On the Drivers of Corporate Bond Lending

Amit Goyal **Yoshio Nozawa** **Yancheng Qiu***

September 2026

Abstract

We present evidence that short sellers in the corporate bond market are primarily dealers, not speculative customers. On the day bond lending increases, dealer sales increase while customer sales decline. Concurrently, the half-spread for customer buy orders and bond prices rise, indicating that short sales reflect customers' buying pressure. This implies that short-sale constraints that inhibit customers' buy orders can leave bonds undervalued. Consequently, bond factors generate alphas from both long and short legs. Dealers earn positive profits by shorting bonds on average but are exposed to the risk of a short squeeze. Their short sales improve bond liquidity.

JEL classification: G12, G14, G23, G24

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

*Amit Goyal is from Swiss Finance Institute at the University of Lausanne, email: Amit.Goyal@unil.ch, Yoshio Nozawa is from University of Toronto, email: yoshio.nozawa@rotman.utoronto.ca, and Yancheng Qiu is from University of Sydney, email: yancheng.qiu@sydney.edu.au. For helpful comments and suggestions, we thank Philip Gharghori (discussant), Xin Liu (discussant), Jeffrey Meli, Adam Reed (discussant), Lukas Schmid (discussant), Taisiya Sikorskaya (discussant), Marliese Uhrig-Homburg (discussant), Qifei Zhu (discussant), Junyuan Zou (discussant), and seminar participants at New York Fed, McMaster University, SUNY Buffalo, BI Norwegian Business School, the Hong Kong Polytechnic University, the University of Hong Kong, the Hong Kong University of Science and Technology, the Australian National University, Macquarie University, and Zhejiang University, as well as the 2026 American Finance Association (AFA) Annual Meeting, the Four Corners Academic Meeting, the 2026 China International Conference in Finance (CICF), the 2026 Finance Down Under Conference, the 14th Fixed Income and Financial Institutions (FIFI) Conference, the 12th SAFE Asset Pricing Workshop, the Microstructure Exchange, the 14th FIRN Annual Conference, and the 4th School of Finance Alumni Forum at Renmin University of China.

1 Introduction

The corporate bond lending market is active and sizable. In 2022, the amount of lendable securities is $1.71 trillion, 21.38% of the underlying bonds outstanding, and the amount lent is $122 billion (1.53%). The percentage of securities on loan is comparable to that of the well-studied equity lending market, where the literature shows that short sellers are informed traders (see, e.g., Dechow, Hutton, Meulbroek, and Sloan 2001; Lamont and Thaler 2003; Desai, Krishnamurthy, and Venkataraman 2006; Saffi and Sigurdsson 2011). Do these findings generalize to other less liquid securities, such as corporate bonds?

There are reasons to suspect that shorting a corporate bond to bet on a falling price is an unlikely driver of lending activity. The average half spreads in our bond sample are 29 basis points (bps) per transaction, which is consistent with high transaction costs in the bond market documented in, for example, Edwards, Harris, and Piwowar (2007). Thus, if a customer borrows a bond, sells it short, and buys it back after a month, the round-trip cost amounts to 58 bps, which is larger than the average monthly bond return of 0.44 percent. Additionally, the short sellers pay a borrowing fee, averaging between 3 and 4 bps per month. These high transaction costs, coupled with cheaper alternatives, such as trading credit default swaps or the issuer's stocks, could make speculative short selling unattractive to informed traders.

If this market is not for speculators, then why and for whom does such a large and active lending market exist? Asquith, Au, Covert, and Pathak (2013) suggest another potential motivation, noting that bonds may be borrowed to facilitate clearing of long trades. When a customer places an urgent buy order, and the dealer does not hold the bond in inventory, the dealer borrows it from buy-and-hold owners and sells it short to fill the order. If this is true, bond lending is a key element of dealers' liquidity provision in the corporate bond market. In this paper, we show empirically that short-selling activity in the corporate bond market is driven primarily by dealers' market-making activities rather than by customers' speculative trading.

We start our analysis with a simple observation: when someone borrows a bond, the borrower must sell it. Thus, when bond lending increases by a dollar, the short seller's sales volume increases by a dollar. A regression of signed trade volume on bond lending should, therefore, reveal the identity of the seller. For this analysis, we construct a panel dataset from 2006 to 2022 combining TRACE transaction volume data, which records customer buy and sell trades separately, with Markit's corporate bond lending data. We regress daily signed volume on same-day changes in the number of bonds lent. The results show that a one-percentage-point (p.p.) increase in bond lending coincides with a 0.21 p.p. increase in customer buy volume and a 0.13 p.p. *decrease* in customer sell volume. The negative coefficient on customer sales 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. For dealers to borrow a bond and serve customers' buy orders, they must be properly rewarded (Glosten and Milgrom 1985). We test this by regressing the half spreads on customer buy and sell transactions on the daily change in bonds lent. A one-percentage-point increase in bond lending corresponds to a 5 bps increase in the half spread for customer buy trades and a 3 bps decrease for customer sell trades. Short sales thus take place as customers' buying pressure rises, and dealers demand higher compensation to absorb that pressure. At the same time, dealers reward customer liquidity provision by narrowing the spread on customer sales.

If bond short sales take place in response to customers' buy orders, the bond price should increase immediately. To see this, 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 ($t = 4.96$). Dealers facing customer buying pressure immediately revise their quotes upward, leading to a positive bond return on that day.

Short sales can also be related to future bond returns; see Diamond and Verrecchia (1987) and Atmaz, Basak, and Ruan (2024) for theoretical foundations. If short sales coincide with informed customers' buy orders, we do not expect a price reversal. Instead, if the customer buy orders are liquidity driven, the positive day-0 returns should be offset by negative returns later. To distinguish between these two possibilities, we sort bonds into three portfolios: those with a decrease in the amount lent, those with no change, and those with an increase. Over the three-day period after portfolio formation, bonds with increased short sales earn an average annualized return of 6.1%, versus 2.9% for bonds with decreased short sales, a difference of 3.2% ($t = 13.32$). Over the following month, the return difference is 0.6% ($t = 6.54$). The economic magnitude is modest, but the direction is clear: bonds with increased short sales appreciate more than those with decreased short sales. This return persistence suggests that customers' buy orders contain positive information about the bond, which is gradually impounded into prices. These results contrast sharply with those in the equity literature, in which short sales predict negative stock returns (see, e.g., Jones and Lamont 2002; Desai, Ramesh, Thiagarajan, and Balachandran 2002; Asquith, Pathak, and Ritter 2005; Boehmer, Jones, and Zhang 2008; Diether, Lee, and Werner 2009b; Engelberg, Reed, and Ringgenberg 2012).

Our results may appear to be at odds with those of Hendershott, Kozhan, and Raman (2020), who demonstrate that corporate bond short interest negatively predicts the cross section of high-yield bond returns. Our results differ because we sort bonds by changes (flow) in short interest, rather than by the level of short interest. Our analysis captures well the latest information contained in shorting activity, which helps establish a robust pattern across both investment-grade and high-yield bonds. Thus, in fact, our paper complements the findings of Hendershott, Kozhan, and Raman (2020) by studying the high-frequency component of short sales.

Because borrowers are dealers, short selling affects dealers' profits and losses. Dealers earn the half spreads charged to buying customers, but lose the lending fees paid to the lender and also incur adverse selection costs. We estimate that dealers earn 0.475% per transaction on average if they cover the short position in five business days, and 0.147% if they cover in twenty days. Being borrowers, dealers do bear the risk of a short squeeze. Using bond tender offers as a negative shock to the supply of lendable bonds, we show that dealers can be forced to buy the bonds back at a price higher than they paid. Short selling thus improves dealers' profitability, but exposes them to an additional source of risk.

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 68.9% 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 (71.3%) and lower for high-yield (HY) bonds (64.6%), consistent with differences in information sensitivity between rating categories.[1]

The role of dealers' market-making activities in bond lending has two important implications. First, a well-functioning lending market improves bond liquidity by alleviating search frictions inherent in over-the-counter trading. Second, dealers' short sales help prevent bonds from being undervalued by facilitating informed customers' buy orders. We present evidence supporting both of these statements.

We test the link between bond liquidity and dealer borrowing by running the variance

[1]We also conduct a similar variance decomposition in the stock market and find that the share of liquidity-taker short sales is around 50%, similar to that of liquidity-maker short sales. These results are broadly consistent with those of Comerton-Forde, Jones, and Putniņš (2016) and Goyal, Reed, Smajlbegovic, and Soebhag (2025), who report that in the stock market, the magnitude of the liquidity-taking and liquidity-supplying short sales is comparable to each other.

decomposition bond by bond and computing each bond's dealer share of short sales. We then compare bonds in the highest quintile of dealer share with those in the lowest. Using eight measures of transaction costs (Schestag, Schuster, and Uhrig-Homburg 2016), we show that bonds with a high dealer share of short sales have lower future costs than those with a low dealer share. In contrast, the dealer share is unrelated to future trading volume. Overall, dealers' commitment to making markets even when they have no inventory translates into better future liquidity. Our results are consistent with Foley-Fisher, Gissler, and Verani (2019a), who argue that short sales in the bond market help dealers make markets and, as a result, improve bond liquidity. Our evidence complements theirs by showing that bonds for which short sales are carried out predominantly by dealers have better liquidity.

With dealer-driven short sales, the alphas of corporate bond factors could differ from those of equity factors. Since there is no constraint on buying a stock, a stock is less likely to remain undervalued than overvalued (Blocher, Reed, and Van Wesep 2013). Thus, alphas of long-short equity strategies come mostly from the short side, especially from stocks with high short-selling costs (Muravyev, Pearson, and Pollet 2025). In contrast, in the bond market, when dealers face short-sales constraints, buying customers will have difficulty obtaining a quote. This leaves the bond undervalued and generates an alpha also on the long side of the trade. Using 13 factors based on past stock and option returns (see, e.g., Gebhardt, Hvidkjaer, and Swaminathan 2005; Jostova, Nikolova, Philipov, and Stahel 2013; Chordia, Goyal, Nozawa, Subrahmanyam, and Tong 2017; Nozawa, Qiu, and Xiong 2026), we show that for bonds, both the long and short legs contribute similarly.

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. As a result, price reactions to bond short sales differ substantially from those in the equity market. This difference between bonds and stocks gives us an important lesson: insights from equity short sales cannot necessarily be extrapolated to other markets without carefully examining the underlying drivers of short-selling activity. This distinction has broad implications for various research agendas on short selling. For example, regulation around short-selling trades off price efficiency against 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 treat short selling as an activity that destabilizes the financial market.

Our paper contributes to the relatively small literature on short selling in the corporate bond market. Prior work, including Asquith, Au, Covert, and Pathak (2013), Anderson, Henderson, and Pearson (2018), and Hendershott, Kozhan, and Raman (2020), examines borrowing costs and the returns that follow bond short sales. Collectively, this work finds that informational trading and price-pressure effects are more pronounced among HY bonds. Foley-Fisher, Gissler, and Verani (2019a), Foley-Fisher, Narajabad, and Verani (2019b), and Bai, Massa, and Zhang (2022), in contrast, study bondholders' motives to lend.[2]

Our paper speaks to the profits and risks of corporate bond dealers. Friewald and Nagler (2019); Anand, Jotikasthira, and Venkataraman (2021); Goldberg and Nozawa (2021); He, Khorrami, and Song (2022); Friewald and Nagler (2024) study the relationship between dealer inventory and bond prices. More closely related, Macchiavelli and Zhou (2022) examine the role of security lending in dealers' liquidity management. We show that short selling is an integral part of dealers' intermediation activity and, thus, contributes to both profits and risks of dealers.

Our paper is also related to the literature on corporate bond illiquidity. A strand of literature (see, 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; Dick-Nielsen and Rossi 2018) measures the illiquidity and studies its impact on bond prices. More recent literature (see, e.g., Bao, O'Hara, and Zhou 2018; Bessembinder, Jacobsen, Maxwell, and Venkataraman 2018; O'Hara and Zhou 2021; Choi, Huh, and Shin 2024; Pinter, Wang, and Zou 2024; Jacobsen and Venkataraman 2025; Comerton-Forde, Ford, Foucault, and Jurkatis 2025; Hendershott, Li, Livdan, Schürhoff, and Venkataraman 2026) studies the drivers of liquidity with a particular focus on the post-financial-crisis regulations. We contribute to this line of work by documenting how short sales can enhance liquidity.

Finally, there is increasing interest in corporate bond factors and implementation issues. Recent works, including Dickerson, Mueller, and Robotti (2023b); Dickerson, Julliard, and Mueller (2023a); Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2026), provide an overview of the factors and identify a variety of empirical challenges. Our paper complements this strand of literature by showing the unique short selling constraints facing bond investors and how this contributes to alphas, particularly on the long leg of trading strategies.

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 studies the implications of short sales on bond liquidity and anomalies. Section 6 concludes.

[2]In addition, Pelizzon, Riedel, Simon, and Subrahmanyam (2024) examine how the eligibility of European corporate bonds as collateral for the central bank facility influences lending activity. Duong, Gorbenko, Kalev, and Tian (2025) show that bond short sales predict the aggregate stock market.

