On The Drivers of Corporate Bond Lending

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Abstract

Short sellers in the corporate bond market are primarily dealers rather than speculative customers. On days when bond lending increases, dealer sales, the half spread of customer buy trades, and bond returns all rise, indicating that bond lending is driven by customer buying pressure. Using a novel empirical framework that decomposes the variance of securities lending, we find that dealer market-making activities account for roughly two-thirds of lending variation. Customer speculation plays a larger role in a small segment of special bonds, but its share never exceeds 50%. Our findings caution against extending insights from the equity short-selling literature to the corporate bond market.

JEL classification: G12, G14, G23, G24

Keywords: Short selling, corporate bonds, securities lending, dealer intermediation, market making

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1 Introduction

The conventional motivation for short selling is informational: short sellers identify overvalued securities and profit when prices decline. Consistent with this view, a vast literature documents that equity short sellers are informed traders whose positions predict low future returns (see, e.g., Boehmer, Jones, and Zhang 2008; Diether, Lee, and Werner 2009; Saffi and Sigurdsson 2011). Do these findings generalize to the corporate bond market? Asquith, Au, Covert, and Pathak (2013) suggest an alternative motivation, noting that bonds may be borrowed to facilitate clearing of long trades rather than to express negative views. This raises a fundamental question: Who borrows corporate bonds, and for what purposes?

We show that short-selling activity in the corporate bond market is driven primarily by dealers' market-making activities rather than by customers' speculative trading. To establish this result, we construct a panel dataset combining transaction volume data from TRACE, which records customer buy and sell trades separately, with corporate bond lending data from Markit. We then regress daily buy and sell volume on daily changes in the bond's quantity on loan. The intuition underlying this test is straightforward: when loan quantity rises by one dollar, either dealer sales or customer sales must increase by one dollar. The sensitivity of signed volume to changes in loan quantity therefore reveals which side drives the bond lending activities. We find that a one-dollar increase in loan quantity coincides with a 0.21 dollar increase in customer buy volume and a 0.11 dollar *decrease* in customer sell volume. The negative coefficient on customer sells is inconsistent with the hypothesis that customers borrow bonds for speculative short selling. Instead, these results support the view that dealer market-making drives bond borrowing: dealers borrow bonds to sell them to buying customers.

To verify this mechanism, we examine the response of half spreads in bond transactions, measured as the price difference between customer trades and preceding interdealer trades. Regressing daily half spreads on changes in loan quantity separately for customer buys and sells, we find that when lending activity intensifies, half spreads on customer buys widen by 5 basis points (bps), while those on customer sales narrow by 3 bps. These results are consistent with the notion that, when facing buying pressure, dealers increase spreads on customer buy transactions, but reduce them on sell transactions to reward liquidity provision (Glosten and Milgrom 1985).

To provide further support for our findings, we examine the return implications of these lending activities. Regressing daily bond returns on changes in loan quantity, we find that on days when short sales increase by one percentage point, the contemporaneous bond return *increases* by 3.3 bps ($t = 5.01$). Dealers facing customer buying pressure immediately revise their quotes upward, leading to a positive bond return on that day.

Bond returns not only move on impact, but also exhibit a drift following short sales. We find that the return predictability persists for up to a month: a portfolio of bonds with increased loan quantity has a higher return than those with decreased loan quantity by 1.2 bps per day over the four business days following the initial short sales, and 0.2 bps afterwards. Because the initial price reaction does not reverse over the medium term, buying customers appear to possess positive information about the bond.

Our findings suggest that dealers, rather than customers, represent the primary short sellers in the corporate bond market. This happens because speculative short sales are prohibitively expensive for customers who pay bid-ask spreads each time they trade. To be concrete, consider the following situation in which a customer short-sells an average corporate bond: the average half spreads in our bond sample are 29 bps per transaction, the average loan tenure is roughly three months, and the average borrowing fee is 44 bps per year. Thus, if the customer borrows the bond, sells it short, and buys it back after three months, the round-trip cost amounts to 58 bps, which is more than half of the average three-month bond return of 1.05 percent. High bid-ask spreads completely dominate the borrowing fee, which is only 11 bps per three months. This high transaction cost, coupled with the cheaper alternative of trading credit default swaps or the issuer's stocks, makes speculative short selling unattractive for customers.

Although the reduced-form analysis highlights the importance of dealer market-making activities, it does not quantify the respective roles of dealers and customers in driving lending activity. To address this, we conduct a variance decomposition of lending activities, which splits the variance into two covariances: one between loan quantity and dealer sales, and the other between loan quantity and customer sales. This approach allows us to estimate the share of lending activity attributable to dealers and customers. The decomposition result reveals that dealer sales account for 68.5% of the variance in bond lending activities, while customer sales account for the remainder. This dealer share is slightly higher for investment-grade (IG) bonds (70.8%) and lower for high-yield (HY) bonds (64.5%), consistent with differences in information sensitivity between rating categories.

To better understand our results, we conduct subsample analyses based on specialness. We divide bonds into four groups by daily lending fee. We find that the dealer share declines monotonically from 70.3% in the low-fee group to 52.2% in the high-fee group, implying that customer short sales are more important in the small subset of bonds with very high lending fees. Even in this segment, however, the dealer share is above 50%.

We next test whether the availability of alternative venues for expressing negative credit views affects these shares. Specifically, we compare bonds issued by public versus private firms, and by firms with and without CDS coverage. The dealer share is 68.7% for public firms and 66.0% for private firms, implying that customer short sales are more prevalent for private firms where stock shorting is unavailable. However, we do not find a significant difference between bonds issued by firms with and without CDS coverage.

As a last step in the variance decomposition analysis, we conduct event studies focusing on information events on bond issuers. Specifically, we examine transactions during the month preceding a rating change or an earnings announcement date. Before these events, investors may acquire information and attempt to sell short in anticipation of negative news. We find that the share of dealer short sales declines to 60.9% before rating downgrades and to 63.4% before earnings announcements with large negative surprises. Therefore, customer short sales are relatively more important before negative news.

The fact that dealer market-making activity is the main driver of corporate bond lending contrasts with the stock market, where customer speculation plays a greater role. For example, Comerton-Forde, Jones, and Putniņš (2016) find that in the stock market, the magnitudes of liquidity-taking and liquidity-supplying short sales are comparable to each other; Goyal, Reed, Smajlbegovic, and Soebhag (2025) show that even liquidity-supplying shorts are informed, as their trades also predict future low returns. This distinction has broad implications for various research agendas on short selling. For example, regulation around short-selling trades off price efficiency and market stability, implicitly assuming that short sellers are informed investors (see Edwards, Reed, and Saffi 2024 for a recent survey). Our results indicate that in the corporate bond market, liquidity provision is the dominant aspect of short selling. Therefore, regulations in this market should not consider short selling as an activity destabilizing the financial market.

To showcase the significance of the difference in borrowing motives in the corporate bond market from those in the stock market, we revisit a widely-studied topic of the effects of increasing passive ownership on securities lending. In the stock market, prior studies such as Sikorskaya (2023), Palia and Sokolinski (2024), and von Beschwitz, Honkanen, and Schmidt (2025) document that borrowing demand for stocks rises with passive ownership. This happens because higher passive ownership inflates stock valuations, motivating speculative investors to borrow stocks to sell them short. Our results suggest that the impact of passive ownership might differ in the corporate bond market, where speculation is less important.

To confirm this, we estimate panel regressions of lending outcome variables, such as lendable supply, loan quantity, and borrowing fees, on the share of bonds held by passive investors with high-dimensional fixed effects to soak up any variation in firm-level characteristics driving both the outcome and passive ownership. The results from these regressions show that the borrowing demand for a bond declines as passive ownership increases. Specifically, a one-standard-deviation increase in passive ownership insignificantly reduces the equilibrium quantity of bonds on loan by 0.031 percentage points (pps), or 2.3% of its inter-quartile range. The effect on lending quantities is modest because the supply expansion and demand contraction cancel each other out. However, the equilibrium lending fee declines substantially because both of these two effects push down the equilibrium price. In our main specification, the fee declines by 0.067 pps, which is equivalent to 51.8% of its inter-quartile range.

The impact on the demand to borrow corporate bonds declines because the increased bond valuation discourages aggressive buyers from sending urgent buy orders, thereby reducing the need for dealers to meet such demand. Consistent with this mechanism, we find that greater passive ownership is associated with narrower credit spreads (as in Dannhauser 2017; Bretscher, Schmid, and Ye 2024) and lower net buy volume.

In summary, our paper revisits the economics of securities lending in the corporate bond market and documents evidence that it is primarily driven by dealer intermediation rather than speculation.

Prior work in the corporate bond market, including Asquith, Au, Covert, and Pathak (2013), Anderson, Henderson, and Pearson (2018), and Hendershott, Kozhan, and Raman (2020), examines borrowing costs and subsequent returns to bond short selling, with evidence that informational trading and temporary price pressure effects are more pronounced among HY bonds. Pelizzon, Riedel, Simon, and Subrahmanyam (2024) examine how the collateral eligibility of European corporate bonds for the central bank facility influences lending activities.[1]

This paper also relates to the extensive literature measuring illiquidity and studying its drivers in the corporate bond market (e.g., Edwards, Harris, and Piwowar 2007; Chen, Lesmond, and Wei 2007; Feldhütter 2012; Bao, Pan, and Wang 2011; Schestag, Schuster, and Uhrig-Homburg 2016; Bao, O'Hara, and Zhou 2018; Bessembinder, Jacobsen, Maxwell, and Venkataraman 2018; Dick-Nielsen and Rossi 2018; O'Hara and Zhou 2021; Hendershott, Livdan, and Schuerhoff 2021; Hendershott, Li, Livdan, Schuerhoff, and Venkataraman 2022; Choi, Huh, and Shin 2024; Pinter, Wang, and Zou 2024; Jacobsen and Venkataraman 2025). Our paper contributes to this line of research by documenting how short sales can enhance liquidity.

Finally, our study contributes to the literature on ownership structure and intermedi-

[1]In contrast to the limited literature on corporate bond short sales, the equity research on shorting activities is vast. For an incomplete list see, D'Avolio (2002); Cohen, Diether, and Malloy (2007); Boehmer, Jones, and Zhang (2008); Saffi and Sigurdsson (2011); Blocher, Reed, and Van Wesep (2013); Boehmer and Wu (2013); Boehmer, Jones, and Zhang (2013); Kolasinski, Reed, and Ringgenberg (2013); Engelberg, Reed, and Ringgenberg (2018); Chen, Joslin, and Ni (2018); Muravyev, Pearson, and Pollet (2022, 2023).

ation. In equity markets, higher passive ownership generally increases short interest and lending activity (e.g., Prado, Saffi, and Sturgess 2016; Coles, Heath, and Ringgenberg 2022; Sikorskaya 2023; Palia and Sokolinski 2024; von Beschwitz, Honkanen, and Schmidt 2025), as passive holdings can elevate valuations and attract speculative short sellers. Our analysis also complements recent research on passive bond investing and dealer behavior (e.g., Dannhauser and Karmaziene 2023; Bretscher, Schmid, and Ye 2024) and highlights how structural differences between equity and bond markets influence the link between ownership composition, intermediation, and securities lending.

The remainder of the paper is structured as follows. Section 2 describes the data. Section 3 presents the reduced-form analysis of the drivers of bond lending activity. Section 4 outlines the variance decomposition framework and reports the estimation results. Section 5 examines the relationship between passive ownership and bond lending activities. Section 6 concludes.

2 Data and Sample Construction

We compile our sample from several sources: (1) IHS Markit for securities lending data, (2) the Mergent Fixed Income Securities Database (FISD) for bond characteristics, (3) the Enhanced Trade Reporting and Compliance Engine (TRACE) database for bond transaction volume and direction, (4) the ICE Bank of America Merrill Lynch (BAML) database for daily bond returns, (5) CRSP, Compustat, I/B/E/S, and the WRDS Intraday Indicators (IID) database for firm- and stock-level variables, and (6) Morningstar and the Thomson Reuters eMAXX database for bond holdings. This section describes the construction of our dataset and variables and presents summary statistics.

2.1 Bond Lending Data

We source our bond lending data from Markit Securities Finance Buy-Side Analytics Data (now part of S&P Global Market Intelligence) through WRDS. This database covers daily data on securities borrowing and lending activity, including quantity on loan, active lendable quantity, utilization rate, rebate fees, borrowing (loan) fees, average loan tenure, and other lending outcomes. It is collected from more than 650 industry practitioners, including custodian banks, prime brokers, and hedge funds. Inventory-based measures (e.g., lendable supply) are derived from major global custodians and large institutional asset managers, whereas loan-based measures (e.g., quantity on loan) are based on loan transaction records contributed by market participants.[2]

We select our sample based on two filters. First, we keep only observations that can be matched to the corporate bond database, created using Mergent FISD and TRACE. We filter corporate bond data following standard approaches in the literature and provide details on the cleaning procedure in Appendix A. Second, we require that the quantity on loan and lending fee variables be non-missing. This implies that all bonds in our sample have non-zero quantity on loan.[3]

We scale the quantity on loan and lendable supply by each bond's amount outstanding, obtained from FISD. Following recent research in the equity lending market (e.g., Muravyev, Pearson, and Pollet 2022, 2023), we use the indicative lending fee as a proxy for the cost of borrowing a bond from the ultimate borrower's perspective.[4]

2.2 Other Data

We construct the customer buy and sell volumes using Enhanced TRACE, which records the direction of trades from the reporting dealers' perspective. For each customer-dealer trade, we treat dealer-buy trades as customer sales and dealer-sell trades as customer buys. We treat missing trading volume and customer buy/sell trade observations in TRACE as zero volume when computing bonds' transaction volume. For each bond, the sample period is bounded by its issue date and either its maturity or last call date.[5] We then merge the TRACE volume into the panel to identify days with zero trading volume.

For bond returns, we compute daily bond returns and volatility using quote prices from the Bank of America Merrill Lynch (BAML) database provided by the Intercontinental Exchange (ICE), which provides non-missing daily returns and helps mitigate the microstructure noise (see Andreani, Palhares, and Richardson 2024).

We obtain stock return, trading volume, and shares outstanding data from CRSP, and

[2]See the IHS Markit Securities Finance Data Feed FAQs (via WRDS) and `https://www.spglobal.com/market-intelligence/en/solutions/products/securities-finance` for additional details.

[3]We observe occasional short gaps in the time series for loan quantity and lending fee within otherwise continuous CUSIP-level records. For example, CUSIP "125523BZ2" has missing values between December 28, 2020 and January 13, 2021, and CUSIP "70109HAJ4" shows a gap from April 1 to September 30, 2022. After consulting S&P Global's data team, we confirm that these interruptions result from temporary lapses in data contribution or reporting, rather than an absence of lending activity. We therefore treat these cases as missing data and exclude them from our main analysis. We discuss the robustness of our main results to using interpolated data in Section 4.2.

[4]Markit estimates the expected cost of borrowing for a hedge fund on a given day taking into account the borrowing costs of prime brokers and hedge funds.

[5]For the list of trading days, we use those in CRSP and exclude bond trades recorded on the days when stock markets are closed. This choice excludes some sparse trades on weekends but includes more trading days than the Treasury market data.

firm fundamentals from Compustat. Our stock sample consists of common stocks (share codes 10 and 11) listed on NYSE, NASDAQ, and AMEX. Signed stock trading volumes come from the WRDS Intraday Indicators (IID) database, which classifies trades as buyer- or seller-initiated using the Lee and Ready (1991) algorithm. Analyst earnings forecasts are from the Institutional Brokers Estimate System (I/B/E/S). Following Dellavigna and Pollet (2009), we reconcile the earnings announcement dates between Compustat and I/B/E/S taking the earlier reported date. Consistent with Johnson and So (2018), we exclude observations where the two sources differ by more than two trading days. When I/B/E/S timestamps indicate that an announcement occurred after market close, we assign the following trading day as the effective announcement date.

We construct two samples for our empirical analysis. For the univariate regression analysis, we merge the Markit bond lending data with TRACE transaction data and ICE BAML bond returns, yielding 16,850,795 bond-day observations for 15,503 bonds spanning September 12, 2006 to December 30, 2022. For the multivariate regression analysis, we require each bond to have at least 252 daily observations and non-missing values for all control variables. The final multivariate regression sample includes 11,341,920 bond-day observations for 11,763 corporate bonds from 2,121 issuers (1,326 public firms) over the same period. To mitigate the influence of outliers, we winsorize continuous variables, except bond returns, at the 1st and 99th percentiles by date. Detailed variable definitions are provided in Appendix Table A1.

Table 1 reports descriptive statistics for both samples. Panel A presents the univariate regression sample, and Panel B presents the multivariate regression sample. The daily change in loan quantity, dQ, has a mean of -0.002% in both samples, with standard deviations of 0.189% and 0.199%, respectively. Customer buy and sell volumes average 0.151% and 0.095% per day in the univariate sample, compared to 0.185% and 0.113% in the multivariate sample, consistent with the 252-observation filter retaining more actively traded bonds.

3 Identifying Short Sellers

3.1 Bond Trading Volume

Before presenting a formal decomposition, we start with a simple univariate regression analysis to show suggestive evidence. Specifically, we first run a panel regression of daily customer buy and sell volume scaled by the amount of bonds outstanding on day $d + h$, $Vol_{i,d+h,\xi}$, on daily changes in the quantity on loan, also scaled by the amount of bonds outstanding,

$dQ_{i,d}$,

$$Vol_{i,d+h,\xi} = a_{h,\xi} + b_{h,\xi} \cdot dQ_{i,d} + \varepsilon_{i,d+h,\xi}, \quad \text{where } \xi \in \{\text{Buy, Sell}\}, \tag{1}$$

for $h = -5, ..., 5$ and ξ indicates a trade side from a customer's point of view. We use daily changes in loan quantity rather than its level to capture the flow of lending activities because trading volume is also a flow variable rather than a stock measure. Since borrowing and selling may occur several days apart from one another, we estimate the relationship allowing for a lag of h days.

The slope coefficient $b_{h,\xi}$ quantifies the sensitivity of customer trades to changes in loan quantity and allows us to distinguish whether customers or dealers are shorting the bonds. Specifically, if bond borrowing increases purely due to speculative short selling by customers, then we expect $b_{h,Sell} = 1$: a one percentage point increase in quantity on loan should translate into an equivalent increase in customer selling volume. It is also possible that the increase in quantity on loan reflects a decrease in the number of customers returning previously borrowed bonds, which corresponds to a decrease in customer purchases (i.e., customers' short covering activities). If this is the only driver of dQ, then we expect $b_{h,Buy} = -1$. More realistically, if the increase in borrowing is driven by both an increase in newly established short positions and a decrease in previously established short positions, we expect $0 < b_{h,Sell} < 1$, $-1 < b_{h,Buy} < 0$ and $b_{h,Sell} - b_{h,Buy} > 0$.

If, on the other hand, it is dealers who borrow bonds and short them for market-making activities, then the prediction for the coefficients is the opposite. An increase in borrowing should correspond to an increase in customer *buy*, implying a positive coefficient, $0 < b_{h,Buy} < 1$. It may also correspond to a decrease in customer selling (as dealers' short covering activity decreases), implying a negative coefficient $-1 < b_{h,Sell} < 0$. Thus, if dealers' short and short-covering activities drive bond lending, $b_{h,Sell} - b_{h,Buy} < 0$ holds.

Finally, if bond lending is motivated by financing reasons, then lending is not associated with buying or selling the bond. Therefore, we expect the slope coefficients to be zero for both customer purchases and sales.

We estimate the regression in equation (1) separately for two subperiods, before and after September 4, 2017. This cutoff corresponds to the SEC's implementation of a shorter settlement cycle for securities transactions. Before this change, transactions generally settled three business days after the trade date; afterwards, the settlement period was reduced to two business days.[6] In the Markit database, the quantity on loan is indexed by settlement date, whereas TRACE records trading volume by trade date. The change in settlement rules

[6] In 2024, the settlement period was further shortened to one business day.

therefore affects the timing relationship between the two variables.[7]

Panel A of Figure 1 plots the coefficient estimates $b_{h,\xi}$ from regression (1) for the first subperiod before September 4, 2017, along with two-standard-error bands. We compute standard errors by double-clustering at the bond and date levels.

The plot reveals a striking pattern for the coefficients on day $d-3$, which represents the sensitivity of day $d-3$ trading volume to day d changes in loan quantity. We find that customer buying is strongly positively correlated with changes in loan quantity, while customer selling is negatively correlated: a one-percentage-point increase in loan quantity corresponds to a 0.18 pp ($t = 12.76$) increase in customer buys and a 0.11 pp ($t = -12.27$) decrease in customer sells. On the other hand, the estimates on the other days are generally small.

Panel B of Figure 1 plots the coefficient estimates $b_{h,\xi}$ for the subperiod after September 5, 2017. The pattern closely resembles that of Panel A, except that the peak in customer buying now shifts from $d-3$ to $d-2$, consistent with the reduction in the settlement period from three to two business days.

The key takeaway from these plots is that customer sales volume does not increase when bond lending increases. This pattern holds across all horizons $h = -5, \ldots, -2$. In contrast, on days $d-3$ or $d-2$, customer buy volume rises, indicating intensified sales by dealers in response to customer demand. Since $b_{h,Sell} - b_{h,Buy} < 0$ in both panels of Figure 1, this is suggestive evidence that dealers' market-making activities are the main driver of bond lending. At the same time, the fact that $|b_{h,Sell} - b_{h,Buy}| < 1$ suggests that dealer short selling is an important but not the sole driver of bond lending. To quantify the contribution of each factor driving lending activities, we undertake a formal decomposition of bond lending into dealer and customer activity in Section 4.

Our analysis also highlights the importance of adjusting for the settlement cycle when linking Markit lending data with TRACE transaction data. On the settlement date, market participants typically do not make decisions to borrow or lend securities; these decisions are made on trade dates, which occur two or three business days before settlement. Therefore, the "contemporaneous" relationship between lending and trading volume is that between the quantity on loan on day d and the trade volume on day $d-2$ or $d-3$. Accordingly, we define the trade date $d^* = d - s$, where s is 3 if d is on or before September 4, 2017, and 2 thereafter. In all subsequent analyses, we combine data from both subperiods after aligning

[7] Consultations with Markit and S&P Global confirm that the variable "`datadate`" in the Markit Securities Finance (MSF) database refers to the settlement date, representing loan positions outstanding as of that date rather than the trade initiation date. Barardehi, Da, Dixon, and Wang (2024) use the same Markit data for equity research and also discuss this settlement timing issue.

trading volume on day d^* with changes in quantity on loan on day d.

Based on the insights of Merton (1974), HY bonds with elevated default risk are more sensitive to information than IG bonds. Therefore, the regression results above may depend on the issuer's credit risk. To this end, we split the sample by credit rating on day d and estimate the regression separately for IG and HY bonds. Figure 2 reports the univariate regression estimates of (1) by credit rating. We find that on trade date, customer sales decrease and purchases increase in both subsamples, confirming our main results.

3.2 Bond Abnormal Half Spreads

Dealers short-sell bonds in response to buying customers' demand for bonds that they do not hold in inventory. To cover the cost of borrowing, dealers should charge a higher half spread. Furthermore, if a buy order is perceived to be informed, dealers should widen the spread to mitigate adverse selection costs (Glosten and Milgrom 1985; Kyle 1985). To study how dealers react to increased buying pressure, we next examine the response of half spreads to changes in quantity on loan.

Following Hendershott and Madhavan (2015), we define the half spread of a customer-dealer transaction ν for bond i as

$$h_{i,\nu} = (\log P_{i,\nu} - \log P_{i,ID}) \times \mathbf{1}_{i,\nu}, \tag{2}$$

where $P_{i,\nu}$ is the price of the dealer-customer trade, and $P_{i,ID}$ is the price of the most recent interdealer transaction preceding trade ν. We use the latest interdealer trade that takes place within the five-business-day period before trade ν. $\mathbf{1}_{i,\nu}$ is an indicator variable equal to one if ν is a customer buy and -1 if ν is a customer sell.

Edwards, Harris, and Piwowar (2007) demonstrate that half spreads of corporate bonds are heavily influenced by mechanical changes in trade size or market microstructure noises. To mitigate potential biases, we compute abnormal half spreads as the volume-weighted average difference between bond i's half spread and a benchmark half spread averaged over the previous 21 days:

$$AbHS_{i,d,\xi} = \sum_{\nu \in (d \cap \xi)} w_{i,\nu}(h_{i,\nu} - \bar{h}_{bench,d(\nu)-21 \to d(\nu)-1,\xi(\nu)}). \tag{3}$$

To construct the benchmark half spreads, $\bar{h}_{bench}$, we form portfolios of bonds based on three dimensions: credit ratings (IG versus HY), trade size (trades up to \$100,000, between \$100,000 and \$1 million, between \$1 million and \$10 million, and above \$10 million), and trade direction (customer buy versus customer sell), and compute equal-weighted average half spreads in each portfolio.

To test how customer transaction costs respond to changes in loan quantity, we estimate a panel regression of abnormal half spreads on day $d^* + h$ on daily changes in quantity on loan on day d,

$$AbHS_{i,d^*+h,\xi} = a_{h,\xi} + b_{h,\xi} \cdot dQ_{i,d} + \varepsilon_{i,d^*+h,\xi}, \quad \text{where } \xi \in \{\text{Buy, Sell}\}. \tag{4}$$

Figure 3 presents the coefficient estimates from these regressions, revealing a pronounced spike on the trade date, d^*. A one percentage point increase in quantity on loan corresponds to a 0.05 pp increase in customer buy spreads and a 0.03 pp decrease in customer sell spreads. These magnitudes are economically large relative to the average half spread of 0.29 pp in our sample.

This pattern is consistent with our earlier evidence that dealers are the primary short sellers in the corporate bond market. When dealers borrow bonds to accommodate strong customer buying pressure, they charge higher spreads to buying customers while offering tighter spreads to selling customers to attract liquidity providers. As shown in Figure 3, on the trade date, the increase in the half spread for buy trades exceeds the decrease for sell trades, leading to a widened bid-ask spread.

3.3 Bond Returns Around Short Sales

We next study corporate bond returns around short-sale events. This analysis of returns serves two purposes. First, on the day of a short sale, a bond price moves in the direction of order flows. If short sales correspond to customer buy (sell) orders, then we would expect a positive (negative) return on that day. Second, returns following the short-sale day help us distinguish informed order flows from uninformed, liquidity-driven trades.

To examine the price impact of lending activity, we regress daily bond returns on changes in the quantity on loan:

$$R_{i,d^*+h,\gamma} = a_{h,\gamma} + b_{h,\gamma} \cdot dQ_{i,d} + \varepsilon_{i,d^*+h,\gamma}, \tag{5}$$

$$R_{i,d^*+h,\gamma} = a_{h,\gamma} + c_{h,\gamma} \cdot \mathbf{1}_{dQ_{i,d}=0} + b_{h,\gamma} \cdot \mathbf{1}_{dQ_{i,d}>0} + \varepsilon_{i,d^*+h,\gamma}, \quad \text{where } \gamma \in \{\text{IG, HY, All}\}, \tag{6}$$

for $h = -5, ..., 5$. The indicator $\mathbf{1}_{dQ_{i,d}=0}$ ($\mathbf{1}_{dQ_{i,d}>0}$) equals one if the change in quantity on loan is zero (positive). We obtain daily bond returns from the ICE BAML bond pricing database and do not winsorize any return observations, which is important given the findings in Dickerson, Robotti, and Rossetti (2024). Because results may be sensitive to outliers, we present both the linear and dummy variable specifications.

Figure 4 Panel A plots the slope coefficient $b_{h,\gamma}$ as a function of h from the linear regression, (5), separately for the sample of all bonds, IG bonds, and HY bonds. We observe significantly positive returns on day d^* using the sample of all bonds, with a point estimate of $b_{0,\text{All}} = 0.033\%$ per day ($t = 5.01$). This pattern suggests that increased lending activity coincides with a simultaneous increase in bond prices, consistent with customer buying pressure. If instead short sales reflect customer speculation exploiting bond overvaluation, then we would expect strongly positive returns before the trade date (i.e, $d^* - 2$ and $d^* - 1$) followed by negative returns on the trade date and thereafter. However, we find that estimates $b_{-2,\text{All}} = -0.0004\%$ and $b_{-1,\text{All}} = 0.0098\%$ are economically small, and $b_{0,All}$ is significantly positive. The pattern is consistent across credit rating categories: both IG and HY bonds exhibit higher returns on day d^* than on other days, with statistically significant positive effects on days d^* and $d^* + 1$.

Panel B plots the coefficient estimates of $b_{h,\gamma}$ from the dummy variable specification in (6). Since observations with a decreased loan quantity, $dQ_{i,d}, < 0$ constitute the omitted category, the coefficient captures the difference in daily return between bonds with increased quantity on loan and those with a decrease. The figure confirms that these return patterns remain qualitatively similar to those from the linear specification in (5). On day d^*, returns on bonds with increased quantity on loan are higher by $b_{0,\gamma} = 0.020\%$ per day ($t = 9.47$) for all bonds, 0.014% ($t = 6.33$) for IG bonds, and 0.044% ($t = 8.82$) for HY bonds.

Next, we study whether the buy order that forces dealers to borrow bonds is informed or not. If the buyer is uninformed, the price pressure due to the dealer's inventory friction will dissipate over the medium term, and we expect the initial return reaction to reverse. If instead the buyer is informed, there will be no reversal. In addition, if the dealer does not fully adjust her quote for the information value of the buy order, we may observe a positive drift after intensified short sales activity.

To examine the price reaction to short-selling activity, every trading day, we form three value-weighted portfolios of corporate bonds based on daily changes in quantity on loan. Specifically, we classify bonds into three groups: those with negative changes in quantity on loan, those with no changes, and those with positive changes. Following the method of Jegadeesh and Titman (1993) and Boehmer, Jones, and Zhang (2008), we construct overlapping value-weighted portfolios using lagged bond market capitalization as weights. For a holding period of K trading days, each day's portfolio return is an average of K overlapping portfolios, with $1/K$ of the portfolio rebalanced each day. In addition to presenting raw returns, we follow Bessembinder, Kahle, Maxwell, and Xu (2008) and compute an adjusted return for each bond by subtracting the return on the value-weighted portfolio of bonds with the same credit rating group (AAA, AA, A, BBB, BB, B, CCC-C, or D). To assess statistical significance, we adjust standard errors using Newey and West (1987) 20 lags.

