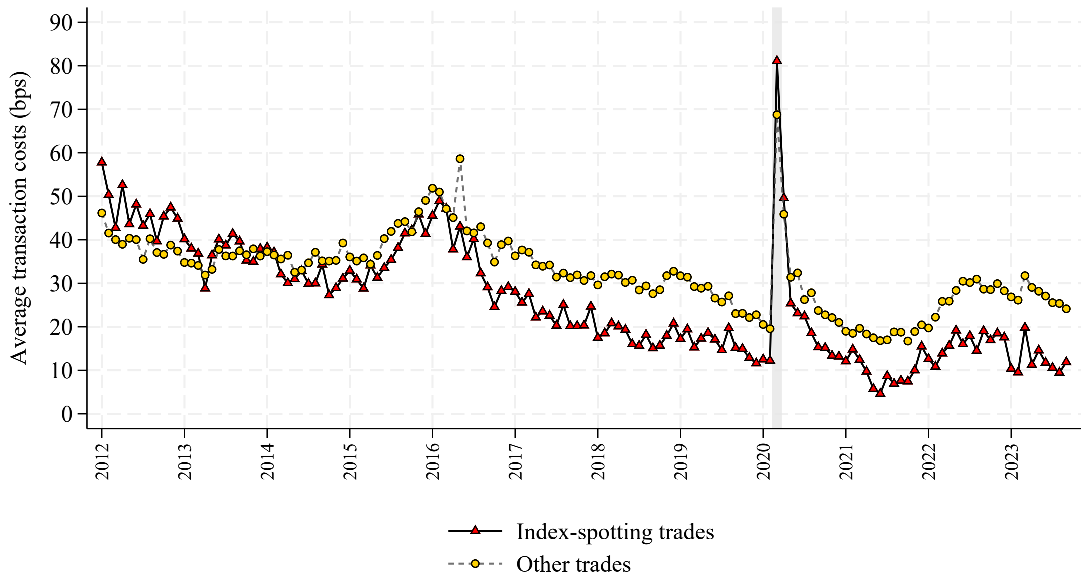


Figure 7: **Ratio of interdealer trade volume to customer trade volume**

This figure presents the interdealer-customer ratio (ICR), which measures the ratio of interdealer trade volumes to customer trade volumes during the 5-minute windows at 15:00 and 16:00. The plot displays the monthly time series of the 3-month moving average of the ICR. A vertical line marks January 2021.

(a) Average transaction costs for index spotting and other trades



(b) Difference of the average transaction costs

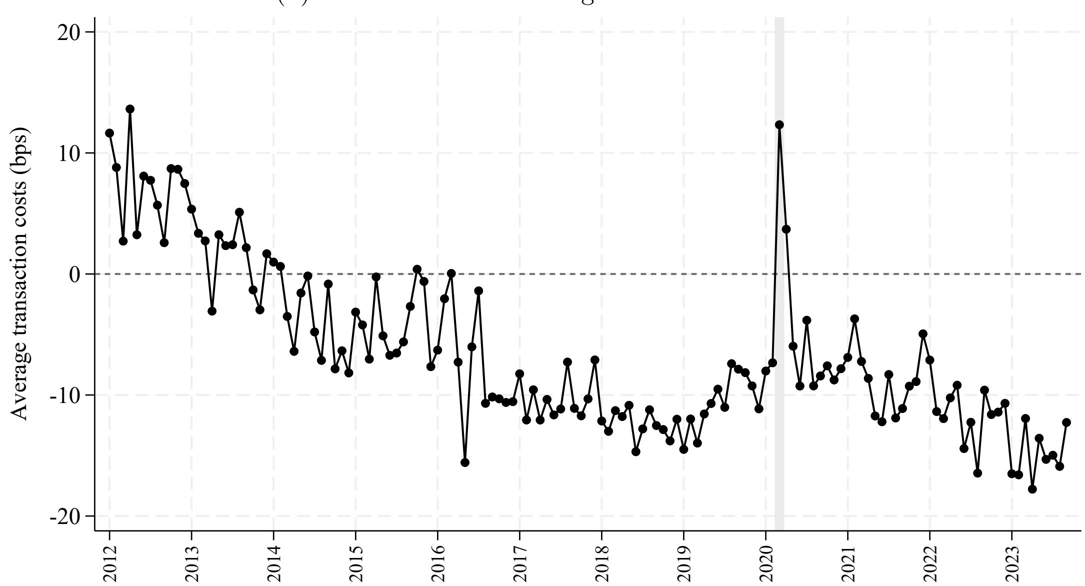


Figure 8: **Average transaction costs for index-closing time trades and other trades**