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, and (5) CRSP, Compustat, the Institutional Brokers Estimate System (I/B/E/S), and the WRDS Intraday Indicators (IID) database for firm- and stock-level variables. 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.[3]

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 the Appendix. 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.

We pay special attention to missing loan quantity data. In the Markit data, we observe occasional short gaps in the time series for loan quantity and lending fee within otherwise continuous CUSIP-level records.[4] After consulting with 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. Therefore, we treat these cases as missing data

[3] 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.

[4] 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.

and exclude them from our main analysis. We discuss the robustness of our main results to alternative treatments of missing observations in Section 4.2.

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 (see, e.g., Muravyev, Pearson, and Pollet 2022, 2025), we use the indicative lending fee as a proxy for the cost of borrowing a bond from the ultimate borrower's perspective.

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 trade observations in TRACE as zero volume when computing bonds' transaction volume. To this end, we set a bond's sample period from its issue date to 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 ICE BAML quote prices, which provide non-missing daily returns and help mitigate the microstructure noise (Andreani, Palhares, and Richardson 2024).

We obtain stock return, trading volume, and shares outstanding data from CRSP, and firm fundamentals from Compustat. Our stock sample consists of common stocks (share codes 10 and 11) listed on the NYSE, NASDAQ, and AMEX. Signed stock trading volumes come from IID, which classifies trades as buyer- or seller-initiated using the Lee and Ready (1991) algorithm. Analyst earnings forecasts are from I/B/E/S. Following Dellavigna and Pollet (2009), we reconcile the earnings announcement dates between Compustat and I/B/E/S by 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.

2.3 Sample Construction

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

[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.

returns, yielding 16,850,795 bond-day observations for 15,503 bonds spanning September 12, 2006 to December 30, 2022.

The multivariate regression analysis requires non-missing values for all control variables. We build this sample in three steps. First, we merge the Markit, TRACE, and ICE panels and require a non-missing ICE return on each bond day. Second, for each bond day, we require non-missing observations for five trading days before and after to calculate the average return, return volatility, average customer buy and sell volumes, and average abnormal half spreads on both sides. Third, we require at least 252 remaining bond-day observations per bond. The final multivariate regression sample includes 11,341,920 bond-day observations for 11,763 corporate bonds from September 13, 2006 to December 30, 2022.

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 0.093% and 0.094% per day in the univariate sample, compared to 0.112% and 0.111% 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 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, $dQ_{i,d}$,

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

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 customer short positions and a decrease in customer short covering, then $b_{h,Sell} - b_{h,Buy} = 1$.

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, $b_{h,Sell} - b_{h,Buy} = -1$ holds.

We estimate the regression in equation (1) separately for two subperiods, before and after September 4, 2017. This cutoff corresponds to the Securities and Exchange Commission'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 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 through 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

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

[7] Consultations with Markit and S&P Global confirm that the variable "`datadate`" in the Markit Securities Finance 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.

corresponds to a 0.18 p.p. ($t = 12.70$) increase in customer buys and a 0.11 p.p. ($t = -12.10$) decrease in customer sells. The estimates on the other days are generally small, except that customer sales coefficients are significantly negative on days $d-4$ and $d-5$.

Panel B of Figure 1 plots the coefficient estimates $b_{h,\xi}$ for the subperiod from September 5, 2017 onward. 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 buy 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 trade-related variables on day d^* with changes in quantity on loan on day d.

The Merton (1974) model implies that 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 verify this, 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 the 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

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

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 trade size and market microstructure noise. 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:

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

To construct the benchmark half spreads, $\overline{HS}_{bench}$, we form portfolios of bonds along three dimensions: credit rating (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 the equal-weighted average half spread 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,

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

for $h = -5, \dots, 5$.

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 5 bps increase in customer buy spreads and a 3 bps decrease in customer sell spreads. These magnitudes are economically large relative to the average half spread of 29 bps in our sample. The coefficients for the customer sell trades remain significantly low for three business days following the short sales.

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 demand, 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. The sell-side half spreads are kept low during the three-day period following the short sale so that dealers can cover the short position soon.

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, the 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:

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

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

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), and zero otherwise. Because we do not winsorize any return observations, estimates from linear regression in (5) may be sensitive to outliers. We therefore present dummy variable specifications in (6) as well.

Figure 4 Panel A plots the slope coefficient $b_{h,g}$ 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 $b_{0,All} = 0.033\%$ per day ($t = 4.96$). 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

$b_{-2,All} = -0.0004\%$ and $b_{-1,All} = 0.0098\%$ 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 $b_{h,g}$ 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 $b_{0,g} = 0.020\%$ per day ($t = 9.46$) for all bonds, 0.014% ($t = 6.31$) for IG bonds, and 0.044% ($t = 8.91$) for HY bonds.

Next, we study whether the customer's buy order is informed. 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 compute a characteristic-adjusted return for each bond by subtracting the return on the value-weighted benchmark of bonds defined by credit rating (AAA, AA, A, BBB, BB, B, and CCC-D) and maturity terciles. To assess statistical significance, we use Newey and West (1987) standard errors with 20 lags.

To confirm the contemporaneous return reaction in Figure 4, we begin with Table 2 Panel A, which 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%, while those with decreased short sales (i.e., $dQ < 0$) earn 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, the prices of bonds experiencing increased short selling tend to appreciate immediately, while those with a decrease in short sales do not.

Panels B and C of Table 2 report the annualized 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 information about the quantity on loan becomes publicly available on day $d^* + 2$ or $d^* + 3$, investors could, in principle, trade on $d^* + 3$ to mimic short sellers' trades. However, the return difference of 0.63% per year is economically negligible and would not constitute a profitable trading strategy. Our central finding is not the return predictability, but rather that prices increase on the day of short sales and do not subsequently reverse.

Table 2 also reports the results based on rating-and-maturity-adjusted returns. Using the sample of all bonds, the return differences between the positive and negative short-sales portfolios are 4.33%, 2.69%, and 0.46% for periods d^*, $[d^* + 1, d^* + 3]$, and $[d^* + 4, d^* + 23]$, respectively, highly similar to the raw return results. Therefore, the return difference is not explained by the differences in credit ratings or maturity.

As noted in Section 2.2, we use bond returns from ICE BAML data to mitigate microstructure noise (Kelly, Palhares, and Pruitt 2023). As an alternative robustness test, we compute daily returns from TRACE transaction data as described in Internet Appendix IA1, paying special attention to minimizing bid-ask bounce. This TRACE return panel covers only 2,903,725 observations, roughly one-sixth of our main sample. Nevertheless, we use these returns for two additional tests. First, we recalculate portfolio returns sorted by $dQ_{i,d}$ and report the results in Internet Appendix Table IA1. The results indicate that the positive return reaction to an increase in lending activity is more pronounced on day d^*, and the subsequent drift is weaker. Second, we repeat the panel regression of daily bond TRACE returns on changes in quantity on loan in Figure 4, and report the results in Internet Appendix Figure IA1. The latter figure shows a very similar pattern in return reactions to short sales. Overall, these results provide additional evidence that the bond price increases when short sales take place, and there is no reversal afterwards.

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 (see, e.g., Jones and Lamont 2002; Boehmer, Jones, and Zhang 2008; Diether, Lee, and Werner 2009b) 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.[8]

Our results on the positive relationship between short-selling activity and bond returns may also seem at odds with those of Hendershott, Kozhan, and Raman (2020). These authors report a negative relation between short interest and bond returns for HY bonds. The key difference is our focus on changes in short interest versus their focus on levels of short interest.[9] We do find that the level of loan quantity negatively predicts future returns of HY bonds, consistent with Hendershott, Kozhan, and Raman (2020). However, changes in loan quantity predict positive returns for both IG and HY bonds. This positive link between increased loan quantity and future returns is offset by the fact that lagged changes in loan quantity over the medium term negatively predict HY bond returns. Thus, our paper complements the findings of Hendershott, Kozhan, and Raman (2020) by studying the high-frequency component of short sales, and by documenting a robust positive relationship between short sales and returns for both IG and HY bonds. Internet Appendix IA2 and the associated Table IA2 provide more details on the relationship between changes and levels of short interest.

3.4 Dealer Profits and Losses From Short Sales

As dealers borrow bonds and sell them short, they earn bid-ask spreads from customers, but suffer from adverse selection costs and have to pay the borrowing fees. Based on our previous estimates, we can measure their profits and losses. To this end, we focus on the portfolio of bonds with $dQ_{i,d} > 0$ and calculate the dealers' cumulative profits and losses on the short position established on day d^* and covered on day $d^* + K$,

$$\begin{aligned} PL_{d^*,k+1} &= (1 + PL_{d^*,k})(1 - r_{d^*+k+1} - Fee_{d^*+k+1} + \mathbf{1}_{k=0}HS_{d^*} + \mathbf{1}_{k=K-1}HS_{d^*+K}) - 1, \\ &\quad k = 0, \ldots, K-1, \end{aligned} \tag{7}$$

where $PL_{d^*,0} \equiv 0$; r_{d^*+k+1} and Fee_{d^*+k+1} are the value-weighted portfolio returns and lending fees; HS_{d^*+k} denotes the value-weighted customer half spread, taken from the buy side at the opening of the short position on d^* (when $k = 0$) and from the sell side at the covering on $d^* + K$ (when $k = K - 1$); and $\mathbf{1}_{k=0,K-1}$ is an indicator variable equal to one if $k = 0$ or $k = K - 1$, and zero otherwise. We subtract portfolio return starting from day $d^* + 1$, one day after the dealers sell the bond short, assuming that the dealers adjust the day-d^* price

[8] Consistent with our results, Bai, Massa, and Zhang (2022) find that an increase in lendable supply predicts a decline in future credit spreads.

[9] Boehmer, Jones, and Zhang (2008) and Diether, Lee, and Werner (2009b) highlight the advantages of focusing on flows to understand short sales and their impact on prices.

immediately as they face buying pressure. Thus, the adverse selection cost, r_{d^*+k+1}, arises from the price drift after the initial short sales.

Table 3 reports the dealer profits and losses, $PL_{d^*,K}$, averaged across calendar day d^*. Since we do not have information on how quickly dealers cover their short positions, we report the results for $K = 5$, 10, and 20 business days. Using the full sample of shorted bonds, we find that the dealer earns an average profit of 0.475% if she can unwind the position in five business days. This profit declines to 0.357% and 0.147% if the time to unwind increases to 10 and 20 business days, respectively. The profit of 0.147% is statistically indistinguishable from zero ($t = 1.41$), implying that if the dealer can find the opposite side within roughly one month, then the trade breaks even.

Table 3 also decomposes dealer profits into revenue from half spreads and costs associated with borrowing fees and bond returns. To assess the contribution of each component, we set that component to zero and recalculate profits using equation (7). The difference between the original and recalculated profits represents the contribution of that component. When positions are unwound after five business days, the contributions of half spreads, borrowing fees, and adverse selection costs associated with bond returns are 0.603%, −0.007%, and −0.121%, respectively. Thus, most of the cost to dealers of shorting bonds arises from bond price appreciation following the short sale, while borrowing fees are largely negligible. Similar conclusions hold for the case of $K = 10$ and $K = 20$.

Even if the short position on the portfolio of bonds yields profit, there is substantial heterogeneity across individual positions. To see this, Figure 5 plots the average and median dealer profits and losses for each bond-level position, along with the interquartile range. When a dealer sells a bond short, she earns the half spread. As k increases, her initial profit gradually declines due to adverse selection. However, it increases when she finds a selling customer and charges the half spread again. After 20 days, when the position is closed, the interquartile range runs from −0.87% to 1.03%. Almost half of the positions (48.9%) lose money, suggesting that dealers face substantial uncertainty with each trade.

Panels B to F of Table 3 provide the subsample analysis. Instead of including all bonds with $dQ_{i,d} > 0$, we impose additional requirements for the bonds to be included in the portfolio, and reestimate the profits and losses. These panels indicate that dealers' profits are higher for special bonds with long maturities and small sizes, and during crisis periods. In most scenarios, dealers on average profit from short positions. This explains why dealers are willing to borrow corporate bonds to make markets for buyers, despite the risk.

3.5 Event Study: Tender Offers

In this section, we conduct an event study on bond tender offers to illustrate the risks facing dealers. The analysis also verifies our claim that short sellers are predominantly dealers. Rather than relying on unconditional panel regressions, we examine how short sales, trading volume, and half spreads respond to tender offers.

Issuers announce tender offers to buy back their bonds, with a deadline typically set about a month later. Bondholders can tender their bonds by transferring the bonds to the tender agent through the Automated Tender Offer Program (ATOP) at the Depository Trust Company (DTC). To tender bonds that are on loan, a bondholder must first recall them so that the bonds are returned to its account and can be delivered through ATOP. As a result, a tender offer generates a negative shock to the bond's lendable supply. This potentially creates a short squeeze for the borrower, who may be forced to buy back the bond.

We use this event to verify whether the short sellers are dealers or customers. If dealers are the short sellers, then they must buy bonds upon the announcement. If customers are the short sellers, then customer purchases must increase upon a tender announcement.

