The Growing Index Effect in the Corporate Bond Market*

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Abstract

Index tracking has created a de facto close in the U.S. corporate bond market. Unlike equities, corporate bonds trade over the counter without an official close, and volume was historically evenly distributed intraday. By 2024, however, 10% of daily volume occurs within one minute of the major indices' pricing time. Liquidity improves around this pricing time but worsens during the rest of the day, yielding a net gain. Bloomberg's change in pricing time shifted both trading concentration and its liquidity effects immediately, establishing causality. These benefits reflect temporal clustering that facilitates dealer inventory management, but weaken or reverse during stress.

JEL classification: G10, G11, G12, G23.

Keywords: indexing, corporate bond market, liquidity, dealer, investment fund, mutual fund, ETF

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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, coupled with their expanding market presence, potentially exert substantial influence on corporate bond market dynamics.

In this paper, we examine the growing adoption of index tracking by investment funds and its impact on trading dynamics and liquidity in the corporate bond market. An increasing number of investment vehicles, including index funds and ETFs, are explicitly designed to track specific bond indices. Unlike equity markets, where the official close serves as a natural focal point for daily price determination and end-of-day trading, the corporate bond market is an over-the-counter (OTC) market without an official close. However, bond indices typically determine daily valuations for constituent bonds at predetermined times (e.g., 3:00 PM or 4:00 PM).[1] As a result, fund managers have incentives to trade around these times to align execution prices more closely with index valuations and thereby reduce tracking error. These index pricing times can therefore function as de facto closing points, concentrating trading demand in constituent bonds around those times. Against this backdrop, we ask two questions: How has the market adapted to the temporal clustering of trading activity driven by index tracking? And more importantly, what are the implications of these structural shifts for corporate bond market liquidity?

We leverage data from actual transactions along with high-frequency, minute-by-minute bond price estimates generated by machine learning algorithms to investigate these questions. Specifically, we focus on the growing demand to trade at the closing time of the Bloomberg

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

bond indices. Bloomberg is a leading index provider in the corporate bond market, with more than 90% of passive bond funds tracking its indices in terms of total assets under management (AUM) as of 2024 (Figure 2). During the early years of our sample period, when investment funds played a modest role in the corporate bond market, trading in investment-grade (IG) bonds was relatively evenly distributed throughout the trading day. However, as index tracking became more widely adopted in bond investments, trading activity for bonds eligible for Bloomberg indices progressively concentrated around the time when bond indices close. By the end of 2024, about 10% of daily trading volume was executed within the *one minute* following Bloomberg's index-closing time.

The most compelling evidence on the causal effect of indexing on trading concentration in the corporate bond market exploits Bloomberg's modification of its index-closing time. On January 14, 2021, Bloomberg shifted the closing time for its bond indices from 3:00 PM to 4:00 PM, resulting in an immediate migration of trades from 3:00 PM to 4:00 PM. We provide additional causal evidence that index tracking drives bond trade clustering through several complementary analyses. Specifically, the clustering effect is notably absent in IG bonds that are ineligible to the Bloomberg indices and high-yield (HY) bonds, a market segment in which passive investment has a substantially lower market presence (Figure 3). Moreover, when bonds exit the Bloomberg index, we document a significant reduction in trade clustering at index closing, further corroborating the causal interpretation of index tracking in reshaping corporate bond trading patterns.

Importantly, evolutions in intraday trading dynamics induced by index tracking have reshaped liquidity conditions in the corporate bond market. We find evidence suggesting that trade clustering at index-closing time has improved liquidity at the closing compared to other periods of the trading day. Using both actual transaction prices and machine-learning-based price estimates, we construct several alternative measures of trade-level transaction costs for customer trades following Hendershott and Madhavan (2015). 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 of trade clustering (induced by index tracking) on bond liquidity, we again leverage the 2021 change in the closing time of the 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 facilitates the matching of customer buy and sell orders, reducing market frictions. This, in turn, lowers search costs, mitigates dealer inventory risks, and ultimately reduces transaction costs for customers. Indeed, our findings show that following the closing time shift, the volume of interdealer trades, which are used by dealers to manage inventory imbalances from customer transactions, declined at the new closing time while increasing at the old closing time. This pattern suggests that better-matched customer trades at the new index close reduced dealers' reliance on interdealer trades for liquidity provision. Choi, Huh, and Shin (2024) document that corporate bond liquidity provision has increasingly relied on the matching of customer trades following the implementation of post-2008 banking regulations. Our results highlight the role of the index-closing time as a market focal point that fosters more efficient trading and enhances bond market liquidity.

Another potential explanation is reduced information asymmetry at index close. Because a large share of trades during this window likely originates from passive investment funds, the likelihood of informed trading in individual bonds may be lower, resulting in reduced

transaction costs.[2] However, our evidence provides little support for this mechanism. Liquidity improvements are present even among high-quality investment-grade bonds (AAA or AA rated), which face little information asymmetry, and the effect is at least as strong, if not stronger, than for lower-rated IG bonds (A and BBB). Moreover, when we analyze a subset of trades executed by insurance companies, we continue to find significant liquidity gains at index close relative to the rest of the day. Since insurer trades at index close and those during the rest of the day are presumably similar in their informativeness, this evidence suggests that liquidity gains at index close are not primarily driven by differences in information asymmetry.

A third potential explanation for lower transaction costs at index close is delayed Treasury spotting. In the IG corporate bond market, the benchmark Treasury yield used for pricing is sometimes fixed later in the day rather than at the time of trade. Delaying Treasury spotting to a later time of day may allow dealers to hedge interest rate risk more effectively and reduce balance sheet usage, thereby potentially enabling them to offer lower transaction costs to clients. Because index-closing times coincide with common spotting windows, one might conjecture that the observed liquidity improvements simply reflect a greater share of delayed-spotting trades at the close. The evidence, however, provides little support for this mechanism. When we exclude the set of delayed Treasury spotting trades flagged by MarketAxess from our sample, the estimated liquidity improvement for index closing trades is virtually unchanged.

Finally, trading arrangements such as portfolio trading and electronic trading may also help explain the liquidity differences between index-closing time and the rest of the day. Funds, for example, may use portfolio trades to rebalance near the index close and align their holdings with benchmark weights. Since portfolio trading can reduce transaction costs Li, O'Hara, Rapp, and Zhou (2025), the lower transaction costs at the index close may reflect

[2]We also acknowledge the possibility that informed traders may choose to "blend" in during the index-closing time, which should mitigate the liquidity improvement associated with lowered information asymmetry.

the use of such trades. In addition, electronic trading has grown rapidly in the corporate bond market and has been shown to involve lower transaction costs than traditional voice trading (Hendershott and Madhavan, 2015; O'Hara and Zhou, 2021). The lower transaction costs at the index close may likewise reflect greater use of electronic trading during this period. However, we find little support for either explanation. The liquidity advantage at the index close persists even after excluding portfolio trades or electronic trades.

Importantly, indexing-induced trade clustering not only redistributes liquidity within the trading day but also significantly affects the average liquidity a bond enjoys over the course of the day. Comparing across bonds, those with greater trade clustering around index-closing times tend to exhibit lower average daily transaction costs, even though they incur higher costs outside the index closing window. On net, our evidence suggests that trade clustering at the index close enhances overall corporate bond liquidity, indicating that the concentrated provision of liquidity during this period more than offsets reduced liquidity at other times of the day.

Since the liquidity benefits of trade clustering at index-closing time primarily derive from the netting of customer demands and the consequent reduction in dealer intermediation requirements, these advantages exhibit considerable state-dependency across market conditions. The benefits may attenuate, or even reverse, when trading demand becomes predominantly unidirectional. Our empirical analysis confirms that during periods of large, unbalanced bond trading, driven by substantial passive fund outflows 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 entirely reversed, resulting in higher transaction costs at index-closing times. These findings underscore the fragility of index-driven trade clustering during periods of market stress and point to important limitations in the resulting liquidity enhancements.

Our findings carry important implications for the design and evolution of corporate bond

markets. We show that index-closing times can serve as a powerful focal point for trading even in a decentralized OTC setting, effectively creating a "thicker" market at predetermined benchmark times. This pattern suggests that a central benefit of market centralization—coordinating order flow to improve liquidity—can arise endogenously through benchmarking and index-driven flows. Consistent with this interpretation, MarketAxess's recent announcement of opening and closing auctions for corporate bonds can be viewed as an institutional response to, and formalization of, the time-based coordination we document, with the potential to strengthen price formation and liquidity around benchmark windows.[3]

More broadly, our evidence informs the longstanding discussion over whether corporate bond trading should be centralized. Prior work suggests that exchange-based trading can support low transaction costs for corporate bonds (Plante, 2017; Abudy and Wohl, 2018), and that centralized auctions can accelerate price discovery relative to decentralized OTC trading (Zhu, 2012). Harris, Kyle, and Sirri (2015) also advocate for greater centralization in corporate bond markets. At the same time, Biais and Green (2019) document that corporate bonds historically traded on exchanges but liquidity migrated to OTC venues as institutional investors and dealers became more dominant and favored decentralized trading. Our results suggest that the continued expansion of indexing may shift market structure toward greater concentration of liquidity at benchmark times, potentially supporting more centralized trading mechanisms, at least in designated windows, even if the market remains OTC for most transactions.

The OTC setting is also central to our empirical identification and differentiates our study from related work in equities. Several papers, including Bogousslavsky and Muravyev (2023), Jegadeesh and Wu (2022), Jiang, Wu, and Yao (2024), document that stock trading volume concentrates near index-closing times. In equity markets, however, index closing times coincide with the end of the regular trading session and are accompanied by a closing

[3]See the MarketAxess (2025) news release, "MarketAxess Unveils Fixed Income's First Opening & Closing Auctions Designed to Improve Pricing and Liquidity," available at `https://investor.marketaxess.com/news/news-details/2025/MarketAxess-Unveils-Fixed-Incomes-First-Opening--Closing-Auctions-Designed-to-Improve-Pricing-and-Liquidity/default.aspx`.

auction, both of which concentrate trading volume at 4 PM and make it difficult to isolate the effect of index closing on trading activity. Consistent with this concern, Comerton-Forde and Rindi (2022) find that increases in auction activity are not explained by index investing. By contrast, the corporate bond market lacks an official end-of-day auction and has no official close. In this setting, Bloomberg's change in index closing time provides a natural experiment that allows us to cleanly identify the causal effect of indexing on intraday trading patterns.

Furthermore, our contribution also extends beyond documenting intraday concentration. We assess the net liquidity effects of indexing. Our results indicate that index tracking not only reallocates liquidity across the trading day toward benchmark times, but can also improve overall liquidity conditions in the corporate bond market by coordinating trading in an otherwise sparse market and mitigating search frictions.

In that sense, our paper contributes to the broader literature on indexing and passive investment. In fixed-income markets, prior research examines how indexing affects asset demand, information efficiency, and liquidity.[4] While evidence on the liquidity effects of index membership is mixed, existing work typically focuses on the substitution between underlying bonds and index baskets.[5] We instead highlight a distinct channel: benchmarking can coordinate the timing of trades and improve overall liquidity by mitigating search frictions in an OTC market.

Finally, our analysis sheds light on the broader discussion on financial stability. A large body of research has examined the growing role of investment funds in bond markets, par-

[4]See, for example, Dannhauser (2017), Dick-Nielsen and Rossi (2019), Pan and Zeng (2020), Dannhauser and Hoseinzade (2022), Dannhauser and Dathan (2024), Holden and Nam (2024), Marta (2024), Bretscher, Schmid, Sen, and Sharma (2025), Koont, Ma, Pastor, and Zeng (2025).

[5]See, for example, Dannhauser (2017), Holden and Nam (2024), and Koont et al. (2025).

ticularly their potential to amplify financial system fragility.[6] 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 index-tracking funds in shaping bond market liquidity. Although liquidity management is generally more straightforward for funds for whom index tracking or benchmarking is important, we show that, despite their passive trading approach, they can still exert significant influence on the underlying bond market. While the growth of index-tracking funds 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.