This figure presents the monthly time series of average transaction costs for index-closing time trades and other trades. The transaction cost is calculated by using interdealer price benchmark following the approach of Hendershott and Madhavan (2015). We compute the daily transaction cost for each bond as the trade-size-weighted transaction cost of trades. The monthly transaction cost is then derived as the average of the bond's daily transaction costs over the month. The gray vertical band highlights March 2020.

Table I: **Relationship between index eligibility and index-closing time volume**

This table examines the relationship between index eligibility and trading volume at the Bloomberg index closing time. The dependent variable, *Index-closing Time Volume%*, is defined as the ratio of customer trading volume within the 5-minute window following the Bloomberg index closing time to the total customer trading volume for each bond-day. The Bloomberg index closing time was 3:00 PM before January 14, 2021, and 4:00 PM thereafter. The key independent variable is *D*(*Index Eligible*), a dummy variable indicating whether a bond qualifies for inclusion in the Bloomberg U.S. Aggregate Bond Index. Control variables include the log of time to maturity (*Ln*(*Time to Maturity*)), log of age (*Ln*(*Age*)), log of amount outstanding (*Ln*(*Amount Outstanding*)), and the fraction of zero trading days over the past three months (*Zero Trading Day*)). The sample consists of IG bonds traded between Q1 2012 and Q3 2023. In Column (4), we restrict the sample to bonds traded from 2020 onward. *Rating FE* and *Day FE* refer to rating fixed effects and day fixed effects, respectively. Standard errors are two-way clustered at the bond and day levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: *Index-closing Time Volume%*				
				2020–2023
	(1)	(2)	(3)	(4)
D(*Index Eligible*)	5.354***	4.217***	4.466***	7.549***
	(0.186)	(0.279)	(0.247)	(0.447)
Ln(*Time to Maturity*)		3.902***	3.601***	5.361***
		(0.104)	(0.090)	(0.152)
Ln(*Age*)		0.312***	-0.387***	-0.305**
		(0.084)	(0.067)	(0.119)
Ln(*Amount Outstanding*)		0.051	0.839***	0.610***
		(0.121)	(0.095)	(0.164)
Zero Trading Day		-3.555***	0.904***	0.738*
		(0.293)	(0.235)	(0.437)
Rating FE	N	Y	Y	Y
Day FE	N	N	Y	Y
Observations	7,535,327	7,535,327	7,535,327	3,215,235
Adjusted R^2	0.00322	0.0255	0.0764	0.0756