To this end, we examine the first tender event for each bond in our sample. Setting the deadline of the offer as the reference date $\tau = 0$, we track the lending outcomes and the cumulative difference between customer sell volume and buy volume over the 63 trading days before and after the event. We study abnormal reactions by subtracting, for each bond and event, the mean over the estimation window $\tau \in [-189, -64]$. For the event to be in our sample, we require at least 40 valid observations in that window. The variables of interest include the cumulative change in quantity on loan, the lending fee, and the cumulative change in lendable supply, each averaged across 3,342 tender events. We also examine the median cumulative abnormal return, the mean cumulative sell minus buy volume, and the mean half spreads. Lendable supply, quantity on loan, and volume are scaled by the amount outstanding at $\tau = -1$, which we require to be at least \$1 million.[10] Since daily half spreads are volatile, we report their 5-day moving averages.

The top three panels of Figure 6 plot the response of the lending activity-related variables. As expected, the tender offer announcement, which is about 20 trading days before the deadline, leads to a sharp decline in quantity on loan and lendable supply. By $\tau = 5$ they reach -0.52% and -8.42%, respectively. In contrast, the lending fee rises to about 0.09% at $\tau = 5$. These results support the validity of the exercise. A tender offer announcement leads to an economically significant contraction in lendable supply.

The bottom three panels report outcomes in the underlying bond market. The median

[10] This requirement removes 64 of the 3,342 events.

cumulative abnormal return jumps at the announcement, rising from about -0.08% at $\tau = -22$ to 0.20% by $\tau = -17$. This price increase captures the effect of the short squeeze on short sellers. They incur losses because they must repurchase the bond to cover their existing short positions at a higher price than the price at which they initially sold it. After the deadline, this buying pressure dissipates, and the cumulative return reverts toward its pre-announcement level.

The bottom middle panel reveals the key insight from this analysis. It plots the cumulative customer sales minus customer buys averaged across events. The customer net sales increase sharply upon the announcement, reaching about 0.41% of the amount outstanding by $\tau = 0$. This suggests that dealers buy back the bonds to cover their short positions. The cumulative net customer sales remain elevated after the event. However, this does not imply that the dealer's inventory remains high because she returns the purchased bond to the lender.

The bottom right panel shows that the tender offer announcement creates buying pressure. Upon announcement, the half spread rises for customer-buy trades but declines for customer-sell trades, confirming the validity of the test. After the tender event, the half spreads rise as the size of the issue shrinks. Taken together, the event study analysis provides additional evidence that dealers are the primary short sellers of corporate bonds. While dealers typically profit from shorting bonds, they are also vulnerable to short squeezes.

3.6 Multivariate Analysis

We present our results using univariate regressions in Section 3.1. To verify these results, we next perform a multivariate analysis on the relationship between trading volume and the quantity on loan. Specifically, we run multivariate panel regressions of changes in scaled quantity on loan on scaled trading volume, following Diether, Lee, and Werner (2009b),

$$dQ_{i,d} = b_0 Vol_{i,d^*,Buy} + b_1 Vol_{i,d^*,Sell} + \gamma_d + \alpha_i + Ctrl_{i,d} + \varepsilon_{i,d}. \tag{8}$$

The set of controls $Ctrl_{i,d}$ includes variables related to the bond's past trading, price movements, and other characteristics. From trading, we include the average change in quantity on loan over days $d-5$ to $d-1$, and the average daily customer buy and sell volume over days d^*-5 to d^*-1. From price movements, we include the average abnormal half spreads on the customer buy and sell sides and the standard deviation of daily returns over the same five days, together with the bond return on day d^* and its average over the prior five days. We also control for the issuer's equity lending, using the daily change in the stock's quantity on loan and its five-day average. Finally, we include three bond characteristics measured on day d^*: the log amount outstanding, the numerical credit rating, and the time to maturity. To facilitate comparisons of economic magnitudes across coefficients, all continuous 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 interest are b_0 and b_1, which measure how sensitive changes in loan quantity are to signed trading volume.

Column (1) of Table 4 reports the regression estimates using customer buying and selling volume before adding the set of control variables. The point estimates for b_0 and b_1 indicate that a one-standard-deviation increase in contemporaneous customer buys is associated with a 5.48 bps simultaneous increase in bond lending, while an increase in customer sells corresponds to a 4.45 bps decrease. 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 daily change in quantity on loan (19.90 bps, see Table 1). The above-100 t-statistic reflects the largely mechanical nature of the relationship: each dollar increase in the loan amount on a given day must correspond to a dollar increase in the bond's sales on that day.

The even-numbered columns add the set of control variables from equation (8). To save space, we report the coefficient estimates on all the control variables in Internet Appendix Table IA3. In Column (2), the estimated b_0 and b_1 are nearly identical to the ones in Column (1), confirming effectively the same results.

In Columns (3) and (4), we replace the continuous volume variable with the tercile dummies to capture the potentially nonlinear link between trading volume and short sales. To create these variables, we cross-sectionally rank bonds based on their signed trading volume and group them into three categories: Low, Med, and High. We include the dummies for Med and High categories, treating Low as the omitted category.

The estimates show that the quantity on loan is a convex function of trading volume. For example, in Column (3), the loadings on Buy_{High} and Buy_{Med} are 5.70 bps and 0.56 bps, respectively. They indicate that the difference between high and medium volumes (5.14 bps) is greater than the difference between medium and low volumes (0.56 bps), suggesting that dealers short-sell bonds when they face unusually large buying volume.

To highlight this point further, we create dummy variables $Block_{Buy}$ and $Block_{Sell}$ for days with at least one block customer buy and sell trade, respectively, where a block trade is defined as a trade with a par value of at least \$15 million. We add interaction terms between these dummies and Buy_{High} and $Sell_{High}$, and estimate the regression (8). The results reported in Column (5) indicate that, within the top volume tercile, a block buy trade corresponds to a 20.31 bps increase in bond lending. The magnitude of the coefficients is nearly as large as the standard deviation of changes in loan quantity. These results indicate that dealers are significantly more likely to borrow bonds to make markets when they face unusually large buy orders.[11]

The coefficients on the control variables, reported in Internet Appendix Table IA3, have sensible signs. For example, a one-standard-deviation increase in lagged weekly customer buy volume predicts a 1.40 bps increase in quantity on loan, while that of lagged weekly sell volume predicts a decrease (−2.22 bps). Thus, a depleted dealers' inventory predicts their increased reliance on short sales.

In Internet Appendix Table IA5, we confirm the positive relationship between increased short sales and returns documented in Section 3.3 using multivariate regressions of bond returns. The results show that the coefficient on bond lending is positive even after controlling for a host of bond characteristics. In contrast, bond returns decrease after the stock lending rises. This sign reversal between bond and equity lending coefficients supports our claim that the motivation to borrow bonds, namely facilitating customer buying rather than selling, is contrary to that for borrowing stocks.

Overall, the analyses confirm that the main results based on univariate regressions remain unaffected by the addition of the host of control variables.

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

[11] In Internet Appendix Table IA4, 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 (8). We find that these additional terms have economically small coefficient estimates, implying that the availability of these alternative financial instruments does not affect our main results.

by dealers and customers, respectively. For ease of exposition, we suppress the subscripts d and d^* throughout the remainder of this derivation and focus on the contemporaneous relationship. Then, a daily change in the quantity on loan is given by

$$dQ = (\text{New Short Positions}) - (\text{Short Covering}) = (S_D + S_C) - (B_D + B_C). \tag{9}$$

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

$$Vol_{Buy} = S_D + B_C + u_{Buy}, \tag{10}$$

$$Vol_{Sell} = S_C + B_D + u_{Sell}, \tag{11}$$

where u_{Buy} and u_{Sell} capture customer buys and sells unrelated to short sales (dQ), respectively. Here, the customer buy volume Vol_{Buy} includes the short sales initiated by dealers, S_D, as these must be matched by customer purchases. Likewise, the customer sell volume Vol_{Sell} includes 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 (9), we take advantage of the fact that short covering B reduces loan quantity, but increases trading volume in equations (10) and (11). Thus, we can decompose the total variance of dQ into the parts driven by customer and dealer activities. Specifically, we regress customer buy and sell volume on dQ in a regression analogous to equation (1) with control variables. Then, the OLS slope coefficients are

$$\begin{aligned} \beta_B &= \frac{\text{cov}\left(\widetilde{dQ}, Vol_{Buy}\right)}{\sigma^2\left(\widetilde{dQ}\right)} = \frac{1}{\sigma^2\left(\widetilde{dQ}\right)}\left(\underbrace{\text{cov}\left(\widetilde{dQ}, S_D\right)}_{\text{Dealer-Driven}} + \underbrace{\text{cov}\left(\widetilde{dQ}, B_C\right)}_{\text{Customer-Driven}}\right), \\ \beta_S &= \frac{\text{cov}\left(\widetilde{dQ}, Vol_{Sell}\right)}{\sigma^2\left(\widetilde{dQ}\right)} = \frac{1}{\sigma^2\left(\widetilde{dQ}\right)}\left(\underbrace{\text{cov}\left(\widetilde{dQ}, S_C\right)}_{\text{Customer-Driven}} + \underbrace{\text{cov}\left(\widetilde{dQ}, B_D\right)}_{\text{Dealer-Driven}}\right), \end{aligned} \tag{12}$$

where $\widetilde{dQ}$ denotes dQ orthogonalized with respect to the controls.

Each coefficient mixes the dealer-driven and customer-driven short sales, and thus neither is informative on its own. However, taking the difference between the two slope coefficients, we obtain the key equation,

$$\begin{aligned}
\beta_S - \beta_B &= \underbrace{\frac{\text{cov}\left(\widetilde{dQ}, S_C - B_C\right)}{\sigma^2\left(\widetilde{dQ}\right)}}_{\text{Customer Share}} - \underbrace{\frac{\text{cov}\left(\widetilde{dQ}, S_D - B_D\right)}{\sigma^2\left(\widetilde{dQ}\right)}}_{\text{Dealer Share}} \\
&\equiv C - D, \qquad (13)
\end{aligned}$$

where C and D are the shares of the variance of $\widetilde{dQ}$ attributable to net customer-driven and net dealer-driven short sales, respectively.

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

$$C = \frac{1}{2} + \frac{1}{2}(\beta_S - \beta_B), \quad D = \frac{1}{2} - \frac{1}{2}(\beta_S - \beta_B). \qquad (14)$$

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

$$\beta_B = \frac{\text{cov}\left(\widetilde{dQ}, B_C\right)}{\sigma^2\left(\widetilde{dQ}\right)}, \quad \beta_S = \frac{\text{cov}\left(\widetilde{dQ}, S_C\right)}{\sigma^2\left(\widetilde{dQ}\right)}, \qquad (15)$$

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

$$\beta_B = \frac{\text{cov}\left(\widetilde{dQ}, S_D\right)}{\sigma^2\left(\widetilde{dQ}\right)}, \quad \beta_S = \frac{\text{cov}\left(\widetilde{dQ}, B_D\right)}{\sigma^2\left(\widetilde{dQ}\right)}, \qquad (16)$$

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, $\beta_{(\cdot)}$, but it does restrict the difference between them.

Our decomposition framework is general in two respects. First, it remains valid even when the underlying drivers for short sales, B and S, are correlated with one another. Second, if a bond characteristic induces correlation between short-sale-driven volume (B and S) and other trades (u), one can eliminate this correlation by orthogonalizing the variables with respect to that characteristic. For example, positive news about an issuer's fundamentals may simultaneously increase purchases unrelated to shorting, u_{Buy}, and increase customer short covering trades, B_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. Ultimately, we only need a relatively mild identifying assumption, $\text{cov}\left(\widetilde{dQ}, u_{Sell} - u_{Buy}\right) = 0$, for equation (13) to hold.

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.[12]

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

$$Vol_{i,d^*,\xi} = b_\xi dQ_{i,d} + \gamma_d + \alpha_i + Ctrl_{i,d} + \varepsilon_{i,d}, \quad \text{where } \xi \in \{Buy, Sell\}, \tag{17}$$

and $Ctrl_{i,d}$ is the same set of controls as equation (8) except that we do not include changes in stocks on loan.[13] We use the b_ξ as an estimate of β_ξ to calculate the share of customer and dealer short sales following equation (14). To calculate the standard error of the difference, $b_S - b_B$, we use seemingly unrelated regression to account for the correlation between the estimated b_S and b_B. In addition, the standard errors are double-clustered at the bond and date levels.

Table 5 reports the estimated share of short sales.[14] Using the full sample of daily panel data with available controls, we find that the difference in slope coefficients is $b_S - b_B = -0.377$ ($t = -59.02$), implying that dealers' short sales exceed those of customers. The estimated dealer share is 68.9%, with the remaining 31.1% attributable to customer short sales. These results suggest that dealers' market-making activities are the main driver

[12] To assess the prevalence of financing-driven bond lending in the Markit data, we plot the average loan quantity and short interest, both scaled by amount outstanding, in Internet Appendix Figure IA2. The two series mostly overlap after 2009.

[13] We do not include stocks on loan so we can later study the subsample of private firms with no publicly listed stocks.