Table 2 Panel A reports average daily returns (annualized) on trade date, d^*. Using the sample of all bonds, we find that bonds with increased short sales (i.e., $dQ > 0$) earn an average return of 7.57% per year, while those with decreased short sales (i.e., $dQ < 0$) have an average return of 2.75%, leading to a difference of 4.81% ($t = 12.77$). As expected, the magnitude of the return difference is greater for HY bonds (10.91%) than for IG bonds (3.12%). Consistent with Figure 4, these results indicate that the prices of bonds experiencing increased short selling tend to appreciate immediately, while those with a decrease in short sales tend to depreciate.

Table 2 Panels B and C report the returns over the periods $[d^* + 1, d^* + 3]$ and $[d^* + 4, d^* + 23]$. Focusing on the portfolios of all bonds across ratings, the return differences are on average 3.20% ($t = 13.32$) and 0.63% ($t = 6.54$), respectively. These results indicate no reversal of the initial price impact over the month following the short sale event. If anything, prices appear to drift in the same direction as the initial impact, indicating the existence of informed customer trades and slow price reactions.

Since the information on quantity on loan becomes publicly available on day $d^* + 2$ or $d^* + 3$, an investor could, in principle, trade on $d^* + 3$ to mimic short sellers' trades. However, the return difference of 0.63% per year is not economically large and would not constitute a profitable trading strategy.

Table 2 also reports the credit-adjusted returns. Using the sample of all bonds, the return differences between the positive and negative short-sales portfolios are 4.46%, 2.91%, and 0.53% for Panels A, B, and C, respectively, highly similar to the raw return results. Therefore, the return difference is not explained by the difference in credit ratings.

The positive relationship between short-selling activity and bond returns may appear surprising at first glance. Indeed, our findings contrast sharply with those in the equity literature (e.g., Jones and Lamont 2002; Boehmer, Jones, and Zhang 2008; Diether, Lee, and Werner 2009) that document a negative relationship between short sales and stock returns. However, these findings are consistent with our argument that customer buying pressure drives dealer short sales in the corporate bond market.

3.4 Multivariate Analysis

We next undertake a multivariate analysis on the link between trading volume and the quantity on loan. In contrast to the univariate relationship studied in Section 3.1, here we include a comprehensive set of control variables to confirm the relationship between trading volume and lending activities. Specifically, we run multivariate panel regressions of changes in quantity on loan, following Diether, Lee, and Werner (2009),

$$\begin{aligned} dQ_{i,d} = {} & b_0 Vol_{i,d^*,Buy} + b_1 Vol_{i,d^*,Sell} + b_2 \overline{dQ}_{i,d-5,d-1} + b_3 \overline{Vol}_{i,d^*-5,d^*-1,Buy} \\ & + b_4 \overline{Vol}_{i,d^*-5,d^*-1,Sell} + b_5 \bar{h}_{i,d^*-5,d^*-1,Buy} + b_6 \bar{h}_{i,d^*-5,d^*-1,Sell} + b_7 \sigma_{i,d^*-5,d^*-1} \\ & + b_8 r_{i,d^*} + b_9 \bar{r}_{i,d^*-5,d^*-1} + b_{10} dQ^{Stock}_{i,d} + b_{11} \overline{dQ}^{Stock}_{i,d-5,d-1} \\ & + \gamma_d + \alpha_i + Ctrl_{i,d} + \varepsilon_{i,d}. \end{aligned} \tag{7}$$

The set of explanatory variables includes $Vol_{i,d^*,\xi}$, the daily volume with a trade side ξ scaled by amount outstanding; $h_{i,d^*,\xi}$, the abnormal half spread with a trade side ξ; σ_{i,d^*-5,d^*-1}, the bond return volatility computed over the five-day period from day d^*-5 to d^*-1; r_{i,d^*}, the daily return on bond i on day d^*; and $dQ^{Stock}_{i,d}$, the quantity on loan of the bond issuer's equity on day d. Variables denoted with an overbar refer to the average of the daily values over the period. The set of control variables includes the logarithm of the bond's amount outstanding, credit rating, and time to maturity. To facilitate comparisons of economic magnitudes across coefficients, all explanatory variables are standardized to have a mean of zero and a standard deviation of one. Standard errors are double-clustered at the bond and day levels. The key coefficients of our interest are b_0 and b_1, which measure how sensitive changes in loan quantity are to signed trading volume.

Column (1) of Table 3 reports the regression estimates using customer buying and selling volume as explanatory variables. The point estimates indicate that a one-standard-deviation increase in contemporaneous customer buys is associated with a 4.27 bps simultaneous increase in bond lending, while an increase in customer sells corresponds to a 3.87 bps decrease in lending activity. These results corroborate the univariate findings presented in the preceding section, demonstrating a positive association between bond lending and contemporaneous customer buys, alongside a negative relationship with customer sales. The magnitude of these coefficient estimates is economically large relative to the standard deviation of the quantity on loan (19.7 bps, as shown in Table 1). The above-100 t-statistic indicates the relationship is nearly mechanical: it is a reflection of the fact that a dollar increase in loan amount on a day must correspond to a dollar increase in the bond's sales on that day.

In Column (2), we incorporate the average of lagged loan quantity as an additional explanatory variable. The coefficient on this lagged measure is negative and statistically significant at -1.41 bps ($t = -25.25$), indicating mean reversion in bond lending activity. This pattern suggests that periods of elevated lending are typically followed by periods of reduced activity. Despite this additional control, the coefficients on contemporaneous customer purchases and sales remain unchanged.

Column (3) extends the specification by including additional control variables: lagged trading volume, abnormal half-spreads (calculated separately for buys and sales), and bond return volatility. The coefficients on contemporaneous customer purchases and sales remain similar to those reported in Column (1). The coefficient on the lagged customer buy volume is positive but much smaller in magnitude (0.54 bps) than contemporaneous buy volume. In contrast, the magnitude of the coefficient on lagged sell volume is negative (-1.57 bps), indicating that before resorting to short sales, the dealers are depleting their inventory.

Column (3) also indicates that the coefficient on bond return volatility is negative (-0.10 bps). While its magnitude is small, the sign is interesting. If speculators are short sellers, higher volatility should create greater profit opportunities and thus encourage short-selling activity. However, if dealers are short sellers, higher volatility impairs their capacity to absorb order flow imbalances due to increased inventory risk, leading to decreased activity. The negative coefficient estimate is consistent with the latter interpretation.

Column (4) examines the role of contemporaneous and lagged bond returns in explaining lending activity. The result indicates that both return coefficients are positive. A one-standard-deviation increase in the contemporaneous (i.e., day $d-s$) return is associated with a 0.21 bps increase in lending, while a corresponding increase in lagged returns generates a 0.03 bps increase. Relative to the standard deviation of daily changes in loan quantity (19.70 bps), the slope estimate for the lagged returns is economically small.

In Column (5), we investigate the relationship between bond lending activity and both contemporaneous and lagged changes in stock loan quantities for the same issuer. Hendershott, Kozhan, and Raman (2020) document that short sellers' information flows from stocks to bonds, but not vice versa. We also find that the loading on contemporaneous changes in stock loan quantities is positive, but with limited economic significance (0.06 bps).

Column (6) presents results from the comprehensive specification incorporating all explanatory variables. The coefficient estimates remain stable across all variables, confirming the robustness of our findings. Notably, the magnitudes of the coefficient on contemporaneous customer buying and selling substantially exceed those of all other variables. Specifically, the coefficient on customer buying is about 30 times as large as that of the return, and that on the customer selling is 25 times as large as that on the return. The third and fourth largest coefficients in absolute terms are those on lagged average changes in quantity on loans (-1.63 bps) and on lagged customer sales (-1.56 bps), respectively.

In Appendix Table B1, we study the effect of the availability of CDS and stocks issued by the bond issuer by including the corresponding dummy variables and interactions between the dummy and trading volume in (7). We find that these additional terms have small coefficient estimates, implying that the availability of these alternative financial instruments does not affect our main results. In summary, the available evidence indicates that dealers' market-making activities, in which they sell short bonds to customers, dominate other variables in explaining the variation in bond lending activity.

For additional robustness, in the Internet Appendix, we confirm the positive link between increased short sales and returns documented in Section 3.3 using multivariate regression similar to those in equation (7). The results reported in the Internet Appendix Table B2 show that the coefficient on bond lending is positive but that on stock lending is negative. This sign reversal between bond and equity lending coefficients supports our claim that the motivation to borrow bonds – facilitating informed buying rather than selling – is contrary to that for borrowing stocks.

4 Variance Decomposition of Short Sales

4.1 Empirical Framework of Decomposition

In this section, we develop a formal framework to decompose the observed quantity of bonds on loan into dealer-driven and customer-driven trades. This framework allows us to interpret the univariate regression coefficients in equation (1) and quantify the share of bond lending attributable to dealer short sales.

Consider a bond traded by both customers and dealers. Let S_D and S_C denote the quantity of bonds sold to initiate new short positions by dealers and customers, respectively, and let B_D and B_C denote the quantity of bonds bought to close existing short positions by dealers and customers, respectively. Then, a daily change in the quantity on loan is given by:

$$dQ = (\text{New Short Positions}) - (\text{Short Covering}) = (S_D + S_C) - (B_D + B_C). \tag{8}$$

Variables S and B are unobservable to econometricians, but in the data we observe customer buy and sell volumes,

$$Vol_{B,C} = S_D + B_C + \varepsilon_{B,C}, \tag{9}$$

$$Vol_{S,C} = S_C + B_D + \varepsilon_{S,C}, \tag{10}$$

where $\varepsilon_{B,C}$ and $\varepsilon_{S,C}$ capture customer buys and sells unrelated to short sales, respectively. Here, the customer buy volume $Vol_{B,C}$ includes the short sales initiated by dealers, S_D, as these must be matched by customer purchases. Likewise, the customer sell volume $Vol_{S,C}$ contains variable B_D, because dealer purchases to cover existing short positions must be satisfied by customer sales.

To disentangle the four drivers of changes in loan quantity in equation (8), we assume that all variables are mutually independent conditional on observed bond characteristics, and take advantage of the fact that short covering B reduces loan quantity, but increases trading volume in equations (9) and (10). Specifically, we regress customer buy and sell volume on dQ as in a regression similar to equation (1) with control variables. Then, the OLS slope coefficients are

$$\begin{aligned}
\beta_B &= \frac{\text{cov}(dQ, Vol_{B,C})}{\sigma^2(dQ)} = \frac{1}{\sigma^2(dQ)}\left(\underbrace{\sigma^2(S_D)}_{\text{Dealer-Driven}} - \underbrace{\sigma^2(B_C)}_{\text{Customer-Driven}}\right) \\
\beta_S &= \frac{\text{cov}(dQ, Vol_{S,C})}{\sigma^2(dQ)} = \frac{1}{\sigma^2(dQ)}\left(\underbrace{\sigma^2(S_C)}_{\text{Customer-Driven}} - \underbrace{\sigma^2(B_D)}_{\text{Dealer-Driven}}\right).
\end{aligned} \tag{11}$$

These coefficients capture the difference between dealer-driven and customer-driven short sales. Taking the difference between the two slope coefficients, we obtain the key equation,

$$\begin{aligned}
\beta_S - \beta_B &= \underbrace{\frac{\sigma^2(S_C) + \sigma^2(B_C)}{\sigma^2(S_C) + \sigma^2(S_D) + \sigma^2(B_C) + \sigma^2(B_D)}}_{\text{Variance Share of Customer Trades}} - \underbrace{\frac{\sigma^2(B_D) + \sigma^2(S_D)}{\sigma^2(S_C) + \sigma^2(S_D) + \sigma^2(B_C) + \sigma^2(B_D)}}_{\text{Variance Share of Dealer Trades}} \\
&\equiv C - D,
\end{aligned} \tag{12}$$

where C denotes the variance ratio of customer-driven trades and D denotes the ratio of dealer-driven trades. This equation establishes that the difference in regression coefficients directly reveals whether customer-driven or dealer-driven trades account for a larger share of the variation in bond lending.

Since $C + D = 1$, we can express the ratio of trades initiated by customers and dealers that explain short sales as:

$$\begin{aligned}
C &= \frac{1}{2} + \frac{1}{2}(\beta_S - \beta_B) \\
D &= \frac{1}{2} - \frac{1}{2}(\beta_S - \beta_B).
\end{aligned} \tag{13}$$

To interpret the regression coefficients, we consider two extreme cases as benchmarks.

First, suppose that only customers short sell, so that $\sigma(S_D) = \sigma(B_D) = 0$. Then:

$$\begin{aligned} \beta_B &= \frac{-\sigma^2(B_C)}{\sigma^2(B_C) + \sigma^2(S_C)} < 0 \\ \beta_S &= \frac{\sigma^2(S_C)}{\sigma^2(B_C) + \sigma^2(S_C)} > 0, \end{aligned} \tag{14}$$

and $\beta_S - \beta_B = 1$, $C = 1$, and $D = 0$ hold. In this case, a one-dollar increase in quantity on loan corresponds to either a one-dollar increase in customer sales to initiate a new short position or a one-dollar reduction in customer buys to cover an existing short position.

Second, suppose that only dealers short sell so that $\sigma(B_C) = \sigma(S_C) = 0$. Then:

$$\begin{aligned} \beta_B &= \frac{\sigma^2(S_D)}{\sigma^2(S_D) + \sigma^2(B_D)} > 0 \\ \beta_S &= \frac{-\sigma^2(B_D)}{\sigma^2(S_D) + \sigma^2(B_D)} < 0, \end{aligned} \tag{15}$$

and $\beta_S - \beta_B = -1$, $C = 0$, and $D = 1$ hold. When this occurs, a one-dollar increase in quantity on loan corresponds to either a one-dollar increase in dealer sales to initiate a new short position or a one-dollar decrease in dealer buys to cover an existing short position. These two examples indicate that whether dealers or customers drive bond lending does not restrict individual regression coefficients, but it does restrict the *difference* between them.

Our decomposition framework is general in two respects. First, it remains valid even when trading volume includes transactions unrelated to short selling. Second, if a bond characteristic induces correlation between variables B and S, one can eliminate this correlation by orthogonalizing with respect to that characteristic. For example, positive news about an issuer's fundamentals may simultaneously increase dealer sales, S_D, and decrease customer sales, S_C. In such cases, we can replace the univariate regression coefficients in equation (1) with their counterparts from a multivariate regression that controls for the issuer's bond return.

Finally, if bond lending is motivated purely by financing reasons, then lending is unrelated to buying or selling the bond, and we would expect the slope coefficients on both customer purchases and sales to be zero. In the Markit data, however, financing transactions play a limited role after 2009, and a large portion of the borrowed bonds are sold short.[8]

[8] To assess the prevalence of financing-driven bond lending, we construct a synthetic borrowing fee defined as the federal funds rate minus the rebate rate. This measure is negative only in 2008, consistent with financing motives during the global financial crisis. In addition, the Markit data team confirms that their proprietary filters are designed to exclude financing, dividend, and nondirectional lending transactions, though a small number of such trades may remain.

4.2 Decomposition Results

In this section, we present the estimated customer and dealer shares controlling for observed bond characteristics. Since Figure 1 suggests that the action occurs on the trade date ($h = 0$), in the following analysis, we focus on the estimate of b_ξ from the multivariate panel regression

$$\begin{aligned} Vol_{i,d^*,\xi} = \; & b_\xi dQ_{i,d} + b_2 \overline{dQ}_{i,d-5,d-1} + b_3 \overline{Vol}_{i,d^*-5,d^*-1,Buy} + b_4 \overline{Vol}_{i,d^*-5,d^*-1,Sell} \\ & + b_5 \bar{h}_{i,d^*-5,d^*-1,Buy} + b_6 \bar{h}_{i,d^*-5,d^*-1,Sell} + b_7 \sigma_{i,d^*-5,d^*-1} + b_8 r_{i,d^*} \\ & + b_9 \bar{r}_{i,d^*-5,d^*-1} + \gamma_d + \alpha_i + Ctrl_{i,d} + \varepsilon_{i,d}. \end{aligned} \tag{16}$$

We report the results of this estimation in the Internet Appendix Table B3 and use the b_ξ estimates to calculate the share of customer and dealer short sales following equation (13).

Table 4 reports the estimated share of short sales.[9] Using the full sample of daily panel data with available controls, we find that the difference in slope coefficients is $b_S - b_B = -0.371$ ($t = -55.52$), implying that dealers' short sales exceed those of customers. The estimated dealer share is 68.5%, with the remaining 31.5% attributable to customer short sales.[10] These results suggest that dealers' market-making activities are the main driver of corporate bond short sales.

While customer short sales may be less important in the entire sample of corporate bonds dominated by safe, information-insensitive IG bonds, informed customers may be more willing to short HY bonds. Panel B of Table 4 reports the estimates by rating on day d^*. We find that the dealer shares of short sales of IG and HY bonds are 70.8% and 64.5%, respectively. Economically, the results appear to be similar to each other, though customers' selling activity is more important for HY bonds than IG bonds.

We next consider the effect of specialness using the sample split by observed lending fee on day d. Specifically, on each day, we cross-sectionally rank bonds based on their fee and classify them into four groups: GC is those with the bottom 90%, SC1 is between the 90th and 95th percentiles, SC2 is between the 95th and 99th percentiles, and SC3 is above the 99th percentiles. Panel C of Table 4 shows that the dealer share declines monotonically across the specialness percentiles from 70.3% for GC, 60.7% for SC1, 56.4% for SC2, and 52.2% for SC3. Therefore, bonds with an extremely high fee are subject to increased customer

[9] We use seemingly unrelated regression to account for the correlation between the estimated b_S and b_B when calculating the standard error of the difference, $b_S - b_B$. In addition, the standard errors are double-clustered at the bond and date levels.

[10] Table B4 in the Internet Appendix shows that the coefficients on dQ and the estimated dealer share remain stable when we estimate univariate regressions instead of (16).

speculation, which results in a lower share of market-making activities. These results are consistent with Anderson, Henderson, and Pearson (2018), who find evidence of speculative short sales for bonds with high lending fees.

Next, we hypothesize that customer short sales are less important in the corporate bond market due to the existence of substitutes, including issuers' stocks and CDS, which are cheaper to trade. We thus split the sample of bonds based on whether the issuer's stocks are listed on exchanges and whether CDS are traded for the issuer. Panels D and E of Table 4 report the estimated dealer shares for the subsamples by issuer types. We find that bonds whose issuers are private companies with no listed stocks have a slightly lower share of dealer short sales. Specifically, the dealer share is 66.0% for private firms, while it is 68.7% for public firms. Thus, the availability of stocks is one of the reasons why customers do not speculate on corporate bonds.

On the other hand, we do not find evidence supporting the availability of CDS as the reason for the subdued speculative short sales of corporate bonds. The estimated share of dealer short sales is 68.5% for issuers with CDS, nearly identical to the estimate of 68.6% for issuers without. While surprising at first glance, the results make sense given that the CDS coverage is an endogenous outcome, which reflects customers' desire to short credit. Issuers covered by CDS can have higher customer short sales of corporate bonds because both are driven by the demand to purchase insurance against default risk. Such an effect is offset by the fact that CDS is available as an alternative means to short, offsetting the higher demand to short the bond.

To dissect into the drivers of short sales a step further, we split the sample by a bond's expensiveness, size, and liquidity on day d^*. We measure the expensiveness using the reaching-for-yield (RFY) measure of Choi and Kronlund (2017), calculated as the difference between a bond's credit spread and the average spread of the bonds with the same rating at the notch level (e.g., we distinguish bonds with a rating of BBB from those with BBB-). We categorize bonds as overvalued if their RFY is below the cross-sectional median, and undervalued if otherwise. The size of a bond is measured by its amount outstanding, and we classify the bond as large or small using the cross-sectional median as a cutoff. Liquidity is measured using the bid-ask spreads averaged over the period from $d^* - 21$ to $d^* - 1$, and bonds are classified as illiquid if the bid-ask spread is above the cross-sectional median and liquid otherwise. Panels F to H of Table 4 show that in all cases the dealer short sales dominate the customer speculation, with a share ranging from 66.7% to 70.8%. Their share is higher for overvalued, large, and liquid bonds, but the difference appears to be small.

In Appendix Table B5, we present the results of splitting the sample before and after September 4, 2017. The results from the two periods are highly similar. In Markit data, we occasionally observe short gaps in the time series for loan quantity and lending fee, and we treat them as missing data to present the main results. For robustness, we consider two approaches for replacing missing data with interpolated values: The first approach is replacement with zero, assuming that missing data represent zero lending activity on the day. The second approach is last observation carried forward, filling observation gaps of less than 21 trading days by carrying forward the last observation, while leaving gaps exceeding 21 trading days as missing. The results reported in Appendix Tables B6 and B7 and Appendix Figure B1 show no material impact on our results.

In summary, in all cases we study, dealers' market-making activity is the main driver of corporate bond short sales, but their share varies depending on the specialness, credit quality, availability of alternative trading venues, and liquidity of the bond.

4.3 Information Events

Customer short sales are likely motivated by negative information about the issuer's credit. Thus, the analysis above may yield different results if we examine the sample before important information on a bond's value is released.

To test this hypothesis, we construct subsamples preceding credit rating changes and earnings announcements. Specifically, we use the 21-trading-day period preceding these events. For rating changes, we treat actions by each rating agency as separate events and take the union of samples when events overlap. For example, if Moody's downgrades a bond on September 26, 2025, and S&P downgrades it on September 29, 2025, then we use the sample from August 28 (i.e., 21 trading days before September 26) through September 26 (i.e., one business day before September 29). Rating changes are measured at the notch level, such that a change from AA+ to AA is considered a downgrade.

Panel A of Table 5 reports the share of dealer short sales over the 21-business-day period before rating changes. We distinguish between rating changes that cross the IG/HY threshold and other rating changes. We find that the dealer share is 62.3% before downgrades crossing the IG/HY threshold and 60.9% before other downgrades. In contrast, before upgrades crossing the IG/HY threshold, the dealer share is 73.2%, while it is 68.6% before other upgrades. Thus, customers engage in more speculative short sales before downgrades. Importantly, before a major upgrade crossing the IG/HY threshold, they place urgent purchase orders, which propel dealers to borrow more and increase the dealer share of short sales.

Panel B of Table 5 repeats the analysis using the 21-business-day period before a scheduled earnings announcement date of the issuer. We classify each announcement into five categories using the difference between released earnings and the median analysts' forecasts. Specifically, in each quarter, firms are ranked cross-sectionally by their standardized unexpected earnings and assigned to one of the five categories: Very Bad (bottom 20%), Bad (21%–40%), Around Expectation (41%–60%), Good (61%–80%), and Very Good (above 80%).

We find that the dealer share of short sales is 63.4% before very bad news, 69.5% before bad news, 71.0% before around expectation news, 70.4% before good news, and 66.9% before very good news. Thus, customers speculate significantly more before very bad news, with the dealer share lower by approximately 8 pp relative to the middle category. This pattern suggests that informed customers increase their short-selling activity when anticipating the most negative earnings surprises, while dealer market-making remains dominant before less extreme news events.

To summarize, we find that customer short sales become more important before rating downgrades and bad earnings news, underscoring the validity of our approach. Nevertheless, we do not find the case where the dealer's share is less than 50%.

4.4 Decomposition in the Stock Market

Since our decomposition of short-selling activities in equation (13) is new in the literature, it is interesting to apply it to the stock market. This exercise serves as a reference to interpret our main results using corporate bonds.

The main challenge in applying our framework to exchange-traded securities is that there is no clear distinction between dealers and customers. Thus, we reinterpret "dealers" as liquidity providers and "customers" as liquidity takers, and apply the standard Lee and Ready (1991) algorithm to classify each trade accordingly. In this case, the same market participant can play the role of a customer or a dealer, depending on the market condition. We aggregate the trades each day to create separate trading volumes for liquidity takers and liquidity makers. We scale the resulting daily volume by the number of outstanding shares and regress it on changes in quantity on loan.

Figure 5 plots the regression slope coefficients of equation (1) using stocks. Consistent with the analysis on bonds, we see a strong reaction of volume on day $d^* = d - s$ and afterward. The key difference from the corresponding Figure 1 for bonds is the sign of customer (liquidity taker) sales, which is estimated at 0.075 ($t = 9.56$) at day d^*. The positive estimates suggest that, in the stock market, an increase in the quantity of stocks on loan corresponds to an increase in liquidity-takers' sales. The estimated slope coefficients are highly similar between liquidity taker buys and sells, and it is not clear which one dominates the other. This pattern is different from what is observed in the bond market.

Table 6 presents the estimated dealer share using equation (13) in the stock market. We present results using all stocks as well as a wide variety of subsamples sliced by market capitalization, (stock) lending fees, bond issuance status and CDS coverage.[11] Across the subsamples, the share of liquidity-taker short sales is around 50%, similar to that of liquidity-maker short sales. Therefore, in the stock market, speculative short sales by liquidity takers are just as important as those of liquidity makers, which underscores the uniqueness of the results in the dealer-driven corporate bond market.[12]

5 Passive Ownership and Bond Lending Activities

To showcase the importance of understanding the drivers of lending activities, we revisit the analysis of the effect of passive ownership on short-selling activities. An increase in passive ownership is an important topic in its own right, due to the increasing popularity of exchange-traded funds (ETFs) for stocks and bonds (see, e.g., Dannhauser 2017; Koont, Ma, Pástor, and Zeng 2024). In our sample, passive ownership of corporate bonds increases from 0.44% in 2006 to 5.21% in 2022. In equity markets, higher passive ownership generally increases short interest and lending activity (see, e.g., Prado, Saffi, and Sturgess 2016; Coles, Heath, and Ringgenberg 2022; Sikorskaya 2023; Palia and Sokolinski 2024; von Beschwitz, Honkanen, and Schmidt 2025), as passive holdings can increase valuations and attract speculative short sellers. However, our evidence so far suggests that short selling in corporate bonds is primarily driven by dealers' market-making activities rather than by informed speculators. Do the results on the impact of passive ownership in equities generalize to bonds? In this section, we explore the relationship between passive bond ownership and various bond lending activities, such as lending supply, loan quantities, and borrowing fees.

[11] Micro-cap stocks include firms below the 20th percentile of NYSE market capitalization. Small-cap stocks include firms between the 20th and 50th percentiles of NYSE market capitalization. Large-cap stocks are firms with market capitalization above the NYSE median. General collateral (GC) loans are those with annualized fees not exceeding 1%, while special collateral (SC) loans have annualized fees greater than 1%. Issuers are firms with outstanding bonds; non-issuers are those without outstanding bonds. CDS coverage indicates firms with (Yes) or without (No) credit default swap contracts.

[12] Comerton-Forde, Jones, and Putniņš (2016) and Goyal, Reed, Smajlbegovic, and Soebhag (2025) find that in the stock market, the magnitude of the liquidity-taking and liquidity-supplying short sales is comparable to each other.

5.1 Empirical Method

For this exercise, we compile a quarterly panel data set of bond ownership and lending outcome variables from 2006 Q3 to 2022 Q4. The unit of analysis is a bond-quarter. We relegate the detailed data descriptions to Appendix Section C.1.

Using the panel data, we estimate a panel regression of the lending activity variable Y of bond i issued by firm k in quarter q on contemporaneous passive ownership shares,

$$Y_{i,k,q} = \beta PassiveFund_{i,k,q} + \gamma X_{i,k,q} + \alpha_{k,q} + \theta_i + \varepsilon_{i,k,q}, \tag{17}$$

where $X_{i,k,q}$ is a vector of control variables, including the log value of the amount outstanding, the credit rating expressed numerically from 1 to 21, the time to maturity, and the percentage of zero-trading days. Standard errors are double-clustered at the firm and quarter levels.

Our primary variable of interest, $PassiveFund$, is defined as the sum of the amount held by all passive funds divided by the bond's amount outstanding and expressed as a percentage. The slope coefficient β allows us to infer the influence of a one-percentage-point increase in passive ownership on lending activities. For comparison, we also construct analogous ownership measures for insurance firms ($Insurer$) and active mutual funds ($ActiveFund$), enabling us to differentiate the effects of passive versus other institutional ownership.

We aim to identify an exogenous variation in bond ownership that is orthogonal to issuer-specific characteristics that could simultaneously affect lending activities. Such a concern arises when, for example, firms with higher default risks might attract increased speculative demand to borrow and short, coinciding with higher passive ownership due to funds' investment focus in HY bonds. To eliminate the confounding factors driving both the ownership and outcome variables, following Choi, Hoseinzade, Shin, and Tehranian (2020), we include firm-quarter fixed effects in the panel regression. This procedure identifies the coefficients based on the variation across bonds in the same quarter, issued by the same firm.

It is still possible that variation in maturity may create a mechanical correlation between the dependent variable and $PassiveFund$. Shorter-maturity bonds, for example, might attract passive ownership by short-maturity bond funds while simultaneously exhibiting lower borrowing fees. In addition, bond-specific features, such as covenants and seniority, could similarly influence both ownership and lending outcomes. Thus, we include bond fixed effects and explicitly control for bonds' maturity, which eliminates bond- and maturity-specific shocks. The remaining variation in $PassiveFund$ comes from the availability of bonds when passive funds are launched or when new fund shares are created. These are the times when passive funds must purchase bonds, and they end up buying what is available, generating a variation in bond ownership. Under the assumption that this residual variation is uncorrelated with unobserved factors influencing lending outcomes, our coefficient estimate β is unbiased.

5.2 Effect of Passive Ownership on Short Sales

We report β estimates, number of observations, and adjusted R^2 in Panel A of Table 7. Columns (1) to (3) indicate that a one-percentage-point increase in passive ownership is associated with a 0.010 pp reduction in loan quantity, a 0.308 pp increase in lendable supply, and a 0.023 pp decrease in borrowing fee. The borrowing cost score provided by Markit (DCBS) in Column (4) declines significantly, confirming the decline in the borrowing fee. Column (5) reports a 0.182 pp reduction in the utilization rate, which is defined as the ratio of quantity on loan to lendable supply.

Since the standard deviation of $PassiveFund$ is 3.06%, a one-standard-deviation increase in passive ownership leads to a 0.031 pp decline in loan quantity, a 0.943 pp increase in lendable supply, and a 0.067 pp reduction in borrowing fee. The magnitudes of the reactions of these three outcome variables correspond to 2.3%, 7.1%, and 51.8% of their inter-quartile range, respectively.[13] While the effect on the borrowing fee is substantial compared to its typical variation, the effect observed for loan quantity appears to be small. This pattern reflects simultaneous shifts in both lending supply and demand triggered by increased passive ownership.