The remainder of the paper is organized as follows. Section II provides institutional background on index tracking in the corporate bond market and details the sample construction. Section III examines the relationship between index tracking and trade clustering. Section IV 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 V 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,

[6]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).

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 (including their predecessors previously managed by Lehman Brothers and then Barclays) have been the predominant benchmarks for passive bond funds. Although other index providers, such as S&P Global and ICE, have entered the market and gradually increased their market shares, Bloomberg remains the top player, with its indices followed by more than 92% of passive funds in terms of AUM at the end of 2024.

One of the most influential indices provided by Bloomberg is the Bloomberg U.S. Aggregate Bond Index ("The Agg"). Originally known as the Lehman U.S. Aggregate Bond Index, The Agg served as the benchmark for the first bond ETF and has been the most popular bond index since its inception in 1973.[7] In 2008, it was renamed as the Barclays Capital U.S. Aggregate Bond Index after Barclays' acquisition of Lehman Brothers' North American businesses. Later, in 2016, it became the Bloomberg Barclays U.S. Aggregate Bond Index as Bloomberg acquired Barclays' index business (Barclays Risk Analytics and Index Solutions). After a five-year co-branding period, it was rebranded as the Bloomberg U.S. Aggregate Bond Index 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

[7]The Lehman bond indices were created by Kuhn, Loeb & Co. in 1973, then acquired by Lehman Brothers in 1977.

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.[8] 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).[9] Additionally, bonds must have at least one year remaining until maturity, a minimum of $300 million outstanding, and a fixed-coupon rate.[10] 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.

Bloomberg indices are valued daily using evaluated bond prices at the index "close." Prior to 2021, the closing time of the Bloomberg indices had been 3:00 PM. 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 4:00 PM close of the U.S. equity markets, 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

[8] 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.

[9] If there are only two ratings available, the lower (more conservative) one is used. The single rating is used if only one is available.

[10] 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.

indices, except taxable municipal bonds.[11]

Mechanically, Bloomberg constructs evaluated end-of-day prices from observed inputs, such as reported trades and contributed quotes, and supplements these inputs with valuation models when necessary. Bloomberg then applies index rules to compute constituent- and index-level values and conducts post-close validation and production checks before disseminating index levels to subscribers. Because this production and quality-control workflow occurs after the close, with preliminary outputs often available roughly 30 minutes later (and final files later still), it is unlikely that the publication of index levels feeds back into transaction pricing or market liquidity within a narrow closing window such as the five minutes immediately following the index close. For passive funds mandated to replicate a Bloomberg index, or any vehicle seeking to minimize tracking error, executing trades at or near the index close helps align transaction prices with those used in the index's daily valuation. This alignment is valuable because trading earlier or later in the day exposes the fund to intraday movements in interest rates, credit spreads, or market liquidity between execution and the index close, which can generate valuation differences between the portfolio and the index and thereby increase tracking error.

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 December 2024, 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 duplicated reports and in applying the price-sequence-based filters (the median and the reversal filters).

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

We complement the TRACE data with high-frequency CP+ pricing data from MarketAxess, a leading electronic trading platform for corporate bonds. The CP+ data provides minute-by-minute estimates of bid and offer prices for a broad set of corporate bonds, particularly those eligible for major fixed-income indices.[12] These price estimates are constructed using information from multiple sources, including TRACE-reported transactions and proprietary data from the MarketAxess platform such as completed trades, dealer runs, and RFQ inquiries. As a result, the dataset incorporates both executed transactions and indicative pricing information observed during the trading process.

MarketAxess generates CP+ prices using an automated pricing framework that combines statistical and machine-learning techniques with available market information to produce real-time price estimates. For bonds with frequent trading activity, the estimates rely more heavily on recent transaction and quote information, whereas for less actively traded bonds, the model extrapolates from related securities and other market inputs. This framework provides high-frequency price estimates for a large cross-section of corporate bonds. Use of CP+ pricing data has expanded in recent years among market participants and data vendors. For example, in October 2024, S&P Global Market Intelligence announced a data partnership with MarketAxess to incorporates CP+ pricing into S&P Global's evaluated pricing services.[13]

We merge TRACE transaction data and CP+ bond pricing data with the London Stock Exchange Group (LSEG) 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

[12] See `https://www.marketaxess.com/price/cp-plus`.
[13] See this press release by S&P.

ratings assigned by the three major agencies: S&P, Moody's, and Fitch.[14] 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-denominated, privately placed, and sinking-fund bonds. We use secondary market trades and exclude those occurring on weekends as well as U.S. holidays and early-close days recommended by Securities Industry and Financial Markets Association (SIFMA). Our TRACE sample, after being merged with the Mergent FISD, comprises 142,435,519 trades spanning July 2002 to December 2024, covering 24,453 bonds issued by 3,904 firms. Additionally, our CP+ bond pricing data include 11,870,186,722 midprice observations for the sample bonds from 2020 to 2024.

We identify insurer trades in our bond transaction data by matching them with purchase and sale records of insurers from the National Association of Insurance Commissioners (NAIC), obtained via LSEG Mergent. We match transactions in the two databases on bond CUSIP, date, volume, price, and trade direction.[15] This procedure yields 602,285 uniquely matched insurer trades.

Finally, we supplement our corporate bond data with bond mutual fund data. Information on fund characteristics is obtained from the Center for Research in Security Prices (CRSP) Survivorship-Bias-Free US Mutual Fund Database. We obtain daily bond fund flows, monthly net assets, and primary prospectus benchmark data from Morningstar.

[14] 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.

[15] We allow a 0.1 bps margin in price matching to account for rounding errors. Matches must be unique; duplicated matches are treated as unmatched. Further details follow Choi et al. (2024).

III. Index Tracking and Intraday Trading Dynamics in Corporate Bonds

In this section, we document a striking pattern in the distribution of intraday corporate bond trades between dealers and customers: bond trades increasingly cluster at specific time points of 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 intraday trade clustering.

A The Changing Landscape of Corporate Bond Intraday Trading

We begin by examining the distribution of intraday dealer-customer corporate bond trading activities in IG bonds eligible for Bloomberg bond indices, using four historical snapshots.[16] About twenty years 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 4, 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 and 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-closing 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 4, 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 intraday trade distribution for 2022), the largest daily trade cluster (about 8%

[16] 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.

of trading volume) shifted to 4:00 PM, while the 3:00 PM cluster diminished significantly. The 4:00 PM cluster becomes about 10% of trading volume during the last quarter of 2024. The quarter-by-quarter evolution of intraday trade distribution from Q3 2002 to Q4 2024 is available online.

There are two other, smaller clusters at 11:00 AM and 4:30 PM in Figure 4. These reflect common Treasury-spotting times.[17] Although 3:00 PM and 4:00 PM are also common spotting times, it is important to note that index tracking is the primary driver of trade clustering regardless of how corporate bond trades are arranged: the index-closing time commands significantly higher trading volume than other popular spotting times. More importantly, immediately after Bloomberg's index-closing time shifted from 3:00 PM to 4:00 PM, the most pronounced clustering shifted to 4:00 PM as well.[18]

These four snapshots in Figure 4 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 5 displays daily time-series heatmaps of the intraday trading volume fraction for each 5-minute interval from 2002 to 2024. As shown in Panel (a), for index-eligible IG bonds, a distinct concentration of trading at 3:00 PM began to emerge after the Global 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

[17] In the corporate bond market, IG bonds are typically quoted as a spread to a benchmark Treasury. Dealers and customers may lock in the benchmark yield at the time of trade execution (immediate spotting) or defer the determination of the yield to a later time (delayed spotting), for example, to take advantage of deeper Treasury market liquidity at some time points. Because a trade is not complete until the reference yield is set, clustering naturally emerges at common Treasury spotting times, such as 11:00 AM, 3:00 PM, 4:00 PM, and 4:30 PM.

[18] The remaining 3:00 PM cluster likely reflects both the popularity of 3:00 PM Treasury spotting and the fact that some other index providers and pricing vendors continued to close at 3:00 PM.

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.

To gauge the magnitude of the impact of index tracking on trade clustering, we focus on four key times during the trading 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 6 shows that for index-eligible IG bonds, Bloomberg's closing time change triggered an immediate reallocation of trading activity. The share of volume within five minutes after 3:00 PM fell from 9.3% in December 2020 to 3.4% in February 2021, while the corresponding share after 4:00 PM rose from 1.3% to 7.7% over the same period, reaching 9.5% in March 2021 and further growing to 12.1% in December 2024. By contrast, non-eligible IG bonds and HY bonds display no comparable shift. Consistent with Figure 5, their trading volume clustered around these intervals remained stable at roughly 5% of total daily activity throughout the observation period (Panels (b) and (c) of Figure 6). If anything, the index-closing-time clustering of high-yield bonds has risen from about 1% in the early 2010s to roughly 3%, likely reflecting increased index tracking in the high-yield sector during the recent years (see Figure 3).

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:

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

where $\textit{Index-closing Time Volume\%}_{i,t}$ 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. $\textit{D(Index Eligible)}_{i,t}$ 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 6.061 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 5.089 to 5.138 percentage points. Finally, in Column (4), we focus on the most recent sample period (2020-2024) and estimate that trading clustering at index-closing time is approximately 7.931 percentage points higher for index-eligible bonds compared to ineligible IG bonds. This finding corroborates the evidence in Figure 5 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 Bloomberg indices. In Column (1) of Table II, we find that, after controlling for bond fixed effects, a higher fraction of trades (about 3.342 percentage points) is 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 its outstanding amount falling below the eligibility threshold because (1) some bonds are partially called by their issuers, and (2) Bloomberg increased Agg's minimum outstanding amount threshold in 2017. In April 2017, the 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 2.346 percentage point increase in trade volume executed around index-closing time when a bond is within the index relative when it becomes ineligible.

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 relax our sample restrictions 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 0.830 percentage points relative to daily volume. Narrowing our focus to bonds with less than two years of remaining maturity, we find that exiting the Index is associated with a 1.599 percentage point decline in trading volume at index-closing time.

To further strengthen the interpretation that indexing drives the clustering of corporate bond trading, we exploit the shift in the closing time of Bloomberg indices. We focus on the sample period of October 14, 2020 to April 13, 2021, a six-month window around the shift of the Bloomberg index-closing time, 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 (*Index Eligible*) is 8.967, 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(*Index Eligible*) and D(*Post Index-closing Time Change*) is -7.039, 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 the index-closing time switch, there is no significant 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 6.937 percentage points increase in trading volume during this window. Notably, the increase in trading volume at 4:00 PM is almost the same in magnitude as 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 the concentration of trading volume following the shift in Bloomberg's 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 III, we further control for bond fixed effects, which absorb the coefficient of D(*Index Eligible*).[19] Consistent with our previous findings, the coefficient on D(*Index Eligible*) $\times$ D(*Post Index-closing Time Change*) indicates that the concentration of trading in the 3:00 PM window decreases, while the concentration of trading in the 4:00 PM window increases by approximately the same magnitude following the Bloomberg index-closing time change.

[19]For this subsample, we exclude a tiny fraction of bonds that changed index eligibility between October 14, 2020 and April 13, 2021, accounting for approximately 0.5% of observations.

IV. The Impact of Indexing-Induced Clustering 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 Intraday 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:

$$Transaction\ Cost_k = \ln(\frac{Trade\ Price_k}{Benchmark\ Price_v}) \times Trade\ Sign_k, \tag{3}$$

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.[20] $Trade\ Sign_k$ 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

[20] 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.

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 interdealer 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 interdealer trade may have occurred days or even weeks before the customer trade. To mitigate this issue, we require that the interdealer 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 interdealer trade takes place on the same day.

To overcome these limitations, we incorporate high-frequency algorithmic pricing data from MarketAxess to calculate an alternative $Benchmark\ Price_v$. These data leverages machine learning and both public and proprietary data from MarketAxess' 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 the 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. During this period, we estimate transaction costs for more than 99% of customer trades using the CP+ midprice benchmark and about 61% using the interdealer price benchmark. The unconditional correlation between the two measures is about 76%.