[14] Internet Appendix Table IA6 reports the estimates on the control variables.

of corporate bond short sales. These results are mostly the same when we replace the multivariate regression in (17) with the univariate version in (1). We relegate these results to the Internet Appendix Table IA7.[15]

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 5 reports the estimates by rating on day d^*. We find that the dealer shares of short sales of IG and HY bonds are 71.3% and 64.6%, respectively. Therefore, as expected, 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: general collateral (GC) bonds are those in the bottom 90%, and special (SP) bonds are those in the top 10%, which are further split into SP1 (between the 90th and 95th percentiles), SP2 (between the 95th and 99th percentiles), and SP3 (above the 99th percentile). Panel C of Table 5 shows that the dealer share declines monotonically across the specialness percentiles from 70.6% for GC, 60.7% for SP1, 56.8% for SP2, and 53.7% for SP3. Therefore, bonds with an extremely high fee are subject to increased customer speculation, which results in a lower share of market-making activities. These results are consistent with those of 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 5 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 69.0% 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 68.8% for issuers with CDS, nearly identical to the estimate of 68.9%

[15]Figures IA3 and IA4 plot specification curves for the regression coefficients, b_ξ, showing they are stable across the $2^8 = 256$ specifications. If unobserved variables driving $\varepsilon_{i,d}$ are correlated with $dQ_{i,d}$ in a manner similar to that of the included controls, this stability indicates that any such correlation is unlikely to bias our estimates significantly (see, e.g., Altonji, Elder, and Taber 2005; Oster 2019).

for issuers without. While surprising at first glance, the results make sense given that CDS coverage is an endogenous outcome that reflects customers' desire to short credit. Issuers covered by CDS can have higher customer short sales of corporate bonds because of the demand to purchase insurance against default risk. Such an effect is mitigated by the fact that CDS is available as an alternative means to short, offsetting the higher demand to short the bond.

To dissect 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 (2018), 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 at or 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 5 show that in all cases the dealer short sales dominate the customer speculation, with a share ranging from 66.8% to 71.4%. Their share is higher for overvalued, large, and liquid bonds, but the difference appears to be small.[16]

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 Internet Appendix Tables IA9 and IA10, as well as Figure IA5, show no material impact on our findings.

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.

[16] In Internet Appendix Table IA8, we present the results of splitting the sample before and after September 4, 2017. The results from the two periods are highly similar.

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 21-trading-day window from August 28 through September 26, where September 26 is 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 6 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 60.7% before downgrades crossing the IG/HY threshold and 60.1% before other downgrades. In contrast, before upgrades crossing the IG/HY threshold, the dealer share is 73.7%, while it is 68.8% 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 6 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%).

Our results indicate that the dealer share of short sales is 63.3% before very bad news, 70.0% before bad news, 71.8% before around expectation news, 70.9% before good news, and 67.0% before very good news. Thus, customers speculate significantly more before very bad news, with the dealer share lower by approximately 8 p.p. 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 demonstrate that customer short sales become more important before rating downgrades and bad earnings news, underscoring the validity of our approach. Nevertheless, we find no subsample in which the dealer's share falls below 50%.

4.4 Decomposition in the Stock Market

Since our decomposition of short-selling activities in equation (14) 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 similarly scaled quantity on loan.

Figure 7 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 7 presents the estimated dealer share using equation (14) 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. Across the subsamples, the share of liquidity-taker short sales is around 50%, similar to that of liquidity-maker short sales. These results are broadly consistent with Comerton-Forde, Jones, and Putniņš (2016) and Goyal, Reed, Smajlbegovic, and Soebhag (2025). These authors find that in the stock market, the magnitude of the liquidity-taking and liquidity-supplying short sales is comparable to each other. Our analysis confirms that, in the stock market, speculative short sales by liquidity takers are just as important as those of liquidity makers. It also underscores the uniqueness of the results in the dealer-driven corporate bond market.

5 The Effect of Short Sales on Bond Liquidity and Prices

5.1 Bond Short Sales and Liquidity

Borrowing bonds is costly for dealers. If they nevertheless borrow bonds to facilitate market making, their willingness reveals their commitment to providing liquidity for these bonds. More intensive dealer short sales may, therefore, signal an improvement in corporate bond liquidity.[17] In this section, we exploit this cross-sectional heterogeneity across bonds to examine the link between dealers' willingness to intermediate via bond lending market and bond liquidity. Using the dealers' share in short sales estimated in the previous section as a proxy for their commitment to market making, we examine whether bonds with a higher dealer share have better liquidity than those with a lower share.

To this end, we estimate the dealer share bond by bond. Specifically, at the end of each month, we use the trailing 252 business days to estimate the univariate regression in equation (1) for each bond, and compute the bond-level dealer share by using equation (14). We require at least 120 non-missing observations and at least 20 observations with $dQ \neq 0$. The sample runs from March 2007 to December 2022, beginning when valid bond-level dealer-share estimates first become available.

Figure 8 plots the cross-sectional median, the 25th, and the 75th percentiles of the estimated dealer share. The dealer share rises sharply after the 2008 financial crisis and declines somewhat in recent years. At the same time, for a median bond, the share remains more than 50% throughout the sample. The figure also reveals substantial heterogeneity across bonds; the 25th and 75th percentiles at the end of our sample are 62% and 84% (with a median of 73%), respectively.

We next sort bonds into quintiles based on the month-t value of the dealer share, and compute the value-weighted average of the illiquidity measure in month $t+1$. Since there is no agreement on the best measure of illiquidity, we use ten proxies, augmenting the set proposed by Schestag, Schuster, and Uhrig-Homburg (2016). Four are direct transaction-cost measures: bid-ask spreads using all trades and using institutional trades of $100,000 or larger, and the intraday interquartile range using the same set of two samples. Four are model-based transaction cost estimates: the high-low estimator of Corwin and Schultz (2012), the Gibbs

[17] Empirically, whether short sales increase or decrease equity liquidity is highly debated. On the one hand, a short sales ban during crises is shown to reduce equity liquidity (see, e.g., Beber and Pagano 2013; Boehmer, Jones, and Zhang 2013). However, the effect of more limited restrictions on short sales during normal times, such as the uptick rule, is more ambiguous (see, e.g., Diether, Lee, and Werner 2009a).

sampler estimate of effective cost of Hasbrouck (2009), the return autocovariance of Roll (1984) and Bao, Pan, and Wang (2011), and the volatility-and-zero-return estimator of Fong, Holden, and Trzcinka (2017). Two capture trading activity: the fraction of zero-trade days in a month and log dollar trading volume. Appendix Table A1 provides the full definitions.

Table 8 reports the difference in illiquidity measures between the highest and lowest dealer share quintiles. We find that across the transaction cost measures, the dealer share is strongly related to a reduction in illiquidity. For example, the bonds in the top dealer-share quintile have 21.0 bps lower bid-ask spreads (using all trades) next month than those in the bottom quintile. Thus, the dealer share predicts economically meaningful variation in illiquidity. Looking at the trading activity-related variables, neither the number of zero trade dates nor log trading volume is significantly related to the dealer share at the conventional 5% level. Thus, the dealer share predicts improved liquidity primarily through lower transaction costs but not necessarily through increased trading volume.

To account for a potential correlation between the dealer share and other bond characteristics, we estimate monthly cross-sectional regressions of Fama and MacBeth (1973). Specifically, we regress the liquidity outcomes on the dealer share and bond characteristics,

$$Liq_{i,t+1} = a_t + b_t \text{DealerShare}_{i,t} + c_t \text{Ctrl}_{i,t} + \varepsilon_{i,t+1}, \tag{18}$$

where the set of control variables includes the log amount outstanding, age, time to maturity, and numerical values of credit rating. The right-hand-side variables are standardized for the ease of interpretation. The standard errors are adjusted for the Newey and West (1987) with 12 lags.

Table 9 reports the estimated coefficients averaged over time.[18] The dealer share negatively predicts the transaction cost estimates. For example, a one-standard-deviation increase in dealer share predicts a 6.25 bps decline ($t = -3.45$) in average bid-ask spreads estimated using all transactions. The coefficients for the interquartile range, the high-low price measure, the Gibbs estimates, and the return autocovariance are all negative and significant. The coefficient for the volatility-and-zero-return estimates is no longer significant, but its sign remains the same. Taken together, these findings indicate that the dealer share signals lower illiquidity in the future.

[18]The number of observations varies across the columns of Table 9 because of the different data requirements to calculate each liquidity measure. The estimators of Roll (1984), Corwin and Schultz (2012), Fong, Holden, and Trzcinka (2017), and Hasbrouck (2009), along with log dollar volume, are computed only for bond-months with at least eight days on which the bond trades. The bid-ask spread measures require both a customer buy and a customer sell on the same day, and the interquartile-range measures require at least three trades on the day. The fraction of zero-trade days carries no trading activity screen.

5.2 Short Sales and Corporate Bond Factors

In this section, we study how short-sale costs limit the correction of corporate bond mispricing. When a security is overvalued for whatever reason, short sellers can in principle short it until the price goes down. However, short-selling constraints can prevent such activities, leaving the price uncorrected (Miller 1977).

In the stock market, the effect of short-sales constraints is asymmetric. Since there is no constraint on buying a stock, a stock is less likely to remain undervalued than overvalued (Blocher, Reed, and Van Wesep 2013). This asymmetry is more pronounced for stocks with higher short-selling costs (Muravyev, Pearson, and Pollet 2025). In contrast, in the bond market, the effect is more likely to be symmetric. When dealers face short-sales constraints, buying customers will have difficulty obtaining a quote, leaving the bond undervalued.

We test this symmetry by sorting corporate bonds into portfolios based on signals plausibly associated with mispricing. As the literature shows (see, e.g., Gebhardt, Hvidkjaer, and Swaminathan 2005; Jostova, Nikolova, Philipov, and Stahel 2013; Chordia, Goyal, Nozawa, Subrahmanyam, and Tong 2017; Nozawa, Qiu, and Xiong 2026), past stock returns of a bond issuing firm strongly predict its bond returns next month. Their results indicate that bonds with a high (low) stock return are undervalued (overvalued). Thus, portfolio analysis provides a clean testing ground for our hypothesis.

To avoid ad-hoc selection of characteristics, we use all 13 characteristics stemming from past stock and option returns used in Dickerson, Nozawa, and Robotti (2025).[19] Every month, we sort bonds into quintiles and compute value-weighted portfolio returns in the following month. The first quintile includes the bonds with the lowest past stock or option returns, while the fifth quintile includes those with the highest. For each quintile, we average monthly returns across 13 characteristics to obtain a composite portfolio.

We quantify the mispricing by two methods. First, we subtract from individual bond returns the matching portfolio returns based on credit rating and maturity as in Section 3.3. Second, following van Binsbergen, Nozawa, and Schwert (2025), we regress portfolio p excess returns on the duration-matched Treasury returns and the duration-adjusted corporate bond market portfolio returns and examine the intercept α_p. Specifically, we estimate

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_{p,Tsy}(r_{Tsy,t} - r_{f,t}) + \beta_{p,DurAdj}(r_{BondMkt,t} - r_{Tsy,t}) + \varepsilon_{p,t}, \qquad (19)$$

[19] These characteristics are in their "Equity Reversal" and "Equity Momentum" categories, including earnings announcement returns, seasonal momentum, trend factor, changes in implied volatility of calls and puts, past 1- and 3-month returns, the maximum returns over the 21-day period adjusted and unadjusted for volatility, seasonally-adjusted momentum over the 1 to 10 months, and industry returns. Internet Appendix Table IA12 provides the list of the factors and their definitions.

where $r_{f,t}$ is the one-month T-bill rate.

Table 10 presents the average characteristic-adjusted returns and the alphas for the first and fifth quintiles. The first three columns report the characteristic-adjusted return, which is -0.12% ($t = -2.93$) for Q1 and 0.08% ($t = 3.86$) for Q5, with the long-short difference of 0.20% per month ($t = 3.46$). Both Q1 and Q5 have statistically significant adjusted returns with opposite signs. Looking across the 13 underlying factors, 8 have significant adjusted returns for Q1, and 8 for Q5. These numbers are similar to each other. This symmetry in mispricing is consistent with our argument that arbitrageurs in the corporate bond market face short-selling constraints when they *buy* bonds from a dealer, who shorts the corporate bond to meet the demand.

To compare the two legs more formally, we compute the sum of Q1 and Q5 returns. The sum measures the difference in contribution to the alpha of the long-short portfolio. We find that the sum is -0.04% per month, which is statistically insignificant ($t = -1.34$). Thus, we cannot reject the null hypothesis that both the long and short legs of the trade contribute equally to the long-short strategy.[20]

The second and third columns of Table 10 report the characteristic-adjusted returns separately for IG and HY bonds. For IG bonds, the average Q1 and Q5 returns are -0.10% ($t = -2.77$) and 0.07% ($t = 3.52$). The sum of the two returns is -0.03% per month, which is insignificantly different from zero. For HY bonds, the corresponding values are -0.18% ($t = -2.63$) and 0.10% ($t = 3.19$), respectively. The sum of -0.08% is again insignificant.