Table II: **Index exclusion and index-closing time volume**

This table examines the relationship between index exclusion and the volume fraction traded during the 5-minute window following the index closing time. The dependent variable is *Index-closing Time Volume%*. Column (1) reproduces Column (3) of Table I, incorporating bond fixed effects (*Bond FE*). Column (2) focuses on a subsample of bonds with an amount outstanding within $250 million of the eligibility cutoff for the Bloomberg U.S. Aggregate Bond Index. Columns (3) and (4) expand the main sample to include maturing bonds (i.e., bonds with less than 1.5 years to maturity). The dummy variable D(*Exclusion by Maturity*) equals one if a bond's remaining time to maturity is less than 12 months and zero otherwise. Column (4) further restricts the sample to bonds with less than two years to maturity. Controls are defined as in Table I. *Rating FE* and *Day FE* refer to rating fixed effects and day fixed effects, respectively. Standard errors are two-way clustered at the bond and day levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: *Index-closing Time Volume%*				
			Including maturing bonds	
		$\lvert amt - cutoff \rvert$ < $250M		$ttm < 2y$
	(1)	(2)	(3)	(4)
D(*Index Eligible*)	3.034***	2.039***		
	(0.264)	(0.319)		
D(*Exclusion by Maturity*)			-0.328***	-1.394***
			(0.107)	(0.068)
Ln(*Time to Maturity*)	5.767***	4.839***	2.501***	-0.355***
	(0.241)	(0.337)	(0.105)	(0.037)
Ln(*Age*)	0.441***	0.433***	-0.173*	-2.079***
	(0.094)	(0.149)	(0.089)	(0.167)
Ln(*Amount Outstanding*)	1.827***	1.772***	2.754***	0.281**
	(0.135)	(0.301)	(0.112)	(0.114)
Zero Trading Day	-0.706***	-1.775***	0.872***	0.128
	(0.204)	(0.299)	(0.179)	(0.116)
Rating FE	Y	Y	Y	Y
Day FE	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y
Observations	7,535,211	2,787,330	8,553,697	1,411,062
Adjusted R^2	0.109	0.129	0.109	0.0318

Table III: **Index-closing time change and shift in trade clustering**

This table examines the effects of the Bloomberg index closing time change on index-closing volume. The dependent variable, $Volume\%^{5\text{-}minute\ window}$, represents the fraction of total trading volume executed within the 5-minute windows following 15:00, 16:00, 11:00, or 16:30, calculated for each bond-day. *D*(*Post Index-closing Time Change*) equals one for observations from January 14, 2021 onward. *D*(*Index Eligible*) equals one for the Bloomberg index-eligible bonds. All controls are defined as in Table II. The sample period spans October 14, 2020 to April 13, 2021. Bonds that experienced changes in index eligibility during this period (approximately 0.5% of observations) are excluded from the sample. Standard errors are two-way clustered at the bond and day levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: $Volume\%^{5\text{-}minute\ window}$								
Trading window:	15:00–15:05	16:00–16:05	11:00–11:05	16:30–16:35	15:00–15:05	16:00–16:05	11:00–11:05	16:30–16:35
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D(*Index Eligible*)	8.975***	0.154	0.229	0.867***				
	(0.696)	(0.312)	(0.172)	(0.325)				
D(*Index Eligible*) × *D*(*Post Index-closing Time Change*)	-7.047***	6.949***	0.043	-0.452	-6.931***	6.521***	0.125	-0.551
	(0.691)	(0.623)	(0.179)	(0.365)	(0.711)	(0.653)	(0.182)	(0.353)
Ln(*Time to Maturity*)	2.844***	2.801***	0.345***	1.073***	-100.987***	82.627***	-7.195***	0.770
	(0.364)	(0.330)	(0.080)	(0.119)	(8.238)	(7.634)	(2.304)	(4.071)
Ln(*Age*)	-0.316**	0.323**	-0.085**	-0.016	5.105***	-2.766*	-0.087	0.685
	(0.146)	(0.124)	(0.042)	(0.083)	(1.830)	(1.481)	(0.512)	(0.790)
Ln(*Amount Outstanding*)	0.119	0.143	0.092*	0.706***	1.617	1.861**	-0.564	2.620***
	(0.189)	(0.175)	(0.052)	(0.127)	(1.788)	(0.896)	(0.493)	(0.973)
Zero Trading Day	-0.894	-0.356	0.469***	-1.092***	2.556**	-2.658***	0.282	-0.613
	(0.645)	(0.529)	(0.160)	(0.344)	(0.987)	(0.917)	(0.318)	(0.462)
Rating FE	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Bond FE	N	N	N	N	Y	Y	Y	Y
Observations	401,995	401,995	401,995	401,995	401,945	401,945	401,945	401,945
Adjusted R^2	0.0693	0.0952	0.00773	0.0257	0.109	0.134	0.0112	0.0803