We can infer these underlying shifts in the supply and demand curves by examining the directional changes in quantity and price. In Column (2) of Table 7, we see an increase in lendable supply associated with higher passive ownership. However, Columns (1) and (3) reveal declines in equilibrium loan quantity and fees. To make sense of these changes, Panel A of Figure 6 visualizes the effect of an increase in passive ownership. The increase in lendable supply indicates that the supply curve shifts outward. However, there is a decrease in the demand for bond lending that more than offsets the increased supply, resulting in even lower lending fees and a slightly lower equilibrium loan quantity. The effect on the equilibrium quantity is insignificant because the increase in supply is offset by the decrease in demand.

The response of borrowing demand in the corporate bond market differs from what is documented in the stock market. Specifically, Sikorskaya (2023) finds that a one-standard-deviation increase in benchmark intensity, another proxy for passive ownership, leads to a

[13] Appendix Table C1 provides the summary statistics of the quarterly variables, including the inter-quartile range.

0.348 pp and 0.032 pp *increase* in the quantity on loan and borrowing fees.[14] Thus, in the stock market, the demand for security lending appears to increase in response to increases in passive ownership.

Are passive funds unique in increasing lendable supply while decreasing demand? To compare the impact of different types of investors, we estimate multivariate regressions including *PassiveFund*, *ActiveFund*, and *Insurer* and report the coefficient estimates in Panel B of Table 7. When the left-hand-side variable is lendable supply, the coefficients on *PassiveFund*, *ActiveFund*, and *Insurer* are 0.336 pp, 0.132 pp, and 0.106 pp, respectively. Thus, an increase in institutional ownership generally leads to an increase in lendable supply.

The distinction between passive funds and other institutional investors becomes evident when examining borrowing fees and utilization rates as dependent variables. A one-percentage-point increase in passive ownership reduces the fee by 0.023 pp, nearly unchanged from the univariate result. In contrast, active ownership exhibits no significant influence on borrowing fee, whereas insurer ownership leads to a much smaller reduction of 0.001 pp ($t = -2.74$). These estimates indicate that the demand for loan responds differently based on the type of institutional ownership. Specifically, when insurer ownership rises, borrowing demand may either increase or decrease. The magnitude of the demand response, however, is outweighed by concurrent changes in supply, and thus we observe price and quantity moving in opposite directions. However, an increase in passive ownership leads to a sufficiently large reduction in demand that dominates the accompanying supply increase, thereby moving price and quantity simultaneously downward. We visualize these findings in Panel B of Figure 6, highlighting the impact of higher insurer ownership on bond lending.

In our sample, passive ownership includes holdings by ETFs and index mutual funds. We study the separate effect of these two kinds of passive ownership on various bond lending activities. Results reported in Appendix Section C.2 indicate that both ETFs and passive index funds facilitate the relaxation of short-sale constraints in the bond market. Importantly, mechanisms unique to ETFs, such as the dual roles of dealers serving as authorized participants (Koont, Ma, Pástor, and Zeng 2024), do not account for the observed effect.

Our main results assess the effect of increased passive ownership using within-firm variation in lending outcomes. While this is a valid approach for identifying ownership shocks, it is not the only one. Bretscher, Schmid, and Ye (2024) propose that one can use maturity cutoffs as a valid instrument for changing passive ownership. In Appendix Section C.3,

[14] To obtain these values, we multiply the standard deviation of benchmark intensity, 2.56% (her Table 1), by the coefficients in Table 2. Prado, Saffi, and Sturgess (2016) examine the effect of total institutional ownership (rather than passive ownership) and find that a one-standard-deviation increase in ownership leads to a 0.056 pp decrease in fees.

we follow their approach to estimate the impact of passive ownership on lending outcomes. Consistent with their findings, we observe a significant increase in passive ownership when a bond's maturity shrinks and crosses the cutoff value. However, we also find that insurance firms' ownership declines significantly. Therefore, this event simultaneously changes the ownership of the two types of investors and prevents us from isolating the impact of increased passive ownership, which our panel regression aims to do.

5.2.1 Subsample of Special Bonds

The effect of passive ownership on bond lending depends on the underlying motivation for lending. For bonds that are considered "special," lending is typically driven by heightened demand for borrowing these securities. Conversely, non-special or general collateral (GC) bonds are frequently lent out to raise cash, which is driven by increased supply.

To understand the potential difference between bonds, we split our sample into special and GC bonds. In the equity literature, a cutoff such as a 1% lending fee is often used to define specialness (see, e.g., Sikorskaya 2023). However, bond lending fees are generally lower compared to stocks, rendering this equity-based threshold inappropriate. Instead, following Palia and Sokolinski (2024), we define a bond as special in quarter q if its average lending fee in the preceding quarter $(q-1)$ is within the top decile of the cross-sectional distribution of corporate bond lending fees. We use lagged lending fees for classification, as our primary objective is to explain the fee in quarter q.

Using the subsample of special and GC bonds, we estimate the panel regression in equation (17). Panel A of Table 8 reports the impact of a one-percentage-point increase in passive ownership on the lending outcome variables, separately for special and GC bonds. Our empirical findings indicate qualitatively consistent effects across both bond categories. Specifically, increased passive ownership is associated with higher lendable supply and reduced borrowing fees in both subsamples, though these effects exhibit stronger magnitudes among special bonds. For instance, a one-percentage-point increase in passive ownership corresponds to a 0.575 pp rise in lendable supply among special bonds, greater than the 0.215 pp increase observed for GC bonds. Similarly, passive ownership growth leads to statistically significant reductions in borrowing fees, amounting to 0.061 pp for special bonds versus a more modest 0.005 pp reduction for GC bonds. In short, while passive ownership universally affects bond lending dynamics, its impact is substantially more pronounced in the market for special bonds.[15]

[15] In contrast to our findings for bonds, Sikorskaya (2023) finds that in response to increase in benchmarking intensity, borrowing fees increase only for special stocks.

5.2.2 Subsample of High Yield Bonds

The demand to short bonds may depend on the information sensitivity of the bonds. Due to their higher default risk, HY bonds are generally more information sensitive than IG bonds. To investigate this potential difference, Table 9 reports the estimation results of equation (17) using the subsample of investment grade and high yield bonds. We define high yield bonds if the numerical rating at the end of quarter $q-1$ is below BBB- and investment grade bonds otherwise.

We find that increased passive fund ownership exerts qualitatively the same effects on both IG and HY bonds with respect to lendable supply and borrowing fees. Specifically, greater passive ownership boosts the lendable supply and reduces borrowing fees across both bond categories, indicative of increased supply for bond lending. Regarding the quantity on loan, we observe divergent effects: a one-percentage-point increase in passive ownership reduces the quantity on loan by 0.017 pp for investment grade bonds, but leads to an increase of 0.045 pp ($t = 2.11$) for HY bonds. However, the increase in the quantity of HY bonds becomes insignificant after controlling for ownership by other types of institutional investors (Panel B), and the response of the utilization rate becomes negative, although insignificant. Thus, the common theme across different rating categories is that passive ownership significantly increases lendable supply and reduces borrowing fees, while the response of loan quantity is insignificant.

5.3 Why Does the Demand to Borrow Bonds Decrease?

In the previous section, we documented a decline in corporate bond borrowing demand associated with increased passive ownership, a finding that contrasts sharply with established evidence in the equity lending literature. This discrepancy arises for two reasons: i) passive ownership elevates bond valuations, and ii) higher valuations alleviate the buying pressure of speculative customers, thus reducing dealers' need to borrow bonds and meet the customer demand. The following subsection provides evidence supporting these two steps in the logical reasoning.

5.3.1 Higher Bond Valuation

Our first step is to show that increased passive ownership leads to a higher valuation of the corporate bonds they hold. To this end, we estimate the panel regression in equation (17) using credit spreads as the left-hand-side variable.

Column (1) of Table 10 reports the association between various types of institutional ownership and corporate bond credit spreads, which is the difference between the corporate bond yield and the maturity-matched Treasury bond yield. Consistent with prior findings of Dannhauser (2017) and Bretscher, Schmid, and Ye (2024), higher passive ownership is associated with lower credit spreads. In our estimates, a one-percentage-point increase in passive ownership leads to a 0.044 pp decline in credit spreads ($t = -10.15$) in the univariate regression, with nearly identical estimates (0.043 pp) obtained from multivariate regressions that control for active fund and insurance ownership.

Recall that in Section 5.2, we show that the borrowing demand for a bond increases in response to an increased bond ownership of insurance firms, contrary to the passive fund ownership. This difference is interesting because insurance firms typically pursue buy-and-hold investment strategies, resulting in relatively low portfolio turnover rates.[16] What then makes passive funds different from insurers? The key to understanding this difference is that passive funds must trade to track the index, which includes and excludes bonds based on predetermined criteria. This generates mechanical transactions and inflates the portfolio turnover rate while pushing bond prices up in the index (Dick-Nielsen and Rossi 2018). In contrast, insurance firms are known to reach for yield (Becker and Ivashina 2015), implying that the bonds they hold tend to be cheaper than those held by their peers.

The results in Panel B of Table 10 support this argument. It indicates that a one-percentage-point increase in insurer ownership leads to a 0.006 pp increase in spreads ($t = 7.89$). In contrast, active ownership exhibits an insignificant effect on credit spreads. Therefore, passive funds are distinct from other institutional investors in that their ownership inflates bond valuations.

5.3.2 Lower Buying Pressure

In the next step, we argue that the decrease in credit spreads alleviates the order imbalance facing dealers. To validate this, we construct a measure of order imbalance, which is the difference between customer buy and customer sell volume within a quarter, normalized by the bond's outstanding amount. Since increased passive ownership mechanically inflates customer buy, we also calculate a net order imbalance measure by removing the quarterly changes in passive fund holdings from the order imbalance. We adjust for index fund holdings, but not for ETF holdings, because bond transfers for ETF creation and redemption are not recorded in TRACE.[17]

Columns (2) and (3) of Table 10 report the regression coefficients on ownership using the

[16] In eMAXX data, the average quarterly portfolio turnover rates for passive funds, active funds, and insurance firms are 3.6%, 4.9% and 1.7%, respectively.

[17] These transactions are exempt from TRACE reporting requirements under FINRA Rule 6730.

gross and net order imbalances as left-hand-side variables in equation (17). We find that a one-percentage-point increase in passive ownership reduces the gross and net order imbalance by 0.020 pp ($t = -3.32$) and 0.096 pp ($t = -12.18$), respectively. This reduction suggests that lower credit spreads induced by passive ownership prompt other investors to curtail bond purchases. Conversely, increased insurance ownership exacerbates order imbalances: a one-percentage-point increase in insurance ownership increases the gross and net order imbalance by 0.0103 and 0.0096 pp, respectively.

Thus, despite their relatively modest share of corporate bond holdings, passive ownership significantly reduces credit spreads, alleviating buying pressure from other market participants. Consequently, this reduction in buying pressure decreases dealers' demand to short bonds for market-making purposes. In contrast, increased insurer ownership contributes to higher credit spreads and intensifies customer buying activity.

The bonds held by passive funds are more expensive, but there may be several mechanisms behind this. For example, Dannhauser (2017) finds that ETF ownership positively influences bond valuation over the long term by mitigating liquidity trading risks. Reilly (2022) observes that dealers tend to include overvalued bonds within ETF creation baskets. Alternatively, direct purchasing by passive funds could generate upward price pressure, further elevating bond prices. Regardless of the specific factor driving higher valuations, our results underscore the unique relationship between security valuation and borrowing demand in the bond market. In the stock market, asset overvaluation tends to increase borrowing demand, as speculators engage in short selling to exploit mispricing and profit opportunities. However, in the bond market, speculative short sales are prohibitively expensive due to bid-ask spreads. Thus, overvaluation of bonds discourages speculative purchases, which decreases dealers' demand to borrow bonds for market-making purposes.

6 Conclusion

In this paper, we examine the drivers of corporate bond lending and their implications for how ownership structure shapes short-selling activity. Using comprehensive data that link bond lending from Markit with trade-level transactions from TRACE, we show that the majority of corporate bond short sales arise from dealers' market-making activities rather than from customers' speculative trades. On days when bond lending intensifies, dealer sales, customer buying volume, and half spreads on customer purchases all increase. At the same time, subsequent bond returns also rise, indicating that these trades are driven by informed customers' buy orders.

To quantify the relative importance of these motives, we introduce a new variance-decomposition framework that attributes roughly two-thirds of bond lending variation to dealers' market-making activities. This dominance persists across credit ratings, liquidity groups, and issuer types, although customer speculation becomes more important for a small segment of special bonds with very high lending fees and before negative information events such as rating downgrades and adverse earnings announcements. These results demonstrate that short selling in the corporate bond market is primarily a function of dealers' liquidity provision, in contrast to the equity market, where speculative short sales by investors play a more important role.

Building on this insight, we study how passive ownership affects corporate bond lending. In contrast to equities, where passive ownership tends to increase borrowing demand and lending fees, greater passive ownership in bonds reduces both. Passive funds expand the lendable supply but simultaneously elevate bond valuations, dampening speculative buying pressure and lowering dealers' need to borrow bonds for market making. The decline in borrowing demand outweighs the supply expansion, resulting in modest reductions in quantities on loan and substantial declines in lending fees.

Taken together, our findings highlight a fundamental difference between short selling in corporate bonds and equities. In the bond market, borrowing primarily supports liquidity provision rather than speculation. Recognizing this distinction helps explain how ownership structure and trading frictions shape short-sale activity, clarifies the transmission of passive-ownership shocks, and advances our understanding of intermediation and securities lending in over-the-counter markets.

References

Anderson, Mike, Brian J. Henderson, and Neil D. Pearson, 2018, Bond lending and bond returns, Working Paper, University of Illinois at Urbana-Champaign.

Andreani, Martina, Diogo Palhares, and Scott Richardson, 2024, Computing corporate bond returns: a word (or two) of caution, *Review of Accounting Studies* 29, 3887–3906.

Asquith, Paul, Andrea S. Au, Thomas R. Covert, and Parag A. Pathak, 2013, The market for borrowing corporate bonds, *Journal of Financial Economics* 107, 155–182.

Augustin, Patrick, Linxiao Francis Cong, Ricardo Lopez A., and Roméo Tédongap, 2025, Downside risk and the cross-section of corporate bond returns, in *Proceedings of Paris December 2020 Finance Meeting EUROFIDAI-ESSEC*.

Bao, Jack, Maureen O'Hara, and Xing Alex Zhou, 2018, The volcker rule and corporate bond market making in times of stress, *Journal of Financial Economics* 130, 95–113.

Bao, Jack, Jun Pan, and Jiang Wang, 2011, The illiquidity of corporate bonds, *Journal of Finance* 66, 911–946.

Barardehi, Yashar H., Zhi Da, Peter Dixon, and Junbo L. Wang, 2024, You can only lend what you own: Inferring daily institutional trading from security lending supply, *Available at SSRN* .

Becker, Bo, and Victoria Ivashina, 2015, Reaching for yield in the bond market, *Journal of Finance* 70, 1863–1902.

Berk, Jonathan B., and Jules H. Van Binsbergen, 2015, Measuring skill in the mutual fund industry, *Journal of Financial Economics* 118, 1–20.

Bessembinder, Hendrik, Stacey Jacobsen, William Maxwell, and Kumar Venkataraman, 2018, Capital commitment and illiquidity in corporate bonds, *Journal of Finance* 73, 1615–1661.

Bessembinder, Hendrik, Kathleen M. Kahle, William F. Maxwell, and Danielle Xu, 2008, Measuring abnormal bond performance, *Review of Financial Studies* 22, 4219–4258.

Blocher, Jesse, Adam V. Reed, and Edward D. Van Wesep, 2013, Connecting two markets: An equilibrium framework for shorts, longs, and stock loans, *Journal of Financial Economics* 108, 302–322.

Boehmer, Ekkehart, Charles M. Jones, and Xiaoyan Zhang, 2008, Which shorts are informed?, *Journal of Finance* 63, 491–527.

Boehmer, Ekkehart, Charles M. Jones, and Xiaoyan Zhang, 2013, Shackling short sellers: The 2008 shorting ban, *Review of Financial Studies* 26, 1363–1400.

Boehmer, Ekkehart, and Juan Wu, 2013, Short selling and the price discovery process, *Review of Financial Studies* 26, 287–322.

Bretscher, Lorenzo, Lukas Schmid, and Tiange Ye, 2024, Passive demand and active supply: Evidence from maturity-mandated corporate bond funds, Working Paper, University of Lausanne.

Chen, Hui, Scott Joslin, and Sophie Xiaoyan Ni, 2018, Demand for crash insurance, intermediary constraints, and risk premia in financial markets, *Review of Financial Studies* 32, 228–265.

Chen, Long, David A. Lesmond, and Jason Wei, 2007, Corporate yield spreads and bond liquidity, *Journal of Finance* 62, 119–149.

Choi, Jaewon, Saeid Hoseinzade, Sean Seunghun Shin, and Hassan Tehranian, 2020, Corporate bond mutual funds and asset fire sales, *Journal of Financial Economics* 138, 432–457.

Choi, Jaewon, Yesol Huh, and Sean Seunghun Shin, 2024, Customer liquidity provision: Implications for corporate bond transaction costs, *Management Science* 70, 187–206.

Choi, Jaewon, and Mathias Kronlund, 2017, Reaching for yield in corporate bond mutual funds, *Review of Financial Studies* 31, 1930–1965.

Cohen, Lauren, Karl B. Diether, and Christopher J. Malloy, 2007, Supply and demand shifts in the shorting market, *Journal of Finance* 62, 2061–2096.

Coles, Jeffrey L., Davidson Heath, and Matthew C. Ringgenberg, 2022, On index investing, *Journal of Financial Economics* 145, 665–683.

Comerton-Forde, Carole, Charles M. Jones, and Tālis J. Putniņš, 2016, Shorting at close range: A tale of two types, *Journal of Financial Economics* 121, 546–568.

Dannhauser, Caitlin D., 2017, The impact of innovation: Evidence from corporate bond exchange-traded funds (ETFs), *Journal of Financial Economics* 125, 537–560.

Dannhauser, Caitlin D., and Michele Dathan, 2023, Passive investors in primary bond markets, *Available at SSRN 4673698* .

Dannhauser, Caitlin D., and Egle Karmaziene, 2023, The dealer warehouse–corporate bond ETFs, *Available at SSRN 4660537* .

Dellavigna, Stefano, and Joshua M. Pollet, 2009, Investor inattention and friday earnings announcements, *Journal of Finance* 64, 709–749.

Dick-Nielsen, Jens, 2014, How to clean enhanced trace data, *Available at SSRN 2337908* .

Dick-Nielsen, Jens, Peter Feldhütter, Lasse Heje Pedersen, and Christian Stolborg, 2023, Corporate bond factors: Replication failures and a new framework, Copenhagen Business School Working Paper.

Dick-Nielsen, Jens, and Marco Rossi, 2018, The cost of immediacy for corporate bonds, *Review of Financial Studies* 32, 1–41.

Dickerson, Alex, Philippe Mueller, and Cesare Robotti, 2023, Priced risk in corporate bonds, *Journal of Financial Economics* 150, 103707.

Dickerson, Alexander, Cesare Robotti, and Giulio Rossetti, 2024, Common pitfalls in the evaluation of corporate bond strategies, Working Paper, UNSW.

Diether, Karl B., Kuan-Hui Lee, and Ingrid M. Werner, 2009, Short-sale strategies and return predictability, *Review of Financial Studies* 22, 575–607.

D'Avolio, Gene, 2002, The market for borrowing stock, *Journal of Financial Economics* 66, 271–306, Limits on Arbitrage.

Edwards, Amy K., Lawrence E. Harris, and Michael S. Piwowar, 2007, Corporate bond market transaction costs and transparency, *Journal of Finance* 62, 1421–1451.

Edwards, Amy K., Adam V. Reed, and Pedro A.C. Saffi, 2024, A survey of short-selling regulations, *Review of Asset Pricing Studies* 14, 613–639.

Engelberg, Joseph E., Adam V. Reed, and Matthew C. Ringgenberg, 2018, Short-selling risk, *Journal of Finance* 73, 755–786.

Feldhütter, Peter, 2012, The Same Bond at Different Prices: Identifying Search Frictions and Selling Pressures, *Review of Financial Studies* 25, 1155–1206.

Glosten, Lawrence R., and Paul R. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71–100.

Goyal, Amit, Adam V. Reed, Esad Smajlbegovic, and Amar Soebhag, 2025, Stealthy shorts: Informed liquidity supply, *Journal of Financial Economics* 172, 104155.

Hendershott, Terrence, Roman Kozhan, and Vikas Raman, 2020, Short selling and price discovery in corporate bonds, *Journal of Financial and Quantitative Analysis* 55, 77–115.

Hendershott, Terrence, Dan Li, Dmitry Livdan, Norman Schuerhoff, and Kumar Venkataraman, 2022, Quote competition in corporate bonds, Working Paper.

Hendershott, Terrence, Dmitry Livdan, and Norman Schuerhoff, 2021, All-to-all liquidity in corporate bonds, Working Paper.

Hendershott, Terrence, and Ananth Madhavan, 2015, Click or call? Auction versus search in the over-the-counter market, *Journal of Finance* 70, 419–447.

Jacobsen, Stacey, and Kumar Venkataraman, 2025, Receiving investors in the block market for corporate bonds, *Journal of Financial Economics* 170, 104061.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Johnson, Travis L, and Eric C So, 2018, Asymmetric trading costs prior to earnings announcements: Implications for price discovery and returns, *Journal of Accounting Research* 56, 217–263.

Jones, Charles M, and Owen A Lamont, 2002, Short-sale constraints and stock returns, *Journal of Financial Economics* 66, 207–239, Limits on Arbitrage.

Kolasinski, Adam C., Adam V. Reed, and Matthew C. Ringgenberg, 2013, A multiple lender approach to understanding supply and search in the equity lending market, *Journal of Finance* 68, 559–595.

Koont, Naz, Yiming Ma, Ľuboš Pástor, and Yao Zeng, 2024, Steering a ship in illiquid waters: Active management of passive funds, *Review of Financial Studies* .

Kyle, Albert S., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315–1335.

Lee, Charles M.C., and Mark J. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733–746.

Merton, Robert C., 1974, On the pricing of corporate debt: the risk structure of interest rates, *Journal of Finance* 29, 449–470.

Muravyev, Dmitriy, Neil D. Pearson, and Joshua M. Pollet, 2022, Is there a risk premium in the stock lending market? Evidence from equity options, *Journal of Finance* 77, 1787–1828.

Muravyev, Dmitriy, Neil D. Pearson, and Joshua M. Pollet, 2023, Anomalies and their short-sale costs, *Available at SSRN 4266059* .

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

O'Hara, Maureen, and Xing Alex Zhou, 2021, Anatomy of a liquidity crisis: Corporate bonds in the covid-19 crisis, *Journal of Financial Economics* 142, 46–68.

Palia, Darius, and Stanislav Sokolinski, 2024, Strategic borrowing from passive investors, *Review of Finance* 28, 1537–1573.

Pelizzon, Loriana, Max Riedel, Zorka Simon, and Marti G. Subrahmanyam, 2024, Collateral eligibility of corporate debt in the eurosystem, *Journal of Financial Economics* 153, 103777.

Pinter, Gabor, Chaojun Wang, and Junyuan Zou, 2024, Size discount and size penalty: Trading costs in bond markets, *Review of Financial Studies* 37, 2156–2190.

Prado, Melissa Porras, Pedro A.C. Saffi, and Jason Sturgess, 2016, Ownership structure, limits to arbitrage, and stock returns: Evidence from equity lending markets, *Review of Financial Studies* 29, 3211–3244.

Reilly, Chris, 2022, The hidden cost of corporate bond ETFs, Working Paper.

Saffi, Pedro A.C., and Kari Sigurdsson, 2011, Price efficiency and short selling, *Review of Financial Studies* 24, 821–852.

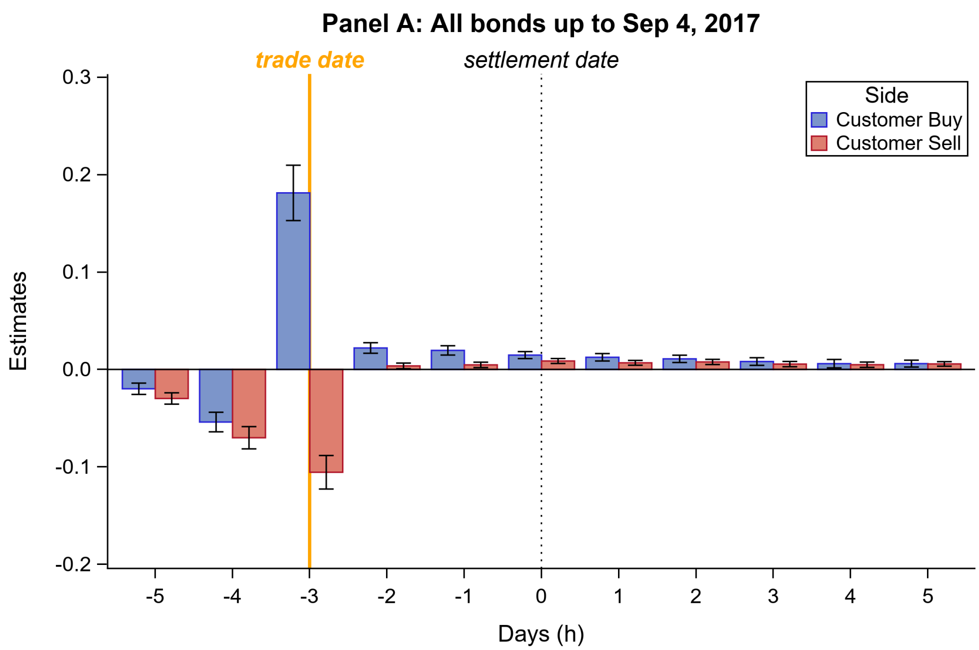
Schestag, Raphael, Philipp Schuster, and Marliese Uhrig-Homburg, 2016, Measuring liquidity in bond markets, *Review of Financial Studies* 29, 1170–1219.

Sikorskaya, Taisiya, 2023, Institutional investors, securities lending, and short-selling constraints, Working Paper, University of Chicago.

von Beschwitz, Bastian, Pekka Honkanen, and Daniel Schmidt, 2025, Passive ownership and short selling, *Review of Finance* 29, 1137–1188.

Figure 1: Panel Regression of Dollar Trading Volume on Changes in Quantity on Loan

This figure plots the slope coefficients from panel regressions of dealer-customer trading volume on the day $d + h$ on the day d changes in quantity on loan, where day d is the settlement date and h ranges from -5 to $+5$. Trading volume and quantity on loan are scaled by the amount outstanding. The y-axis represents a change (in percent) of the scaled trading volume associated with a one percentage point change in the scaled quantity on loan. The figure also shows two-standard-error bands, computed by double clustering observations at the bond and date levels. The vertical dotted line indicates the settlement date at day $d = 0$. The orange solid line denotes the trade date, which occurs on day $d = -3$ in Panel A and day $d = -2$ in Panel B. Panel A is for all bonds up to Sep 4, 2017, and Panel B is for all bonds after Sep 5, 2017.



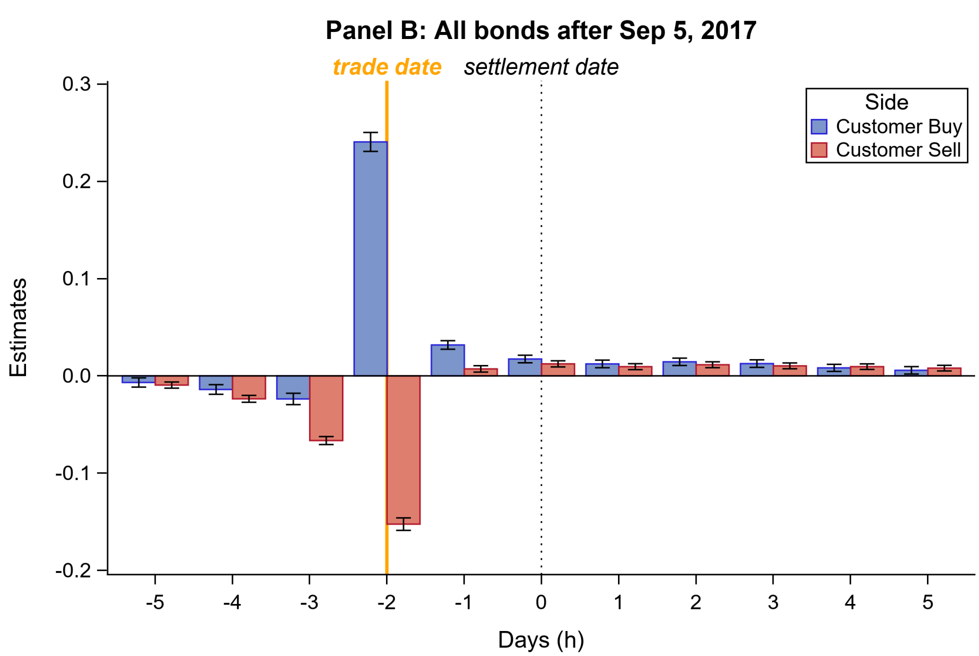
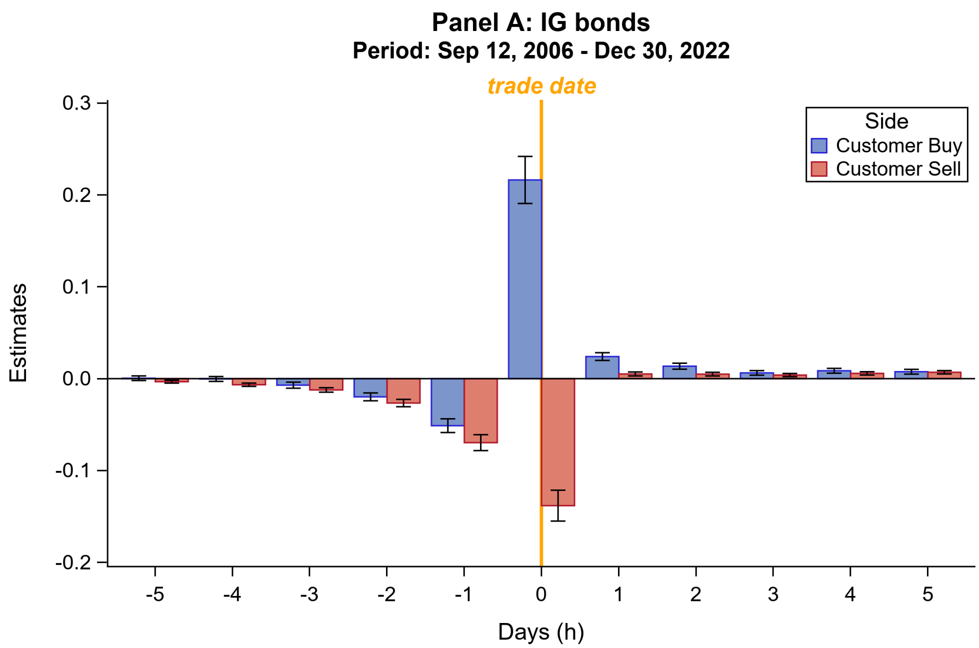


Figure 2: Panel Regression of Dollar Trading Volume on Changes in Quantity on Loan, IG vs HY

The figure plots the slope coefficients from panel regressions of dealer-customer trading volume on day $d^* + h$ on day d changes in quantity on loan. Trading volume and quantity on loan are scaled by the amount outstanding. The y-axis represents a change (in percent) of the scaled dollar trading volume associated with a one percentage point change in the scaled quantity on loan. The figure also shows two-standard-error bands, computed by double clustering observations at the bond and date levels. The orange solid line denotes the trade date at $d^* = 0$. To account for the gap between trade date d^* and settlement date d, we set $d^* = d - s$, where s equals 3 if d occurs on or before September 4, 2017, and 2 thereafter. Panel A reports results for IG bonds and Panel B reports results for HY bonds.