The final three columns of Table 10 repeat the analysis using the duration-adjusted CAPM alpha in equation (19). The results are similar, with 8 significant characteristics for the short leg and 9 for the long leg.

To provide more direct evidence that the patterns in returns across quintiles are a reflection of short selling activity, we report the average quantity on loan (scaled by amount outstanding) for each quintile in Figure 9. Each month, we subtract the average across the quintiles from each quintile, and plot the time-series average of the deviation. The plot reveals a clear U-shaped pattern, regardless of whether we look at all, IG, or HY bonds. The bonds in the first quintile are shorted more than those in the middle quintiles because they are overvalued. The bonds in the fifth quintile are also more shorted because they are undervalued, which encourages informed customers to buy them from the dealers.

Taking these results together, in the corporate bond market, the long legs of the trade significantly contribute to bond factor performance. While shorting overvalued bonds is

[20] Internet Appendix Tables IA13 and IA14 report the long-short difference and sum for each of the 13 characteristics.

expensive due to half spreads, taking a long position on undervalued bonds can also be a challenge when dealers face short-sales constraints.

6 Conclusion

In this paper, we examine the drivers of corporate bond lending and their implications for dealer intermediation and bond market liquidity. 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 purchases, half spreads on customer purchases, and bond prices all increase. At the same time, we find no reversal in subsequent bond returns, which is consistent with dealers accommodating informed customer buying.

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, specialness, liquidity, 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.

We further show that the bid-ask spread dealers earn from intermediating customer buying pressure on average dominates both the borrowing fee and the price drift against their short position. This positive expected profit explains dealers' willingness to borrow corporate bonds despite the cost of doing so. In the cross-section, bonds with a higher dealer share also exhibit lower subsequent transaction costs, consistent with the view that dealer market-making activity supports bond market liquidity.

Dealer-driven short selling also influences where corporate bond factors come from. Using 13 signals built from past stock and option returns, we find that the long and short legs contribute almost equally to the long-short spread. This symmetry contrasts with the equity market, where anomaly profits concentrate in the short leg. Instead, we demonstrate that short-sale constraints in corporate bonds bind on dealers filling customer buy orders.

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 clarifies how dealer intermediation shapes short-sale activity and liquidity supply in over-the-counter markets.

References

Altonji, Joseph G, Todd E Elder, and Christopher R Taber, 2005, Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools, *Journal of Political Economy* 113, 151–184.

An, Byeong-Je, Andrew Ang, Turan G Bali, and Nusret Cakici, 2014, The joint cross section of stocks and options, *Journal of Finance* 69, 2279–2337.

Anand, Amber, Chotibhak Jotikasthira, and Kumar Venkataraman, 2021, Mutual fund trading style and bond market fragility, *Review of Financial Studies* 34, 2993–3044.

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.

Asness, Cliff, Andrea Frazzini, Niels Joachim Gormsen, and Lasse Heje Pedersen, 2020, Betting against correlation: Testing theories of the low-risk effect, *Journal of Financial Economics* 135, 629–652.

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.

Asquith, Paul, Parag A. Pathak, and Jay R. Ritter, 2005, Short interest, institutional ownership, and stock returns, *Journal of Financial Economics* 78, 243–276.

Atmaz, Adem, Suleyman Basak, and Fangcheng Ruan, 2024, Dynamic equilibrium with costly short-selling and lending market, *Review of Financial Studies* 37, 444–506.

Augustin, Patrick, Linxiao Francis Cong, Ricardo Lopez A., and Roméo Tédongap, 2025, Downside risk and the cross-section of corporate bond returns, Working Paper.

Bai, Jennie, Massimo Massa, and Hong Zhang, 2022, Securities lending and corporate financing: Evidence from bond issuance, Working Paper.

Bali, Turan G, Stephen J Brown, Scott Murray, and Yi Tang, 2017, A lottery-demand-based explanation of the beta anomaly, *Journal of Financial and Quantitative Analysis* 52, 2369–2397.

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, Working Paper.

Beber, Alessandro, and Marco Pagano, 2013, Short-selling bans around the world: Evidence from the 2007–09 crisis, *Journal of Finance* 68, 343–381.

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.

Chan, Louis K.C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51, 1681–1713.

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

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, 2018, Reaching for yield in corporate bond mutual funds, *Review of Financial Studies* 31, 1930–1965.

Chordia, Tarun, Amit Goyal, Yoshio Nozawa, Avanidhar Subrahmanyam, and Qing Tong, 2017, Are capital market anomalies common to equity and corporate bond markets? an empirical investigation, *Journal of Financial and Quantitative Analysis* 52, 1301–1342.

Comerton-Forde, Carole, Billy Ford, Thierry Foucault, and Simon Jurkatis, 2025, Investors as a liquidity backstop in corporate bond market, Working Paper.

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.

Corwin, Shane A, and Paul Schultz, 2012, A simple way to estimate bid-ask spreads from daily high and low prices, *Journal of Finance* 67, 719–760.

Dechow, Patricia M, Amy P Hutton, Lisa Meulbroek, and Richard G Sloan, 2001, Short-sellers, fundamental analysis, and stock returns, *Journal of Financial Economics* 61, 77–106.

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

Desai, Hemang, Srinivasan Krishnamurthy, and Kumar Venkataraman, 2006, Do short sellers target firms with poor earnings quality? evidence from earnings restatements, *Review of Accounting Studies* 11, 71–90.

Desai, Hemang, K. Ramesh, S. Ramu Thiagarajan, and Bala V. Balachandran, 2002, An investigation of the informational role of short interest in the nasdaq market, *Journal of Finance* 57, 2263–2287.

Diamond, Douglas W., and Robert E. Verrecchia, 1987, Constraints on short-selling and asset price adjustment to private information, *Journal of Financial Economics* 18, 277–311.

Dick-Nielsen, Jens, 2014, How to clean enhanced trace data, Working Paper.

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, Peter Feldhütter, Lasse Heje Pedersen, and Christian Stolborg, 2026, Corporate bond factors: Replication failures and a new framework, Working Ppaer.

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

Dickerson, Alex, Christian Julliard, and Philippe Mueller, 2023a, The corporate bond factor zoo, Working Paper.

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

Dickerson, Alexander, Yoshio Nozawa, and Cesare Robotti, 2025, Factor investing with delays, Working Paper, UNSW.

Diether, Karl B., Kuan-Hui Lee, and Ingrid M. Werner, 2009a, It's SHO time! Short-sale price tests and market quality, *Journal of Finance* 64, 37–73.

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

Duong, Huu Nhan, Arseny Gorbenko, Petko S. Kalev, and Jason Tian, 2025, Short interest in bonds and aggregate stock returns, Working Paper.

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, 2012, How are shorts informed?: Short sellers, news, and information processing, *Journal of Financial Economics* 105, 260–278.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy* 81, 607–636.

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

Foley-Fisher, Nathan, Stefan Gissler, and Stéphane Verani, 2019a, Over-the-counter market liquidity and securities lending, *Review of Economic Dynamics* 33, 272–294.

Foley-Fisher, Nathan, Borghan Narajabad, and Stéphane Verani, 2019b, Securities lending as wholesale funding: Evidence from the u.s. life insurance industry, Working Paper.

Fong, Kingsley YL, Craig W Holden, and Charles A Trzcinka, 2017, What are the best liquidity proxies for global research?, *Review of Finance* 21, 1355–1401.

Friewald, Nils, and Florian Nagler, 2019, Over-the-counter market frictions and yield spread changes, *Journal of Finance* 74, 3217–3257.

Friewald, Nils, and Florian Nagler, 2024, Dealer inventory and the cross-section of corporate bond returns, *Economics Letters* 239, 111710.

Gebhardt, William R., Soeren Hvidkjaer, and Bhaskaran Swaminathan, 2005, Stock and bond market interaction: Does momentum spill over?, *Journal of Financial Economics* 75, 651–690.

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.

Goldberg, Jonathan, and Yoshio Nozawa, 2021, Liquidity supply in the corporate bond market, *Journal of Finance* 76, 755–796.

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

Han, Yufeng, Guofu Zhou, and Yingzi Zhu, 2016, A trend factor: Any economic gains from using information over investment horizons?, *Journal of Financial Economics* 122, 352–375.

Hasbrouck, Joel, 2009, Trading costs and returns for us equities: Estimating effective costs from daily data, *Journal of Finance* 64, 1445–1477.

He, Zhiguo, Paymon Khorrami, and Zhaogang Song, 2022, Commonality in credit spread changes: Dealer inventory and intermediary distress, *Review of Financial Studies* 35, 4630–4673.

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 Schürhoff, and Kumar Venkataraman, 2026, Quote competition in corporate bonds, *Journal of Finance* 81, 2165–2216.

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

Heston, Steven L, and Ronnie Sadka, 2008, Seasonality in the cross-section of stock returns, *Journal of Financial Economics* 87, 418–445.

Hou, Kewei, 2007, Industry information diffusion and the lead-lag effect in stock returns, *Review of Financial Studies* 20, 1113–1138.

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

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881–898.

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.

Jostova, Gergana, Stanislava Nikolova, Alexander Philipov, and Christof W. Stahel, 2013, Momentum in corporate bond returns, *Review of Financial Studies* 26, 1649–1693.

Kelly, Bryan, Diogo Palhares, and Seth Pruitt, 2023, Modeling corporate bond returns, *Journal of Finance* 78, 1967–2008.

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

Lamont, Owen A., and Richard H. Thaler, 2003, Can the market add and subtract? mispricing in tech stock carve-outs, *Journal of Political Economy* 111, 227–268.

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

Macchiavelli, Marco, and Xing (Alex) Zhou, 2022, Funding liquidity and market liquidity: The broker-dealer perspective, *Management Science* 68, 3379–3398.

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

Miller, Edward M., 1977, Risk, uncertainty, and divergence of opinion, *Journal of Finance* 32, 1151–1168.

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, 2025, Anomalies and their short-sale costs, *Journal of Finance* 80, 3639–3694.

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

Nozawa, Yoshio, Yancheng Qiu, and Yan Xiong, 2026, Disagreement and bond pead, *Management Science* forthcoming.

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.

Oster, Emily, 2019, Unobservable selection and coefficient stability: Theory and evidence, *Journal of Business & Economic Statistics* 37, 187–204.

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.

Roll, Richard, 1984, A simple implicit measure of the effective bid-ask spread in an efficient market, *Journal of Finance* 39, 1127–1139.

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.

van Binsbergen, Jules H, Yoshio Nozawa, and Michael Schwert, 2025, Duration-based valuation of corporate bonds, *Review of Financial Studies* 38, 158–191.

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 dotted vertical line indicates the settlement date at day d. The orange vertical 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 from Sep 5, 2017 onward.

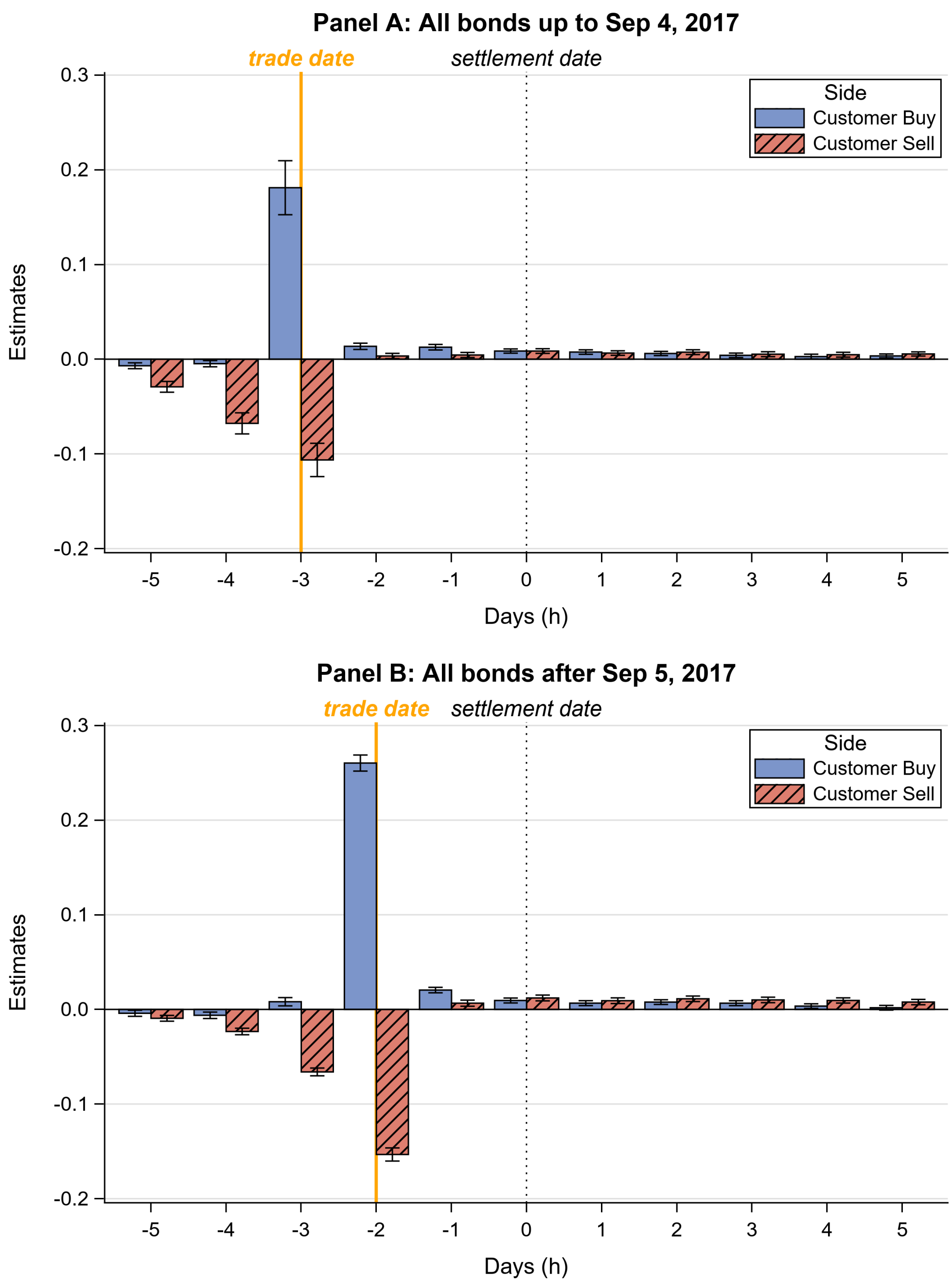


Figure 2: Panel Regression of Dollar Trading Volume on Changes in Quantity on Loan, IG vs HY

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 vertical line denotes the trade date, $d^* = d - s$. 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.