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

$$Transaction\ Cost_k = \alpha + \beta D(Index\text{-}closing\ Time)_t + \mu_s + \mu_d + \mu_{i,t} + \epsilon_k, \tag{4}$$

where $D(\textit{Index-closing Time})$ 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.[21] Standard errors are double-clustered at the bond and the day levels.

Table IV shows that trading activities clustered around the index-closing time are associated with lower transaction costs. As shown in Panel A, where transaction costs are estimated using the interdealer price as the benchmark, trades executed at index-closing time incur transaction costs that are 5.967 basis points lower than those executed at other times of the day (Column (1)). This difference represents about 21.6% of the average transaction cost of 27.6 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, $D(\textit{Other Clustering Time})$, to account for potential differences in liquidity at these times. Specifically, $D(\textit{Other Clustering Time})$ is set to one for trades executed within the 5-minute windows 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. Column (4) of Table IV shows that trades executed during other spotting times exhibit a moderate reduction in transaction costs of 2.173 basis points. However, this effect is much less pronounced than the reduction observed at index-closing time. This pattern is consistent with the idea that the improvement in liquidity is commensurate with the clustering of trades.

[21] 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).

The lower transaction cost at index-closing time is also evident when we use the CP+ midprice as the benchmark. The results are shown in Panel B of Table IV. On average, trades executed at index-closing time have transaction costs that are 7.657 basis points lower than trades executed outside of index-closing time. This reduction accounts for approximately 36.2% of the average CP+ midprice benchmarked transaction cost of 21.1 basis points. The larger reduction in transaction costs documented in Panel B, relative to those documented in Panel A, can be attributed to the fact 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.[22] Combined with our earlier findings on trade clustering around index-closing time, these results suggest that index tracking has shifted intraday liquidity to the index-closing time.

A potential concern is that our transaction cost measure may appear mechanically lower at the index close because benchmark prices are less noisy. When trading is sparse, benchmark prices can be noisier. If the benchmark noises systematically inflate measured transaction costs, then the burst in trading volume at the close could mechanically compress our estimates. In addition, transaction prices at the index close may serve as salient reference points for subsequent trades, further lowering measured transaction costs for trades executed shortly after the close if their benchmarks are constructed from these salient prices.[23] To address this concern, we re-estimate regressions in Table IV using a deliberately lagged benchmark: for each trade, we compute transaction costs relative to benchmark prices (either interdealer prices or CP+ midprices) from prices lagged by at least 15 minutes. This lag ensures that benchmarks for index-close trades are not mechanically influenced by the close-related surge in trading or by immediate post-close benchmark updating. Appendix

[22] Although the sample period for the tests in Panel B is five 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 the CP+ midprice serves as the benchmark. When we repeat the analysis using interdealer transaction price as the benchmark over the same sample period as in the CP+ regressions, we obtains very similar estimate (-7.263) for *D(Index-closing Time)*.

[23] For example, 4:01 PM trades are still within our index-closing time window and can use 4:00 PM CP+ prices as the benchmark.

Table A1 shows that the results are robust—coefficient estimates are qualitatively unchanged and quantitatively nearly identical.

To further establish the causal effect of index tracking on the redistribution of intraday 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:

$$\begin{aligned} \textit{Transaction Cost}_k = \alpha &+ \beta_1 D(\text{15:00–15:05})_t + \beta_2 D(\text{15:00–15:05})_t \times D(\textit{Post Index-closing Time Change}) \\ &+ \gamma_1 D(\text{16:00–16:05})_t + \gamma_2 D(\text{16:00–16:05})_t \times D(\textit{Post Index-closing Time Change}) \\ &+ \mu_s + \mu_d + \mu_{i,t} + \epsilon_k, \end{aligned} \tag{5}$$

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 $D(\text{15:00–15:05})$ and $D(\text{16:00–16:05})$ 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 (4), and standard errors are double-clustered at the bond and the day levels.

The results in Table V provide strong support for the causal impact of index tracking on the redistribution of intraday 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 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 5.115 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 5.558 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 2.674 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-closing 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.[24] In Table A2, we re-estimate the regressions in Table V using benchmark prices lagged by at least 15 minutes and find results that are both qualitatively and quantitatively similar. 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 7 provides corroborative graphical evidence that index tracking leads to lower transaction costs.[25] 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 was 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 costs before and after 3:00 PM tightened significantly.[26]

The lower panels of Figure 7 plot the average transaction cost of trades executed between

[24]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.

[25]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.

[26]The sharp decline in estimated transaction costs at 3:00 PM and 4:00 PM (computed using benchmarks set before the index close) suggests that our results are not driven by index-close trading bursts affecting benchmark prices. If that was the case, the dip should instead occur one or two minutes after 3:00 PM and 4:00 PM.

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 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.

B.1. Index Closing as a Focal Point

The index-closing time can serve as a focal point for trades among institutions aiming to minimize tracking error. This synchronization 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, Üslü 2019, and Colliard, Foucault, and Hoffmann 2021) 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.[27]

[27] Admati and Pfleiderer (1988) argues that when liquidity traders have discretion over the timing of their trades, trading concentration emerges as an equilibrium as "liquidity begets liquidity". In their model, however, multiple equilibria exist in term of the exact timing of the trading concentration. In our context of corporate bond market, index closing coordinates liquidity traders. Hence the trading concentration always coincides with the index closing time (even as the index closing time shifted).

To empirically examine this trading focal point, 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 are 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 this focal point, 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 8 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%–25%. 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 focal point hypothesis, 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.

B.2. Information Asymmetry

An alternative explanation for the decline in transaction costs at index-closing time is the mitigation of 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-asymmetry mechanism suggests that the concentration of relatively uninformed index-tracking trades at closing time contributes to the observed liquidity improvements.

To test this hypothesis, 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 4 for each of the two subsamples, with the results presented in Columns (1) and (2) of Table VI, Panel A. Contrary to this prediction, 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 greater than that observed for A- and BBB-rated bonds, which are more likely to be affected by information asymmetry. These results challenge the view that reduced information asymmetry is the main source of liquidity improvements at index-closing time.

We further investigate this mechanism by focusing on a subsample of trades executed by insurance firms. U.S. insurers are the largest domestic investors in the corporate bond market, and their bond demand is driven primarily by hedging needs to match long-dated liabilities and by regulatory requirements, rather than by private information.[28] If the lower

[28]See, for example, Ellul, Jotikasthira, and Lundblad (2011), Koijen, Koulischer, Nguyen, and Yogo (2021), and Domanski, Shin, and Sushko (2017).

transaction costs we observed earlier reflect a comparison between relatively uninformed index-closing trades and more informed trades during the rest of the day, then we should not expect to find a significant difference in transaction costs between index-closing and other trades once we restrict the sample to similarly informed trades made by a homogeneous group of investors—insurers.

To test this prediction, we obtain data on insurance-company transactions from Parts 3–5 of Schedule D in NAIC regulatory filings and merge them with TRACE data to identify trades executed by insurers. Because NAIC data lack timestamps, matching relies on CUSIP, trade date, quantity, and direction, which prevents a substantial share of transactions from being linked to TRACE. Nevertheless, even in the conservative sample of uniquely matched trades, we find that transaction costs at the close are significantly lower compared with other trades at the same bond-day, with magnitudes only slightly smaller than that in the full sample (Column (3) of Table VI). This evidence further undermines the information-asymmetry explanation and suggests that the liquidity benefits of indexing extend beyond index trackers to other investors in the corporate bond market.

B.3. Delayed Treasury Spotting

Another potential driver of lower transaction costs at index-closing time is the use of delayed Treasury spotting. Compared to immediate spotting, delayed spotting can reduce dealers' hedging costs by allowing them to net exposures across trades before entering the Treasury market, rather than hedging each trade separately. This reduces transaction costs and balance sheet usage, making it cheaper for dealers to manage risk and, in turn, enabling them to pass some of these savings on to clients in the form of lower trading costs. Because index-closing time is also a common time for delayed Treasury spotting, this mechanism could contribute to the observed cost reductions.

To examine this possibility, we use MarketAxess data that flag trades executed with delayed Treasury spotting on their platform between March 2021 and December 2024, the

period for which the flag is available. Although the flag applies only to MarketAxess trades, the Bond Dealers of America (BDA) notes that delayed Treasury spotting is typically conducted through electronic platforms,[29] suggesting that these data capture the majority of such trades. When we exclude delayed Treasury spotting trades flagged in the MarketAxess data, however, we continue to find a significant reduction in transaction costs at index-closing time (Column (4) of Table VI). The estimated reduction of transaction cost for index-closing trades relative to rest-of-day trades within the same bond-day ranges from 7.549 bps (based on interdealer price) to 7.779 bps (based on CP+ midprice).[30] These results suggest that delayed Treasury spotting is unlikely to account for the lower costs observed at index-closing time.

B.4. Portfolio Trading

We also examine portfolio trading as a potential economic channel driving the observed liquidity improvement at index-closing time. Portfolio trading involves trading a basket of corporate bonds, sometimes exceeding 100 issues, as a single, all-or-none transaction. It has increasingly been adopted by investment funds as a means to rebalance their portfolios and trade in response to investor flows. Li et al. (2025) show that portfolio trading incurs lower transaction 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 the index, then the lower transaction costs observed at index-closing time could be attributed to the benefits of portfolio trading.

To examine this mechanism, we obtain portfolio-trade flags from two sources. Beginning on May 15, 2023, TRACE reports include a portfolio-trade modifier, as FINRA requires

[29] See `www.finra.org/sites/default/files/NoticeComment/Bond%20Dealers%20of%20America_22-26_1.30.23_Delayed_Spot_Trades.pdf` for reference.

[30] This regression is estimated over March 2021 to December 2024, the period for which the delayed Treasury spotting trade designation is available. Without excluding delayed Treasury spotting trades, the coefficient on *D(index-closing time)* is -7.643 when the interdealer price is used as the benchmark and -7.813 when the CP+ midprice is used as the benchmark.

member firms to append this modifier when reporting qualifying trades. For the earlier period, from January 2020 to May 14, 2023, we use the portfolio-trade flag provided in MarketAxess TRACE Context data.[31] We exclude these trades from the sample and re-estimate Equation (4). As shown in Column (5) of Table VI, Panel A, transactions executed within the five-minute window around index-closing time continue to exhibit lower transaction costs. We find a similar pattern when transaction costs are measured relative to the CP+ midprice, as reported in Column (5) of Panel B. The estimated reduction in transaction costs is broadly similar to that in the full sample (Table IV).[32] These findings indicate that although portfolio trading may contribute to lower costs at index-closing time, it does not fully explain the effect. More broadly, they suggest that the liquidity improvement at index-closing time extends beyond passive funds engaging in portfolio trading and may benefit the broader market.

B.5. Electronic Trading

Finally, we assess the robustness of our results by excluding electronic trades executed on MarketAxess. Electronic trading expanded rapidly in the U.S. corporate bond market during our sample period, and prior work suggests that electronic trades tend to involve lower transaction costs than traditional voice trades (Hendershott and Madhavan, 2015; O'Hara and Zhou, 2021). If trades near the index close are disproportionately electronic, this could help explain the lower transaction costs we observe during that window. To examine this possibility, we identify electronic trades using TRACE Context data from MarketAxess, which are available beginning in January 2020, and restrict the sample for this test accordingly. As shown in Column (6) of Table VI, excluding these trades does not weaken our

[31] The portfolio-trade flag in TRACE Context data is available beginning in January 2020 and covers all TRACE-reported trades, not just those executed on the MarketAxess platform. The flag is inferred rather than directly reported.

[32] These regressions are estimated over January 2020 to December 2024, the period for which the portfolio-trade flag is available. Over this sample period, if portfolio trades are not excluded, the coefficient on $D(\textit{index-closing time})$ is -7.263 when the interdealer price is used as the benchmark and -7.657 when CP+ midprice is ued as the benchmark.

conclusions. If anything, the effect is somewhat stronger. Transaction costs remain 10.260 to 11.231 bps lower than for same-bond-day transactions executed outside the index-closing window. These results suggest that the liquidity improvement at index-closing time is not driven by platform-specific differences.