Table IV: **Market conditions and index-closing time volume**

This table examines the relationship between index-closing time volume and index eligibility under various market conditions. The dependent variable is *Index-closing Time Volume%*. In Column (1), the index eligibility dummy $D(\textit{Index Eligible})$ is interacted with $D(\textit{Large Flow-induced Trading})$, a dummy indicating periods in the top or bottom 5% of expected flow-induced trading by passive bond funds. Expected flow-induced trading is calculated for each bond and month following Lou (2012), assuming that funds trade on their monthly flows proportionally to their portfolio weights, scaled by total customer trading volume during the month. In Column (2), the index eligibility dummy is interacted with $D(\textit{High VIX})$, a dummy indicating days in the top 5% of VIX. In Column (3), the index eligibility dummy is interacted with *D(COVID)*, a dummy for the March 6–March 19, 2020 period. All controls are defined as in Table II. Columns (4)–(6) reproduce the specifications from Columns (1)–(3) while incorporating issuer-day fixed effects to further control for issuer-specific shocks. Standard errors are two-way clustered at the bond and day levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: *Index-closing Time Volume%*						
	(1)	(2)	(3)	(4)	(5)	(6)
$D(\textit{Index Eligible}) \times D(\textit{Large Flow-induced Trading})$	0.474**			0.673**		
	(0.220)			(0.270)		
$D(\textit{Index Eligible}) \times D(\textit{High VIX})$		2.579***			2.161***	
		(0.418)			(0.468)	
$D(\textit{Index Eligible}) \times D(\textit{COVID})$			4.790***			3.691***
			(1.224)			(0.905)
$D(\textit{Index Eligible})$	3.011***	2.848***	2.996***	3.073***	2.975***	3.098***
	(0.265)	(0.264)	(0.264)	(0.304)	(0.304)	(0.303)
$D(\textit{Large Flow-induced Trading})$	-0.551***			-0.719***		
	(0.200)			(0.259)		
$Ln(\textit{Time to Maturity})$	5.766***	5.764***	5.766***	5.252***	5.253***	5.252***
	(0.241)	(0.241)	(0.241)	(0.216)	(0.216)	(0.216)
$Ln(\textit{Age})$	0.444***	0.428***	0.441***	0.511***	0.503***	0.509***
	(0.094)	(0.094)	(0.094)	(0.099)	(0.099)	(0.099)
$Ln(\textit{Amount Outstanding})$	1.830***	1.816***	1.830***	2.401***	2.397***	2.403***
	(0.135)	(0.135)	(0.135)	(0.227)	(0.226)	(0.227)
Zero trading day	-0.697***	-0.684***	-0.703***	-0.936***	-0.931***	-0.941***
	(0.203)	(0.203)	(0.203)	(0.209)	(0.209)	(0.210)
Rating FE	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	-	-	-
Bond FE	Y	Y	Y	Y	Y	Y
Issuer × Day FE	N	N	N	Y	Y	Y
Observations	7,535,211	7,535,211	7,535,211	6,911,803	6,911,803	6,911,803
Adjusted R^2	0.109	0.109	0.109	0.124	0.124	0.124

Table V: **Transaction cost of index-closing time trades**

This table presents the results from a regression analyzing the relationship between transaction costs and a dummy variable for index-closing time trades. The dependent variable, *Transaction Cost*, is estimated following the approach of Hendershott and Madhavan (2015). In Panel A, transaction costs are estimated using the most recent interdealer trade price as the benchmark, while in Panel B, the CP+ midprice is used as the benchmark. The dummy variable $D($*Index-closing Time*$)$ equals one for trades executed between 15:00:00–15:04:59 before January 14, 2021, and between 16:00:00–16:04:59 thereafter. The dummy variable $D($*Other DTS Time*$)$ equals one for trades executed during the 5-minute windows at 11:00, 15:00 (*after* January 14, 2021), 16:00 (*before* January 14, 2021), and 16:30. All specifications include bond-day fixed effects (*Bond* $\times$ *Day FE*), trade size group fixed effects (*Trade Size FE*), and trade direction fixed effects (*Trade Direction FE*). The sample consists of all customer transactions of index-eligible bonds in our sample from Q1 2012 to Q3 2023. Standard errors are two-way clustered at the bond and day levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Interdealer transaction price as benchmark