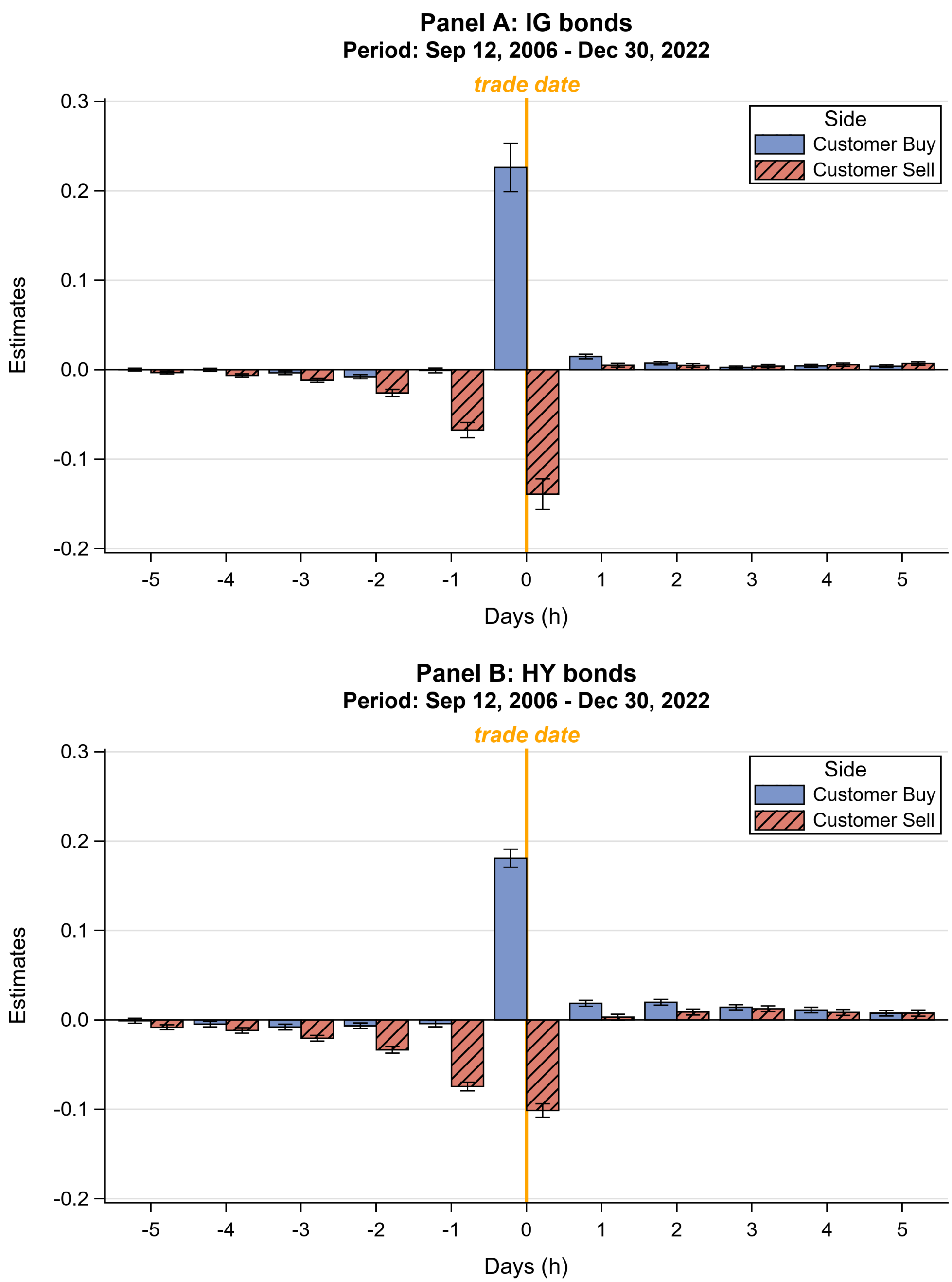


Figure 3: Panel Regression of Abnormal Half Spreads on Changes in Quantity on Loan

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 vertical line denotes the trade date, d^*. 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.

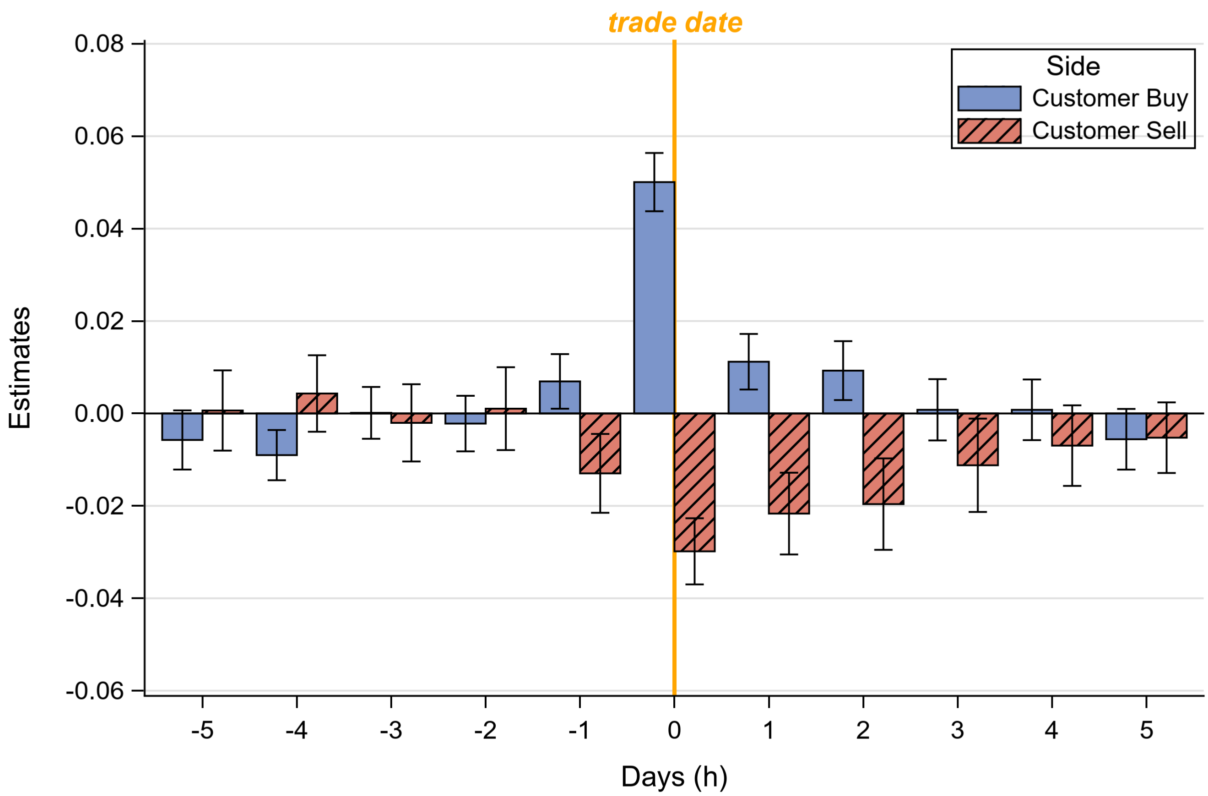
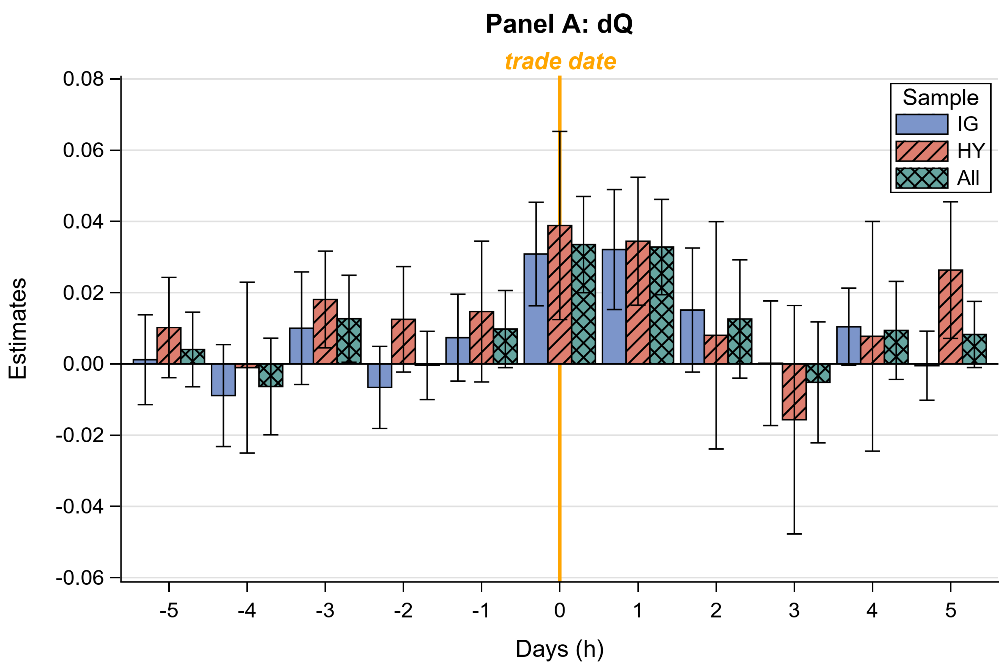


Figure 4: Panel Regression of Daily Bond Returns on Changes in Quantity on Loan

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 when the day d change in quantity on loan is positive (Panel B). The figure also shows two-standard-error bands, computed by double clustering observations at the bond and date levels. The orange vertical line denotes the trade date, d^*. 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 $\mathbf{1}_{dQ>0}$ and $\mathbf{1}_{dQ=0}$, where $\mathbf{1}_{dQ>0}$ is an indicator equal to one if $dQ > 0$, and plots the coefficients on $\mathbf{1}_{dQ>0}$. Results are reported for investment-grade (IG), high-yield (HY), and all bonds.