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 transaction cost. We then regress the daily average transaction cost on the fraction of the total daily trading volume executed at index-closing time:

$$\textit{Transaction Cost}_{i,t} = \alpha + \beta \textit{Index-closing Time Volume\%}_{i,t} + \gamma X_{i,t} + \mu_t + \mu_r + \mu_i + \epsilon_{i,t}, \quad (6)$$

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 VII 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 -10.001, sug-

gesting 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, a one-standard-deviation increase in index-closing trading volume corresponds to 2.47 basis-point reduction in average daily transaction costs, representing approximately 10% 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 -9.767, 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 6 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 VII 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—an increase in index-closing trading volume of one-standard-deviation is associated with a reduction in transaction costs of approximately

12% relative to the sample's average daily transaction cost.

D The Limitations of Index-Tracking-Induced Clustering

It is important to note that the focal point 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, if the focal point mechanism is the main source for liquidity improvement.

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:

$$\begin{aligned} \textit{Transaction Cost}_{i,t} = \alpha &+ \beta_1 \textit{Index-closing Time Volume\%}_{i,t} \\ &+ \beta_2 \textit{Index-closing Time Volume\%}_{i,t} \times \textit{D(High Trade Imbalance)}_{i,t} \\ &+ \gamma X_{i,t} + \mu_t + \mu_r + \mu_i + \epsilon_{i,t}. \end{aligned} \tag{7}$$

We employ three distinct measures to identify periods of high trade imbalance, captured by the indicator variable *D(High Trade Imbalance)*. The first measure focuses on periods when passive funds experience large net flows. Because these funds are explicitly mandated to track indices, substantial net inflows tend to generate buy pressure, while significant net outflows lead to sell pressure, both contributing to elevated trade imbalances.

To construct this fund-flow-based measure, we begin by estimating daily flows for passive mutual funds and ETFs. Using daily data on returns and total net assets (TNA) from Morningstar, we define fund flows as follows:

$$Flow_{f,t} = \frac{TNA_{f,t} - TNA_{f,t-1} \times (1 + Ret_{f,t-1})}{TNA_{f,t-1}}, \tag{8}$$

where $TNA_{f,t}$ represents the total net assets of fund f on day t, and $Ret_{f,t}$ denotes the daily return of fund f on day t. We then construct the daily aggregate net flow from passive bond funds and ETFs:

$$Net\ Fund\ Flow_t = \sum_{f \in \mathcal{F}} (Flow_{f,t} \times TNA_{f,t-1}) / \sum_{f \in \mathcal{F}} TNA_{f,t-1}. \tag{9}$$

We define an indicator, $D(Large\ Net\ Fund\ Flow)$, which equals one on days when *Net Fund Flow* falls within the top or bottom 5th percentile of the sample distribution. This measure captures periods of extreme imbalances in flow-driven trading demand from investment funds. To further disentangle the effects of fund inflows and outflows, we define two additional indicator variables. The indicator $D(Large\ Net\ Fund\ Inflow)$ equals one on days when *Net Fund Flow* falls within the top 5th percentile of the sample distribution, while the indicator $D(Large\ Net\ Fund\ Outflow)$ equals one on days when *Net Fund Flow* falls within the bottom 5th percentile.

We also examine periods when market-wide conditions trigger large-scale selling by passive funds, particularly during episodes of heightened volatility and the COVID-19 liquidity crisis. During times of market stress, investment funds often experience substantial investor outflows, increasing pressure to liquidate bond holdings to meet redemptions. Given their index-tracking mandates, passive funds concentrate their trading around the index-closing time, leading to intensified trade clustering during such episodes. To capture these trading patterns during market stress, we construct two additional measures of high trade imbalance: A binary variable, *D(High VIX)*, equals one on days when the VIX index falls in the top 5th percentile of our sample period. This captures periods of elevated market volatility that are typically associated with large-scale selling and increased trade imbalances. Our final measure, *D(COVID)*, is a binary indicator equals one for the period from March 6 to March 19, 2020, which corresponds to the peak of bond market dislocation during the COVID-19 crisis. All the other variables are defined as in Equation 6. Transaction costs are estimated

using either the interdealer price or the CP+ midprice as the benchmark, with the results presented in Table VIII.

Column (1) of Panel A shows that when passive funds and ETFs experience extreme flows, the liquidity benefits of trade clustering are diminished. The coefficient on *Index-closing Time Volume%* is significantly negative at -10.292, indicating that under normal market conditions, bonds with a large share of trading at the index-closing time tend to have lower average transaction costs. However, the interaction term of *Index-closing Time Volume%* and D(*Large Net Fund Flow*) is positive and highly significant, with a coefficient of 3.200. These results suggest that when passive funds experience large flows, the resulting imbalance in trading demand weakens the overall liquidity benefits typically associated with trade clustering.

We also decompose fund net flows into inflows and outflows to examine how trade clustering affects liquidity under different market conditions. Column (2) shows that the dissipation of liquidity benefits associated with trade clustering primarily occurs on days with large fund outflows. The interaction between *Index-closing Time Volume%* and D(*Large Net Fund Outflow*) is positive and significant, whereas the interaction with D(*Large Net Fund Inflow*) is positive but not significant. This finding suggests that dealers charge higher transaction costs when the demand for balance-sheet space and funding increases, as is the case during periods of substantial fund outflows. The higher costs may also reflect dealers' greater difficulty in locating counterparties, since selling pressure from fund outflows often coincides with broader market sell-offs by other institutions—a pattern commonly observed during times of market stress.

To further examine how stressed market conditions affect the liquidity benefits of trade clustering, we focus on periods of heightened volatility and the COVID-induced liquidity crisis. In Column (3), using D(*High VIX*) as a proxy for *High Trade Imbalance*, the coefficient of the interaction term increases to 9.758. This interaction effect almost fully offsets the -10.734 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 (4) when we interact *Index-closing Time Volume%* with $D(COVID)$, the coefficient of the interaction term rises sharply to 28.085. This shift turns the coefficient of *Index-closing Time Volume%* from -10.136 into 17.949 (statistically significant at the 5% level) 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 9), 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 (5) to (8)). Additionally, when using transaction costs estimated with the CP+ benchmark and focusing on a more recent sample period, the dissipation of liquidity benefits from trade clustering under conditions of excessive selling pressure becomes more pronounced (Panel B). For instance, Column (2) shows that the coefficient on the interaction between *Index-closing Time Volume%* and $D(\textit{Large Net Fund Outflow})$ increases to 9.163, almost fully offsetting the baseline coefficient on *Index-closing Time Volume%* of -9.871. As a result, trade clustering no longer has a statistically significant impact on bond liquidity during periods when passive funds face extreme outflows. Together, 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 reverse 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 trading 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. Choi et al. (2024) document that customers increasingly provide liquidity in the corporate bond market following the adoption of post-2008 banking regulations. 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 in corporate bond markets. 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, a natural question arises: will index tracking fundamentally transform the structure of the corporate bond market? Recent developments suggest that such changes may already be underway. In November 2025, MarketAxess announced the launch of the first-ever opening and closing

auctions for corporate bonds, an unprecedented step toward formalizing the very trading concentration our study documents. By institutionalizing benchmark-based trading windows, this initiative marks a structural shift toward more coordinated, exchange-like mechanisms in what has historically been a decentralized, over-the-counter market. More broadly, it underscores the pressing challenge for market designers and regulators: how to preserve liquidity and stability while accommodating the growing dominance of index-driven trading. Our study provides an early empirical foundation for understanding this evolution and highlights directions for future research on the optimal design of the modern bond market.

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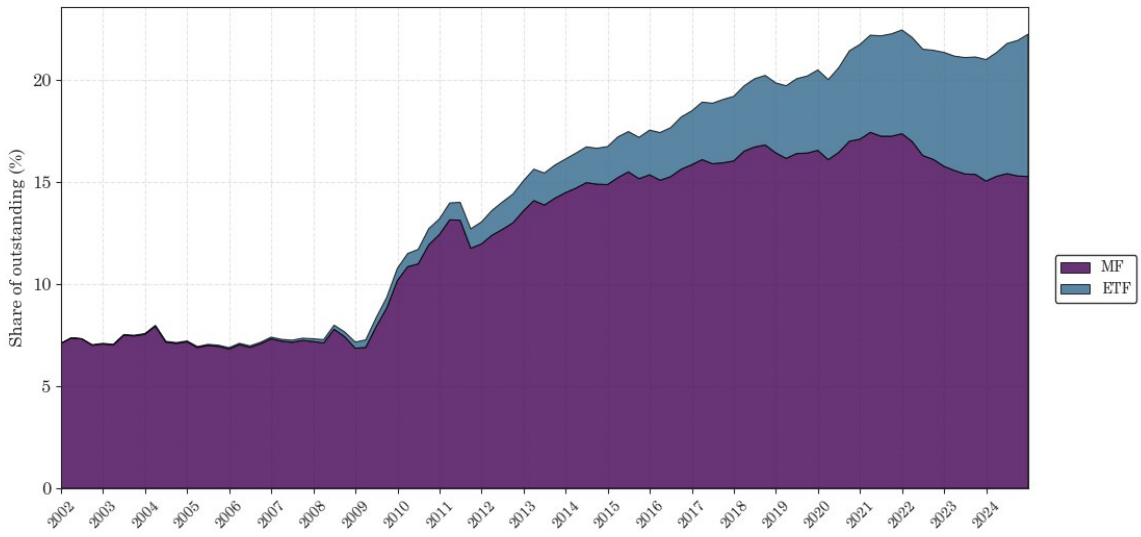


Figure 1: **Share of corporate bonds held by mutual funds and ETFs**

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

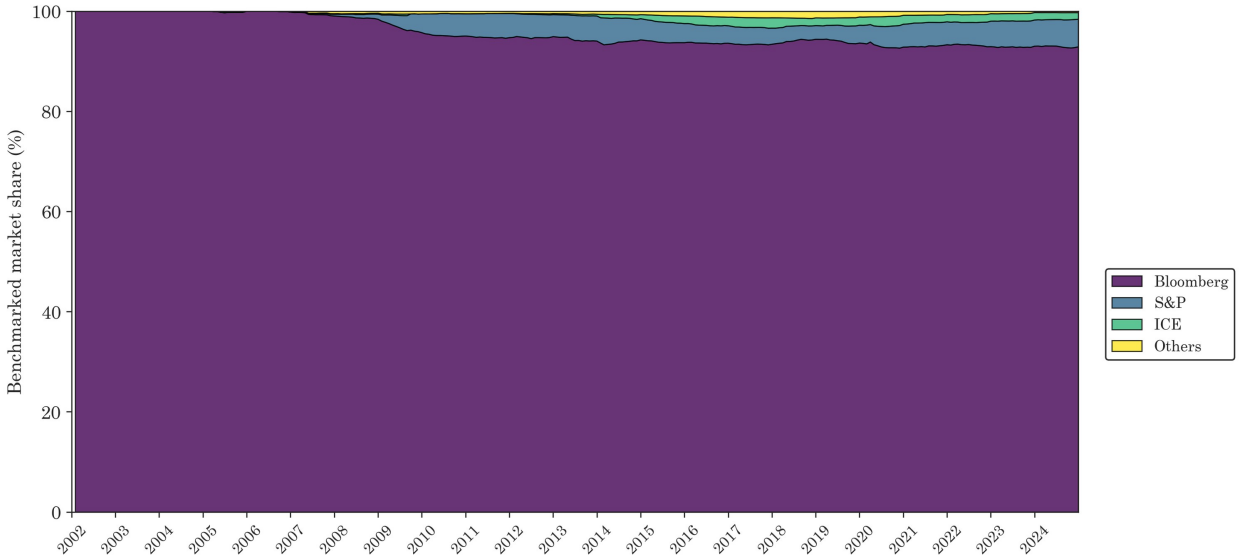


Figure 2: **Market shares of passive bond funds by benchmark provider**

This figure presents the market shares of passive bond funds by benchmark provider. Market shares are calculated based on fund net assets. We classify passive funds into four groups based on their primary benchmark: *Bloomberg* (including Bloomberg indices and their predecessors), *S&P* (including S&P and Markit iBoxx indices), *ICE* (including ICE and ICE Bank of America indices), and *Others* (all other primary benchmarks). Primary prospectus benchmark information and monthly net assets are obtained from Morningstar. The passive bond fund sample consists of all passive open-end mutual funds and ETFs in Morningstar's global category "US Fixed Income," after excluding funds whose Morningstar category name contains "bank loan", "government", "inflation", "muni", "nontraditional", "preferred stock", or "ultrashort", as these funds are less likely to focus on U.S. corporate bonds. The sample covers 2002–2024 at the monthly frequency.