Dependent variable: *Transaction Cost* (bps)						
Trade direction:	All (1)	Buy (2)	Sell (3)	All (4)	Buy (5)	Sell (6)
$D($*Index-closing Time*$)$	-5.280***	-7.931***	-4.450***	-5.355***	-8.038***	-4.549***
	(0.249)	(0.373)	(0.328)	(0.252)	(0.377)	(0.332)
$D($*Other DTS Time*$)$				-1.079***	-1.800***	-1.239***
				(0.151)	(0.221)	(0.202)
Bond $\times$ Day FE	Y	Y	Y	Y	Y	Y
Trade Size Group FE	Y	Y	Y	Y	Y	Y
Trade Direction FE	Y	-	-	Y	-	-
Observations	17,831,971	10,668,373	6,021,754	17,831,971	10,668,373	6,021,754
Adjusted R^2	0.381	0.487	0.448	0.381	0.487	0.448

Panel B. CP+ midprice as benchmark

Dependent variable: *Transaction Cost* (bps)						
Trade direction:	All (1)	Buy (2)	Sell (3)	All (4)	Buy (5)	Sell (6)
$D($*Index-closing Time*$)$	-7.589***	-9.906***	-5.891***	-7.904***	-10.252***	-6.177***
	(0.286)	(0.428)	(0.391)	(0.289)	(0.434)	(0.395)
$D($*Other DTS Time*$)$				-3.593***	-4.401***	-3.035***
				(0.164)	(0.244)	(0.275)
Bond $\times$ Day FE	Y	Y	Y	Y	Y	Y
Trade size FE	Y	Y	Y	Y	Y	Y
Trade direction FE	Y	Y	Y	Y	Y	Y
Observations	14,038,707	7,607,133	5,329,486	14,038,707	7,607,133	5,329,486
Adjusted R^2	0.339	0.508	0.544	0.340	0.508	0.544

Table VI: **Transaction cost changes around the index-closing time shift**

This table examines the impact of the Bloomberg index-closing time shift on transaction costs for index-closing time trades. The dependent variable, *Transaction Cost*, is estimated following the approach of Hendershott and Madhavan (2015). In Panel A, transaction costs are estimated using the most recent interdealer trade price as the benchmark, while in Panel B, the CP+ midprice is used as the benchmark. The dummy variable D(*Post Index-closing Time Change*) equals one for trades occurring after the index-closing time shift on January 14, 2021. The dummy variable D(15:00–15:05) is one for trades executed between 15:00:00–15:04:59 and zero otherwise. Similarly, D(16:00–16:05) is one for trades executed between 16:00:00–16:04:59 and zero otherwise. Columns (1)–(3) restrict the sample to trades occurring one, three, and six months before and after the index closing-time change, respectively. All controls are defined as in Table V. Standard errors are two-way clustered at the bond and day levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Interdealer transaction price as benchmark

Dependent variable: *Transaction Cost* (bps)			
Sample window:	1 month (1)	3 months (2)	6 months (3)
D(15:00–15:05)	-5.129***	-5.927***	-5.682***
	(0.923)	(0.770)	(0.549)
D(15:00–15:05) × D(*Post Index-closing Time Change*)	2.675**	2.800***	2.731***
	(1.299)	(0.962)	(0.660)
D(16:00–16:05)	-0.487	-1.295	-1.093**
	(1.442)	(0.812)	(0.529)
D(16:00–16:05) × D(*Post Index-closing Time Change*)	-5.509***	-3.743***	-4.976***
	(1.841)	(1.419)	(0.957)
Bond × Day FE	Y	Y	Y
Trade Size Group FE	Y	Y	Y
Trade Direction FE	Y	Y	Y
Observations	252,437	770,631	1,425,177
Adjusted R^2	0.319	0.321	0.342