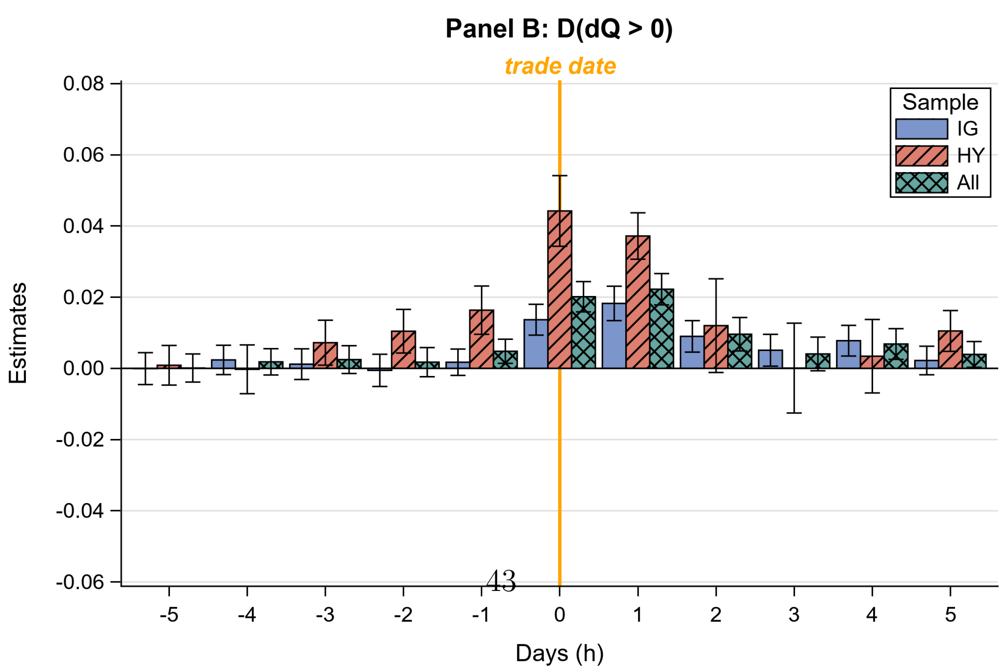


Figure 5: Distribution of Cumulative Dealer Profit and Loss

This figure plots the distribution, across individual dealer positions, of the cumulative profit and loss (P&L) of a dealer who short sells a bond on day d^* in response to a customer buy order, over an event-time horizon of $K = 20$ trading days. A position is a bond–formation-date pair (i, d^*) with $\Delta Q > 0$ on d^*. 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. We compute each position's cumulative P&L by compounding the daily values, $PL_{i,d^*,k} = (1 + PL_{i,d^*,k-1}) \times (1 - r_{i,d^*+k} - Fee_{i,d^*+k} + \mathbf{1}_{\{k=1\}}\, HS_{\text{buy}} + \mathbf{1}_{\{k=K\}}\, HS_{\text{sell}}) - 1$, with $PL_{i,d^*,0} \equiv 0$, where r_{i,d^*+k} is the bond's daily total return, Fee_{i,d^*+k} is its daily borrowing fee, HS_{buy} is its customer buy half-spread on d^*, and HS_{sell} is its customer sell half-spread on $d^* + K$. A position enters only if the bond has a non-missing return at every $k \in [1, K]$, a non-missing customer buy half-spread at d^*, and a non-missing customer sell half-spread at $d^* + K$. At each horizon k, all qualifying positions are pooled across i and d^* to compute the mean (dashed line), median (solid line), and the interquartile range (shaded band). The y-axis reports the cumulative P&L in percent.

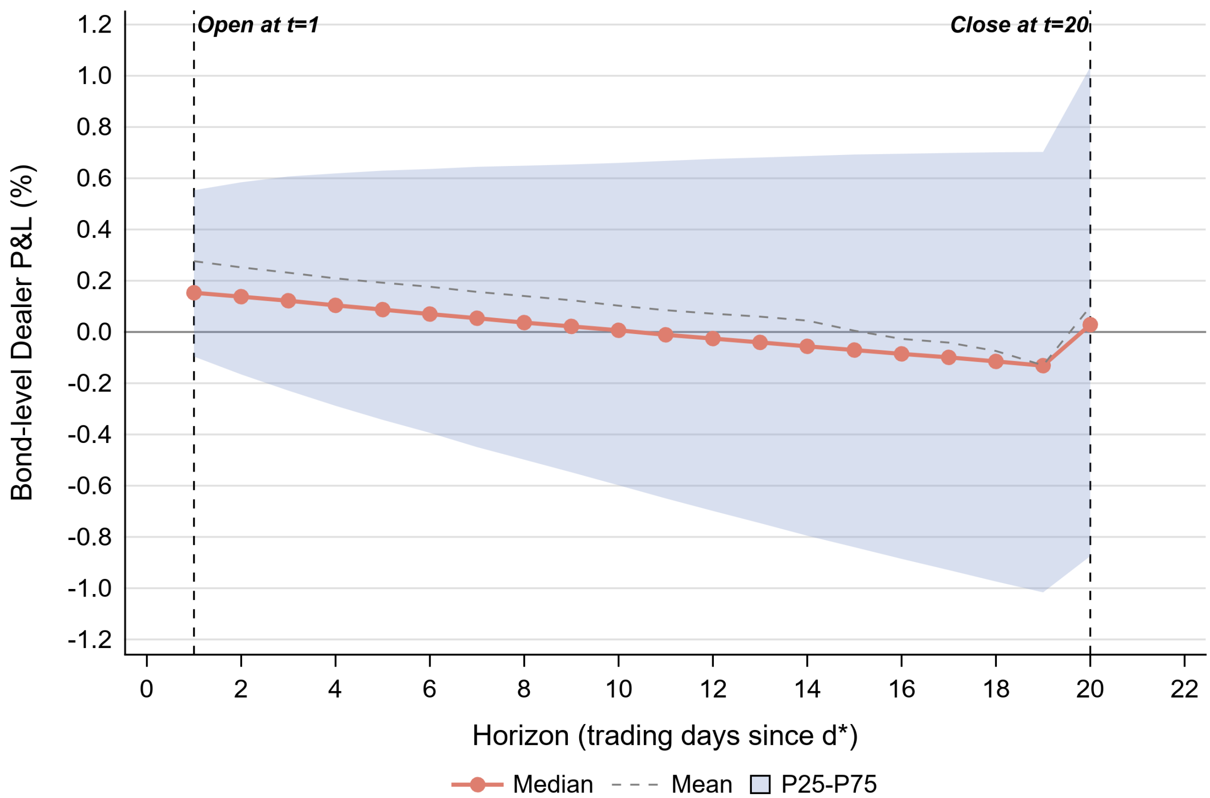


Figure 6: Lending Outcomes Around Bond Tender Offers

This figure plots the lending outcomes, bond returns, trading volume, and half spreads against event time τ, measured in trading days relative to the deadline of tender offers. The event is the first tender offer for each CUSIP, encompassing 3,342 events between September 13, 2006 and December 30, 2022. All outcomes are bond-specific abnormal values expressed as a percentage. The abnormal value on a day is the realized daily value minus the bond's own mean over the estimation window $\tau \in [-189, -64]$. We require at least 40 valid daily observations. Quantity on Loan, Lendable Supply, and Cumulative Customer Sales and Buys are scaled by amount outstanding on day $\tau = -1$. We require this amount outstanding to be at least \$1 million. Of the 3,342 events, 64 fall below the threshold and are excluded from the scaled panels (A, C, and E), while remaining in the unscaled panels (B, D, and F). Cumulative Abnormal Return is the cross-event median of the cumulative abnormal bond return in percent. Cumulative CSell−CBuy is the cross-event average of customer sell volume minus customer buy volume scaled by amount outstanding, summed over τ. Half Spread (5-Day Moving Average) is the cross-event average of the abnormal customer-buy and customer-sell half-spreads in percent. Half spreads show a 5-day centered moving average: for each τ, we take the equal-weighted average over the period from $\tau - 2$ to $\tau + 2$. All continuous variables except bond returns are winsorized at the 1st and 99th percentiles by calendar date. Shaded bands represent the 95% confidence interval clustered by event date. The median panel uses the Woodruff cluster-sampling standard error of the median.

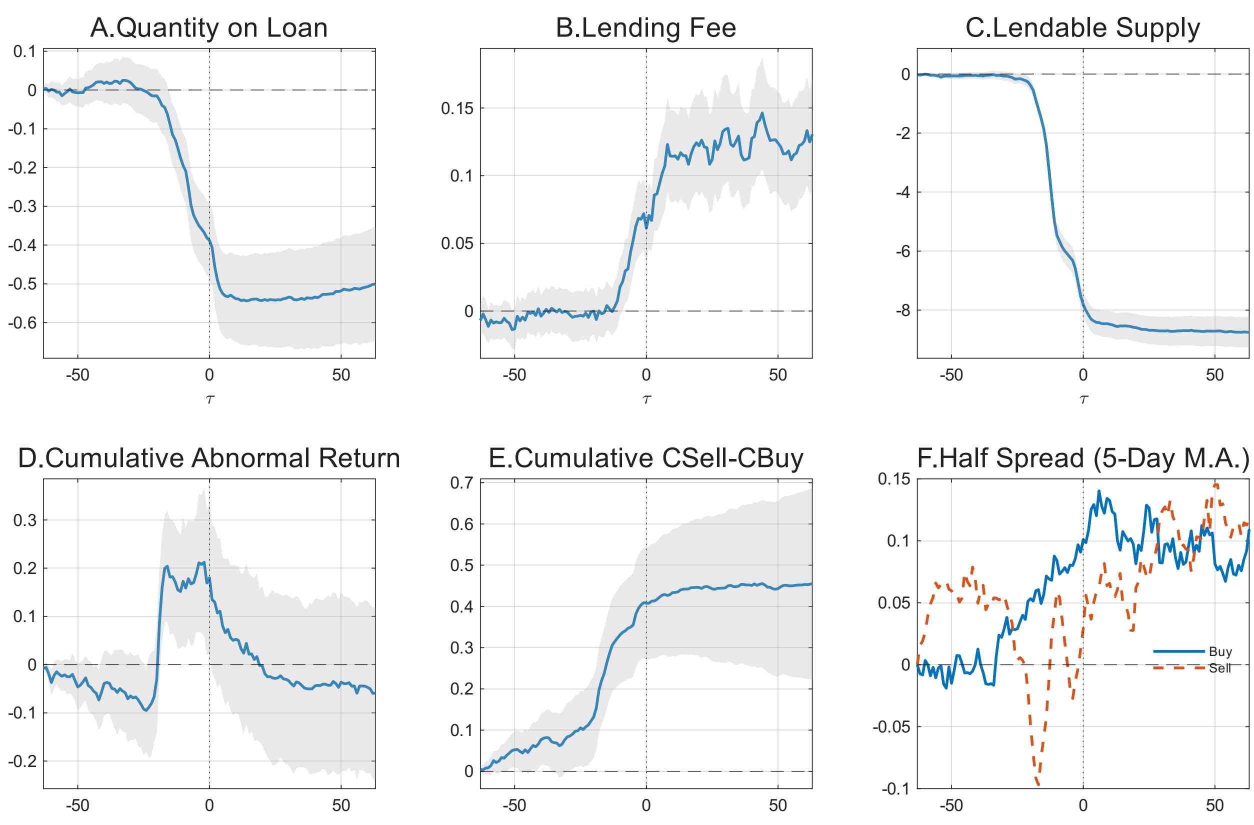


Figure 7: Panel Regression of Dollar Trading Volume on Changes in Quantity on Loan: Stocks

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 stock and date levels. The orange vertical line denotes the trade date, d^*. 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.

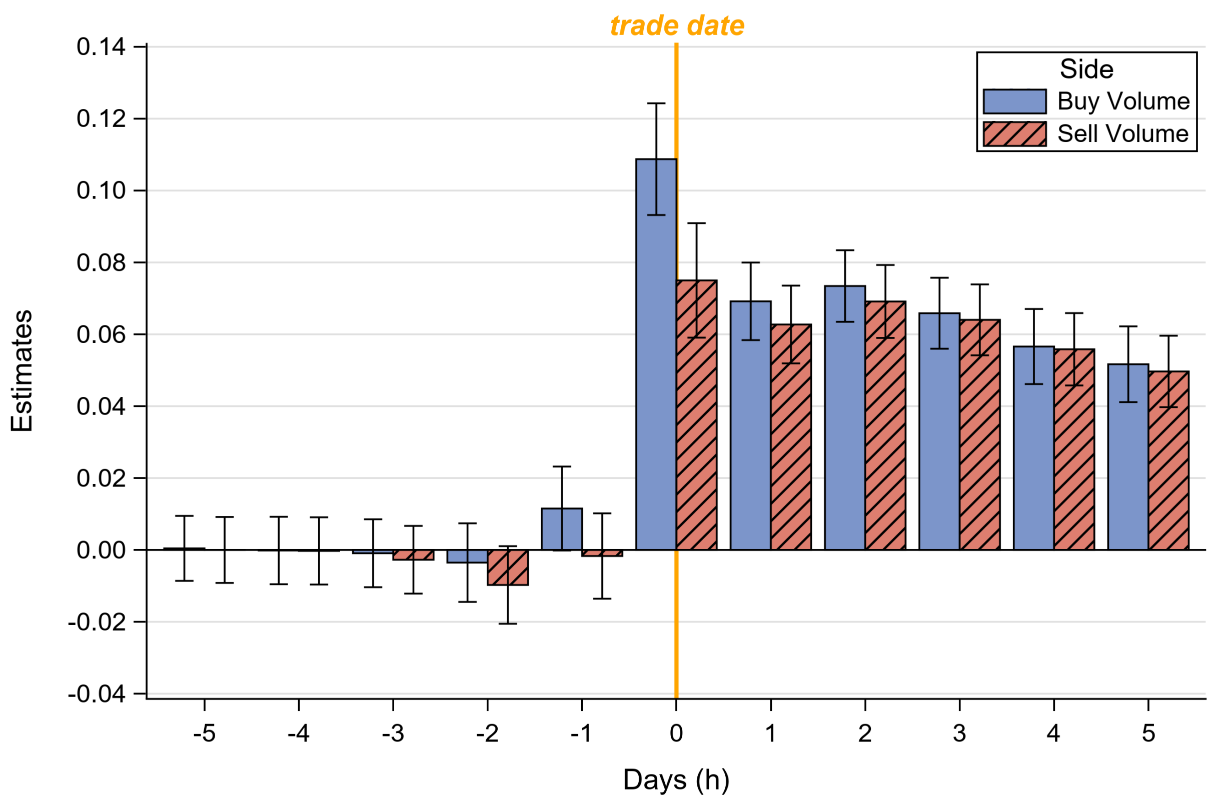


Figure 8: Cross-Sectional Distribution of Bond-Level Dealer Share

The figure plots the cross-sectional median (solid line) and the interquartile range (shaded band) of the bond-level dealer share from March 2007 to December 2022. For each bond i and trading day d, we estimate the regressions of customer buy and sell trading volumes, $Vol_{i,d^*,Buy}$ and $Vol_{i,d^*,Sell}$, on $dQ_{i,d}$, the change in loan quantity using a trailing 252-trading-day window. Customer volumes are measured on the settlement-aligned trade date $d^* = d - s$, where s equals 3 if d occurs on or before September 4, 2017, and 2 thereafter. All three variables are scaled by amount outstanding. The dealer share on day d is $D_{i,d} = \frac{1}{2} - \frac{1}{2}(\beta_{S,i,d} - \beta_{B,i,d})$, where $\beta_{S,i,d}$ and $\beta_{B,i,d}$ are the OLS slopes from the customer sell and customer buy regressions, respectively. The monthly observation $D_{i,t}$ is the estimate on the most recent valid trading day in calendar month t. We require at least 120 observations in the window and at least 20 with $dQ \neq 0$.