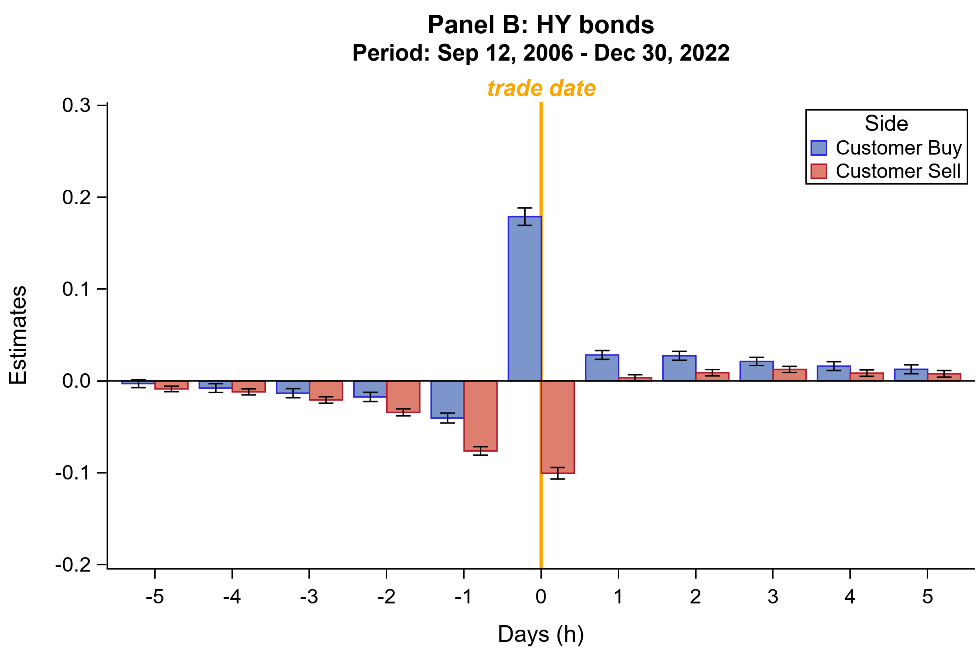


Figure 3: Panel Regression of Abnormal Half Spreads on Changes in Quantity on Loan

This figure plots the slope coefficients from panel regressions of abnormal half spreads on day $d^* + h$ on the day d changes in quantity on loan. Abnormal half-spreads are computed as deviations from 21-trading-day averages within buckets defined by credit rating, trade size, and trade direction. The y-axis represents a change in abnormal half spreads (in percent) associated with a one percentage point change in the scaled quantity on loan. The figure also shows two-standard-error bands, computed by double clustering observations at the bond and date levels. The orange solid line denotes the trade date at $d^* = 0$. To account for the gap between trade date d^* and settlement date d, we set $d^* = d - s$, where s equals 3 if d occurs on or before September 4, 2017, and 2 thereafter.

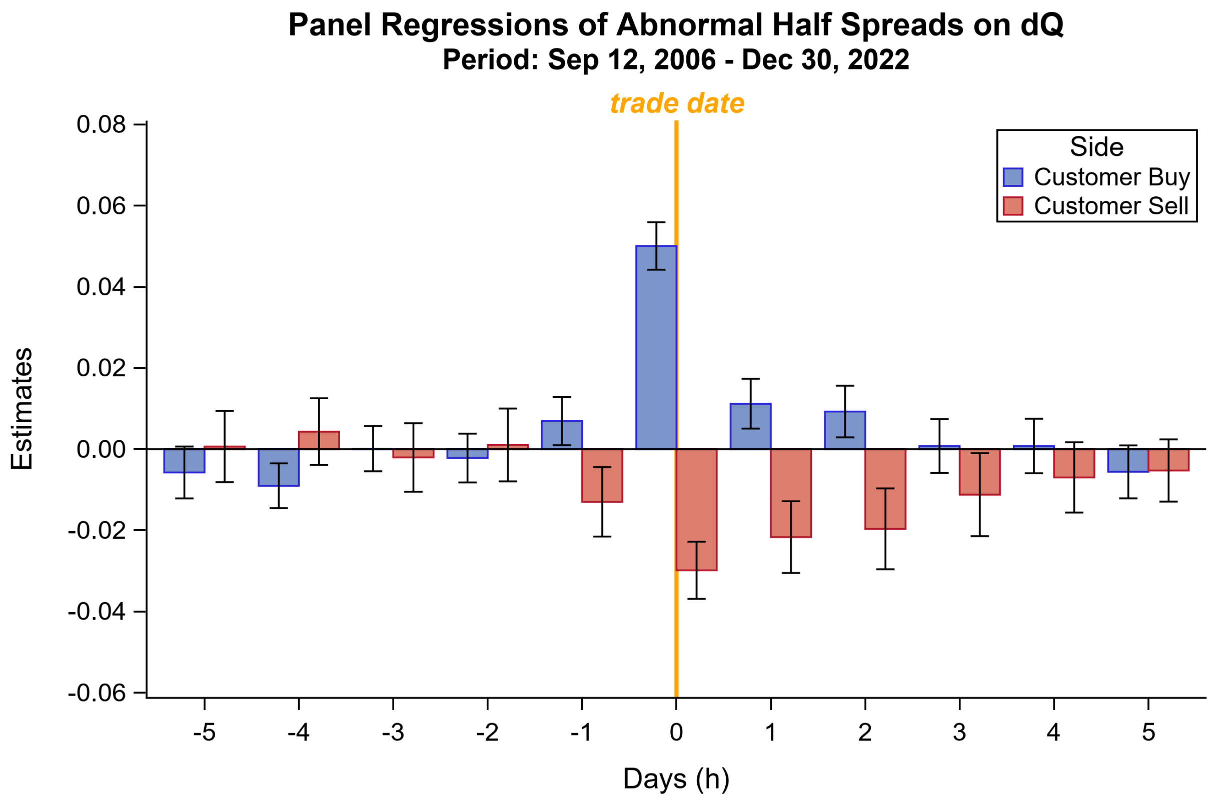
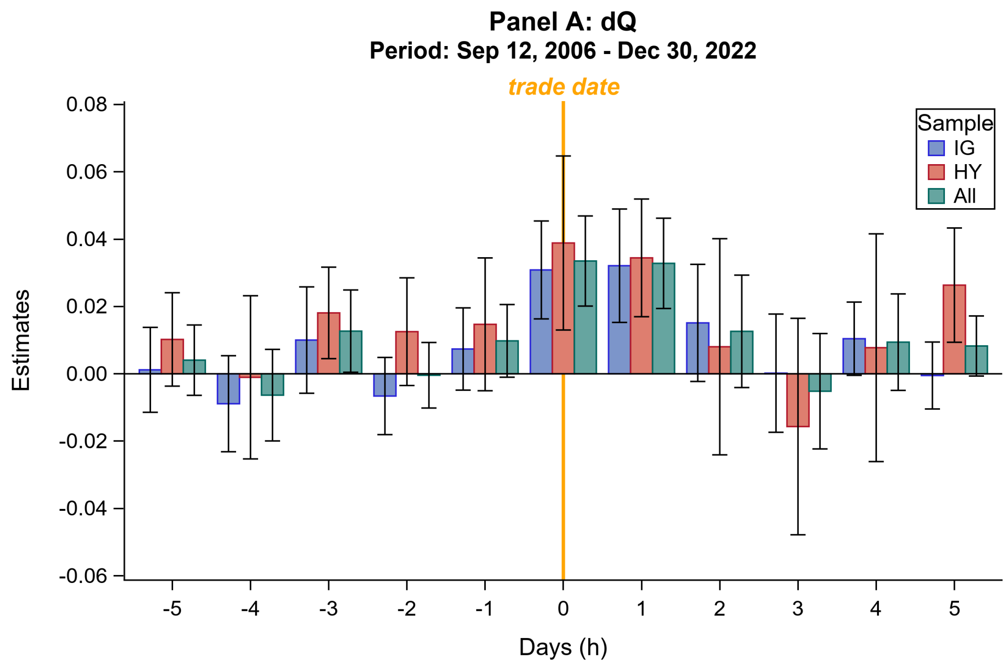


Figure 4: Panel Regression of Daily Bond Returns on Changes in Quantity on Loan

The figure plots the slope coefficients from panel regressions of daily bond returns on day $d^* + h$ on day d changes in quantity on loan. Daily bond returns are obtained from the ICE BAML bond pricing database and are not winsorized. The y-axis represents a change in daily bond returns (in percent) associated with a one percentage point change in the scaled quantity on loan (Panel A) or a positive change in quantity on loan (Panel B). The figure also shows two-standard-error bands, computed by double clustering observations at the bond and date levels. The orange solid line denotes the trade date at $d^* = 0$. To account for the gap between trade date d^* and settlement date d, we set $d^* = d - s$, where s equals 3 if d occurs on or before September 4, 2017, and 2 thereafter. Panel A reports results using dQ as the independent variable. Panel B replaces dQ with $D(dQ > 0)$ and $D(dQ = 0)$, where $D(dQ > 0)$ is an indicator equal to one if $dQ > 0$, and plots the coefficients on $D(dQ > 0)$. Results are reported for investment-grade (IG), high-yield (HY), and all bonds.



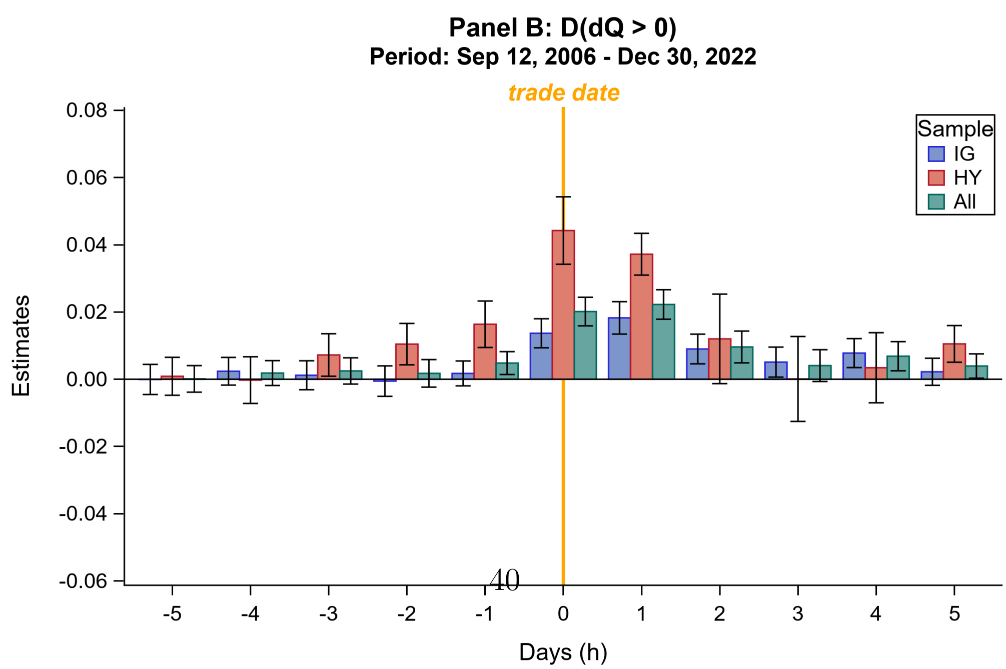


Figure 5: Panel Regression of Dollar Trading Volume on Changes in Quantity on Loan: Stocks

The figure plots the slope coefficients from panel regressions of stock trading volume on day $d^* + h$ on day d changes in quantity on loan. The sample is restricted to common stocks traded on NYSE, NASDAQ, and AMEX. We obtain buy and sell volume from the WRDS Intraday Indicator database. Trading volume and quantity on loan are scaled by shares outstanding. The y-axis represents a change (in percent) of scaled share trading volume associated with a one percentage point change in the scaled quantity on loan. The figure also shows two-standard-error bands, computed by double clustering observations at the bond and date levels. The orange solid line denotes the trade date at $d^* = 0$. To account for the gap between trade date d^* and settlement date d, we set $d^* = d - s$, where s equals 3 if d occurs on or before September 4, 2017, and 2 thereafter.

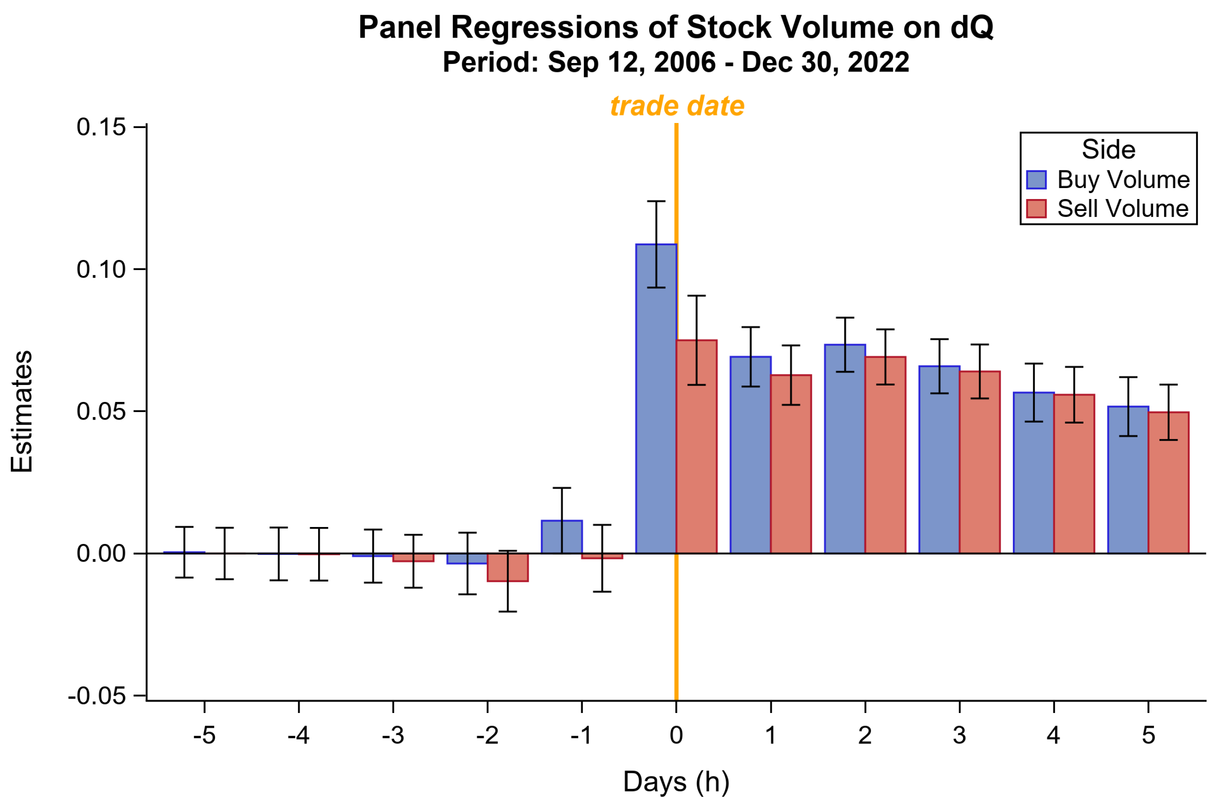


Figure 6: Securities Lending Supply and Demand

This figure illustrates the supply and demand curves for securities lending markets. In Panel A, we consider an increase in passive ownership, which leads to a decreased quantity on loan and lower fees. In Panel B, we consider an increase in insurance ownership, which leads to an increase in quantity on loan and lower fees.

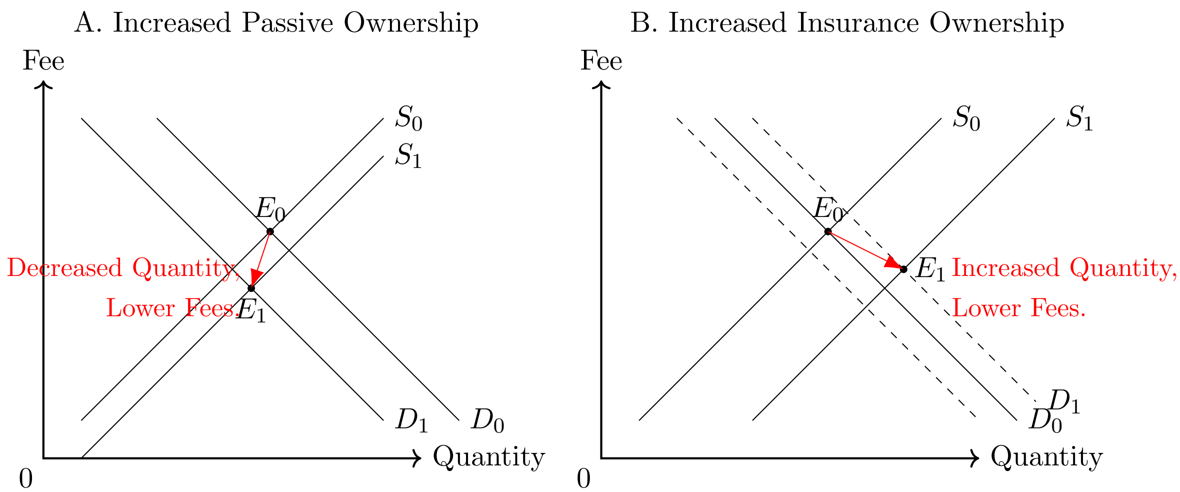


Table 1: Descriptive Statistics

This table presents summary statistics for the main variables. Panel A reports summary statistics for the univariate regression analysis in Figures 1 to 4. The univariate sample consists of 15,503 corporate bonds issued by public and private U.S. firms from September 12, 2006 to December 30, 2022, yielding 16,850,795 bond-day observations. Panel B reports summary statistics for the multivariate regression analysis in Tables 3 and 4. The multivariate sample includes corporate bonds issued by public and private U.S. firms with at least 252 daily observations after applying our filters, resulting in 11,763 bonds from 2,121 issuers. Of these, 1,326 are public firms matched to CRSP via PERMNO. The sample spans September 12, 2006 to December 30, 2022, yielding 11,341,920 bond-day observations. All continuous variables, except bond returns (r), are winsorized at the 1st and 99th percentiles by date. Variable definitions are provided in Table A1.

Variable	Mean	SD	P1	P25	P50	P75	P99	Obs
			Panel A: Univariate Regression Sample					
dQ (%)	−0.002	0.189	−0.664	−0.003	0.000	0.001	0.667	16,850,795
Vol_{Buy} (%)	0.151	0.401	0.000	0.000	0.009	0.091	2.143	16,850,795
Vol_{Sell} (%)	0.095	0.302	0.000	0.000	0.000	0.025	1.700	16,850,795
r (%)	0.018	1.389	−1.792	−0.154	0.018	0.196	1.811	16,850,795
h_{Buy} (%)	−0.015	0.888	−1.951	−0.364	−0.104	0.216	2.653	8,333,958
h_{Sell} (%)	0.016	0.949	−2.190	−0.286	−0.057	0.240	2.750	8,011,401
			Panel B: Multivariate Regression Sample					
dQ (%)	−0.002	0.199	−0.719	−0.011	0.000	0.007	0.730	11,341,920
dQ^{Stock} (%)	0.000	0.219	−0.595	−0.039	−0.001	0.037	0.607	10,494,672
Vol_{Buy} (%)	0.185	0.434	0.000	0.001	0.026	0.142	2.281	11,341,920
Vol_{Sell} (%)	0.113	0.323	0.000	0.000	0.004	0.045	1.782	11,341,920
r (%)	0.017	1.186	−1.756	−0.144	0.017	0.182	1.791	11,341,920
$\bar{r}_{d-5,d-1}$ (%)	0.019	0.471	−0.862	−0.057	0.016	0.100	0.861	11,341,920
$\sigma_{d-5,d-1}$ (%)	0.428	0.990	0.018	0.140	0.277	0.518	2.477	11,341,920
$Amount$ ($ mil)	871	635	250	500	698	1,000	3,250	11,341,920
$Rating$	8.594	3.288	1.000	6.500	8.500	10.000	17.000	11,341,920
Age (years)	4.110	3.573	0.175	1.564	3.203	5.677	18.077	11,341,920
$Maturity$ (years)	8.678	7.808	1.148	3.518	5.926	9.249	29.400	11,341,920
$\overline{dQ}_{d-5,d-1}$ (%)	−0.001	0.093	−0.314	−0.016	0.000	0.013	0.322	11,341,920
$\overline{dQ}^{Stock}_{d-5,d-1}$ (%)	0.000	0.127	−0.271	−0.021	0.000	0.020	0.284	10,494,672
$\overline{Vol}_{d-5,d-1,Buy}$ (%)	0.205	0.293	0.002	0.033	0.097	0.251	1.445	11,341,920
$\overline{Vol}_{d-5,d-1,Sell}$ (%)	0.130	0.211	0.000	0.010	0.043	0.155	1.051	11,341,920
$\bar{h}_{d-5,d-1,Buy}$ (%)	0.007	0.750	−1.572	−0.282	−0.082	0.190	2.348	11,341,920
$\bar{h}_{d-5,d-1,Sell}$ (%)	0.053	0.784	−1.684	−0.208	−0.032	0.225	2.473	11,341,920

Table 2: Portfolio Returns Sorted by Daily Changes in Quantity on Loan

This table reports value-weighted portfolio returns sorted by daily changes in bond loan quantity (dQ). Every trade day d^*, bonds are sorted into tercile portfolios based on the sign of dQ observed on the settlement date d: Portfolio 1 (P1) contains bonds with decreased loan quantity ($dQ < 0$), Portfolio 2 (P2) contains bonds with unchanged loan quantity ($dQ = 0$), and Portfolio 3 (P3) contains bonds with increased loan quantity ($dQ > 0$). The long-short portfolio (P3 − P1) is long P3 and short P1. Due to the settlement cycle (T+3 before September 5, 2017, and T+2 thereafter), the corresponding trade date, d^*, is 3 days (or 2 days) before the settlement date. Value-weighted portfolios are constructed using lagged bond market capitalization as weights and rebalanced daily. For a holding period of K trading days, the daily portfolio return is an average of K overlapping portfolios, with $1/K$ of the portfolio rebalanced each day. Raw returns are unadjusted bond returns. Excess returns are computed as the difference between raw bond returns and value-weighted returns of bonds with the same credit rating group (AAA, AA, A, BBB, BB, B, CCC-C, or D) in the ICE data. Returns are reported in percent multiplied by 252 to reflect annualized returns. Panel A reports returns on day d^* ($K = 1$). Panel B reports returns for portfolios held from $d^* + 1$ to $d^* + 3$ ($K = 3$). Panel C reports returns for portfolios held from $d^* + 4$ to $d^* + 23$ ($K = 20$). Results are reported separately for all bonds, investment-grade (IG) bonds, and high-yield (HY) bonds. The t-statistics in parentheses are Newey and West (1987) adjusted with a lag of 20. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Raw Return				Excess Return			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
				Panel A: Return on Day d^*				
All	2.75	2.86	7.57***	4.81***	−1.30***	−1.37***	3.17***	4.46***
	(1.51)	(1.62)	(4.10)	(12.77)	(−4.74)	(−4.41)	(8.52)	(13.78)
IG	3.17*	3.00*	6.29***	3.12***	−0.73***	−0.97***	2.35***	3.08***
	(1.87)	(1.70)	(3.74)	(10.43)	(−3.38)	(−2.94)	(8.23)	(10.73)
HY	2.07	2.09	12.98***	10.91***	−3.56***	−3.46***	7.09***	10.65***
	(0.66)	(0.82)	(3.86)	(9.12)	(−4.24)	(−5.72)	(5.89)	(9.18)
				Panel B: Return Window $[d^* + 1, d^* + 3]$				
All	2.88	4.13**	6.09***	3.20***	−1.16***	−0.15	1.75***	2.91***
	(1.64)	(2.28)	(3.42)	(13.32)	(−5.17)	(−0.55)	(6.29)	(14.10)
IG	3.08*	3.77**	5.48***	2.40***	−0.84***	−0.24	1.48***	2.32***
	(1.82)	(2.13)	(3.27)	(13.18)	(−4.34)	(−0.88)	(6.33)	(13.39)
HY	3.12	6.05**	8.89***	5.76***	−2.44***	0.43	3.16***	5.60***
	(1.10)	(2.18)	(2.95)	(8.62)	(−4.37)	(0.65)	(4.21)	(8.85)
				Panel C: Return Window $[d^* + 4, d^* + 23]$				
All	3.80**	4.25**	4.42**	0.63***	−0.27	−0.01	0.26	0.53***
	(2.14)	(2.36)	(2.54)	(6.54)	(−1.13)	(−0.04)	(1.19)	(6.44)
IG	3.76**	3.88**	4.30**	0.55***	−0.17	−0.15	0.34*	0.50***
	(2.21)	(2.18)	(2.58)	(6.12)	(−0.81)	(−0.59)	(1.78)	(5.77)
HY	4.75	6.22**	5.37*	0.62***	−0.58	0.78	0.01	0.59***
	(1.63)	(2.38)	(1.89)	(3.92)	(−1.06)	(1.45)	(0.02)	(4.63)

Table 3: Panel Regression of Daily Changes in Quantity on Loan

This table reports the estimates from the panel regression of changes in the quantity on loan for all bonds, as specified in equation (7). The set of explanatory variables includes the daily bond return r_{d^*} on trade date d^*, the average return over the preceding five trading days $\bar{r}_{d^*-5,d^*-1}$, the daily customer buy and sell trading volumes scaled by amount outstanding ($Vol_{d^*,Buy}$ and $Vol_{d^*,Sell}$, respectively) and their five-day moving averages (i.e., $\overline{Vol}_{d^*-5,d^*-1,Buy}$ and $\overline{Vol}_{d^*-5,d^*-1,Sell}$). We also control for abnormal half spreads on buy trades ($\bar{h}_{d^*-5,d^*-1,Buy}$) and sell trades ($\bar{h}_{d^*-5,d^*-1,Sell}$), and bond return volatility (σ_{d^*-5,d^*-1}), each computed over the five-day period from d^*-5 to d^*-1. To account for the gap between trade date d^* and settlement date d, we set $d^* = d - s$, where s equals 3 if d occurs on or before September 4, 2017, and 2 thereafter. Bond controls include the natural logarithm of the amount outstanding, credit ratings, and time to maturity. The variables on the right-hand side are standardized so that they have a mean of zero and a standard deviation of one. We include bond and date fixed effects in each regression specification. We double cluster standard errors by bond and date, and t-statistics are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$Vol_{d^*,Buy}$	0.0427^{***}	0.0430^{***}	0.0447^{***}			0.0447^{***}
	(108.90)	(109.13)	(111.82)			(111.67)
$Vol_{d^*,Sell}$	-0.0387^{***}	-0.0386^{***}	-0.0380^{***}			-0.0380^{***}
	(−123.31)	(−123.11)	(−122.26)			(−122.32)
$\overline{dQ}_{d-5,d-1}$		-0.0141^{***}	-0.0163^{***}			-0.0163^{***}
		(−25.25)	(−27.52)			(−27.55)
$\overline{Vol}_{d^*-5,d^*-1,Buy}$			0.0054^{***}			0.0054^{***}
			(20.07)			(19.89)
$\overline{Vol}_{d^*-5,d^*-1,Sell}$			-0.0157^{***}			-0.0156^{***}
			(−56.99)			(−56.93)
$\bar{h}_{d^*-5,d^*-1,Buy}$			0.0004^{***}			0.0002^{**}
			(3.65)			(2.24)
$\bar{h}_{d^*-5,d^*-1,Sell}$			0.0001			0.0003^{***}
			(0.92)			(3.25)
σ_{d^*-5,d^*-1}			-0.0010^{***}			-0.0012^{***}
			(−4.85)			(−5.67)
r_{d^*}				0.0021^{***}		0.0016^{***}
				(9.70)		(8.19)
$\bar{r}_{d^*-5,d^*-1}$				0.0003^{*}		0.0013^{***}
				(1.81)		(6.93)
dQ_d^{Stock}					0.0006^{***}	0.0006^{***}
					(3.10)	(3.10)
$\overline{dQ}_{d-5,d-1}^{Stock}$					0.0001	0.0002^{**}
					(1.53)	(2.08)
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,447,842	10,447,842	10,447,842	10,447,842	10,447,842	10,447,842
Adjusted R^2	0.049	0.054	0.058	0.010	0.009	0.058