Panel B. CP+ midprice as benchmark

Dependent variable: *Transaction Cost* (bps)			
Sample window:	1 month (1)	3 months (2)	6 months (3)
D(15:00–15:05)	-6.384***	-6.722***	-6.599***
	(1.149)	(0.674)	(0.479)
D(15:00–15:05) × D(*Post Index-closing Time Change*)	3.499**	3.552***	3.919***
	(1.566)	(0.895)	(0.607)
D(16:00–16:05)	-1.977	-1.596**	-1.990***
	(1.489)	(0.733)	(0.539)
D(16:00–16:05) × D(*Post Index-closing Time Change*)	-5.756***	-6.750***	-5.541***
	(1.833)	(0.949)	(0.689)
Bond × Day FE	Y	Y	Y
Trade size FE	Y	Y	Y
Trade direction FE	Y	Y	Y
Observations	494,779	1,485,851	2,769,862
Adjusted R^2	0.333	0.335	0.356

Table VII: **Alternative Explanations for Low Transaction Costs at Index Closing Time**

This table replicates Column (4) of Table V using various alternative specifications. The dependent variable, *Transaction Cost*, is estimated following the approach of Hendershott and Madhavan (2015). In Panel A, transaction costs are estimated using the most recent interdealer trade price as the benchmark, while in Panel B, the CP+ midprice is used as the benchmark. In Column (1), we exclude trades executed at timestamps (date-hour-minute-second) where more than 25 distinct bonds were traded simultaneously. In Column (2), we restrict the sample to AAA–AA rated bonds. In Column (3), we restrict the sample to A–BBB rated bonds. Standard errors are two-way clustered at the bond and day levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Interdealer transaction price as benchmark

Dependent variable: *Transaction Cost* (bps)	Excluding portfolio trade (1)	AAA-AA (2)	A-BBB (3)
D(*Index-closing Time*)	-4.158***	-5.658***	-5.338***
	(0.215)	(0.516)	(0.257)
D(*Other DTS Time*)	-0.207	-1.462***	-1.033***
	(0.132)	(0.259)	(0.157)
Bond × Day FE	Y	Y	Y
Trade Size Group FE	Y	Y	Y
Trade Direction FE	Y	Y	Y
Observations	17,097,225	1,494,348	16,337,623
Adjusted R^2	0.390	0.232	0.387

Panel B. CP+ midprice as benchmark

Dependent variable: *Transaction Cost* (bps)	Excluding portfolio trade (1)	AAA-AA (2)	A-BBB (3)
D(*Index-closing Time*)	-3.878***	-7.917***	-7.905***
	(0.217)	(0.533)	(0.296)
D(*Other DTS Time*)	-1.986***	-2.974***	-3.636***
	(0.129)	(0.305)	(0.169)
Bond × Day FE	Y	Y	Y
Trade size FE	Y	Y	Y
Trade direction FE	Y	Y	Y
Observations	12,707,864	1,150,366	12,888,341
Adjusted R^2	0.358	0.257	0.343

Table VIII: **Effects of index-closing time volume on daily transaction costs**

This table examines the relationship between the index-closing time volume fraction and daily transaction costs. The dependent variable is the daily average bond transaction cost, calculated as the trade-size weighted average transaction cost, either using all customer trades within a day (Columns (1) and (2)) or excluding customer trades executed at index-closing times (Columns (3) and (4)). Trade level *Transaction Cost* is estimated following the approach of Hendershott and Madhavan (2015). In Panel A, transaction costs are estimated using the interdealer trade price as the benchmark, while in Panel B, the CP+ midprice is used as the benchmark. *Index-closing Time Volume%* is defined as the ratio of customer trading volume within the 5-minute window following the Bloomberg index closing time to the total customer trading volume for each bond and day. All controls are defined as in Table IV. The sample consists of index-eligible bonds from Q1 2012 to Q3 2023. Standard errors are two-way clustered at the bond and day levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Interdealer transaction price as benchmark