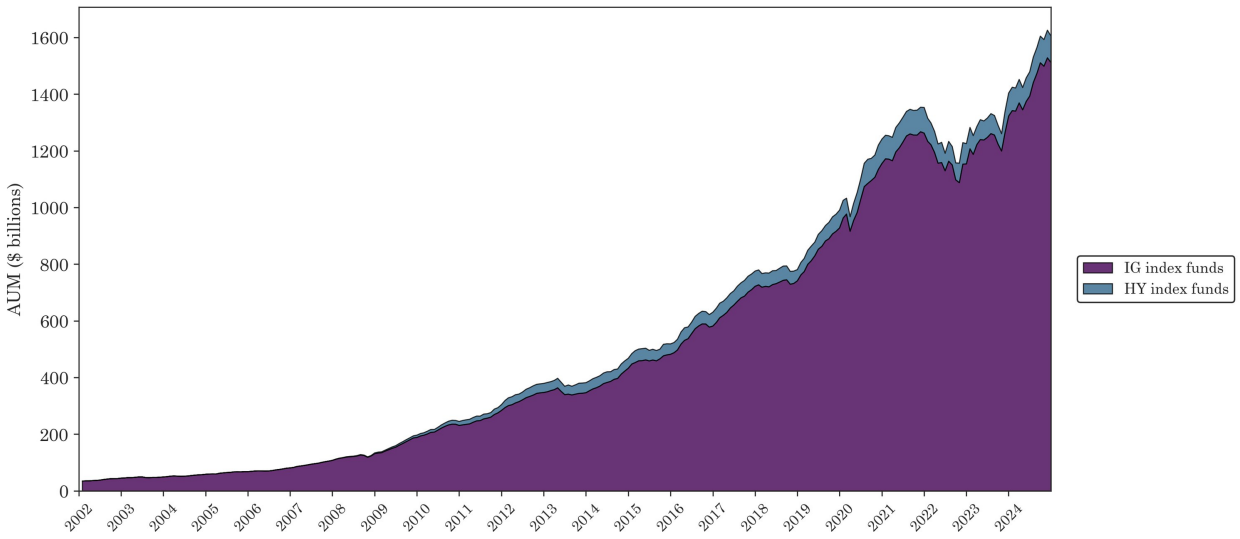


Figure 3: **Asset under management of passive IG and HY funds**

This figure presents assets under management (AUM, in $ billions) for passive bond funds, split into investment-grade and high-yield segments. Monthly net assets come from Morningstar. We classify a fund as high-yield if its Morningstar category name contains "high yield" or its fund name contains "high yield" or "HY". We classify all other funds as investment-grade funds. The sample matches Figure 1 and spans 2002–2024 at a monthly frequency.

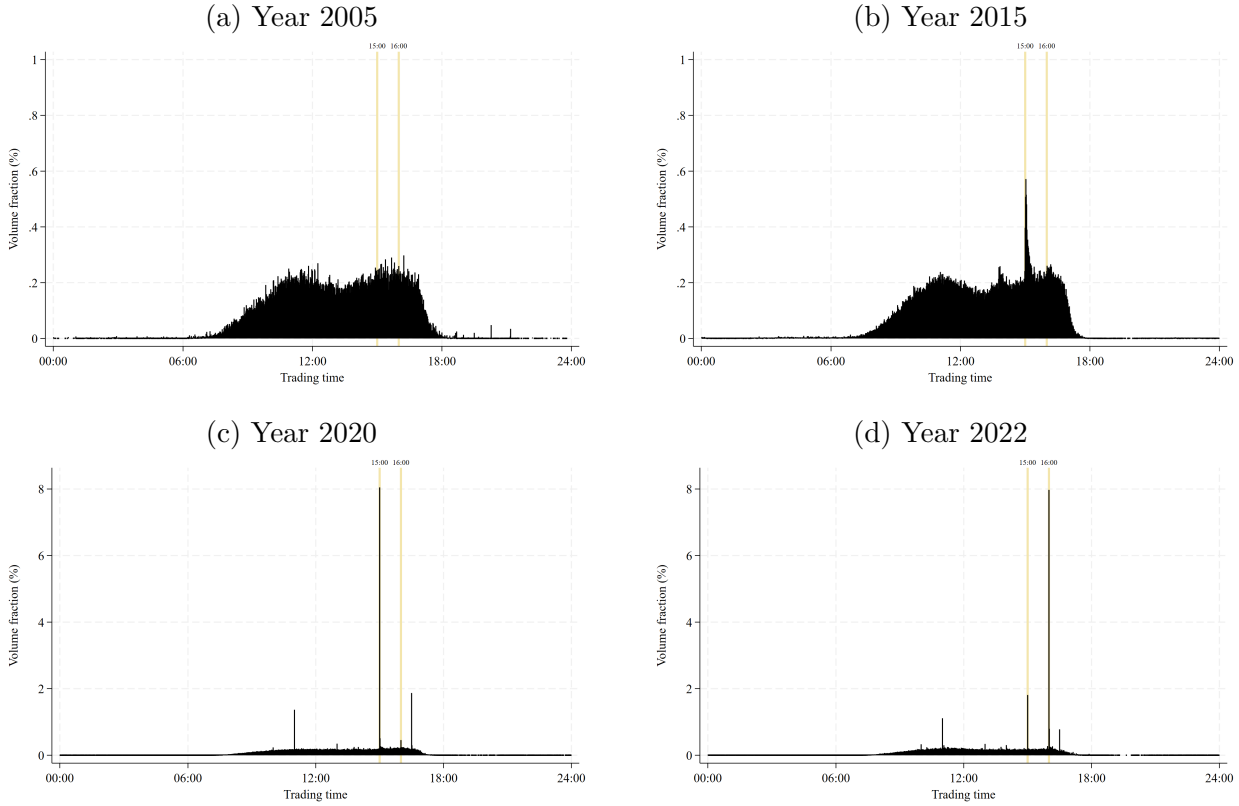
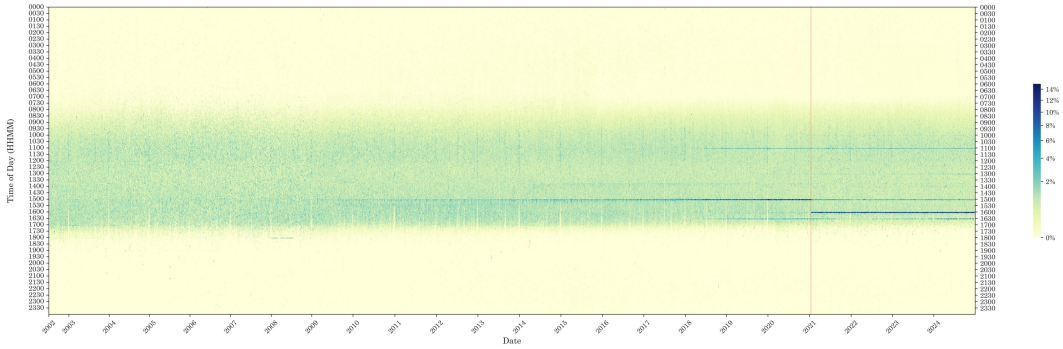


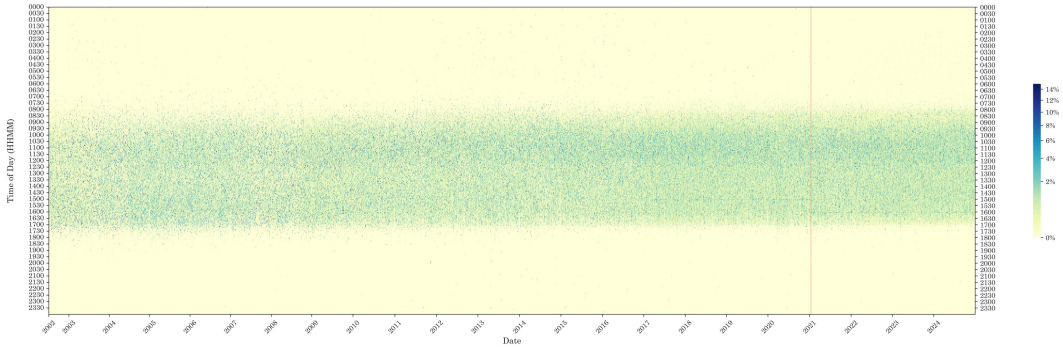
Figure 4: **Intraday distribution of trading volume**

The figure presents histograms of intraday trading volume distribution, where each bin represents the fraction of total daily customer volume executed per minute (the customer volume during a given minute divided by the total customer volume for the day). The histograms display the average intraday volume fraction per minute for the years 2005, 2015, 2020, and 2022, shown in Panels (a)–(d). The sample is restricted to IG bonds eligible for Bloomberg bond indices. 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

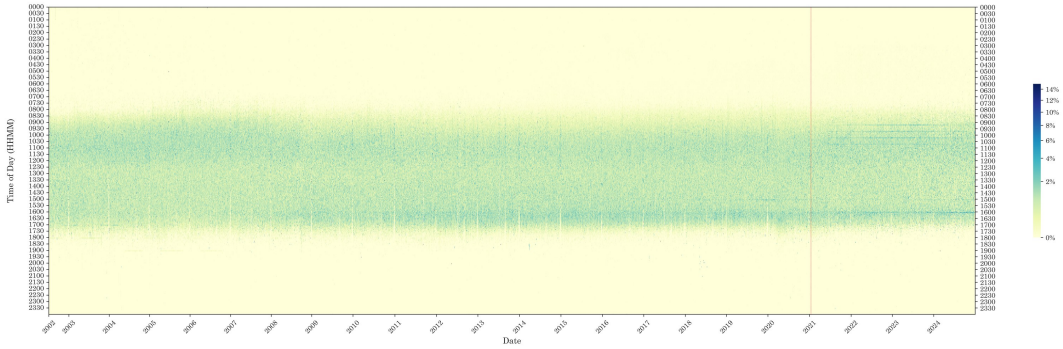
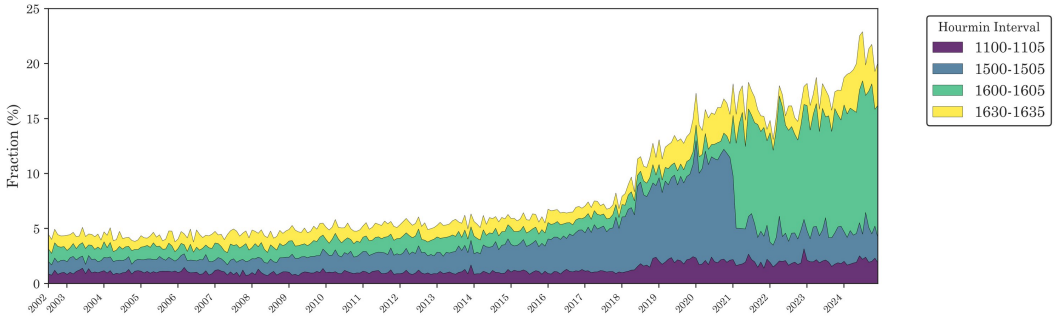