Table 4: Customer and Dealer Shares in Daily Changes in Loan Quantity

This table reports estimates of customer and dealer shares in daily changes in bond loan quantities following the decomposition procedure in Section 4. Panel A presents results for the full sample. Panels B through H split the sample across various characteristics. Panel B separates bonds by credit quality. Investment-grade (IG) bonds are those with numerical ratings of 10 or below, while high-yield (HY) bonds have ratings above 10, where ratings are coded from 1 (AAA) to 21 (C) based on S&P and Moody's classifications. Panel C groups bonds by collateral specialness using daily cross-sectional distributions of borrowing fees: general collateral (GC) includes bonds below the 90th percentile; special collateral categories include SC1 (90th–95th percentile), SC2 (95th–99th percentile), and SC3 (above 99th percentile). Panel D separates public issuers with valid PERMNO identifiers from private issuers without such identifiers. Panel E splits the sample by CDS coverage availability. Panel F uses a reaching-for-yield (RFY) measure, calculated as the difference between a bond's option-adjusted spread (OAS) and the average spread of similarly rated bonds. Bonds with RFY at or below the cross-sectional median are classified as overvalued, while those above the median are classified as undervalued. Panel G divides bonds by issue size relative to the cross-sectional median of amounts outstanding. Panel H groups bonds by liquidity, where bonds with 21-day average bid-ask spreads above (below) the cross-sectional median are classified as illiquid (liquid). We double cluster standard errors by bond and date, and t-statistics are in parentheses.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel A: Whole Sample						
All	−0.122	0.248	−0.371	0.315	0.685	11,341,920
	(−40.89)	(54.19)	(−55.52)	(94.19)	(205.22)	
Panel B: By Credit Rating						
IG	−0.142	0.274	−0.416	0.292	0.708	8,809,554
	(−38.68)	(48.21)	(−49.44)	(69.28)	(168.15)	
HY	−0.088	0.202	−0.290	0.355	0.645	2,532,366
	(−24.26)	(38.72)	(−40.39)	(98.79)	(179.57)	
Panel C: By Collateral Specialness						
GC	−0.132	0.275	−0.406	0.297	0.703	10,543,958
	(−41.37)	(56.03)	(−56.86)	(83.11)	(196.83)	
SC1	−0.059	0.154	−0.213	0.393	0.607	389,820
	(−11.10)	(19.77)	(−25.31)	(93.36)	(143.98)	
SC2	−0.063	0.066	−0.129	0.436	0.564	330,179
	(−10.50)	(9.23)	(−19.55)	(132.05)	(171.16)	
SC3	−0.088	−0.044	−0.043	0.478	0.522	77,963
	(−7.94)	(−4.22)	(−4.74)	(104.55)	(114.04)	

Table 4, Continued.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel D: By Public Status						
Public Firm	−0.124	0.250	−0.374	0.313	0.687	10,657,984
	(−41.35)	(54.90)	(−56.45)	(94.35)	(207.25)	
Private Firm	−0.096	0.224	−0.320	0.340	0.660	683,936
	(−13.73)	(21.62)	(−23.29)	(49.40)	(95.99)	
Panel E: By CDS Coverage						
Yes	−0.121	0.249	−0.370	0.315	0.685	6,050,583
	(−34.74)	(46.26)	(−47.70)	(81.30)	(176.70)	
No	−0.124	0.248	−0.372	0.314	0.686	5,291,337
	(−35.97)	(52.48)	(−53.73)	(90.55)	(198.00)	
Panel F: By Expensiveness						
Overvalued	−0.164	0.236	−0.400	0.300	0.700	6,088,637
	(−45.90)	(51.81)	(−57.98)	(87.02)	(202.98)	
Undervalued	−0.092	0.257	−0.349	0.325	0.675	5,225,044
	(−30.18)	(46.36)	(−46.98)	(87.48)	(181.45)	
Panel G: By Issuance Size						
Large	−0.124	0.264	−0.387	0.306	0.694	6,981,985
	(−37.36)	(51.67)	(−51.87)	(82.03)	(185.78)	
Small	−0.120	0.220	−0.340	0.330	0.670	4,359,935
	(−30.83)	(40.85)	(−44.02)	(85.61)	(173.64)	
Panel H: By Bid-ask Spread						
Illiquid	−0.105	0.229	−0.334	0.333	0.667	6,040,556
	(−32.83)	(43.99)	(−45.30)	(90.14)	(180.74)	
Liquid	−0.143	0.273	−0.416	0.292	0.708	5,133,242
	(−42.86)	(59.29)	(−63.95)	(89.61)	(217.52)	

Table 5: Customer and Dealer Shares in Daily Changes in Loan Quantity Before Information Events

This table reports estimates of customer and dealer shares in daily changes in bond loan quantities during the 21 trading days preceding information events. Panel A examines credit rating changes, defined as events where at least one of the three major rating agencies (S&P, Moody's, or Fitch) modifies its rating. Rating changes are classified into two mutually exclusive categories: crossing events, where at least one agency's rating crosses the IG/HY boundary, and non-crossing events, where ratings change within IG or HY categories without crossing the threshold. Panel B examines earnings announcements. For each calendar quarter, firms are ranked cross-sectionally by their standardized unexpected earnings, calculated as the difference between actual earnings and the median analyst forecast scaled by the stock price. Based on these rankings, firms are assigned to deciles and grouped into five news categories: Very Bad (deciles 1–2, bottom 20%), Bad (deciles 3–4), Around Expectation (deciles 5–6, middle 20%), Good (deciles 7–8), and Very Good (deciles 9–10, top 20%). We double cluster standard errors by bond and date, and t-statistics are in parentheses.

Regression Coefficients			Variance Ratio		
β_S	β_B	Diff.	Customer	Dealer	Observations
Panel A: 21 Trading Days Before Rating Changes					
Downgrade Crossing IG/HY Threshold					
−0.002	0.243	−0.245	0.377	0.623	27,038
(−0.09)	(8.76)	(−10.71)	(32.98)	(54.40)	
Other Downgrades					
−0.037	0.181	−0.218	0.391	0.609	273,498
(−5.56)	(15.22)	(−19.83)	(71.07)	(110.72)	
Upgrade Crossing IG/HY Threshold					
−0.118	0.346	−0.464	0.268	0.732	21,213
(−4.68)	(11.90)	(−14.73)	(17.05)	(46.52)	
Other Upgrades					
−0.113	0.259	−0.371	0.314	0.686	184,412
(−10.85)	(20.09)	(−28.96)	(49.00)	(106.93)	
Panel B: 21 Trading Days Before Earnings News					
Very Bad News					
−0.065	0.202	−0.267	0.366	0.634	288,233
(−8.61)	(18.00)	(−19.90)	(54.61)	(94.40)	
Bad News					
−0.123	0.268	−0.391	0.305	0.695	775,640
(−20.13)	(30.35)	(−34.10)	(53.12)	(121.32)	
Around Expectation News					
−0.148	0.272	−0.420	0.290	0.710	1,053,254
(−31.02)	(37.68)	(−48.71)	(67.26)	(164.69)	
Good News					
−0.137	0.272	−0.409	0.296	0.704	760,137
(−26.03)	(35.21)	(−45.23)	(65.40)	(155.86)	
Very Good News					
−0.107	0.232	−0.339	0.331	0.669	425,834
(−18.58)	(25.48)	(−32.01)	(62.49)	(126.51)	

Table 6: Customer and Dealer Shares in Daily Changes in Stock Loan

This table reports estimates of customer and dealer shares in daily changes in stock loan quantities. The sample is restricted to common stocks traded on NYSE, NASDAQ, and AMEX with at least 252 daily observations. Since the equity market is not a dealer-intermediated over-the-counter (OTC) market, the term "dealer" here refers to the liquidity provider, and "customer" refers to the liquidity taker. Following Diether, Lee, and Werner (2009), we control for stock returns, effective spreads, order imbalances, intraday volatility, share turnover, their trailing five-day averages, and log market capitalization. Panel A presents results for the full sample. Panels B through E split the sample by stock characteristics. Panel B groups stocks by market capitalization relative to NYSE breakpoints: micro-cap (below 20th percentile), small-cap (20th–50th percentile), and large-cap (above median). Panel C separates stocks by collateral specialness: general collateral (GC) loans have annualized fees at or below 1%, while special collateral (SC) loans exceed 1%. Panel D divides the sample by bond issuance status, where issuers are firms with outstanding bonds and non-issuers are those without outstanding bonds. Panel E splits the sample by CDS coverage availability. We double cluster standard errors by stock and date, and t-statistics are in parentheses. The sample period spans September 12, 2006 to December 30, 2022.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel A: Whole Sample						
All	0.055	0.054	0.001	0.500	0.500	14,431,379
	(10.66)	(22.24)	(0.14)	(232.93)	(232.65)	
Panel B: By Market Capitalization						
Micro	0.069	0.082	−0.013	0.494	0.506	7,273,346
	(5.65)	(18.33)	(−1.11)	(86.38)	(88.59)	
Small	0.055	0.038	0.017	0.508	0.492	3,499,760
	(10.16)	(14.47)	(4.61)	(277.94)	(268.73)	
Large	0.039	0.040	−0.001	0.499	0.501	3,658,273
	(9.40)	(14.50)	(−0.61)	(485.05)	(486.26)	
Panel C: By Collateral Specialness						
GC	0.050	0.044	0.006	0.503	0.497	11,233,529
	(14.08)	(22.85)	(2.60)	(428.17)	(422.97)	
SC	0.075	0.090	−0.014	0.493	0.507	3,197,850
	(6.03)	(14.35)	(−1.23)	(85.09)	(87.55)	
Panel D: By Bond Issuance						
Issuer	0.037	0.039	−0.002	0.499	0.501	3,981,118
	(13.06)	(18.28)	(−1.11)	(596.27)	(598.48)	
Non-Issuer	0.064	0.063	0.002	0.501	0.499	10,450,261
	(9.31)	(20.41)	(0.31)	(170.96)	(170.35)	
Panel E: By CDS Coverage						
Yes	0.039	0.037	0.001	0.501	0.499	1,711,903
	(10.94)	(13.40)	(0.79)	(545.56)	(543.97)	
No	0.057	0.057	0.000	0.500	0.500	12,719,476
	(10.21)	(21.83)	(0.10)	(212.00)	(211.80)	

Table 7: Passive Ownership and Bond Lending Activities

This table presents the results from regressing bond lending outcomes on ownership of institutional investors. The dependent variables are quarterly averages of loan quantity, lendable supply, borrowing fee, DCBS, and utilization rate. *Passive Fund*, *Active Fund*, and *Insurer* represent fractions of bond par amount held by passive mutual funds, actively managed mutual funds, and insurance firms, respectively. Bond control variables include the log value of amount outstanding, rating, time to maturity, and the fraction of zero-trading days. Variable definitions are provided in Table A1. We include bond and firm × quarter effects in each regression. We double cluster standard errors by firm and year-quarter, and t-statistics are in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from 2006 Q3 to 2022 Q4.

	Loan Quantity (1)	Lendable Supply (2)	Borrowing Fee (3)	DCBS (4)	Utilization Rate (5)
			Panel A: Passive Funds Only		
Passive Fund	−0.0103	0.3082***	−0.0229***	−0.0133***	−0.1818***
	(−1.13)	(8.05)	(−4.95)	(−5.32)	(−5.37)
Bond Controls	Yes	Yes	Yes	Yes	Yes
Firm×Qtr FE	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes
Observations	281,886	281,886	281,886	281,886	281,886
Adjusted R^2	0.597	0.811	0.472	0.489	0.629
			Panel B: Passive Funds Plus Other Investors		
Passive Fund	−0.0050	0.3355***	−0.0232***	−0.0134***	−0.1718***
	(−0.52)	(9.10)	(−4.94)	(−5.32)	(−5.02)
Active Fund	0.0442***	0.1316***	0.0006	0.0004	0.1380***
	(10.78)	(7.67)	(0.95)	(0.99)	(7.40)
Insurer	0.0194***	0.1056***	−0.0012***	−0.0006**	0.0317***
	(5.17)	(9.58)	(−2.74)	(−2.42)	(3.45)
Bond Controls	Yes	Yes	Yes	Yes	Yes
Firm×Qtr FE	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes
Observations	281,886	281,886	281,886	281,886	281,886
Adjusted R^2	0.602	0.815	0.472	0.490	0.630

Table 8: Passive Ownership and Bond Lending Activities, Subsample Results by Specialness

This table presents the results from regressing bond lending outcomes on ownership of institutional investors as in Table 7, except that we report results separately for special bonds and general collateral (GC) bonds. A bond is defined as special in a given quarter if its lagged borrowing fee is in the top decile of the fee distribution across bonds, and as GC, otherwise. Variable definitions are provided in Table A1. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from 2006 Q3 to 2022 Q4.

	Special					GC				
	Loan Quantity (1)	Lendable Supply (2)	Borrowing Fee (3)	DCBS (4)	Utilization Rate (5)	Loan Quantity (6)	Lendable Supply (7)	Borrowing Fee (8)	DCBS (9)	Utilization Rate (10)
Panel A: Passive Funds Only										
Passive Fund	0.0559	0.5750***	−0.0611***	−0.0390***	−0.4983	−0.0126	0.2151***	−0.0051***	−0.0031***	−0.1693***
	(1.05)	(3.59)	(−3.07)	(−3.08)	(−1.54)	(−1.38)	(5.91)	(−4.13)	(−4.50)	(−5.58)
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm×Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,465	12,465	12,465	12,465	12,465	245,177	245,177	245,177	245,177	245,177
Adjusted R^2	0.771	0.751	0.611	0.615	0.742	0.571	0.831	0.246	0.162	0.541
Panel B: Passive Funds Plus Other Investors										
Passive Fund	0.0412	0.5668***	−0.0612***	−0.0389***	−0.5719*	−0.0069	0.2468***	−0.0052***	−0.0032***	−0.1583***
	(0.78)	(3.75)	(−3.09)	(−3.05)	(−1.74)	(−0.71)	(7.12)	(−4.16)	(−4.51)	(−5.10)
Active Fund	0.0657***	0.0948***	-0.0011	0.0000	0.2522***	0.0384***	0.1375***	0.0000	0.0001	0.1127***
	(4.50)	(3.38)	(−0.30)	(0.00)	(2.88)	(9.47)	(7.77)	(0.21)	(0.80)	(7.99)
Insurer	0.0156	0.0873***	−0.0021	0.0001	−0.0231	0.0179***	0.1051***	−0.0003*	−0.0001	0.0319***
	(1.59)	(4.00)	(−0.54)	(0.03)	(−0.40)	(4.56)	(9.78)	(−1.86)	(−1.09)	(3.42)
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm×Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,465	12,465	12,465	12,465	12,465	245,177	245,177	245,177	245,177	245,177
Adjusted R^2	0.777	0.753	0.611	0.615	0.743	0.575	0.835	0.246	0.162	0.543

Table 9: Passive Ownership and Bond Lending Activities, Subsample Results by Credit Rating

This table presents the results from regressing bond lending outcomes on ownership of institutional investors as in Table 7, except that we report results separately for investment grade (IG) and high yield (HY) bonds. A bond is classified as high yield if its credit rating at the end of the previous quarter is below BBB; otherwise, it is categorized as investment grade. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from 2006 Q3 to 2022 Q4.

	IG					HY				
	Loan Quantity	Lendable Supply	Borrowing Fee	DCBS	Utilization Rate	Loan Quantity	Lendable Supply	Borrowing Fee	DCBS	Utilization Rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Passive Funds Only										
Passive Fund	−0.0166	0.2666***	−0.0217***	−0.0124***	−0.1899***	0.0453**	0.5391***	−0.0216***	−0.0134***	0.0089
	(−1.67)	(6.53)	(−4.78)	(−4.99)	(−5.40)	(2.11)	(7.80)	(−4.21)	(−4.32)	(0.08)
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm×Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	234,539	234,539	234,539	234,539	234,539	46,535	46,535	46,535	46,535	46,535
Adjusted R^2	0.567	0.818	0.316	0.322	0.532	0.665	0.804	0.706	0.692	0.676
Panel B: Passive Funds Plus Other Investors										
Passive Fund	−0.0101	0.3006***	−0.0219***	−0.0125***	−0.1764***	0.0299	0.5191***	−0.0217***	−0.0135***	−0.0568
	(−0.96)	(7.65)	(−4.78)	(−4.98)	(−4.97)	(1.36)	(7.58)	(−4.26)	(−4.39)	(−0.49)
Active Fund	0.0348***	0.1596***	0.0013*	0.0009**	0.0903***	0.0565***	0.1042***	0.0001	0.0002	0.2188***
	(7.95)	(7.06)	(1.83)	(2.07)	(5.10)	(8.81)	(4.03)	(0.07)	(0.23)	(6.70)
Insurer	0.0179***	0.0976***	−0.0010**	−0.0004*	0.0334***	0.0174**	0.1349***	−0.0009	−0.0007	0.0001
	(4.45)	(9.08)	(−2.20)	(−1.73)	(3.50)	(2.61)	(6.07)	(−0.71)	(−0.82)	(0.00)
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm×Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	234,539	234,539	234,539	234,539	234,539	46,535	46,535	46,535	46,535	46,535
Adjusted R^2	0.570	0.821	0.316	0.322	0.533	0.672	0.808	0.706	0.692	0.680

Table 10: Passive Ownership and Bond Market Outcomes

This table presents the results from regressing bond market outcomes on ownership of institutional investors. The dependent variables are quarterly averages of credit spread and order imbalance measures. *Passive Fund*, *Active Fund*, and *Insurer* represent fractions of bond par amount held by passive mutual funds, actively managed mutual funds, and insurance firms, respectively. Bond control variables include the log value of amount outstanding, rating, time to maturity, and the fraction of zero-trading days. Variable definitions are provided in Table A1. We include bond and firm × quarter effects in each regression. We double cluster standard errors by firm and year-quarter, and t-statistics are in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from 2006 Q3 to 2022 Q4.

	Credit Spread (1)	OIMB (2)	Net OIMB (3)
	Panel A: Passive Funds Only		
Passive Fund	-0.0443^{***}	-0.0198^{***}	-0.0964^{***}
	(-10.15)	(-3.32)	(-12.18)
Bond Controls	Yes	Yes	Yes
Firm × Qtr FE	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes
Observations	277,403	281,886	281,413
Adjusted R^2	0.953	0.039	0.043
	Panel B: Passive Funds Plus Other Investors		
Passive Fund	-0.0429^{***}	-0.0170^{***}	-0.0938^{***}
	(-10.02)	(-2.76)	(-11.33)
Active Fund	-0.0017	0.0217^{***}	0.0159^{***}
	(-1.09)	(10.22)	(6.44)
Insurer	0.0062^{***}	0.0103^{***}	0.0096^{***}
	(7.89)	(5.89)	(5.56)
Bond Controls	Yes	Yes	Yes
Firm × Qtr FE	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes
Observations	277,403	281,886	281,413
Adjusted R^2	0.953	0.040	0.044

Appendices
"On The Drivers of Corporate Bond Lending"

A Corporate Bond Filters

In this section, we describe our procedure to filter corporate bonds based on the Mergent Fixed Income Securities Database (FISD) database and the Enhanced Trade Reporting and Compliance Engine (TRACE) database from WRDS.

TRACE data contains transaction prices and volume, trade direction, and the exact date and time of each trade. Following Dick-Nielsen (2014), we clean the TRACE data, remove canceled transaction records, and adjust records that are subsequently corrected or reversed. We also follow Bessembinder, Kahle, Maxwell, and Xu (2008) to correct potential data errors and remove observations in enhanced TRACE data with large return reversals, defined as a 20% or greater return followed by a 20% or greater return of the opposite sign. We merge the TRACE database with Mergent FISD to collect information on bond characteristics such as amount outstanding, credit rating, and time to maturity.

Following the recent literature (see, e.g., Dickerson, Mueller, and Robotti 2023; Dick-Nielsen, Feldhütter, Pedersen, and Stolborg 2023), we apply additional filters to eliminate (1) bonds that are not listed or traded in the U.S. public market; (2) bonds that are U.S. Government, private placements, mortgage-backed, asset-backed, agency-backed, or equity-linked;[18] (3) convertible bonds or bonds with a floating coupon rate or an odd frequency of coupon payments; (4) bonds that have less than one year to maturity; (5) bond transactions that are labeled as when-issued, locked-in, have special sales conditions, or non-regular;[19] (6) transaction records with trade size larger than issue size or trade size is not an integer; (7) bonds that do not have a principal value of $1,000; and (8) bonds with incomplete issuance information (offering date, amount, and maturity) or non-positive historical amount outstanding (e.g., bonds are called).

[18] Following Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2023), we define equity-linked bonds, as those whose field "issue name" in Mergent FISD contains any of the following strings: "`EQUITYLINKED`," "`EQUITY LINKED`," and "`INDEX-LINKED`." Additionally, we require that "`SCRTY_TYPE_CD`" does not equal "`E`" in TRACE data files before February 6, 2012 and that "`SUB_PRDCT`" does not equal "`ELN`" in TRACE data files afterwards.

[19] Following Augustin, Cong, Lopez A., and Tédongap (2025), we retain only regular trades by requiring "`SALE_CNDTN_CD`" to equal "`@`" with non-missing "`SALE_CNDTN2_CD`" in TRACE data files before February 6, 2012. For data from February 6, 2012 onward, we exclude trades where "`TRD_MOD_3`" equals ("`Z`," "`T`," "`U`") and where "`TRD_MOD_4`" equals "`W`." More importantly, we do not impose any filters on days to settlement.

Table A1: Variable Definitions

Variable	Definition	Frequency	Data Source
dQ (%)	Daily changes in loan quantity scaled by amount outstanding for bonds or shares outstanding for stocks	daily	Markit, Mergent FISD, CRSP
$\overline{dQ}_{d-5,d-1}$ (%)	Five-day average of loan quantity changes over days $d-5$ to $d-1$, scaled by amount outstanding for bonds or shares outstanding for stocks	daily	Markit, Mergent FISD, CRSP
Vol_{Buy} (%)	Customer buy trading volume as a fraction of amount outstanding	daily, monthly	Mergent FISD, TRACE
Vol_{Sell} (%)	Customer sell trading volume as a fraction of amount outstanding	daily, monthly	Mergent FISD, TRACE
r_d (%)	Daily bond return	daily	ICE
$\bar{r}_{d-5,d-1}$ (%)	Average daily bond returns over days $d-5$ to $d-1$	daily	ICE
$\sigma_{d-5,d-1}$ (%)	Standard deviation of daily bond returns over days $d-5$ to $d-1$	daily	ICE
h_{Buy} (%)	Abnormal half spread from the customer buy side, defined as the volume-weighted average difference between a bond's half spread and the benchmark half spread. The benchmark is the equal-weighted average half spread over the previous 21 days for bonds matched on credit rating, trade size, and trade direction.	daily	Mergent FISD, TRACE
h_{Sell} (%)	Abnormal half spread from the customer sell side, defined as the volume-weighted average difference between a bond's half spread and the benchmark half spread. The benchmark is the equal-weighted average half spread over the previous 21 days for bonds matched on credit rating, trade size, and trade direction.	daily	Mergent FISD, TRACE
$h_{d-5,d-1,Buy}$ (%)	Average daily abnormal half spread from the customer buy side over trading days $d-5$ to $d-1$	daily	Mergent FISD, TRACE
$h_{d-5,d-1,Sell}$ (%)	Average daily abnormal half spread from the customer sell side over trading days $d-5$ to $d-1$	daily	Mergent FISD, TRACE

Table A1, Continued

Variable	Definition	Frequency	Data Source
$\overline{Vol}_{d-5,d-1,Buy}$ (%)	Average daily customer buy volume over days $d-5$ to $d-1$	daily	Mergent FISD, TRACE
$\overline{Vol}_{d-5,d-1,Sell}$ (%)	Average daily customer sell volume over days $d-5$ to $d-1$	daily	Mergent FISD, TRACE
Loan Quantity (%)	Quantity on loan from Markit divided by the amount outstanding from Mergent FISD	daily, monthly, quarterly	Markit, Mergent FISD
Lendable Supply (%)	Active lendable quantity from Markit divided by the amount outstanding	daily, monthly, quarterly	Markit, Mergent FISD
Utilization Rate (%)	Ratio of the quantity on loan to the lendable quantity	daily, monthly, quarterly	Markit
Loan Tenure (days)	Average number of days that bond loans have been open	monthly, quarterly	Markit
Borrowing Fee (%)	Buy-side fee paid by the ultimate borrower ("IndicativeFee" in Markit)	monthly, quarterly	Markit
Rebate Rate (%)	Interest rate paid to borrowers on cash collateral net of lending fees ("IndicativeRebate" in Markit)	monthly, quarterly	Markit
DCBS	Cost of borrow score provided by Markit, ranging from 1 (low cost) to 10 (high cost)	monthly, quarterly	Markit
Fee Risk	Natural logarithm of within-period borrowing fee standard deviation	monthly, quarterly	Markit
Recall Risk	Natural logarithm of within-period utilization rate standard deviation	monthly, quarterly	Markit
Lender Concentration	Herfindahl index measuring bond-level lender concentration	monthly, quarterly	Markit
Special	Indicator variable equal to one for securities with high borrowing costs (top decile of cross-sectional distribution for corporate bonds, above 1% annualized fee for equities), zero for general collateral	daily, monthly, quarterly	Markit

Table A1, Continued

Variable	Definition	Frequency	Data Source
Credit Spread (%)	Average credit spread, defined as the difference between corporate bond yield and matched Treasury yield over the period	monthly, quarterly	TRACE
OIMB (%)	Order imbalance, defined as the quarterly sum of customer buy volume minus the quarterly sum of customer sell volume scaled by the bond amount outstanding	quarterly	Mergent FISD, TRACE
Net OIMB (%)	Order imbalance minus changes in index fund ownership	quarterly	Mergent FISD, TRACE, Morningstar
Passive Fund (%)	Share of bonds held by index funds and ETFs	monthly, quarterly	Morningstar
ETF (%)	Share of bonds held by ETFs	quarterly	Morningstar
Index Fund (%)	Share of bonds held by index funds	quarterly	Morningstar
Active Fund (%)	Share of bonds held by actively managed mutual funds	monthly, quarterly	Morningstar
Insurer (%)	Share of bonds held by insurance firms	monthly, quarterly	eMAXX
Amount ($ mil)	Amount of bonds outstanding in millions of dollars	daily, monthly, quarterly	Mergent FISD
Rating	Numerical rating score, where 1 refers to AAA/Aaa and 21 refers to C rating for both S&P and Moody's	daily, monthly, quarterly	Mergent FISD
Age (years)	Age of a bond in years since issuance	daily, monthly, quarterly	Mergent FISD
Maturity (years)	Time to maturity in years	daily, monthly, quarterly	Mergent FISD
ZTD (%)	Percentage of zero trading days in a given quarter	quarterly	TRACE

B Additional Results

B.1 Availability of CDS

In Table B1, we study the effect of the availability of CDS and stocks issued by the bond issuer by including the corresponding dummy variables and interactions between the dummy and trading volume in equation (7). We find that these additional terms have small coefficient estimates, implying that the availability of these alternative financial instruments does not affect the results. Although the availability of alternatives would have a strong explanatory power if short sales were conducted for speculation, our empirical test shows otherwise.

B.2 Multivariate Analysis of Bond Returns

We confirm the positive link between increased short sales and returns documented in Section 3.3 using multivariate regression. Specifically, we regress cumulative bond returns from d^*+1 to d^*+5 on the daily change in quantity on loan and the same set of control variables as in equation (7):

$$\begin{aligned} CumRet_{i,d^*+1,d^*+5} = {} & b_0 dQ_{i,d} + b_1 \overline{dQ}_{i,d-5,d-1} + b_2 \overline{Vol}_{i,d^*-5,d^*-1,Buy} \\ & + b_3 \overline{Vol}_{i,d^*-5,d^*-1,Sell} + b_4 \bar{h}_{i,d^*-5,d^*-1,Buy} \\ & + b_5 \bar{h}_{i,d^*-5,d^*-1,Sell} + b_6 \sigma_{i,d^*-5,d^*-1} + b_7 \bar{r}_{i,d^*-5,d^*-1} \\ & + b_8 dQ^{Stock}_{i,d} + b_9 \overline{dQ}^{Stock}_{i,d-5,d-1} + \gamma_d + \alpha_i + Ctrl_{i,d} + \varepsilon_{i,d}. \end{aligned} \tag{B1}$$

Table B2 reports the estimates on the return forecasting regression. Our interest is in the loading on changes in quantity on loan, b_0, which is positive and highly significant at 1.42 bps ($t = 11.16$) in Column (1). Across the five specifications, the estimates range from 1.42 bps to 1.49 bps, all significantly positive, indicating that increased bond lending predicts higher subsequent bond returns. In stark contrast, the coefficient on stock lending in Column (4) is negative and significant at -1.60 bps ($t = -3.75$), consistent with the notion that stocks are mainly borrowed by hedge funds that possess negative information on the issuing firm (e.g., Boehmer, Jones, and Zhang 2008).

B.3 Multivariate analysis of Bond Trading Volume

Table B3 presents the results from estimating equation (16). The coefficients from this regression are used in Table 4.

B.4 Dealer Share from Univariate Regression Estimates

Table B4 shows the estimated dealer share (similar to those in Table 4) when we estimate univariate regressions instead of equation (16).

B.5 Sub-sample Results

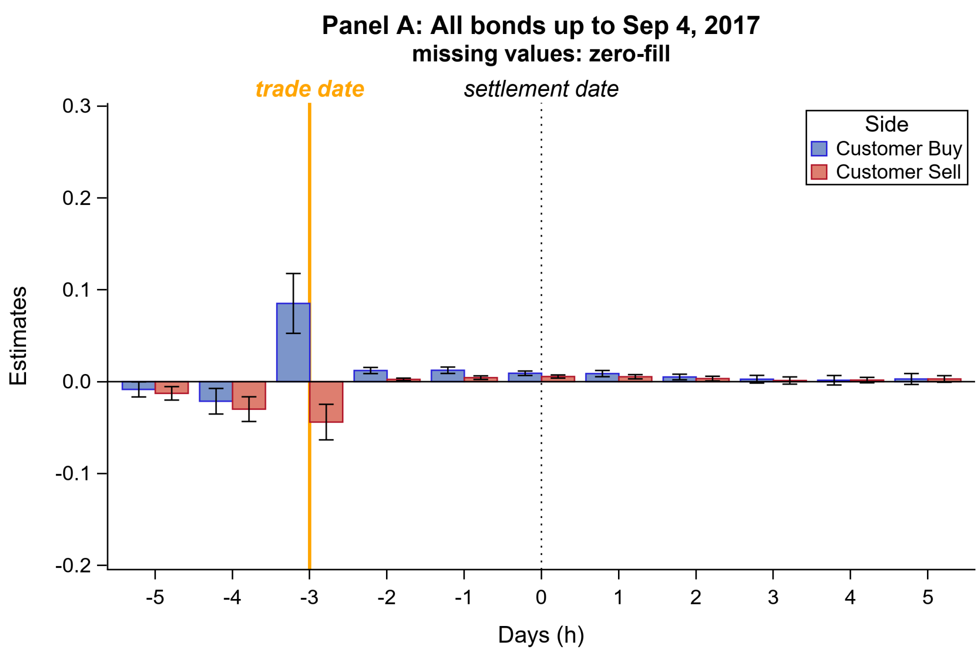
Table B5 presents the results of Table 4, splitting the sample before and after September 4, 2017.