Dependent variable: *Transaction Cost* (bps)				
			Excluding Index-closing Time	
	(1)	(2)	(3)	(4)
Index-closing Time Volume%	-9.512***	-9.495***	4.153***	4.554***
	(0.290)	(0.299)	(0.214)	(0.238)
Ln(Time to Maturity)	10.574***	8.502***	11.492***	9.317***
	(0.620)	(0.536)	(0.643)	(0.557)
Ln(Age)	2.994***	2.377***	2.643***	2.032***
	(0.350)	(0.328)	(0.363)	(0.343)
Ln(Amount Outstanding)	-16.418***	-14.994***	-16.336***	-15.171***
	(0.902)	(1.033)	(0.915)	(1.058)
Zero Trading Day	-0.444	8.862***	-0.601	9.145***
	(0.758)	(0.654)	(0.780)	(0.688)
Day FE	Y	-	Y	-
Rating FE	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y
Issuer × Day FE	N	Y	N	Y
Observations	3,311,700	2,804,616	3,227,196	2,721,994
Adjusted R^2	0.199	0.242	0.200	0.241

Panel B. CP+ midprice as benchmark

Dependent variable: *Transaction Cost* (bps)				
			Excluding Index-closing Time	
	(1)	(2)	(3)	(4)
Index-closing Time Volume%	-9.133***	-8.768***	2.048***	2.366***
	(0.474)	(0.462)	(0.232)	(0.228)
Ln(Time to Maturity)	-3.025	-2.253	0.600	0.730
	(2.010)	(1.785)	(1.770)	(1.616)
Ln(Age)	2.523***	3.158***	2.014**	2.551***
	(0.803)	(0.858)	(0.784)	(0.831)
Ln(Amount Outstanding)	-20.126***	-15.141***	-20.148***	-15.811***
	(2.029)	(1.462)	(2.022)	(1.525)
Zero Trading Day	8.956***	9.419***	9.229***	10.298***
	(0.851)	(0.708)	(0.878)	(0.729)
Day FE	Y	-	Y	-
Rating FE	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y
Issuer × day FE	N	Y	N	Y
Observations	2,960,425	2,807,525	2,821,166	2,664,970
Adjusted R^2	0.166	0.233	0.168	0.233

Table IX: **Market conditions and the effects of index closing time volume on daily transaction costs**

This table examines the relationship between transaction costs and index-closing time volume under conditions of high trade imbalances and market stress. The dependent variable is the daily average bond transaction cost, calculated as the trade-size weighted average transaction cost. Trade level *Transaction Cost* is estimated following the approach of Hendershott and Madhavan (2015). In Panel A, transaction costs are estimated using the interdealer trade price as the benchmark, while in Panel B, the CP+ midprice is used as the benchmark. *Index-closing Time Volume%* is interacted with three dummy variables indicating high trade imbalance conditions. In Column (1), it is interacted with D(*Large Flow-induced Trading*), a dummy variable identifying bond-months in the top and bottom 5% of flow-induced trading by passive bond funds. Flow-induced trading is calculated under the assumption that funds trade on flows proportionally to their portfolio weights and is scaled by the bond's amount outstanding. In Column (2), it is interacted with D(*High VIX*), a dummy for days in the highest 5% of VIX during the sample period. In Column (3), it is interacted with D(*COVID*), a dummy for the March 6–19, 2020 period. To facilitate interpretation, coefficient estimates on *Index-closing Time Volume%* and its interaction terms are scaled by a factor of 100. The dependent variable is the bond-day average *Transaction Cost*, calculated using all customer trades. Additionally, the table reports the sum of estimated coefficients for *Index-closing Time Volume%* and its interaction terms. All controls are defined as in Table IV. The sample consists of index-eligible bonds from Q1 2012 to Q3 2023. Standard errors are two-way clustered at the bond and day levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Interdealer transaction price as benchmark