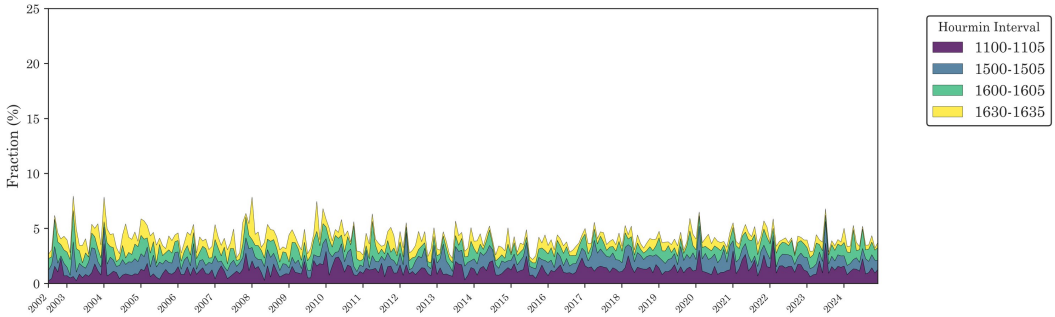
Figure 5: **Time-series heatmaps of intraday trading volume distribution**

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 December 2024. 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

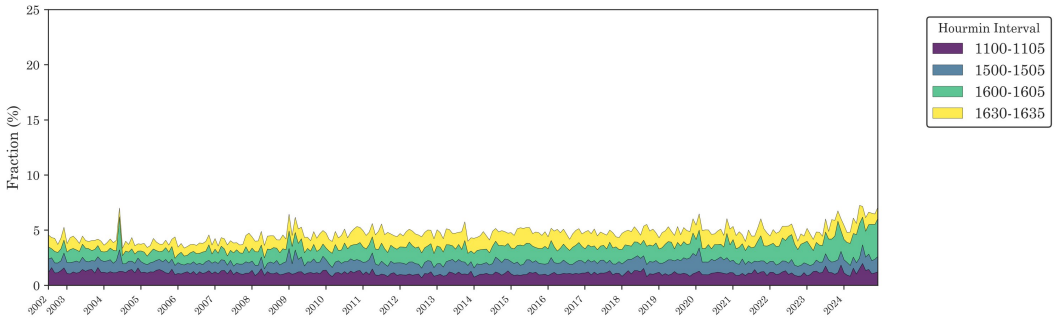
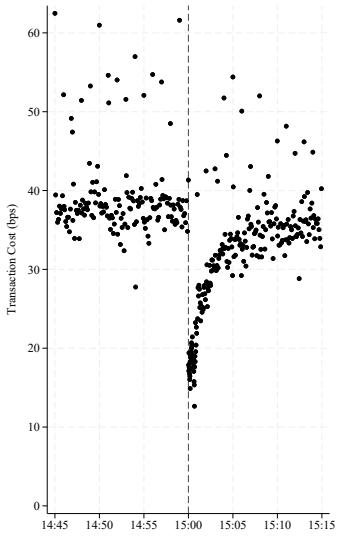


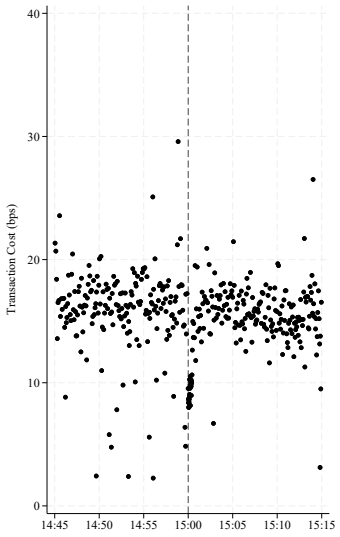
Figure 6: **Intraday trading volume distribution at index-closing time and other delayed Treasury spotting times**

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 December 2024. Panels (a), (b), and (c) display the trends for index-eligible investment-grade bonds, non-eligible investment-grade bonds, and high-yield bonds, respectively.

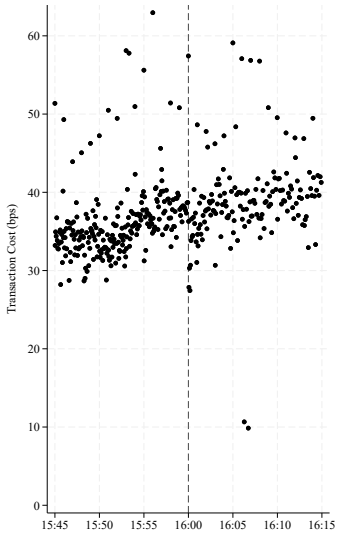
(a) 14:45–15:15 before Jan 14, 2021



(b) 14:45–15:15 from Jan 14, 2021



(c) 15:45–16:15 before Jan 14, 2021



(d) 15:45–16:15 from Jan 14, 2021

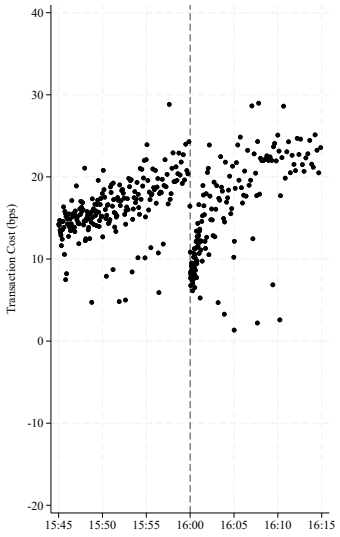


Figure 7: **Transaction costs during the 30-minute windows around the Bloomberg index-closing time**

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

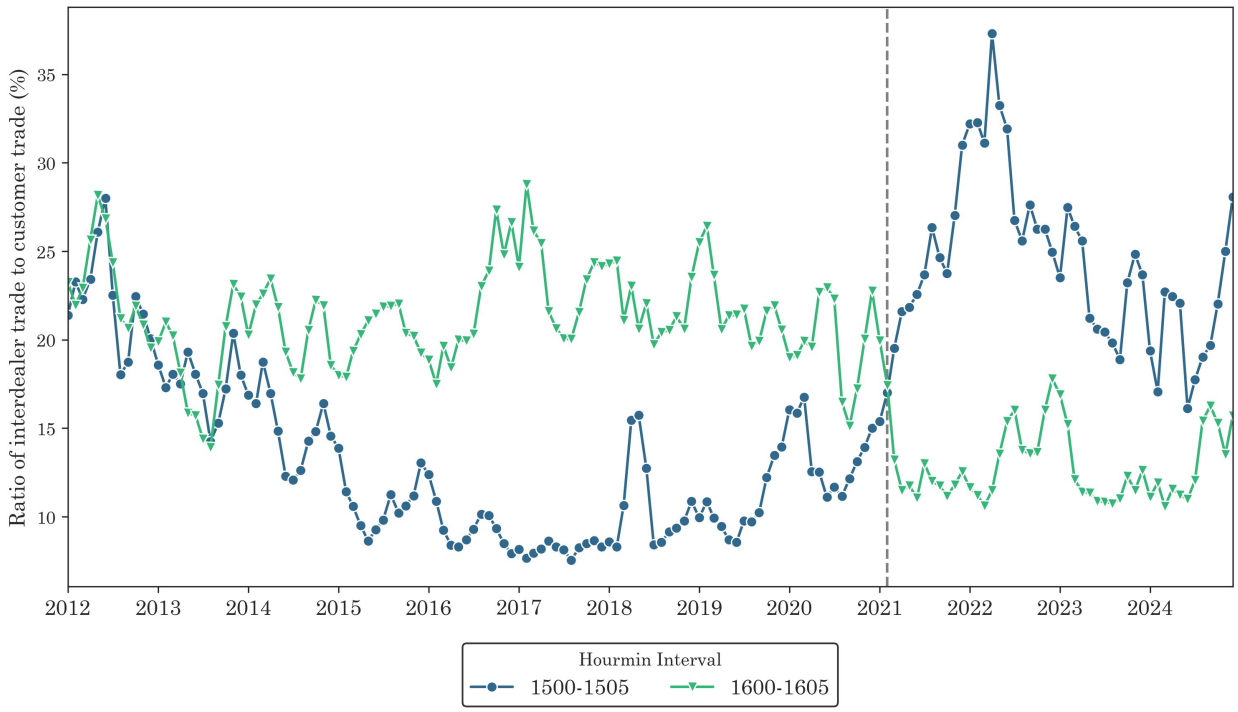


Figure 8: **Ratio of interdealer trade volume to customer trade volume**

This figure presents the interdealer-customer ratio (ICR), which measures the ratio of interdealer trading volume to customer trading volume during the 5-minute windows at 15:00 and 16:00. The plot shows the monthly time series of three-month moving average of the ICR from 2012 to 2024. A vertical line marks January 2021.

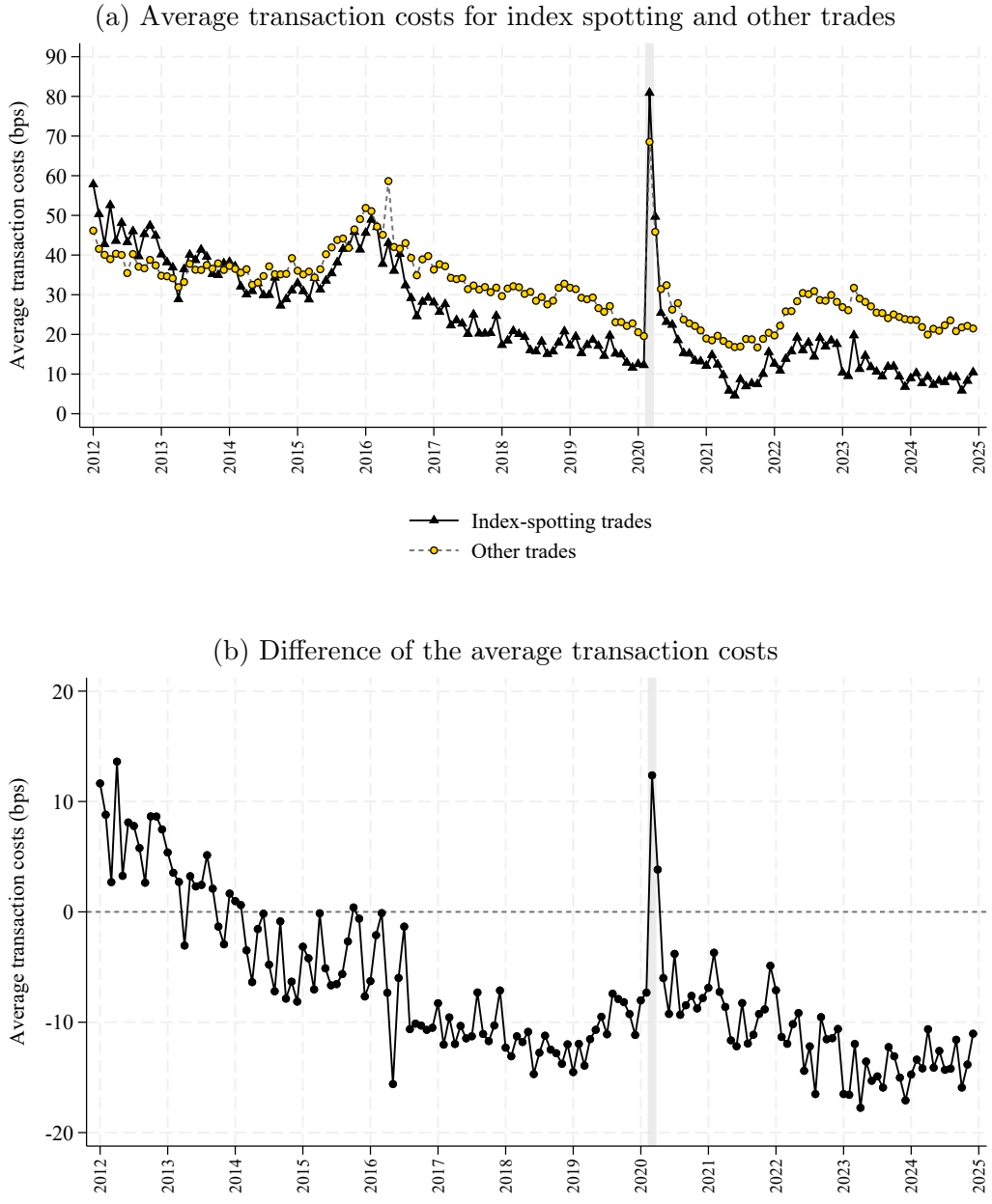


Figure 9: **Average transaction costs for index-closing time trades and other trades**