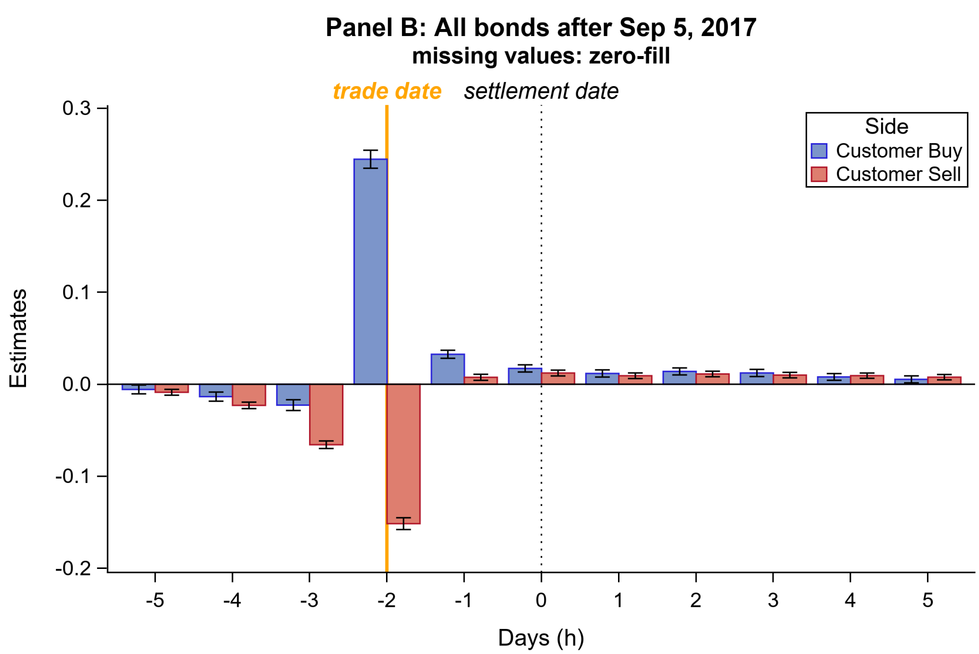
B.6 Results with Interpolated Data

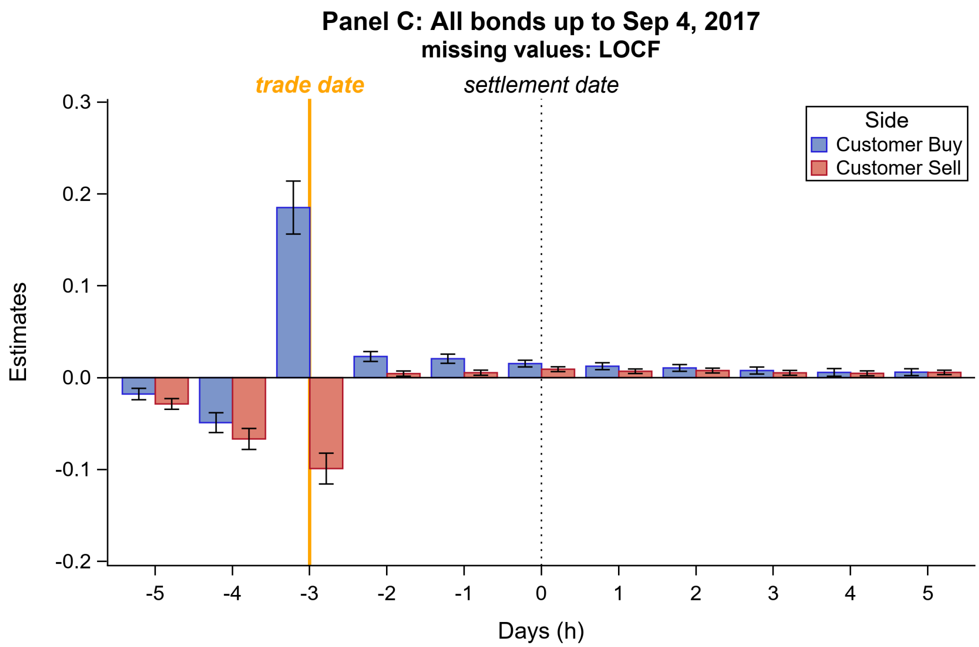
We consider two approaches to replacing missing data with interpolated values. (1) zero-fill, assuming no lending activity, and (2) last observation carried forward (LOCF), assuming persistence in prior lending levels. Gaps exceeding 21 trading days are left missing. Missing borrowing fees within 21-day gaps are always interpolated using LOCF. Tables B6 and B7 report the main results of Table 4 using these two approaches, respectively. We also replicate results in Figure 1 using the two interpolation methods and present these results in Figure B1.

Figure B1: Robustness of Panel Regression of Dollar Trading Volume on Changes in Quantity on Loan

The figure plots the slope coefficients of the panel regression of dealer-customer trading volume on day $d+h$ on day d changes in quantity on loan as in Figure 1 except that we replace missing values with interpolated numbers. Panels A1 and B1 use zero-fill interpolation for missing loan quantities, while Panels A2 and B2 use last-observation-carried-forward (LOCF) interpolation. Panels A1 and A2 cover the period up to September 4, 2017, and Panels B1 and B2 cover the period after September 5, 2017.






Panel C: All bonds up to Sep 4, 2017
missing values: LOCF
trade date
settlement date
Side
Customer Buy
Customer Sell
Estimates
0.3
0.2
0.1
0.0
-0.1
-0.2
-5
-4
-3
-2
-1
0
1
2
3
4
5
Days (h)

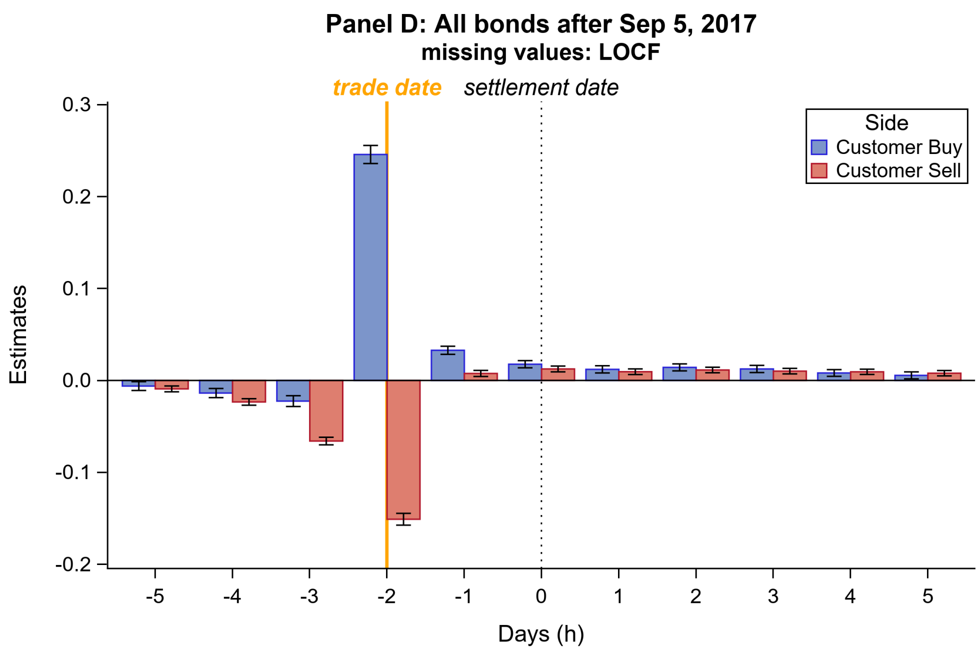

Panel D: All bonds after Sep 5, 2017
missing values: LOCF
trade date
settlement date
Side
Customer Buy
Customer Sell
Estimates
0.3
0.2
0.1
0.0
-0.1
-0.2
-5
-4
-3
-2
-1
0
1
2
3
4
5
Days (h)

Table B1: Panel Regression of Daily Changes in Quantity on Loan: CDS Coverage and Public Status

This table presents panel regression estimates examining changes in bond loan quantities as in Table 3 except that we include interaction terms for CDS coverage and public firm indicators. The sample includes bonds issued by both public and private firms, where public (private) firms are identified as those with (without) valid PERMNO identifiers in the Bond-CRSP link table from WRDS, and a bond is considered CDS-covered if its issuer has outstanding CDS contracts in the Markit database at day d^*. Columns (1)-(3) examine CDS interactions, while columns (4)-(6) examine public firm interactions. Columns (1) and (4) report baseline specifications with customer buy and sell volumes and their respective interactions with CDS coverage indicators or public firm dummies. Columns (2) and (5) augment the baseline model with control variables identical to those in Table 3, excluding daily changes in stock loan quantities. Columns (3) and (6) extend the analysis by incorporating interaction terms between the CDS/PUB indicators and all control variables. All explanatory variables are standardized to have zero mean and unit variance. All specifications include bond and date fixed effects with standard errors double-clustered by bond and date, and t-statistics are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$Vol_{d^*,Buy}$	0.0425^{***}	0.0446^{***}	0.0445^{***}	0.0395^{***}	0.0413^{***}	0.0411^{***}
	(90.69)	(93.48)	(92.60)	(36.29)	(37.43)	(36.69)
$Vol_{d^*,Sell}$	-0.0383^{***}	-0.0376^{***}	-0.0377^{***}	-0.0362^{***}	-0.0351^{***}	-0.0352^{***}
	(−95.30)	(−93.99)	(−94.34)	(−37.69)	(−36.40)	(−36.88)
$CDS \times Vol_{d^*,Buy}$	0.0000	−0.0000	0.0003			
	(0.08)	(−0.04)	(0.47)			
$CDS \times Vol_{d^*,Sell}$	−0.0004	−0.0004	−0.0003			
	(−0.82)	(−0.79)	(−0.62)			
CDS	−0.0002	−0.0003	−0.0004			
	(−0.58)	(−0.77)	(−0.94)			
$PUB \times Vol_{d^*,Buy}$				0.0033^{***}	0.0035^{***}	0.0037^{***}
				(3.05)	(3.18)	(3.26)
$PUB \times Vol_{d^*,Sell}$				-0.0025^{***}	-0.0029^{***}	-0.0028^{***}
				(−2.59)	(−2.99)	(−2.91)
PUB				0.0003	0.0000	−0.0003
				(0.68)	(0.06)	(−0.60)
Controls	No	Yes	Yes	No	Yes	Yes
CDS/PUB × Controls	No	No	Yes	No	No	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,341,920	11,341,920	11,341,920	11,341,920	11,341,920	11,341,920
Adjusted R^2	0.048	0.057	0.057	0.048	0.057	0.057

Table B2: Panel Regression of Future Returns on Changes in Quantity on Loan
This table reports the estimates from the panel regression of cumulative bond returns from d^*+1 to d^*+5 for all bonds, as specified in equation (B1). The explanatory variables include the daily change in quantity on loan, dQ_d, and the same set of control variables as in Table 3. To account for the gap between trade date d^* and settlement date d, we set $d^* = d - s$, where s equals 3 if d occurs on or before September 4, 2017, and 2 thereafter. Bond controls include the natural logarithm of the amount outstanding, credit ratings, and time to maturity. The variables on the right-hand side are standardized so that they have a mean of zero and a standard deviation of one. We include bond and date fixed effects in each regression specification. We double cluster standard errors by bond and date, and t-statistics are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
dQ_d	0.0142^{***}	0.0149^{***}	0.0148^{***}	0.0142^{***}	0.0148^{***}
	(11.17)	(11.28)	(11.12)	(11.26)	(11.18)
$\overline{dQ}_{d-5,d-1}$		0.0109^{***}	0.0062^{***}		0.0059^{***}
		(6.71)	(3.73)		(3.61)
$\overline{Vol}_{d^*-5,d^*-1,Buy}$			0.0262^{***}		0.0258^{***}
			(10.80)		(10.44)
$\overline{Vol}_{d^*-5,d^*-1,Sell}$			-0.0227^{***}		-0.0224^{***}
			(-9.58)		(-9.34)
$\bar{h}_{d^*-5,d^*-1,Buy}$			0.0267^{***}		0.0247^{***}
			(3.96)		(4.08)
$\bar{h}_{d^*-5,d^*-1,Sell}$			0.0133^{**}		0.0161^{***}
			(2.05)		(2.99)
σ_{d^*-5,d^*-1}			0.1007^{***}		0.0996^{***}
			(4.08)		(3.93)
$\bar{r}_{d^*-5,d^*-1}$				0.0223	0.0172
				(0.99)	(0.74)
dQ_d^{Stock}				-0.0160^{***}	-0.0152^{***}
				(-3.75)	(-3.56)
$\overline{dQ}_{d-5,d-1}^{Stock}$				-0.0073	-0.0067
				(-1.26)	(-1.17)
Bond Controls	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Observations	10,409,033	10,409,033	10,409,033	10,409,033	10,409,033
Adjusted R^2	0.232	0.232	0.234	0.232	0.234

Table B3: Panel Regression of Daily Trading Volume on *dQ*

This table reports the estimates from panel regressions in which the dependent variables are daily customer buy and sell trading volumes scaled by amount outstanding ($Vol_{d^*,Buy}$ and $Vol_{d^*,Sell}$, respectively). The key explanatory variable is the change in the quantity on loan dQ_d on the settlement date d. Additional right-hand variables and sample construction are the same as in Table 3. To account for the gap between trade date d^* and settlement date d, we set $d^* = d - s$, where s equals 3 if d occurs on or before September 4, 2017, and 2 thereafter. Bond controls include the natural logarithm of the amount outstanding, credit ratings, and time to maturity. We include bond and date fixed effects in each regression specification. We double cluster standard errors by bond and date, and t-statistics are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	$Vol_{d^*,Buy}$				$Vol_{d^*,Sell}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
dQ_d	0.235***	0.241***	0.253***	0.252***	−0.136***	−0.135***	−0.129***	−0.129***
	(57.23)	(58.91)	(61.10)	(61.09)	(−47.58)	(−46.75)	(−45.71)	(−45.65)
$\overline{dQ}_{d-5,d-1}$		0.149***	0.161***	0.162***		0.037***	0.044***	0.043***
		(39.47)	(49.06)	(49.13)		(13.96)	(18.09)	(17.93)
$\overline{Vol}_{d^*-5,d^*-1,Buy}$			0.185***	0.185***			0.092***	0.092***
			(58.60)	(58.48)			(65.44)	(65.11)
$\overline{Vol}_{d^*-5,d^*-1,Sell}$			0.263***	0.263***			0.133***	0.133***
			(101.21)	(101.20)			(74.46)	(74.66)
$\bar{h}_{d^*-5,d^*-1,Buy}$			−0.005***	−0.005***			−0.003***	−0.003***
			(−14.38)	(−12.37)			(−9.82)	(−9.06)
$\bar{h}_{d^*-5,d^*-1,Sell}$			0.001*	−0.001			−0.002***	−0.002***
			(1.88)	(−1.39)			(−8.85)	(−9.00)
σ_{d^*-5,d^*-1}			0.015***	0.015***			0.014***	0.014***
			(9.21)	(10.25)			(10.44)	(10.72)
r_{d^*}				0.012***				0.005***
				(9.67)				(6.02)
$\bar{r}_{d^*-5,d^*-1}$				−0.017***				−0.002
				(−9.80)				(−1.37)
dQ_d^{Stock}				0.001				0.002**
				(1.31)				(2.02)
$\overline{dQ}_{d-5,d-1}^{Stock}$				0.008***				0.007***
				(3.99)				(3.94)
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,447,842	10,447,842	10,447,842	10,447,842	10,447,842	10,447,842	10,447,842	10,447,842
Adjusted R^2	0.092	0.093	0.138	0.139	0.066	0.066	0.087	0.087

Table B4: Customer and Dealer Shares in Daily Changes in Loan Quantity: Univariate Regressions

This table reports estimates of customer and dealer shares in daily changes in bond loan quantities, similar to those in Table 4, except that we use univariate regressions to estimate β_ξ. We double cluster standard errors by bond and date, and t-statistics are in parentheses. The sample period spans September 12, 2006 to December 30, 2022. Unlike Table 4, this sample requires only trading volumes and dQ rather than the full control set and does not impose the 252-observation minimum.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel A: Whole Sample						
All	−0.114	0.205	−0.320	0.340	0.660	19,760,148
	(−17.49)	(18.32)	(−18.41)	(39.20)	(76.02)	
Panel B: By Credit Rating						
IG	−0.122	0.217	−0.339	0.330	0.670	15,838,462
	(−13.20)	(13.57)	(−13.59)	(26.49)	(53.68)	
HY	−0.098	0.180	−0.278	0.361	0.639	3,849,681
	(−26.37)	(33.41)	(−36.35)	(94.42)	(167.12)	
Panel C: By Collateral Specialness						
GC	−0.118	0.225	−0.343	0.328	0.672	18,078,758
	(−16.26)	(17.05)	(−17.06)	(32.61)	(66.72)	
SC1	−0.074	0.137	−0.211	0.395	0.605	779,493
	(−13.83)	(17.16)	(−24.04)	(89.96)	(138.05)	
SC2	−0.079	0.038	−0.116	0.442	0.558	728,314
	(−13.11)	(5.47)	(−16.63)	(126.14)	(159.40)	
SC3	−0.114	−0.085	−0.029	0.486	0.514	173,583
	(−9.70)	(−6.74)	(−3.32)	(111.65)	(118.28)	
Panel D: By Public Status						
Public Firm	−0.117	0.209	−0.326	0.337	0.663	18,329,642
	(−17.55)	(18.40)	(−18.48)	(38.20)	(75.16)	
Private Firm	−0.086	0.153	−0.239	0.380	0.620	1,430,506
	(−12.39)	(13.51)	(−14.38)	(45.77)	(74.54)	

Table 4, Continued.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel E: By CDS Coverage						
Yes	−0.112	0.206	−0.318	0.341	0.659	10,063,123
	(−16.58)	(17.38)	(−17.53)	(37.52)	(72.58)	
No	−0.117	0.204	−0.321	0.340	0.660	9,697,025
	(−17.73)	(18.82)	(−18.93)	(40.05)	(77.90)	
Panel F: By Expensiveness						
Overvalued	−0.154	0.192	−0.346	0.327	0.673	8,508,050
	(−20.55)	(21.18)	(−21.53)	(40.66)	(83.72)	
Undervalued	−0.103	0.224	−0.327	0.337	0.663	8,491,350
	(−19.37)	(21.12)	(−21.39)	(44.10)	(86.89)	
Panel G: By Issuance Size						
Large	−0.122	0.237	−0.359	0.321	0.679	9,252,010
	(−23.97)	(26.15)	(−26.54)	(47.47)	(100.55)	
Small	−0.106	0.168	−0.274	0.363	0.637	10,508,138
	(−12.70)	(13.18)	(−13.22)	(35.00)	(61.44)	
Panel H: By Bid-ask Spread						
Illiquid	−0.115	0.203	−0.317	0.341	0.659	8,437,248
	(−21.55)	(22.81)	(−23.35)	(50.27)	(96.96)	
Liquid	−0.133	0.247	−0.380	0.310	0.690	8,426,423
	(−30.12)	(33.83)	(−35.27)	(57.54)	(128.08)	

Table B5: Customer and Dealer Shares in Daily Changes in Loan Quantity: Sub-periods

This table reports estimates of customer and dealer shares in daily changes in bond loan quantities as in Table 4 except that we present results for two subperiods: September 12, 2006 to September 4, 2017 (Panels A1 through H1) and September 5, 2017 to December 30, 2022 (Panels A2 through H2). We double cluster standard errors by bond and date, and t-statistics are in parentheses.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Period 1: 2006.09.12 – 2017.09.04						
Panel A1: Whole Sample						
All	−0.114	0.249	−0.363	0.319	0.681	6,272,862
	(−27.41)	(36.63)	(−36.61)	(64.27)	(137.50)	
Panel B1: By Credit Rating						
IG	−0.132	0.284	−0.416	0.292	0.708	4,643,613
	(−24.30)	(30.63)	(−30.45)	(42.83)	(103.74)	
HY	−0.088	0.196	−0.284	0.358	0.642	1,629,249
	(−18.50)	(28.57)	(−29.89)	(75.38)	(135.16)	
Panel C1: By Collateral Specialness						
GC	−0.123	0.280	−0.403	0.299	0.701	5,819,191
	(−27.28)	(37.33)	(−36.88)	(54.71)	(128.48)	
SC1	−0.062	0.137	−0.200	0.400	0.600	181,174
	(−8.08)	(11.74)	(−15.53)	(62.27)	(93.33)	
SC2	−0.061	0.066	−0.127	0.437	0.563	221,169
	(−8.37)	(7.53)	(−15.47)	(106.67)	(137.62)	
SC3	−0.081	−0.048	−0.033	0.484	0.516	51,328
	(−5.97)	(−3.78)	(−3.15)	(93.12)	(99.42)	
Panel D1: By Public Status						
Public Firm	−0.117	0.251	−0.369	0.316	0.684	5,890,282
	(−27.67)	(36.91)	(−36.95)	(63.32)	(137.23)	
Private Firm	−0.080	0.215	−0.295	0.353	0.647	382,580
	(−9.63)	(16.35)	(−17.84)	(42.73)	(78.41)	

Table B5, Continued.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Period 1: 2006.09.12 – 2017.09.04						
Panel E1: By CDS Coverage						
Yes	−0.114	0.246	−0.360	0.320	0.680	3,471,933
	(−24.08)	(31.89)	(−32.33)	(57.45)	(122.11)	
No	−0.115	0.252	−0.367	0.316	0.684	2,800,929
	(−23.61)	(35.22)	(−35.24)	(60.77)	(131.24)	
Panel F1: By Expensiveness						
Overvalued	−0.156	0.236	−0.391	0.304	0.696	3,192,993
	(−29.86)	(34.91)	(−37.51)	(58.35)	(133.36)	
Undervalued	−0.087	0.257	−0.344	0.328	0.672	3,055,335
	(−20.90)	(31.80)	(−31.73)	(60.56)	(124.01)	
Panel G1: By Issuance Size						
Large	−0.116	0.266	−0.382	0.309	0.691	3,927,777
	(−25.43)	(35.22)	(−34.72)	(56.25)	(125.69)	
Small	−0.110	0.216	−0.326	0.337	0.663	2,345,085
	(−20.31)	(27.11)	(−28.68)	(59.42)	(116.78)	
Panel H1: By Bid-ask Spread						
Illiquid	−0.099	0.226	−0.324	0.338	0.662	3,432,523
	(−22.26)	(29.69)	(−30.06)	(62.60)	(122.71)	
Liquid	−0.134	0.279	−0.412	0.294	0.706	2,741,820
	(−28.53)	(40.72)	(−42.27)	(60.23)	(144.77)	

Table B5, Continued.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Period 2: 2017.09.05 – 2022.12.30						
Panel A2: Whole Sample						
All	−0.136	0.248	−0.385	0.308	0.692	5,069,058
	(−41.03)	(56.44)	(−70.95)	(113.48)	(255.37)	
Panel B2: By Credit Rating						
IG	−0.156	0.262	−0.419	0.291	0.709	4,165,941
	(−43.74)	(54.58)	(−72.99)	(101.32)	(247.30)	
HY	−0.090	0.214	−0.304	0.348	0.652	903,117
	(−18.33)	(35.61)	(−38.90)	(88.94)	(166.74)	
Panel C2: By Collateral Specialness						
GC	−0.146	0.267	−0.413	0.294	0.706	4,724,767
	(−43.47)	(59.04)	(−75.64)	(107.63)	(258.90)	
SC1	−0.055	0.176	−0.231	0.385	0.615	208,646
	(−7.65)	(20.34)	(−25.31)	(84.35)	(134.96)	
SC2	−0.067	0.069	−0.136	0.432	0.568	109,010
	(−7.25)	(6.29)	(−15.07)	(95.97)	(126.11)	
SC3	−0.107	−0.031	−0.076	0.462	0.538	26,635
	(−7.61)	(−1.80)	(−5.22)	(63.24)	(73.68)	
Panel D2: By Public Status						
Public Firm	−0.136	0.248	−0.384	0.308	0.692	4,767,702
	(−40.34)	(55.91)	(−70.19)	(112.42)	(252.79)	
Private Firm	−0.141	0.250	−0.392	0.304	0.696	301,356
	(−16.48)	(21.01)	(−24.59)	(38.20)	(87.38)	

Table B5, Continued.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Period 2: 2017.09.05 – 2022.12.30						
Panel E2: By CDS Coverage						
Yes	−0.135	0.253	−0.388	0.306	0.694	2,578,650
	(−33.84)	(50.59)	(−62.47)	(98.52)	(223.47)	
No	−0.138	0.243	−0.381	0.309	0.691	2,490,408
	(−33.90)	(49.33)	(−57.07)	(92.71)	(206.85)	
Panel F2: By Expensiveness						
Overvalued	−0.177	0.236	−0.413	0.293	0.707	2,895,644
	(−46.29)	(46.62)	(−64.34)	(91.44)	(220.12)	
Undervalued	−0.102	0.258	−0.360	0.320	0.680	2,169,709
	(−27.70)	(51.39)	(−60.71)	(107.72)	(229.15)	
Panel G2: By Issuance Size						
Large	−0.137	0.261	−0.398	0.301	0.699	3,054,208
	(−37.81)	(56.45)	(−68.13)	(103.01)	(239.28)	
Small	−0.134	0.227	−0.361	0.319	0.681	2,014,850
	(−28.79)	(40.50)	(−48.84)	(86.27)	(183.94)	
Panel H2: By Bid-ask Spread						
Illiquid	−0.117	0.236	−0.352	0.324	0.676	2,608,033
	(−31.34)	(48.24)	(−57.74)	(106.19)	(221.67)	
Liquid	−0.159	0.264	−0.424	0.288	0.712	2,391,422
	(−42.32)	(53.88)	(−73.64)	(100.23)	(247.51)	

Table B6: Customer and Dealer Shares in Daily Changes in Loan Quantity: Zero-fill Interpolation

This table reports estimates of customer and dealer shares in daily changes in bond loan quantities as in Table 4, except that we use data in which missing loan quantities are interpolated using the zero-fill method, assuming no lending activity during short gaps. Missing values are interpolated only when gaps between adjacent valid observations do not exceed 21 trading days. Gaps longer than 21 trading days are left missing. Missing borrowing fees within 21-day gaps are always interpolated using the last observation carried forward (LOCF) method. We double cluster standard errors by bond and date, and t-statistics are reported in parentheses. The sample period spans September 12, 2006 to December 30, 2022.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel A: Whole Sample						
All	−0.086	0.183	−0.269	0.365	0.635	11,703,646
	(−6.21)	(7.13)	(−6.83)	(18.52)	(32.17)	
Panel B: By Credit Rating						
IG	−0.104	0.208	−0.312	0.344	0.656	9,092,877
	(−8.28)	(8.81)	(−8.66)	(19.05)	(36.37)	
HY	−0.057	0.144	−0.200	0.400	0.600	2,610,769
	(−4.05)	(5.41)	(−4.98)	(19.89)	(29.84)	
Panel C: By Collateral Specialness						
GC	−0.095	0.208	−0.303	0.349	0.651	10,885,390
	(−7.31)	(8.23)	(−7.95)	(18.29)	(34.18)	
SC1	−0.039	0.104	−0.143	0.429	0.571	397,967
	(−3.36)	(3.59)	(−3.59)	(21.54)	(28.72)	
SC2	−0.034	0.046	−0.081	0.460	0.540	340,070
	(−2.68)	(4.97)	(−3.94)	(44.83)	(52.72)	
SC3	−0.045	−0.019	−0.026	0.487	0.513	80,219
	(−2.49)	(−1.77)	(−2.79)	(104.26)	(109.85)	
Panel D: By Public Status						
Public Firm	−0.088	0.186	−0.274	0.363	0.637	10,991,234
	(−6.38)	(7.28)	(−6.99)	(18.52)	(32.49)	
Private Firm	−0.059	0.152	−0.211	0.394	0.606	712,412
	(−3.95)	(5.33)	(−4.94)	(18.44)	(28.32)	

Table B6, Continued.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel E: By CDS Coverage						
Yes	−0.081	0.176	−0.257	0.372	0.628	6,232,810
	(−5.30)	(6.20)	(−5.91)	(17.10)	(28.91)	
No	−0.093	0.194	−0.287	0.356	0.644	5,470,836
	(−7.94)	(8.89)	(−8.61)	(21.34)	(38.55)	
Panel F: By Expensiveness						
Overvalued	−0.131	0.193	−0.324	0.338	0.662	6,279,372
	(−11.12)	(11.73)	(−11.56)	(24.17)	(47.30)	
Undervalued	−0.059	0.177	−0.236	0.382	0.618	5,394,645
	(−4.69)	(5.69)	(−5.42)	(17.55)	(28.40)	
Panel G: By Issuance Size						
Large	−0.089	0.198	−0.287	0.356	0.644	7,194,440
	(−6.58)	(7.57)	(−7.26)	(18.02)	(32.54)	
Small	−0.080	0.157	−0.237	0.381	0.619	4,509,206
	(−5.47)	(6.30)	(−6.03)	(19.40)	(31.47)	
Panel H: By Bid-ask Spread						
Illiquid	−0.071	0.163	−0.234	0.383	0.617	6,254,929
	(−5.61)	(6.46)	(−6.20)	(20.35)	(32.75)	
Liquid	−0.107	0.214	−0.321	0.339	0.661	5,270,027
	(−7.04)	(8.19)	(−7.81)	(16.51)	(32.13)	

Table B7: Customer and Dealer Shares in Daily Changes in Loan Quantity: LOCF Interpolation

This table reports estimates of customer and dealer shares in daily changes in bond loan quantities as in Table 4 except that we use data in which missing loan quantities and borrowing fees are interpolated using the last observation carried forward (LOCF) method, assuming persistence in prior lending levels during short gaps. Missing values are interpolated only when gaps between adjacent valid observations do not exceed 21 trading days. Gaps longer than 21 trading days are left missing. We double cluster standard errors by bond and date, and t-statistics are reported in parentheses. The sample period spans September 12, 2006 to December 30, 2022.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel A: Whole Sample						
All	−0.120	0.250	−0.370	0.315	0.685	11,703,646
	(−35.99)	(51.18)	(−50.11)	(85.36)	(185.57)	
Panel B: By Credit Rating						
IG	−0.139	0.277	−0.416	0.292	0.708	9,092,877
	(−35.80)	(46.15)	(−46.25)	(65.03)	(157.52)	
HY	−0.086	0.204	−0.289	0.355	0.645	2,610,769
	(−21.66)	(37.20)	(−36.62)	(89.93)	(163.17)	
Panel C: By Collateral Specialness						
GC	−0.128	0.276	−0.405	0.298	0.702	10,885,390
	(−37.14)	(52.56)	(−51.54)	(75.76)	(178.85)	
SC1	−0.058	0.154	−0.212	0.394	0.606	397,967
	(−10.97)	(18.34)	(−24.03)	(89.19)	(137.25)	
SC2	−0.060	0.069	−0.128	0.436	0.564	340,070
	(−9.55)	(9.86)	(−19.32)	(131.07)	(169.70)	
SC3	−0.086	−0.040	−0.045	0.477	0.523	80,219
	(−7.36)	(−3.65)	(−4.89)	(102.98)	(112.77)	
Panel D: By Public Status						
Public Firm	−0.121	0.252	−0.373	0.313	0.687	10,991,234
	(−36.35)	(51.60)	(−50.63)	(84.98)	(186.23)	
Private Firm	−0.093	0.228	−0.321	0.340	0.660	712,412
	(−13.07)	(21.78)	(−23.25)	(49.25)	(95.75)	

Table B7, Continued.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel E: By CDS Coverage						
Yes	−0.118	0.251	−0.369	0.316	0.684	6,232,810
	(−30.86)	(44.88)	(−44.14)	(75.55)	(163.82)	
No	−0.121	0.250	−0.371	0.314	0.686	5,470,836
	(−33.25)	(48.94)	(−48.73)	(82.44)	(179.89)	
Panel F: By Expensiveness						
Overvalued	−0.162	0.238	−0.400	0.300	0.700	6,279,372
	(−44.59)	(51.45)	(−56.53)	(84.72)	(197.78)	
Undervalued	−0.089	0.258	−0.348	0.326	0.674	5,394,645
	(−25.82)	(42.73)	(−41.17)	(77.23)	(159.57)	
Panel G: By Issuance Size						
Large	−0.121	0.265	−0.386	0.307	0.693	7,194,440
	(−33.64)	(50.15)	(−48.46)	(77.02)	(173.94)	
Small	−0.116	0.222	−0.338	0.331	0.669	4,509,206
	(−28.21)	(38.13)	(−39.59)	(77.39)	(156.58)	
Panel H: By Bid–Ask Spread						
Illiquid	−0.103	0.231	−0.334	0.333	0.667	6,254,929
	(−30.52)	(41.59)	(−41.91)	(83.56)	(167.38)	
Liquid	−0.140	0.275	−0.415	0.292	0.708	5,270,027
	(−36.17)	(56.83)	(−56.11)	(79.08)	(191.29)	

C Further Details and Results on Passive Ownership

C.1 Quarterly Bond Sample Construction

The Markit sample, after applying the filters described in Section 2.1, contains 300,282 bond-quarter observations for 17,363 bonds issued by 1,709 firms over 66 quarters from 2006 Q3 to 2022 Q4. We take the average of the daily lending variables within each bond-quarter observation to construct the quarterly panel used in this section.