Dependent variable: *Transaction Cost* (bps)						
	(1)	(2)	(3)	(4)	(5)	(6)
Index-closing Time Volume%	-10.108***	-10.417***	-9.688***	-10.139***	-10.449***	-9.715***
	(0.288)	(0.269)	(0.284)	(0.295)	(0.281)	(0.290)
Index-closing Time Volume% × D(*Large Flow-induced Trading*)	3.408***			3.626***		
	(0.646)			(0.702)		
Index-closing Time Volume% × D(*High VIX*)		9.982***			10.451***	
		(1.650)			(1.655)	
Index-closing Time Volume% × D(*COVID*)			27.441***			34.418***
			(8.772)			(10.309)
D(*Large Flow-induced Trading*)	-1.103***			-0.929***		
	(0.147)			(0.159)		
Ln(*Time to Maturity*)	10.525***	10.548***	10.566***	8.463***	8.470***	8.486***
	(0.620)	(0.620)	(0.620)	(0.535)	(0.535)	(0.536)
Ln(*Age*)	3.010***	2.992***	2.993***	2.397***	2.376***	2.374***
	(0.350)	(0.350)	(0.350)	(0.328)	(0.328)	(0.328)
Ln(*Amount Outstanding*)	-16.389***	-16.417***	-16.416***	-14.978***	-15.001***	-14.991***
	(0.902)	(0.901)	(0.902)	(1.033)	(1.033)	(1.033)
Zero trading day	-0.492	-0.437	-0.441	8.819***	8.866***	8.869***
	(0.758)	(0.758)	(0.758)	(0.655)	(0.654)	(0.655)
$\beta_1 + \beta_2$	-6.701***	-0.435	17.753**	-6.513***	0.001	24.703**
	(0.650)	(1.622)	(8.773)	(0.704)	(1.625)	(10.305)
Rating FE	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	-	-	-
Bond FE	Y	Y	Y	Y	Y	Y
Issuer × day FE	N	N	N	Y	Y	Y
Observations	3,311,700	3,311,700	3,311,700	2,804,616	2,804,616	2,804,616
Adjusted R^2	0.199	0.199	0.199	0.242	0.242	0.242

Panel B. CP+ midprice as benchmark

Dependent variable: *Transaction Cost* (bps)						
	(1)	(2)	(3)	(4)	(5)	(6)
Index-closing Time Volume%	-10.076***	-10.406***	-9.614***	-9.560***	-10.035***	-9.261***
	(0.445)	(0.393)	(0.435)	(0.414)	(0.371)	(0.408)
Index-closing Time Volume% $\times$ *D*(*Large Flow-induced Trading*)	5.247***			4.422***		
	(1.498)			(1.408)		
Index-closing Time Volume% $\times$ *D*(*High VIX*)		8.608***			8.644***	
		(2.404)			(2.357)	
Index-closing Time Volume% $\times$ *D*(*COVID*)			45.190**			47.852**
			(18.484)			(19.303)
D(*Large Flow-induced Trading*)	-0.793**			-1.313***		
	(0.349)			(0.245)		
Ln(*Time to Maturity*)	-3.038	-2.765	-2.977	-2.162	-2.024	-2.215
	(2.062)	(1.977)	(2.001)	(1.808)	(1.755)	(1.778)
Ln(*Age*)	2.551***	2.545***	2.547***	3.185***	3.174***	3.172***
	(0.806)	(0.806)	(0.809)	(0.859)	(0.860)	(0.861)
Ln(*Amount Outstanding*)	-20.106***	-20.120***	-20.086***	-15.135***	-15.151***	-15.102***
	(2.020)	(2.026)	(2.023)	(1.462)	(1.462)	(1.461)
Zero trading day	8.922***	8.946***	8.974***	9.335***	9.405***	9.428***
	(0.848)	(0.850)	(0.851)	(0.706)	(0.708)	(0.708)
$\beta_1 + \beta_2$	-4.829***	-1.797	35.576*	-5.137***	-1.391	38.591**
	(1.469)	(2.349)	(18.444)	(1.419)	(2.317)	(19.280)
Rating FE	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	-	-	-
Bond FE	Y	Y	Y	Y	Y	Y
Issuer $\times$ day FE	N	N	N	Y	Y	Y
Observations	2,960,425	2,960,425	2,960,425	2,807,525	2,807,525	2,807,525
Adjusted R^2	0.166	0.167	0.167	0.233	0.234	0.234