This figure presents the monthly time series of average transaction costs for index-closing-time trades and other trades. The transaction cost is calculated using the interdealer price benchmark following 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 the fraction of volume traded during the 5-minute window following the 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 $D(\textit{Index Eligible})$, 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 ($Ln(\textit{Time to Maturity})$), log of age ($Ln(\textit{Age})$), log of amount outstanding ($Ln(\textit{Amount Outstanding})$), and the fraction of zero trading days over the past three months (*Zero Trading Day*). The sample includes IG bonds traded between 2012 and 2024. 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%*				
				2020–2024
	(1)	(2)	(3)	(4)
$D(\textit{Index Eligible})$	6.061***	5.089***	5.138***	7.931***
	(0.183)	(0.284)	(0.252)	(0.401)
$Ln(\textit{Time to Maturity})$		4.193***	3.829***	5.243***
		(0.103)	(0.089)	(0.135)
$Ln(\textit{Age})$		0.472***	-0.424***	-0.460***
		(0.084)	(0.066)	(0.103)
$Ln(\textit{Amount Outstanding})$		-0.251**	0.997***	0.848***
		(0.119)	(0.093)	(0.141)
Zero Trading Day		-4.299***	1.539***	1.918***
		(0.303)	(0.241)	(0.400)
Rating FE	N	Y	Y	Y
Day FE	N	N	Y	Y
Observations	8,929,870	8,929,870	8,929,870	4,618,349
Adjusted R^2	0.00397	0.0281	0.0802	0.0774

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

This table examines the relationship between index exclusion and the fraction of volume 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. The sample includes IG bonds, and the sample period runs from 2012 to 2024. 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	
	(1)	$\lvert amt - cutoff \rvert$ < $250M (2)	(3)	$ttm < 2y$ (4)
D(*Index Eligible*)	3.342***	2.346***		
	(0.252)	(0.306)		
D(*Exclusion by Maturity*)			-0.830***	-1.599***
			(0.106)	(0.067)
Ln(*Time to Maturity*)	5.010***	4.279***	2.266***	-0.400***
	(0.221)	(0.307)	(0.097)	(0.037)
Ln(*Age*)	0.497***	0.562***	-0.112	-2.097***
	(0.087)	(0.137)	(0.082)	(0.167)
Ln(*Amount Outstanding*)	1.935***	1.916***	2.878***	0.317**
	(0.128)	(0.296)	(0.109)	(0.126)
Zero Trading Day	-0.136	-0.972***	1.184***	0.156
	(0.197)	(0.274)	(0.176)	(0.114)
Rating FE	Y	Y	Y	Y
Day FE	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y
Observations	8,929,707	3,312,643	10,163,891	1,696,602
Adjusted R^2	0.114	0.134	0.114	0.0385

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

This table examines the effects of the Bloomberg index-closing time change on the index-closing time 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. $D(Post\ Index\text{-}closing\ Time\ Change)$ equals one for observations from January 14, 2021 onward. $D(Index\ Eligible)$ equals one for Bloomberg index-eligible bonds. All controls are defined as in Table II. The sample period spans October 14, 2020 to April 13, 2021. The sample includes IG bonds; bonds that experienced changes in index eligibility during this period (approximately 0.5% of observations) are excluded. 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)
$D(Index\ Eligible)$	8.967***	0.134	0.219	0.882***				
	(0.694)	(0.310)	(0.172)	(0.324)				
$D(Index\ Eligible) \times D(Post\ Index\text{-}closing\ Time\ Change)$	-7.039***	6.937***	0.058	-0.453	-6.895***	6.489***	0.142	-0.554
	(0.689)	(0.623)	(0.179)	(0.364)	(0.709)	(0.654)	(0.182)	(0.351)
$Ln(Time\ to\ Maturity)$	2.841***	2.794***	0.347***	1.078***	-100.872***	82.328***	-7.170***	0.747
	(0.363)	(0.329)	(0.080)	(0.119)	(8.234)	(7.620)	(2.301)	(4.074)
$Ln(Age)$	-0.319**	0.317**	-0.084**	-0.021	5.143***	-2.719*	-0.095	0.706
	(0.146)	(0.124)	(0.042)	(0.083)	(1.830)	(1.481)	(0.513)	(0.791)
$Ln(Amount\ Outstanding)$	0.127	0.152	0.090*	0.699***	1.595	1.866**	-0.567	2.614***
	(0.190)	(0.175)	(0.052)	(0.127)	(1.788)	(0.895)	(0.492)	(0.973)
$Zero\ Trading\ Day$	-0.872	-0.343	0.464***	-1.064***	2.522**	-2.632***	0.267	-0.625
	(0.647)	(0.528)	(0.160)	(0.343)	(0.983)	(0.916)	(0.318)	(0.463)
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	401,269	401,269	401,269	401,269	401,219	401,219	401,219	401,219
Adjusted R^2	0.0693	0.0951	0.00772	0.0256	0.109	0.134	0.0112	0.0802

Table IV: **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 same-day 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 Clustering 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 in index-eligible bonds from 2012 to 2024. 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	Buy	Sell	All	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
D(*Index-closing Time*)	-5.967***	-8.447***	-4.496***	-6.148***	-8.657***	-4.673***
	(0.231)	(0.344)	(0.309)	(0.236)	(0.350)	(0.314)
D(*Other Clustering Time*)				-2.173***	-2.960***	-1.852***
				(0.149)	(0.206)	(0.179)
Bond $\times$ Day FE	Y	Y	Y	Y	Y	Y
Trade Size FE	Y	Y	Y	Y	Y	Y
Trade Direction FE	Y	-	-	Y	-	-
Observations	23,436,481	14,115,322	7,935,312	23,436,481	14,115,322	7,935,312
Adjusted R^2	0.385	0.485	0.459	0.385	0.485	0.459

Panel B. CP+ midprice as benchmark

Dependent variable: *Transaction Cost* (bps)						
Trade direction:	All	Buy	Sell	All	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
D(*Index-closing Time*)	-7.657***	-10.035***	-5.339***	-8.074***	-10.480***	-5.691***
	(0.227)	(0.339)	(0.324)	(0.230)	(0.345)	(0.327)
D(*Other Clustering Time*)				-4.318***	-5.116***	-3.395***
				(0.143)	(0.199)	(0.202)
Bond $\times$ Day FE	Y	Y	Y	Y	Y	Y
Trade Size FE	Y	Y	Y	Y	Y	Y
Trade Direction FE	Y	-	-	Y	-	-
Observations	22,574,060	12,566,823	8,450,575	22,574,060	12,566,823	8,450,575
Adjusted R^2	0.344	0.479	0.529	0.345	0.479	0.530

Table V: **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 same-day 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 IV. The sample includes all customer transactions in index-eligible 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)			
Sample window:	1 month	3 months	6 months
	(1)	(2)	(3)
D(15:00–15:05)	-5.115***	-5.928***	-5.701***
	(0.920)	(0.771)	(0.550)
D(15:00–15:05) × D(*Post Index-closing Time Change*)	2.674**	2.799***	2.741***
	(1.299)	(0.962)	(0.661)
D(16:00–16:05)	-0.454	-1.304	-1.095**
	(1.419)	(0.794)	(0.522)
D(16:00–16:05) × D(*Post Index-closing Time Change*)	-5.558***	-3.756***	-4.986***
	(1.825)	(1.409)	(0.953)
Bond × Day FE	Y	Y	Y
Trade Size FE	Y	Y	Y
Trade Direction FE	Y	Y	Y
Observations	250,940	765,955	1,417,341
Adjusted R^2	0.320	0.321	0.342

Panel B. CP+ midprice as benchmark

Dependent variable: *Transaction Cost* (bps)			
Sample window:	1 month	3 months	6 months
	(1)	(2)	(3)
D(15:00–15:05)	-6.401***	-6.734***	-6.617***
	(1.148)	(0.674)	(0.479)
D(15:00–15:05) × D(*Post Index-closing Time Change*)	3.534**	3.566***	3.932***
	(1.569)	(0.894)	(0.607)
D(16:00–16:05)	-2.023	-1.617**	-2.002***
	(1.488)	(0.728)	(0.537)
D(16:00–16:05) × D(*Post Index-closing Time Change*)	-5.707***	-6.736***	-5.529***
	(1.830)	(0.945)	(0.688)
Bond × Day FE	Y	Y	Y
Trade Size FE	Y	Y	Y
Trade Direction FE	Y	Y	Y
Observations	492,783	1,479,870	2,759,630
Adjusted R^2	0.334	0.335	0.356

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

This table replicates Column (1) of Table IV across six alternative samples: two rating subgroups (Columns 1–2), an NAIC-matched subsample (Column 3), and three trade-type exclusions (Columns 4–6). 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 same-day interdealer trade price as the benchmark; in Panel B, the CP+ midprice is used instead. In Columns (1) and (2), we run the regression on the subsample of AAA–AA-rated and A–BBB-rated bonds, respectively. In Column (3), we restrict the sample to NAIC-matched trades only. In Column (4), we exclude delayed Treasury spotting trades (DTSTs). In Column (5), we exclude portfolio trades, where the portfolio trade flag is obtained from TRACE Context data (prior to May 15, 2023) and FINRA TRACE (from May 15, 2023 onward). In Column (6), we exclude electronic trades via MarketAxess (MKTX) platform. Due to data availability, the sample period varies across columns. The baseline sample covers January 2012–December 2024 in Panel A and January 2020–December 2024 in Panel B. Column (4) begins in March 2021 (DTST flag availability); Columns (5) and (6) begin in January 2020 (TRACE Context data availability). 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)						
	AAA-AA	A-BBB	NAIC only	Excl. DTST	Excl. PT	Excl. MKTX
	(1)	(2)	(3)	(4)	(5)	(6)
D(index-closing time)	-6.878***	-5.883***	-5.147**	-7.549***	-6.031***	-10.260***
	(0.495)	(0.234)	(2.411)	(0.347)	(0.258)	(0.380)
Bond×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	1,992,386	21,444,095	9,515	12,005,202	13,348,461	10,619,805
Adjusted R^2	0.237	0.391	0.569	0.305	0.297	0.339

Panel B. CP+ midprice as benchmark

Dependent variable: *Transaction Cost* (bps)						
	AAA-AA	A-BBB	NAIC only	Excl. DTST	Excl. PT	Excl. MKTX
	(1)	(2)	(3)	(4)	(5)	(6)
D(index-closing time)	-8.426***	-7.590***	-4.422***	-7.779***	-6.594***	-11.231***
	(0.465)	(0.232)	(1.615)	(0.289)	(0.239)	(0.331)
Bond×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	1,840,354	20,733,706	7,868	18,742,096	21,094,523	15,525,278
Adjusted R^2	0.260	0.349	0.270	0.340	0.354	0.393

Table VII: **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. We do not scale it to percentage points (it is kept as a 0–1 fraction) to improve the readability of coefficient estimates. All controls are defined as in Table II. The sample consists of index-eligible bonds from 2012 to 2024. 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%	-10.001***	-9.767***	3.985***	4.293***
	(0.260)	(0.264)	(0.179)	(0.196)
Ln(Time to Maturity)	8.980***	6.779***	9.997***	7.650***
	(0.534)	(0.459)	(0.556)	(0.483)
Ln(Age)	3.015***	2.355***	2.656***	2.051***
	(0.329)	(0.289)	(0.343)	(0.306)
Ln(Amount Outstanding)	-16.539***	-15.428***	-16.396***	-15.658***
	(0.918)	(1.027)	(0.935)	(1.061)
Zero Trading Day	1.174*	9.364***	1.199	9.834***
	(0.707)	(0.594)	(0.733)	(0.630)
Day FE	Y	-	Y	-
Rating FE	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y
Issuer × Day FE	N	Y	N	Y
Observations	4,038,001	3,465,802	3,924,058	3,353,383
Adjusted R^2	0.200	0.245	0.201	0.243