To construct the holdings dataset, we begin with dollar-denominated bonds issued by U.S. firms in the Mergent FISD database. We restrict the sample to corporate bonds that have at least one recorded transaction in the Enhanced TRACE database to ensure data availability and market activity. Mutual fund and exchange-traded fund (ETF) holdings are sourced from Morningstar, which provides comprehensive coverage of portfolio holdings across asset classes, including bonds, preferred stocks, equities, futures, options, and cash. We identify ETFs using Morningstar's ETF flag and classify index funds following the methodology of Berk and Van Binsbergen (2015) and Dannhauser and Dathan (2023).[20]

In our analysis, we define passive funds as either index mutual funds or ETFs, excluding leveraged or inverse products.[21] The reporting frequency of fund holdings varies across funds, particularly in the earlier part of the sample period. To address reporting inconsistencies, we impute missing monthly fund holdings using the nearest available observations.[22] When no data are available for all months within a quarter, we assign a holding value of zero to reflect the most plausible scenario. To ensure that we capture a comprehensive representation of institutional bond ownership, we include holdings from all passive and active funds, including funds that are not exclusively dedicated to corporate bonds.

We obtain insurance company holdings data from the Thomson Reuters eMAXX database, which provides fixed-income holdings at a quarterly frequency.[23] To ensure data accuracy, we identify and remove duplicate observations, which may arise for two reasons.

[20] We first identify index funds using Morningstar's index fund flag. Then, we further classify funds as index funds if the fund name contains indicators such as "DOW," "DJ," or the lowercase version includes keywords such as "index," "idx," "msci," "ishare," or numerical index identifier (e.g., "100," "500," "1000," "2000"). We exclude enhanced index funds and target-date funds misclassified as index funds when names include terms such as "select," "adv," "hedge," "manage," "enhance," or specific vintage years.

[21] Inverse and leveraged funds are identified if the lowercase version of fund names contains any of the following strings: plus, enhanced, inverse, ultra, 1.5x, 2.5x, 2x, 3x, 4x, or 5x.

[22] Suppose a fund reports a holding of 3,024 (in thousands) in March 2017, missing in April and May, and 3,040 in June. The missing value for April is filled with 3,024, and the missing value for May with 3,040. If July is also missing, we impute 3,040. This procedure ensures completeness in monthly regressions without materially affecting quarterly data, except when a fund reports only in non-quarter-end months, in which case quarter-end values are derived accordingly.

[23] The eMAXX version used in our analysis covers fixed-income holdings data for North America.

First, eMAXX reports holdings based on disclosure timing. For example, a fund's holdings as of 2002 Q4 may be reported in 2003 Q1, 2003 Q2, or both. As a result, identical bond holdings data can appear in multiple reporting quarters. To address this issue, we retain only the earliest available report for each bond-quarter-fund-managing firm pair. In the example above, we keep the holdings reported in 2003 Q1 and discard the duplicate entry from 2003 Q2.

Second, duplicate entries can arise from co-managed funds, where multiple managing firms oversee a single fund's portfolio. In such cases, eMAXX records separate entries for each managing firm, in addition to an aggregated entry for the fund's total holdings.[24] To prevent double counting, we eliminate redundant observations associated with co-managed funds.

We integrate holdings from Morningstar and eMAXX to construct our bond ownership variables. Holdings are aggregated across investor types at the bond level each month, and quarter-end values are used in the analysis. Missing insurance holdings are imputed using the nearest available data. We exclude cases in which total investor holdings exceed the bond's amount outstanding. Finally, we normalize holdings by the bond's amount outstanding for active funds, passive funds, and insurance companies.

Before merging with the IHS Markit bond lending data, the holdings sample contains 2,423,423 bond-month observations for 55,517 bonds from July 2006 to December 2022. After merging quarterly bond lending data with monthly holdings, the baseline dataset contains 297,693 bond-quarter observations for 17,140 bonds issued by 1,705 firms from 2006 Q3 to 2022 Q4. To mitigate the influence of outliers while avoiding look-ahead bias, we winsorize continuous variables at the 1st and 99th percentiles within each quarter. Table C1, Panel A presents summary statistics for key variables in our quarterly panel.

Figure C1 plots the time series of average ownership shares across bonds. Insurance companies hold the largest share throughout the sample, although their ownership declines from 42.2% in 2006 to 27.0% in 2022. In contrast, passive mutual fund ownership, initially negligible, rises steadily from 0.4% in 2006 to 5.2% by 2022, mirroring the broader shift toward passive investment in fixed-income markets.

Figure C2 plots average lending outcomes for all corporate bonds and for IG and HY subsamples. Panel A shows that the average lendable supply exceeded 30% of the amount outstanding in 2007 and 2008, but declined to roughly 20% thereafter, comparable to the equity market levels.

Panels B and C plot the quantity on loan and the short loan quantity, defined as the

[24]These observations are identified when the entry for FIRMID is "CO-MANAGED."

share of borrowed bonds used for short sales.[25] Consistent with Hendershott, Kozhan, and Raman (2020), both measures decline sharply in 2009. Before the financial crisis, about 4% of bonds were lent out; after 2009, the level drops to around 1% and remains stable. HY bonds exhibit higher loan quantities than IG bonds throughout the period.

Comparing Panels B and C, the short loan quantity is slightly smaller than the quantity on loan before 2008, especially among IG bonds. This is because these bonds are often used as collateral in financing trades. However, after 2009, the two variables are almost identical. Therefore, these data suggest that the role of financing transactions is limited, and that a large portion of the borrowed bonds are sold short.

Panel D shows that the average borrowing fee ranges from 0.31% to 0.58% with no clear time trend. Consistent with Asquith, Au, Covert, and Pathak (2013), the level of the borrowing fee is similar to or even slightly lower than the equity borrowing fee.[26] HY bonds have higher borrowing fees than IG bonds, ranging from 0.42% to 0.81%. Panel E reports median fees ranging from 0.24% to 0.43% for all bonds, closely matching the median equity borrowing fee.

C.2 ETFs and Index Mutual Funds

In our sample, passive ownership includes holdings by ETFs and index mutual funds. Table C1 shows that the average passive ownership is 3.43%, comprising 1.27% ETF ownership and 2.15% index fund ownership. According to our proposed mechanism, both investor types track predetermined indices, thereby exerting upward pressure on bond prices. Thus, one may anticipate similar impacts on bond lending outcomes from ETFs and index mutual funds. Nevertheless, recent literature (see, e.g., Koont, Ma, Pástor, and Zeng 2024) highlight a distinctive feature of ETFs, as they rely on authorized participants to manage fund flows, a feature absent in traditional passive index funds. To examine potential differences between ETFs and index mutual funds, we include their respective ownership shares in the multivariate regression in equation (17) and examine how lending outcomes respond.

Table C2 reports the results, presenting coefficients on ETF ownership and index fund ownership. Since Panels A and B (with and without controls for active fund and insurance ownership, respectively) yield similar results, we focus on Panel A. The estimates indicate

[25] The variable "*Short Loan Quantity*" in Markit represents the number of securities on loan with dividend trading and financing trades removed. Markit uses a proprietary algorithm to strip out these trades.

[26] The level of the fee in our sample is higher than some of the previous research that uses the sell-side database. Our database measures the borrowing fee from the perspective of ultimate borrowers. The sell-side data takes the perspective of ultimate lenders and, thus, their fee level is lower because intermediating dealers charge a higher fee to lend than to borrow.

that a one-percentage-point increase in ETF ownership raises the lendable supply by 0.675 pp, whereas a similar increase in index fund ownership results in a comparatively modest increase of 0.084 pp. Consistent with our main findings, the change in loan quantity is much smaller: +0.044 pp and −0.043 pp, respectively. The significantly negative response to the increased index fund ownership implies that borrowing demand must decline. One cannot, however, reach a definitive conclusion about ETF ownership because the supply effect dominates any changes in demand.

We note that the decline in utilization rate is similar across both investor types, with one-percentage-point increases in ETF and index fund ownership associated with reductions of 0.149 pp and 0.196 pp, respectively. Consequently, both types of ownership result in a reduced equilibrium quantity of bonds relative to the amount available for lending, and a significant decline in equilibrium lending fees. Specifically, a one-percentage-point increase in either ETF or index fund ownership leads to a fee reduction of 0.023 pp. This estimate aligns precisely with our main results reported in Table 7 (−0.023 pp with $t = -4.95$). Finally, in Table C3, we show that an increase in ETF and index fund ownership reduces credit spreads and net order imbalance, which is consistent with the baseline results in Table 10.

Our findings indicate that both ETFs and passive index funds facilitate the relaxation of short-sale constraints in the bond market. Importantly, the mechanisms unique to ETFs, such as the dual roles of dealers serving as authorized participants, do not account for the observed effects. Instead, our proposed channel operating through bond valuations presents a common mechanism across both ETFs and passive index funds, and is consistent with the empirical results reported in Table C2.

C.3 Identification Based on Maturity Cutoffs

Bretscher, Schmid, and Ye (2024) propose that one can use maturity cutoffs as a valid instrument for changing passive ownership. Specifically, they show that when the remaining maturity of a bond shrinks beyond a certain threshold, such as three or ten years, passive ownership increases. This happens because there are more short-term index funds than long-term index funds. This provides another clean identification of shocks to passive ownership, because the fundamental values of a bond remain very similar when its maturity changes from (say) 10.1 years to 9.9 years. Since Bretscher, Schmid, and Ye (2024) study the effect of ownership on bond pricing and liquidity, we revisit their results focusing on bond lending outcomes.[27]

C.3.1 Monthly Bond Sample Construction

To do this analysis, we first construct a monthly bond panel dataset. We begin with daily bond lending data from IHS Markit, which we match to the merged Mergent FISD-TRACE bond sample. We then compute the monthly averages of lending outcome variables by aggregating the daily Markit data within each bond-month observation. Following Bretscher, Schmid, and Ye (2024), we exclude bonds issued within the past six months to ensure a more stable sample. This process yields 815,719 observations for 17,214 corporate bonds issued by 1,718 firms over 196 months from September 2006 to December 2022.

Next, we merge the monthly bond lending data with bond holdings data from Morningstar and eMAXX, aligning them based on bond CUSIPs and calendar months. We define a *Switch* indicator that equals one if a bond crosses one of the three cutoffs: 10-, 5-, and 3-year time to maturity. We compute the change of passive ownership and lending outcome variables from month $t-1$ to month $t+h$ and require all the outcome variable changes to be available for $h \in [-4, 24]$. These filtering criteria yield a final sample of 318,279 bond-month observations for 9,754 corporate bonds issued by 1,184 firms from February 2007 to December 2022. To mitigate the influence of outliers, we winsorize continuous variables at the 1st and 99th percentiles within each month. Table C1, Panel B presents descriptive statistics for the final monthly bond panel dataset.

C.3.2 Results

To assess the impact of switching ownership, we define a dummy variable that takes on a value of one if a bond's remaining time to maturity crosses the three, five, and ten year cutoffs on any day in month t and zero otherwise, denoted $Switch_{i,t}$. We then regress changes in lending outcome variables for bond i, including lending supply, quantity on loan, and lending fees. In addition, we use passive ownership as another outcome variable to verify that crossing maturity increases ownership.

Specifically, we estimate a panel regression,

$$\Delta Outcome_i^{t-1 \to t+h} = \beta^h Switch_{i,t} + Controls_{i,t-1} + \alpha_i + \lambda_t + e_{i,t}^h, \tag{C1}$$

where $\Delta Outcome_i^{t-1 \to t+h}$ is the change of the bond lending and ownership variables for bond

[27] Internet Appendix of Bretscher, Schmid, and Ye (2024) also study several bond lending outcomes. Our results are very similar to theirs, but we extend the horizon for the outcome variables to examine the medium-term effect of increased passive ownership.

i from $t-1$ to $t+h$. We set $h = -4, \ldots, 24$ to study the pre-trends, short- and medium-term impacts. $Controls_{i,t-1}$ includes the log of amount outstanding of the bond, numerical credit rating, and the fraction of zero trading days in a month. Each regression includes bond and year-month fixed effects. For this regression, we restrict to the sample that $\Delta Outcome_i^{t-1\to t+h}$ are all available across h for comparability. Standard errors are double-clustered at the bond and year-month levels.

Panel A of Table C4 reports the coefficient estimates for passive ownership and the corresponding panel in Figure C3 plots the estimated coefficients with two-standard-error bars to visualize them. Consistent with Bretscher, Schmid, and Ye (2024), we find that when a bond crosses the maturity cutoff, its passive ownership increases significantly. Specifically, the ownership increases 0.365 pp in the month when the bond maturity becomes less than the cutoff ($h = 0$) from a month before. The ownership gradually increases for the following nine months, with β^9 being estimated at 0.515 pp ($t = 19.01$). About a half of this increase is permanent, as the increase in ownership 24 months after crossing the cutoff is still high at 0.264 pp ($t = 8.81$). Thus, we confirm that our instrument is valid and generates non-trivial variation in passive ownership when compared with its sample average (3.43 pp) and inter-quartile range (4.59 pp).

Panels D to F of Table C4 and Figure C3 report the regression estimates in equation (C1) for changes in quantity on loan, lendable supply, and lending fees. The response of the loan quantity three, nine, 18, and 24 months after the bond crosses the cutoff is 0.06 pp, -0.03 pp, -0.13 pp, and -0.14 pp, respectively. That is, in the first three months, the loan quantity increases by a small amount, reflecting the buying pressure created by passive funds that must buy those bonds to track a bond index. However, over the medium term, the initial reaction reverses, and the quantity on loan declines. This happens because, consistent with the mechanism described in Section 5.3, the increased passive ownership reduces the bonds' credit spreads and reduces the buying pressure from other speculative investors. As a result, dealers have to sell short bonds less than before, leading to a lower quantity on loan.

The decrease of quantity on loan identified using maturity cutoff as an instrument is qualitatively consistent with our main results based on the quarterly panel regressions with firm-quarter fixed effects. However, quantitatively, the point estimate is economically more significant. In our main result, a one-percentage-point increase in passive ownership reduces the quantity on loan by 0.010 pp. In the maturity cutoff analysis, for $h = 24$, the reaction of quantity on loan to the one-percentage-point increase in passive ownership generates a 0.530 pp (=0.140/0.264) decline in quantity on loan. This reaction is substantial given the average and inter-quartile range of quantity on loan (1.45 pp and 1.35 pp, respectively). In addition, in Panel E, lendable supply declines substantially after a bond crosses the maturity cutoff.

The estimated change from $h = -1$ to $h = 24$ is -0.367 pp, which is 3.67 standard errors below zero. This is in contrast to our main results, where an increase in passive ownership raises the lendable supply.

To reconcile the apparent discrepancy in estimated reactions between two types of instruments, one must understand the nature of the maturity cutoff event. That is, when a bond crosses the maturity cutoff, different types of investors react *simultaneously*. To see this, in Panels B and C of Table C4, we report the changes in ownership share of insurance firms and active mutual funds. The corresponding panels in Figure C3 show the regression coefficient estimates.

When the bond crosses the cutoff, insurance firms gradually reduce their ownership share. While the changes in ownership in the month of crossing the maturity cutoff are close to zero, the cumulative changes become more negative as the horizon h increases. For $h = 24$, insurance firms' ownership declines 0.518 pp ($t = -5.00$). In contrast, the reactions of active mutual funds are muted and insignificant for all horizons.

Taken together, over the medium term, crossing the maturity cutoff significantly increases passive ownership and decreases insurance ownership. The decrease in insurance ownership reduces the lendable supply and dominates the increase in passive funds. Changes in insurance ownership dominate because the magnitude of the change is larger (-0.518 pp) than that of passive ownership (0.264 pp). As a result, the maturity cutoff event significantly reduces lendable supply, as shown in Panel E of Figure C3. This reduction in supply leads to a more pronounced decline in quantity on loan (Panel B) than that in our main results. In contrast, the borrowing fee (Panel F) reacts little when a bond crosses the maturity cutoff. This is because the increase in passive ownership decreases the fee, while the decreased insurance ownership increases it. Since the two forces cancel each other out, the resulting reactions in the lending fee are insignificant for all horizons.

In summary, because the event simultaneously increases passive ownership and decreases insurance ownership, it reduces lendable supply and quantity on loan. To isolate the effect of changing passive ownership from insurance ownership, one has to examine the multivariate regression as presented in Table 7.

Figure C1: Time Series Plots of Bond Ownership

This figure plots six-month moving average of the percentage share of actively lent corporate bonds held by insurance companies (orange dashed line), active mutual funds (blue dotted line), passive funds (red dashed line), index funds (purple dash–dot line), and exchange-traded funds (green dotted line), covering the period from September 2006 to December 2022. The passive fund series represents the combined holdings of index funds and ETFs. We identify actively lent bonds as those with non-missing outstanding lending quantities in the Markit securities lending database (now S&P Global Market Intelligence). Institutional holdings data are obtained from eMAXX and Morningstar, and bond amount outstanding data are sourced from Mergent FISD. Further details on sample construction are provided in Section 2.

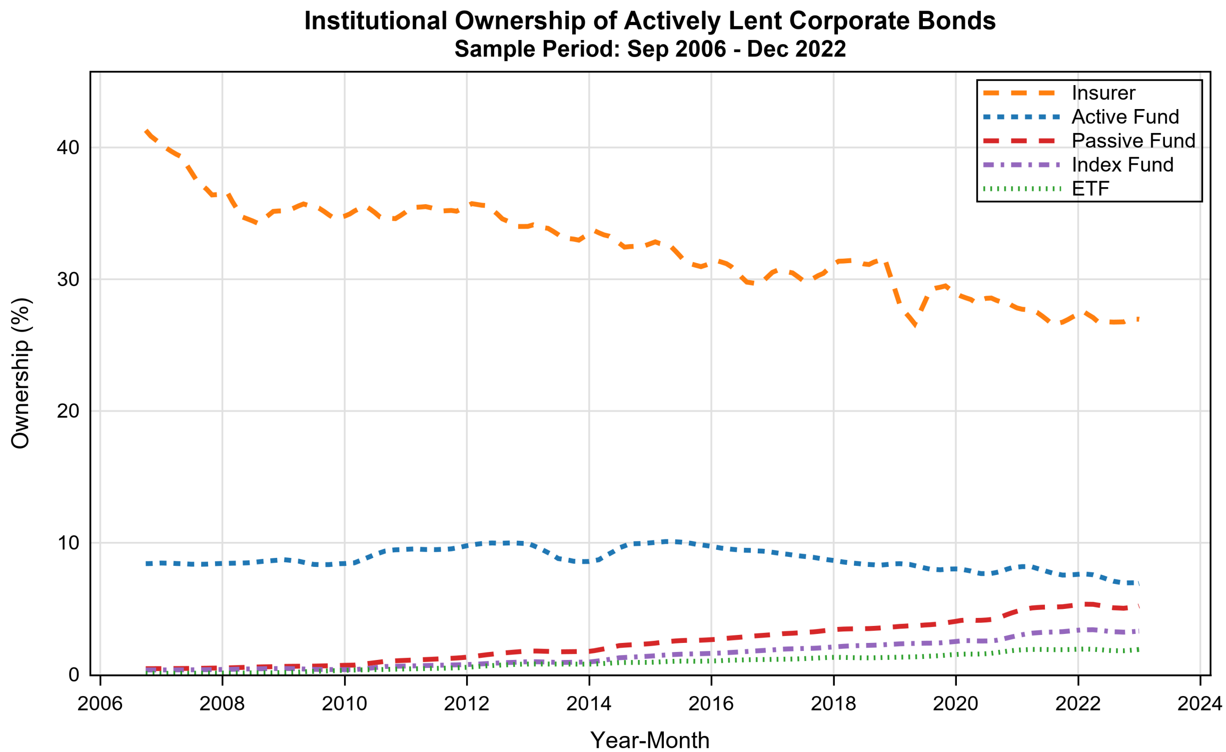
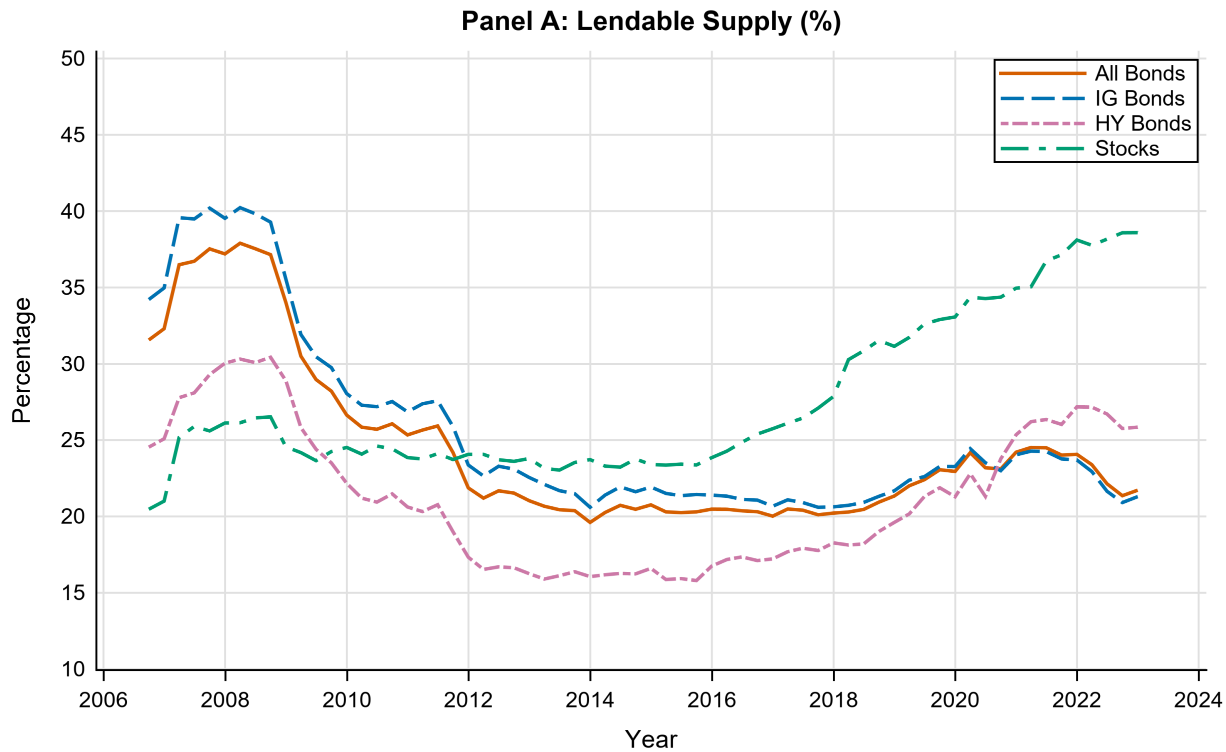
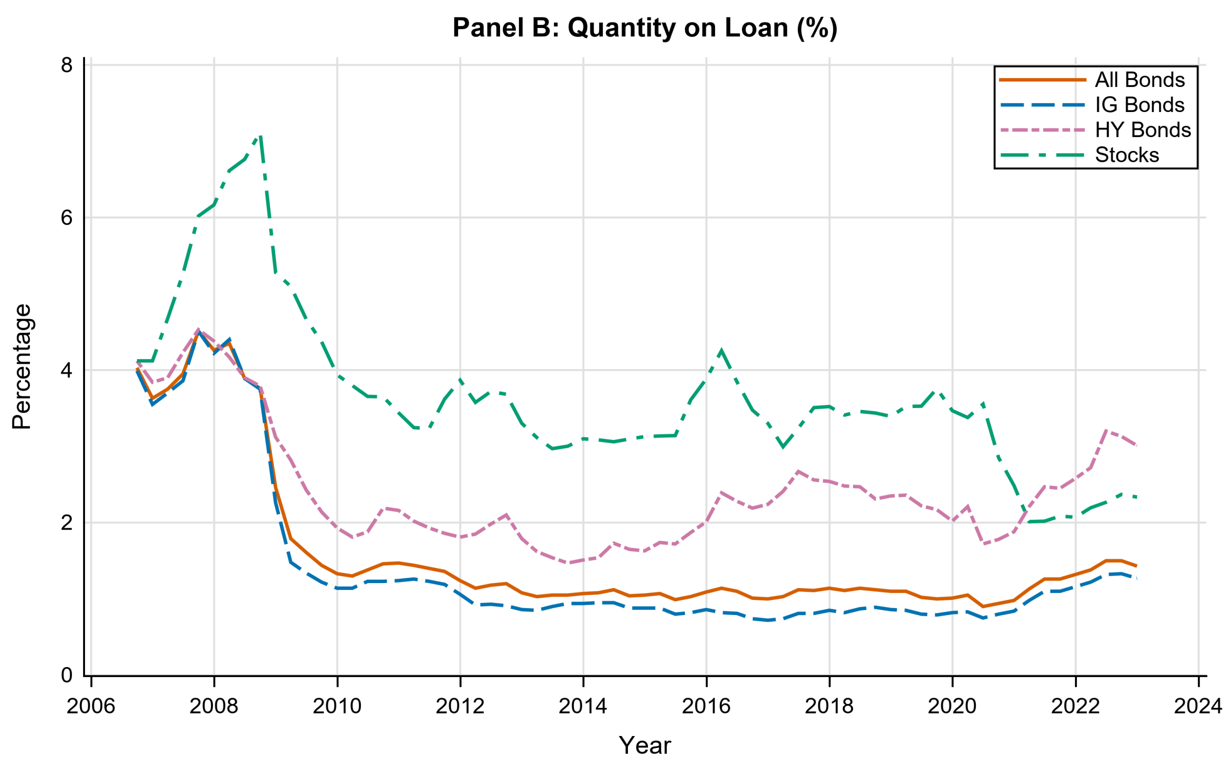


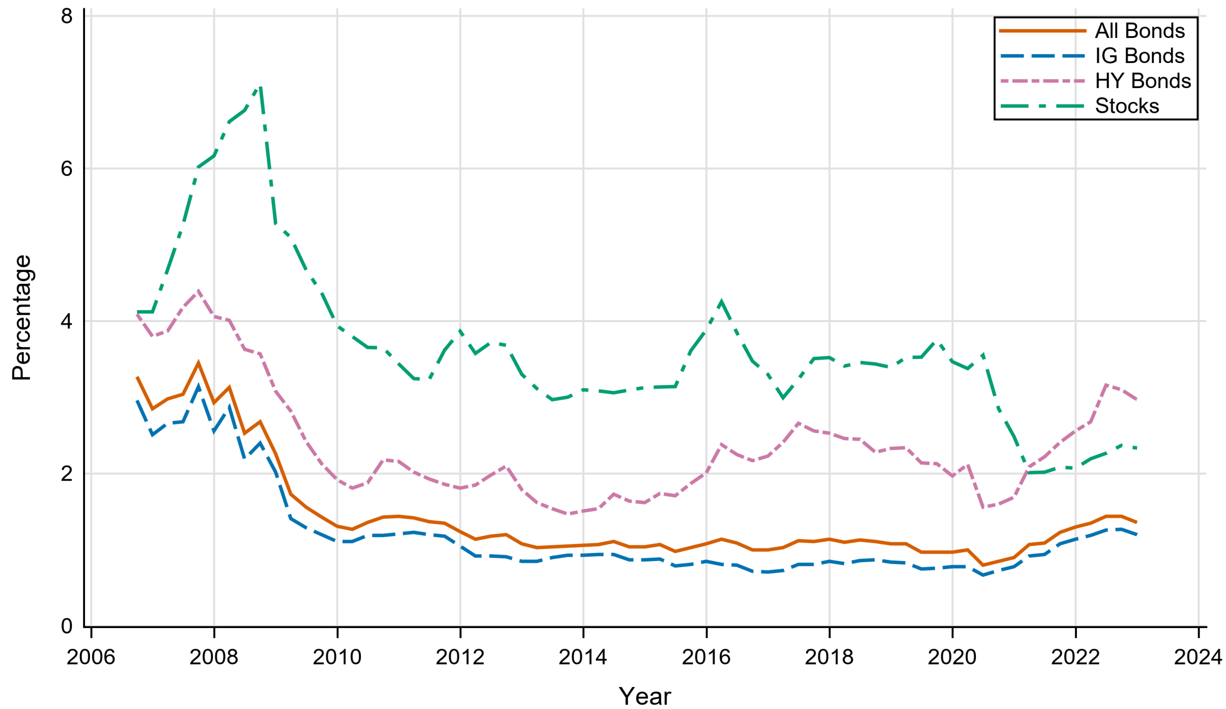
Figure C2: Time Series Plots of Bond Lending Activities

This figure plots the average lending market outcomes for corporate bonds and matched issuer stocks included in our baseline quarterly panel dataset from 2006 Q3 to 2022 Q4. The solid orange line represents all corporate bonds, the dashed blue line denotes IG bonds, the dash–dot pink line corresponds to HY bonds, and the dashed green line indicates matched issuer stocks.