Panel B. CP+ midprice as benchmark

Dependent variable: *Transaction Cost* (bps)				
			Excluding Index-closing Time	
	(1)	(2)	(3)	(4)
Index-closing Time Volume%	-9.435***	-8.975***	2.375***	2.599***
	(0.361)	(0.347)	(0.176)	(0.172)
Ln(*Time to Maturity*)	-2.247*	-3.022***	-0.051	-1.220
	(1.231)	(1.104)	(1.098)	(1.010)
Ln(*Age*)	3.661***	4.295***	3.490***	4.019***
	(0.558)	(0.582)	(0.546)	(0.566)
Ln(*Amount Outstanding*)	-19.466***	-14.645***	-19.579***	-15.395***
	(1.849)	(1.331)	(1.848)	(1.410)
Zero Trading Day	8.542***	9.095***	9.199***	10.127***
	(0.676)	(0.566)	(0.706)	(0.591)
Day FE	Y	-	Y	-
Rating FE	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y
Issuer × Day FE	N	Y	N	Y
Observations	4,250,119	4,042,246	4,060,951	3,848,877
Adjusted R^2	0.170	0.238	0.172	0.237

Table VIII: **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 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. We do not scale it in percentage points (it is kept as a 0–1 fraction) to improve the readability of coefficient estimates. *Index-closing Time Volume%* is interacted with three dummy variables indicating high trade imbalance conditions. In Column (1), it is interacted with D(*Large Net Fund Flow*), a dummy variable indicating days in the top and bottom 5% of daily net flows of passive bond funds. In Column (2), it is interacted with D(*Large Net Fund Inflow*) and D(*Large Net Fund Outflow*), which indicate days in the top and bottom 5% of daily net flows of passive bond funds, respectively. In Column (3), it is interacted with D(*High VIX*), a dummy equal to one for days in the highest 5% of VIX during the sample period. In Column (4), it is interacted with D(*COVID*), a dummy equal to one for the March 6–19, 2020 period. 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 II. Columns (5)–(8) report results from reproducing Columns (1)–(4) with issuer-day fixed effects. The sample consists of index-eligible bonds from 2012 to 2024. 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)	(7)	(8)
Index-closing Time Volume%	-10.292***	-10.291***	-10.734***	-10.136***	-10.070***	-10.070***	-10.516***	-9.934***
	(0.258)	(0.258)	(0.249)	(0.256)	(0.263)	(0.263)	(0.254)	(0.258)
Index-closing Time Volume% × D(*Large Net Fund Flow*)	3.200**				3.397***			
	(1.279)				(1.306)			
Index-closing Time Volume% × D(*Large Net Fund Inflow*)		1.594				1.659		
		(1.605)				(1.614)		
Index-closing Time Volume% × D(*Large Net Fund Outflow*)		4.585**				4.860**		
		(1.891)				(1.929)		
Index-closing Time Volume% × D(*High VIX*)			9.758***				10.095***	
			(1.539)				(1.550)	
Index-closing Time Volume% × D(*COVID*)				28.085***				35.420***
				(8.693)				(10.034)
Ln(*Time to Maturity*)	8.984***	8.984***	8.977***	8.971***	6.783***	6.783***	6.773***	6.764***
	(0.534)	(0.534)	(0.534)	(0.534)	(0.460)	(0.460)	(0.459)	(0.459)
Ln(*Age*)	3.017***	3.017***	3.020***	3.014***	2.357***	2.357***	2.360***	2.353***
	(0.329)	(0.329)	(0.329)	(0.329)	(0.289)	(0.289)	(0.289)	(0.289)
Ln(*Amount Outstanding*)	-16.539***	-16.540***	-16.536***	-16.538***	-15.432***	-15.432***	-15.434***	-15.427***
	(0.918)	(0.918)	(0.918)	(0.918)	(1.027)	(1.027)	(1.027)	(1.027)
Zero Trading Day	1.176*	1.173*	1.185*	1.176*	9.365***	9.361***	9.373***	9.369***
	(0.707)	(0.707)	(0.707)	(0.707)	(0.594)	(0.594)	(0.594)	(0.594)
$\beta_1 + \beta_2$	-7.091***	-8.697***	-0.976	17.949**	-6.673***	-8.411***	-0.422	25.486**
	(1.250)	(1.587)	(1.516)	(8.693)	(1.275)	(1.594)	(1.526)	(10.029)
$\beta_1 + \beta_3$		-5.706***				-5.210***		
		(1.868)				(1.906)		
Rating FE	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	-	-	-	-
Bond FE	Y	Y	Y	Y	Y	Y	Y	Y
Issuer × Day FE	N	N	N	N	Y	Y	Y	Y
Observations	4,038,001	4,038,001	4,038,001	4,038,001	3,465,802	3,465,802	3,465,802	3,465,802
Adjusted R^2	0.200	0.200	0.200	0.200	0.245	0.245	0.245	0.245

Panel B. CP+ midprice as benchmark

Dependent variable: *Transaction Cost* (bps)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Index-closing Time Volume%	-9.874***	-9.871***	-10.358***	-9.774***	-9.389***	-9.388***	-9.878***	-9.321***
	(0.347)	(0.347)	(0.308)	(0.338)	(0.338)	(0.338)	(0.286)	(0.312)
Index-closing Time Volume% × *D*(*Large Net Fund Flow*)	4.870**				4.679**			
	(2.195)				(2.005)			
Index-closing Time Volume% × *D*(*Large Net Fund Inflow*)		-0.495				0.051		
		(1.937)				(2.183)		
Index-closing Time Volume% × *D*(*Large Net Fund Outflow*)		9.163**				8.412***		
		(3.564)				(3.112)		
Index-closing Time Volume% × *D*(*High VIX*)			8.144***				8.108***	
			(2.215)				(2.182)	
Index-closing Time Volume% × *D*(*COVID*)				45.419**				48.340**
				(18.574)				(19.544)
Ln(*Time to Maturity*)	-2.195*	-2.231*	-2.041*	-2.223*	-2.980***	-3.004***	-2.842***	-3.005***
	(1.224)	(1.230)	(1.208)	(1.228)	(1.098)	(1.102)	(1.083)	(1.102)
Ln(*Age*)	3.668***	3.671***	3.676***	3.677***	4.301***	4.303***	4.306***	4.304***
	(0.559)	(0.559)	(0.560)	(0.562)	(0.583)	(0.583)	(0.583)	(0.584)
Ln(*Amount Outstanding*)	-19.463***	-19.462***	-19.459***	-19.439***	-14.647***	-14.639***	-14.656***	-14.619***
	(1.849)	(1.848)	(1.847)	(1.846)	(1.332)	(1.331)	(1.332)	(1.332)
Zero Trading Day	8.550***	8.532***	8.560***	8.558***	9.100***	9.086***	9.114***	9.106***
	(0.676)	(0.675)	(0.676)	(0.675)	(0.566)	(0.567)	(0.565)	(0.565)
$\beta_1 + \beta_2$	-5.004**	-10.366***	-2.214	35.646*	-4.710**	-9.336***	-1.770	39.019**
	(2.147)	(1.932)	(2.176)	(18.544)	(1.961)	(2.173)	(2.155)	(19.528)
$\beta_1 + \beta_3$		-0.708				-0.976		
		(3.518)				(3.069)		
Rating FE	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	-	-	-	-
Bond FE	Y	Y	Y	Y	Y	Y	Y	Y
Issuer × day FE	N	N	N	N	Y	Y	Y	Y
Observations	4,250,119	4,250,119	4,250,119	4,250,119	4,042,246	4,042,246	4,042,246	4,042,246
Adjusted R^2	0.170	0.170	0.170	0.170	0.238	0.238	0.238	0.238

Table A1: **Transaction cost of index-closing time trades using the benchmark prices lagged by 15 minutes**

This table replicates Table IV, using benchmark prices measured at least 15 minutes prior to each transaction to compute transaction costs.

Panel A. Interdealer transaction price as benchmark

Dependent variable: *Transaction Cost* (bps)						
Trade direction:	All	Buy	Sell	All	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
D(*Index-closing Time*)	-6.091***	-8.175***	-4.596***	-6.293***	-8.401***	-4.781***
	(0.252)	(0.372)	(0.333)	(0.257)	(0.379)	(0.339)
D(*Other Clustering Time*)				-2.270***	-3.006***	-1.862***
				(0.163)	(0.235)	(0.201)
Bond × Day FE	Y	Y	Y	Y	Y	Y
Trade Size FE	Y	Y	Y	Y	Y	Y
Trade Direction FE	Y	-	-	Y	-	-
Observations	20,497,910	12,113,184	7,145,426	20,497,910	12,113,184	7,145,426
Adjusted R^2	0.374	0.492	0.468	0.374	0.492	0.468

Panel B. CP+ midprice as benchmark

Dependent variable: *Transaction Cost* (bps)						
Trade direction:	All	Buy	Sell	All	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
D(*Index-closing Time*)	-7.731***	-9.653***	-5.833***	-8.154***	-10.111***	-6.179***
	(0.240)	(0.434)	(0.431)	(0.244)	(0.438)	(0.435)
D(*Other Clustering Time*)				-4.379***	-5.259***	-3.336***
				(0.144)	(0.214)	(0.228)
Bond × Day FE	Y	Y	Y	Y	Y	Y
Trade Size FE	Y	Y	Y	Y	Y	Y
Trade Direction FE	Y	-	-	Y	-	-
Observations	22,574,678	12,567,087	8,451,125	22,574,678	12,567,087	8,451,125
Adjusted R^2	0.342	0.483	0.534	0.343	0.483	0.535

Table A2: **Transaction cost changes around the index-closing time shift using the benchmark prices lagged by 15 minutes**

This table replicates Table V, using benchmark prices measured at least 15 minutes prior to each transaction time to compute transaction costs.

Panel A. Interdealer transaction price as benchmark

Dependent variable: *Transaction Cost* (bps)			
Sample window:	1 month	3 months	6 months
	(1)	(2)	(3)
D(15:00–15:05)	-6.066***	-6.746***	-6.763***
	(0.940)	(0.853)	(0.606)
D(15:00–15:05) × D(*Post Index-closing Time Change*)	3.471**	3.392***	3.801***
	(1.412)	(1.041)	(0.725)
D(16:00–16:05)	0.311	-1.320	-1.473**
	(1.718)	(0.949)	(0.636)
D(16:00–16:05) × D(*Post Index-closing Time Change*)	-7.007***	-4.184***	-4.717***
	(2.110)	(1.537)	(1.036)
Bond × Day FE	Y	Y	Y
Trade Size FE	Y	Y	Y
Trade Direction FE	Y	Y	Y
Observations	215,197	658,989	1,207,399
Adjusted R^2	0.320	0.303	0.322

Panel B. CP+ midprice as benchmark

Dependent variable: *Transaction Cost* (bps)			
Sample window:	1 month	3 months	6 months
	(1)	(2)	(3)
D(15:00–15:05)	-6.297***	-6.972***	-6.734***
	(1.164)	(0.681)	(0.500)
D(15:00–15:05) × D(*Post Index-closing Time Change*)	3.855**	4.327***	4.328***
	(1.440)	(0.818)	(0.582)
D(16:00–16:05)	-1.867	-1.636**	-1.980***
	(1.325)	(0.704)	(0.530)
D(16:00–16:05) × D(*Post Index-closing Time Change*)	-5.836***	-6.030***	-5.079***
	(1.871)	(1.272)	(0.848)
Bond × Day FE	Y	Y	Y
Trade Size FE	Y	Y	Y
Trade Direction FE	Y	Y	Y
Observations	492,749	1,479,702	2,759,334
Adjusted R^2	0.330	0.326	0.351