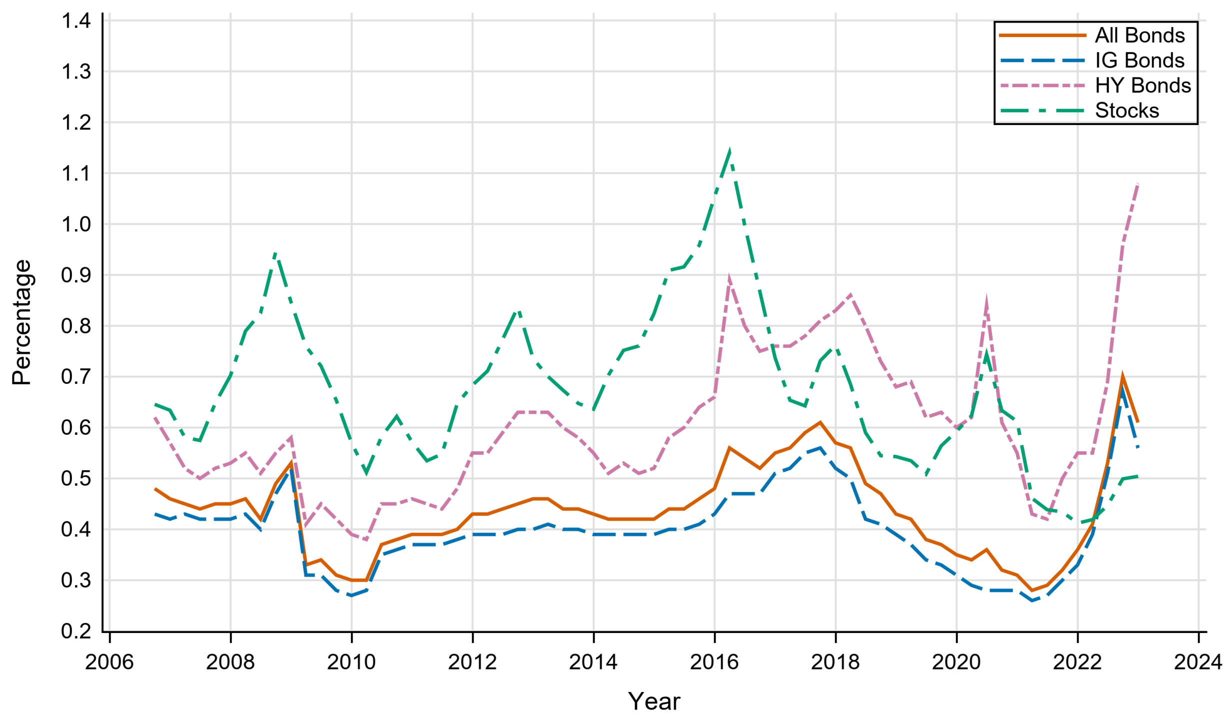




Panel C: Short Loan Quantity (%)



Panel D: Borrowing Fee (%)



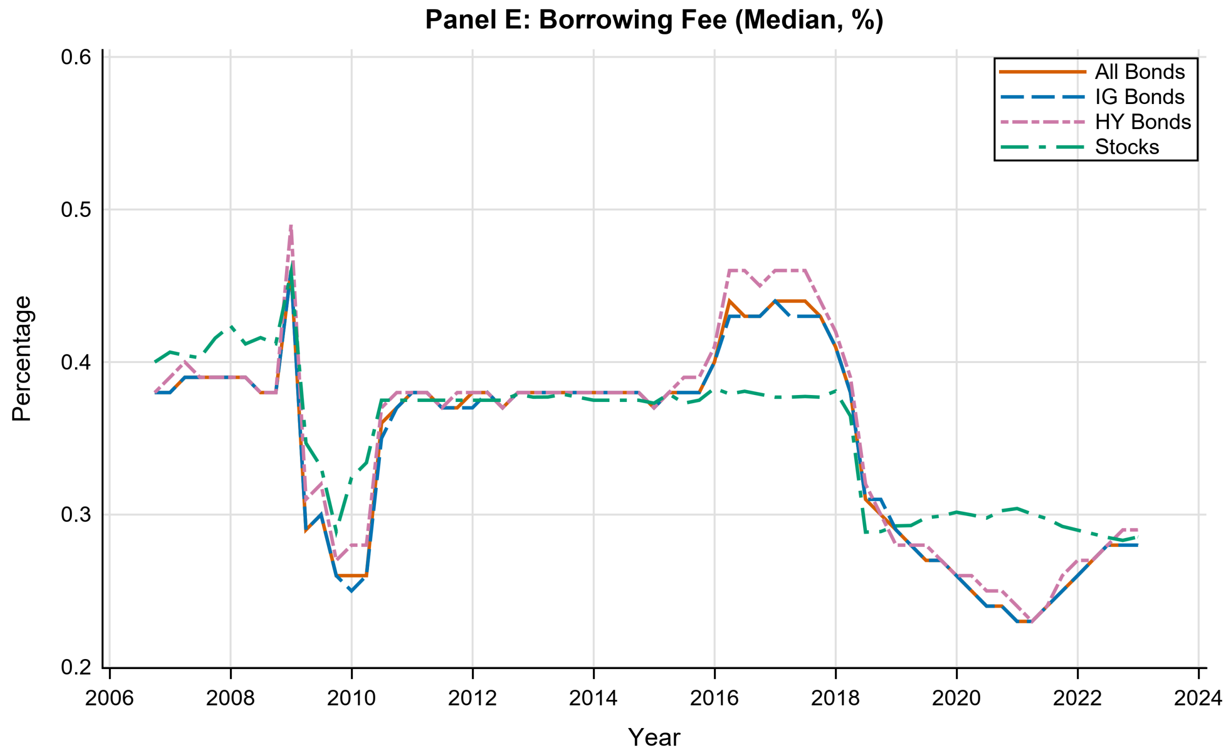
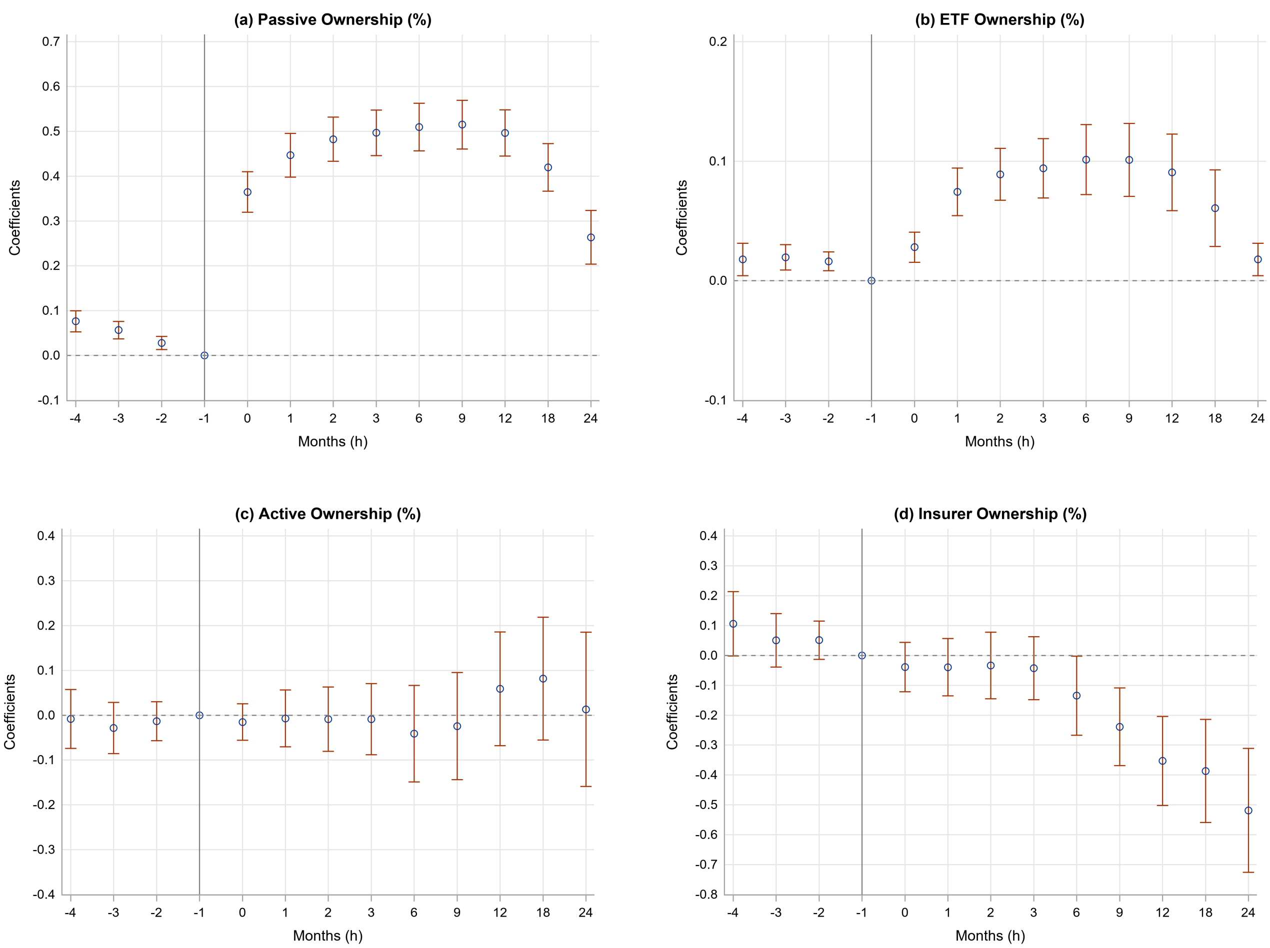

Panel E: Borrowing Fee (Median, %)
All Bonds
IG Bonds
HY Bonds
Stocks
Percentage
Year
0.2
0.3
0.4
0.5
0.6
2006
2008
2010
2012
2014
2016
2018
2020
2022
2024

Figure C3: Investor Ownership and Bond Lending around Maturity Cutoffs

The figure plots the slope coefficients β^h from the following regression for $h \in [-4, 24]$

$$\Delta Outcome_i^{t-1 \rightarrow t+h} = \beta^h Switch_{i,t} + Controls_{i,t-1} + \alpha_t + \gamma_i + \varepsilon_{i,t}^h,$$

where $\Delta Outcome_i^{t-1 \rightarrow t+h}$ is the change of investor ownership and lending variables for bond i from $t-1$ to $t+h$. $Switch_{i,t}$ is an indicator variable equal to one if bond i crosses any one of the maturity cutoffs (i.e., 10 years, 5 years, and 3 years) in month t, and 0 otherwise. Thus, the y-axis represents the change of outcome variables relative to the pre-crossing level after a bond crosses the maturity cutoffs. Control variables include the log of the amount outstanding, credit rating, time to maturity, and the percentage of zero trading days. Each regression includes bond and year-month fixed effects. Error bars represent the two-standard-error confidence intervals, where standard errors are clustered at both the bond and year-month levels.



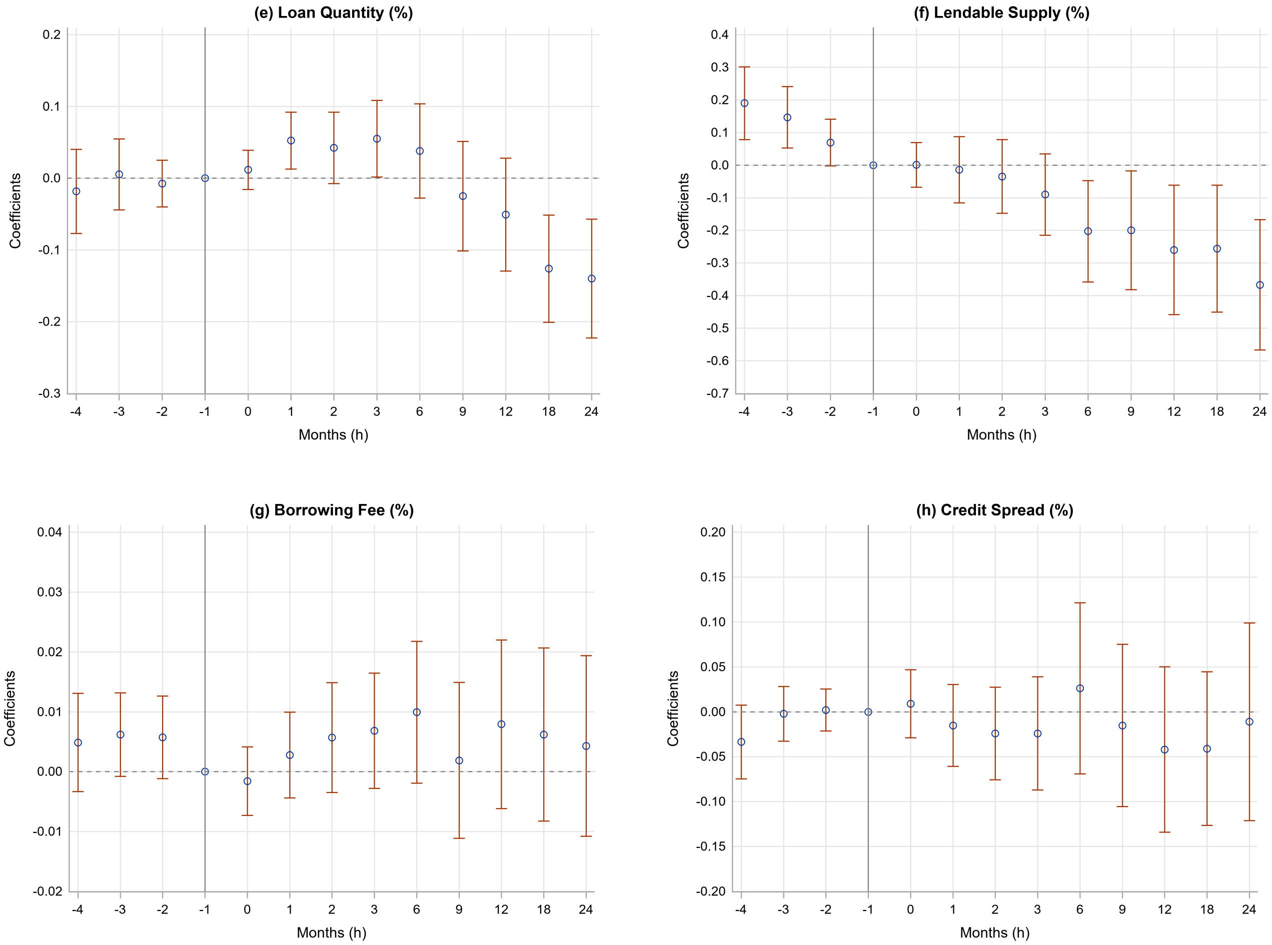

(e) Loan Quantity (%)
(f) Lendable Supply (%)
(g) Borrowing Fee (%)
(h) Credit Spread (%)
Coefficients
Months (h)
-4
-3
-2
-1
0
1
2
3
6
9
12
18
24

Table C1: Descriptive Statistics of Monthly and Quarterly Panels

This table presents summary statistics for the main variables used in our analysis. Panel A reports statistics at the bond-quarter level for 17,140 bonds issued by 1,705 firms from 2006:Q3 through 2022:Q4, representing the sample used in Table 7. Panel B reports statistics at the bond-month level for 9,668 bonds issued by 1,181 firms from February 2007 to December 2022, which constitute the sample analyzed in Figure C3. Variable definitions are provided in Table A1. All continuous variables are winsorized at the 1st and 99th percentiles within each time period to mitigate the influence of outliers.

Variable	Mean	SD	P1	P25	P50	P75	P99	IQR	Obs
				Panel A: Quarterly Bond Panel					
Loan Quantity (%)	1.45	2.58	0.01	0.16	0.51	1.51	12.06	1.35	297,693
Lendable Supply (%)	23.74	10.95	1.78	16.38	22.70	29.72	56.79	13.34	297,693
Utilization Rate (%)	6.71	11.98	0.03	0.78	2.46	6.98	65.01	6.20	297,693
Loan Tenure (days)	74.27	86.56	1.00	23.27	44.08	88.92	455.55	65.66	297,693
Borrowing Fee (%)	0.44	0.47	0.17	0.28	0.37	0.40	2.94	0.13	297,693
Rebate Rate (%)	0.56	1.44	−2.12	−0.25	−0.12	1.08	4.90	1.33	297,693
DCBS	1.06	0.29	1.00	1.00	1.00	1.00	2.75	0.00	297,693
Fee Risk	−2.85	1.01	−5.25	−3.45	−2.90	−2.48	0.14	0.97	253,298
Recall Risk	−0.28	1.74	−6.64	−1.07	0.02	0.86	2.69	1.93	291,480
Lender Concentration	0.49	0.32	0.00	0.29	0.49	0.73	1.00	0.44	297,693
Special	0.10	0.30	0.00	0.00	0.00	0.00	1.00	0.00	297,693
Credit Spread (%)	2.13	2.67	0.23	0.88	1.41	2.40	11.51	1.52	293,193
OIMB (%)	−0.07	2.18	−6.33	−0.86	−0.03	0.69	6.53	1.54	297,693
Net OIMB (%)	−0.12	2.22	−6.56	−0.96	−0.05	0.66	6.50	1.62	297,174
h_{Buy} *(%)*	0.28	0.87	−1.59	0.01	0.14	0.43	3.15	0.43	286,041
h_{Sell} *(%)*	0.26	0.97	−2.10	0.00	0.16	0.45	3.09	0.45	284,634
Passive Fund (%)	3.43	3.06	0.00	0.70	2.93	5.29	12.24	4.59	297,693
ETF (%)	1.27	1.46	0.00	0.03	0.78	2.03	6.21	2.01	297,693
Index Fund (%)	2.15	2.28	0.00	0.03	1.56	3.48	9.04	3.45	297,693
Active Fund (%)	9.65	10.07	0.00	2.05	6.28	13.92	43.27	11.87	297,693
Insurer (%)	31.29	20.70	0.21	13.96	28.29	45.89	82.06	31.93	297,693
Amount ($ mil)	679	569	105	300	500	799	3,000	499	297,693
Rating	8.45	3.10	1.50	6.50	8.00	10.00	17.00	3.50	297,693
Age (years)	4.92	4.45	0.32	1.80	3.63	6.59	21.22	4.79	297,693
Maturity (years)	9.98	8.70	1.13	3.71	6.55	14.39	29.69	10.68	297,693
ZTD (%)	34.77	29.78	0.00	6.35	28.57	59.38	96.72	53.03	297,693
				Panel B: Monthly Bond Panel					
Loan Quantity (%)	1.55	2.59	0.01	0.19	0.59	1.69	12.34	1.50	318,319
Lendable Supply (%)	24.80	9.87	4.92	18.21	23.85	30.17	54.37	11.96	318,319
Borrowing Fee (%)	0.40	0.32	0.16	0.28	0.38	0.39	2.02	0.11	318,319
Credit Spread (%)	2.03	2.06	0.32	0.96	1.44	2.36	9.74	1.40	312,921
Passive Fund (%)	3.38	2.50	0.00	1.33	3.15	4.91	10.41	3.58	318,319
ETF (%)	1.23	1.30	0.00	0.14	0.85	1.93	5.64	1.78	318,319
Active Fund (%)	9.31	9.70	0.00	2.30	5.98	12.94	42.69	10.65	318,319
Insurer (%)	32.44	18.52	1.40	17.27	30.76	45.40	78.80	28.12	318,319
Amount ($ mil)	800	616	158	400	600	1,000	3,000	600	318,319
Rating	8.15	2.97	1.00	6.00	8.00	9.50	16.50	3.50	318,319
Age (years)	4.48	3.64	0.96	1.96	3.49	5.64	18.99	3.68	318,319
Maturity (years)	11.53	8.66	3.08	5.13	7.47	19.10	29.11	13.97	318,319

Table C2: Passive Ownership Decomposition

This table presents the results from regressing bond lending outcomes on ownership of institutional investors as in Table 7 except that we decompose *Passive Fund* into *ETF* and *Index Fund*. We include bond and firm × quarter effects in each regression. We double cluster standard errors by firm and year-quarter, and t-statistics are in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from 2006 Q3 to 2022 Q4.

	Loan Quantity (1)	Lendable Supply (2)	Borrowing Fee (3)	DCBS (4)	Utilization Rate (5)
			Panel A: Passive Funds Only		
ETF	0.0435^{**}	0.6749^{***}	-0.0232^{***}	-0.0137^{***}	-0.1492^{**}
	(2.53)	(12.35)	(−4.21)	(−4.69)	(−2.10)
Index Fund	-0.0427^{***}	0.0838^{*}	-0.0228^{***}	-0.0130^{***}	-0.1961^{***}
	(−4.20)	(1.82)	(−4.63)	(−4.65)	(−4.33)
Bond Controls	Yes	Yes	Yes	Yes	Yes
Firm×Qtr FE	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes
Observations	281,886	281,886	281,886	281,886	281,886
Adjusted R^2	0.597	0.812	0.472	0.489	0.629
			Panel B: Passive Funds Plus Other Investors		
ETF	0.0439^{**}	0.6965^{***}	-0.0238^{***}	-0.0140^{***}	-0.1604^{**}
	(2.41)	(13.15)	(−4.20)	(−4.69)	(−2.21)
Index Fund	-0.0341^{***}	0.1154^{**}	-0.0228^{***}	-0.0130^{***}	-0.1731^{***}
	(−3.30)	(2.59)	(−4.66)	(−4.67)	(−3.81)
Active Fund	0.0438^{***}	0.1283^{***}	0.0006	0.0004	0.1380^{***}
	(10.69)	(7.47)	(0.96)	(1.01)	(7.40)
Insurer	0.0196^{***}	0.1066^{***}	-0.0012^{***}	-0.0006^{**}	0.0318^{***}
	(5.18)	(9.61)	(−2.74)	(−2.42)	(3.45)
Bond Controls	Yes	Yes	Yes	Yes	Yes
Firm×Qtr FE	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes
Observations	281,886	281,886	281,886	281,886	281,886
Adjusted R^2	0.602	0.815	0.472	0.490	0.630

Table C3: Passive Ownership Decomposition and Bond Market Outcomes

This table presents the results from regressing bond market outcomes on ownership of institutional investors as in Table 10 except that we decompose *Passive Fund* into *ETF* and *Index Fund*. Bond control variables include the log value of amount outstanding, rating, time to maturity, and the fraction of zero-trading days. Variable definitions are provided in Table A1. We include bond and firm × quarter effects in each regression. We double cluster standard errors by firm and year-quarter, and t-statistics are in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from 2006 Q3 to 2022 Q4.

	Credit Spread (1)	OIMB (2)	Net OIMB (3)
Panel A: Passive Funds Only			
ETF	-0.0660^{***}	-0.0762^{***}	-0.0477^{***}
	(-8.36)	(-6.54)	(-3.87)
Index Fund	-0.0310^{***}	0.0145^{*}	-0.1267^{***}
	(-8.56)	(1.98)	(-12.36)
Bond Controls	Yes	Yes	Yes
Firm × Qtr FE	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes
Observations	277,403	281,886	281,413
Adjusted R^2	0.953	0.039	0.043
Panel B: Passive Funds Plus Other Investors			
ETF	-0.0632^{***}	-0.0759^{***}	-0.0463^{***}
	(-8.14)	(-6.34)	(-3.65)
Index Fund	-0.0304^{***}	0.0189^{**}	-0.1233^{***}
	(-8.45)	(2.45)	(-11.64)
Active Fund	-0.0015	0.0222^{***}	0.0154^{***}
	(-0.96)	(10.42)	(6.12)
Insurer	0.0061^{***}	0.0101^{***}	0.0097^{***}
	(7.90)	(5.81)	(5.61)
Bond Controls	Yes	Yes	Yes
Firm × Qtr FE	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes
Observations	277,403	281,886	281,413
Adjusted R^2	0.953	0.041	0.044

Table C4: Investor Ownership and Bond Lending Activities around Maturity Cutoffs

The table reports the slope coefficients β^h from the following regression for $h \in [-4, 24]$

$$\Delta Outcome_i^{t-1\rightarrow t+h} = \beta^h Switch_{i,t} + Controls_{i,t-1} + \alpha_t + \gamma_i + \varepsilon_{i,t}^h,$$

where $\Delta Outcome_i^{t-1\rightarrow t+h}$ is the change of investor ownership and lending variables for bond i from $t-1$ to $t+h$. We require the outcome variable changes to be available for all h. $Switch_{i,t}$ is an indicator variable equal to one if bond i crosses any one of the maturity cutoffs (i.e., 10 years, 5 years, and 3 years) in month t, and 0 otherwise. Control variables include the log of the amount outstanding, credit rating, time to maturity, and the percentage of zero trading days. Variable definitions are provided in Table A1. Each regression includes bond and year-month fixed effects. We double cluster standard errors by firm and year-month, and t-statistics are in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample comprises 318,279 bond-month observations for 9,754 corporate bonds issued by 1,184 firms, covering the period from February 2007 to December 2022.

h	−4	−3	−2	0	1	2	3	6	9	12	18	24
$\Delta Passive$	0.076***	0.056***	0.028***	0.365***	0.447***	0.482***	0.497***	0.509***	0.515***	0.496***	0.420***	0.264***
	(6.48)	(5.84)	(3.81)	(16.07)	(18.36)	(19.57)	(19.57)	(19.21)	(19.01)	(19.31)	(15.80)	(8.81)
ΔETF	0.018***	0.020***	0.016***	0.028***	0.074***	0.089***	0.094***	0.101***	0.101***	0.091***	0.061***	0.018***
	(2.63)	(3.69)	(4.12)	(4.47)	(7.46)	(8.18)	(7.59)	(6.93)	(6.64)	(5.66)	(3.79)	(2.63)
$\Delta Active$	−0.008	−0.029	−0.013	−0.015	−0.007	−0.009	−0.009	−0.041	−0.024	0.059	0.082	0.013
	(−0.25)	(−1.01)	(−0.62)	(−0.75)	(−0.23)	(−0.25)	(−0.22)	(−0.77)	(−0.41)	(0.93)	(1.19)	(0.15)
$\Delta Insurer$	0.106*	0.051	0.051	−0.039	−0.039	−0.034	−0.043	−0.135**	−0.239***	−0.353***	−0.386***	−0.518***
	(1.96)	(1.13)	(1.60)	(−0.95)	(−0.82)	(−0.61)	(−0.81)	(−2.03)	(−3.68)	(−4.74)	(−4.48)	(−5.00)
$\Delta Quantity$	−0.018	0.005	−0.007	0.012	0.052***	0.042*	0.055**	0.038	−0.025	−0.051	−0.126***	−0.140***
	(−0.63)	(0.22)	(−0.45)	(0.86)	(2.64)	(1.70)	(2.07)	(1.16)	(−0.66)	(−1.29)	(−3.38)	(−3.38)
$\Delta Supply$	0.190***	0.147***	0.069*	0.001	−0.014	−0.035	−0.090	−0.203***	−0.200**	−0.260***	−0.256***	−0.367***
	(3.39)	(3.11)	(1.94)	(0.03)	(−0.28)	(−0.62)	(−1.44)	(−2.61)	(−2.20)	(−2.62)	(−2.63)	(−3.67)
ΔFee	0.005	0.006*	0.006*	−0.002	0.003	0.006	0.007	0.010*	0.002	0.008	0.006	0.004
	(1.19)	(1.78)	(1.67)	(−0.55)	(0.78)	(1.24)	(1.42)	(1.68)	(0.29)	(1.13)	(0.86)	(0.57)
$\Delta Spread$	−0.033	−0.002	0.002	0.009	−0.015	−0.024	−0.024	0.026	−0.015	−0.042	−0.041	−0.011
	(−1.63)	(−0.14)	(0.17)	(0.47)	(−0.67)	(−0.94)	(−0.76)	(0.55)	(−0.34)	(−0.91)	(−0.96)	(−0.20)