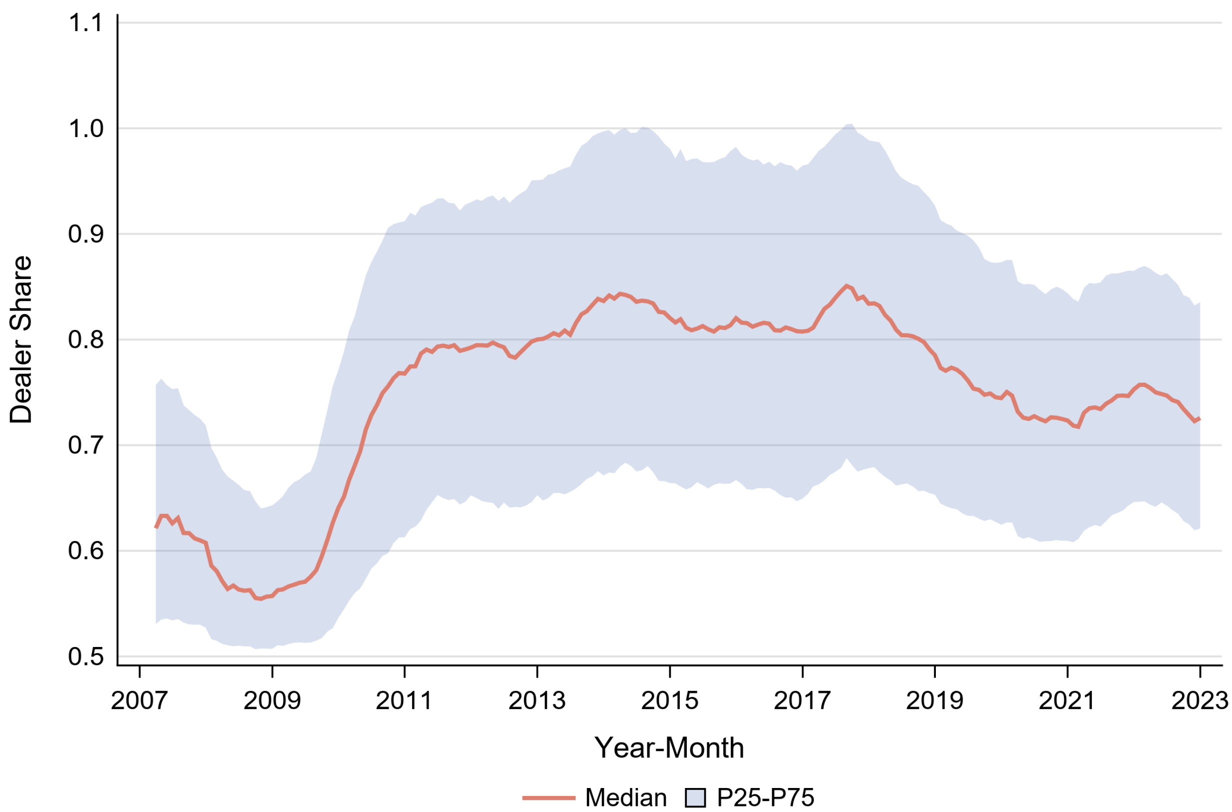


Figure 9: Loan Quantity Across Equity Characteristic Quintiles

This figure plots loan quantity across the equity characteristic quintile portfolios of Table 10, for all bonds (Panel A) and separately for investment-grade (Panel B) and high-yield (Panel C) bonds. Portfolio formation follows Table 10: characteristics are signed so that Q1 is the short leg and Q5 is the long leg, quintile breakpoints are computed separately within each sample and month, and portfolios are value weighted using lagged bond market capitalization. For each characteristic-month, we subtract the average loan quantity across the five quintile portfolios from each portfolio's loan quantity and then average these deviations across characteristics. A characteristic-month enters the composite only when all five quintiles are populated, so the five portfolio estimates in a given month use the same set of characteristics. The factor based on industry returns of big firms (`IndRetBig`) does not have enough cross-sectional variation to form five portfolios, and thus does not enter the figure. The monthly composite contains eleven to twelve characteristics for all bonds and investment-grade bonds, and nine to twelve characteristics for high-yield bonds. Loan quantity is expressed as a percentage of bond amount outstanding and is winsorized at the 1st and 99th percentiles within each month. The sample period is September 2006 to November 2022 (195 months). The y-axis reports deviations in percentage points (p.p.). The vertical bars show plus and minus two Newey and West (1987) standard errors with 12 lags.

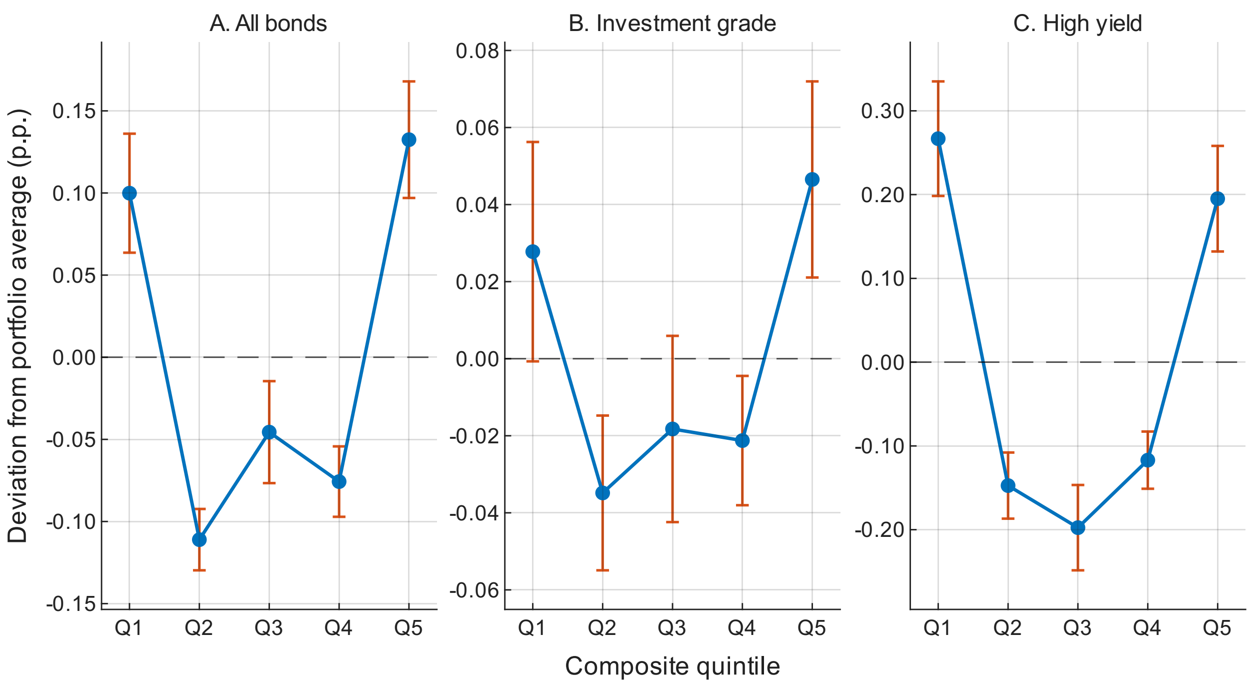


Table 1: Descriptive Statistics

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 Table 5. 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 13, 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 Appendix 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} (%)	0.093	0.284	0.000	0.000	0.001	0.034	1.602	16,850,795
Vol_{Sell} (%)	0.094	0.298	0.000	0.000	0.000	0.024	1.679	16,850,795
r (%)	0.018	1.389	−1.792	−0.154	0.018	0.196	1.811	16,850,795
$AbHS_{Buy}$ (%)	−0.015	0.888	−1.951	−0.364	−0.104	0.216	2.653	8,333,958
$AbHS_{Sell}$ (%)	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} (%)	0.112	0.304	0.000	0.000	0.007	0.059	1.671	11,341,920
Vol_{Sell} (%)	0.111	0.319	0.000	0.000	0.003	0.044	1.761	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
$\overline{Vol}_{d-5,d-1,Buy}$ (%)	0.128	0.202	0.000	0.013	0.048	0.152	1.020	11,341,920
$\overline{Vol}_{d-5,d-1,Sell}$ (%)	0.128	0.208	0.000	0.010	0.043	0.153	1.038	11,341,920
$\overline{HS}_{d-5,d-1,Buy}$ (%)	0.007	0.750	−1.572	−0.282	−0.082	0.190	2.348	11,341,920
$\overline{HS}_{d-5,d-1,Sell}$ (%)	0.053	0.784	−1.684	−0.208	−0.032	0.225	2.473	11,341,920

Table 2: Annualized Portfolio Returns (Percent) 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 three 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 ($dQ > 0$). 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. Adjusted returns are computed as the difference between raw bond returns and value-weighted returns of bonds in the same credit rating group (AAA, AA, A, BBB, BB, B, or CCC-D) and time-to-maturity tercile in the ICE data. Returns are reported in percent and are annualized by multiplying by 252. 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 20 lags. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Raw Return				Adjusted 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^{***}	-1.20^{***}	-1.25^{***}	3.13^{***}	4.33^{***}
	(1.51)	(1.62)	(4.10)	(12.77)	(−4.51)	(−4.36)	(8.77)	(15.40)
IG	3.17^{*}	3.00^{*}	6.29^{***}	3.12^{***}	-0.64^{***}	-0.89^{***}	2.37^{***}	3.01^{***}
	(1.87)	(1.70)	(3.74)	(10.43)	(−3.10)	(−2.90)	(9.16)	(12.80)
HY	2.07	2.09	12.98^{***}	10.91^{***}	-3.37^{***}	-3.31^{***}	6.82^{***}	10.19^{***}
	(0.66)	(0.82)	(3.86)	(9.12)	(−3.96)	(−5.37)	(6.14)	(10.19)
				Panel B: Return Window $[d^* + 1,\ d^* + 3]$				
All	2.88	4.13^{**}	6.09^{***}	3.20^{***}	-1.01^{***}	−0.16	1.68^{***}	2.69^{***}
	(1.64)	(2.28)	(3.42)	(13.32)	(−4.55)	(−0.66)	(6.17)	(14.97)
IG	3.08^{*}	3.77^{**}	5.48^{***}	2.40^{***}	-0.68^{***}	−0.27	1.44^{***}	2.11^{***}
	(1.82)	(2.13)	(3.27)	(13.18)	(−3.64)	(−1.10)	(6.46)	(15.03)
HY	3.12	6.05^{**}	8.89^{***}	5.76^{***}	-2.26^{***}	0.39	3.01^{***}	5.27^{***}
	(1.10)	(2.18)	(2.95)	(8.62)	(−4.08)	(0.56)	(4.18)	(9.52)
				Panel C: Return Window $[d^* + 4,\ d^* + 23]$				
All	3.80^{**}	4.25^{**}	4.42^{**}	0.63^{***}	−0.21	0.01	0.25	0.46^{***}
	(2.14)	(2.36)	(2.54)	(6.54)	(−0.89)	(0.05)	(1.17)	(6.84)
IG	3.76^{**}	3.88^{**}	4.30^{**}	0.55^{***}	−0.10	−0.14	0.33^{*}	0.43^{***}
	(2.21)	(2.18)	(2.58)	(6.12)	(−0.51)	(−0.63)	(1.83)	(6.11)
HY	4.75	6.22^{**}	5.37^{*}	0.62^{***}	−0.54	0.76	0.02	0.56^{***}
	(1.63)	(2.38)	(1.89)	(3.92)	(−0.98)	(1.39)	(0.04)	(4.66)

Table 3: Cumulative Dealer Profit and Loss (Percent): Decomposition by Horizon and Subsample

This table reports the terminal cumulative profit and loss (P&L) of a dealer who intermediates customer buying pressure in corporate bonds, evaluated at three horizons ($K = 5$, 10, or 20 trading days). On each trade date d^*, we form a value-weighted portfolio of all bonds with $\Delta Q > 0$ observed on the settlement date d, using lagged bond market capitalization as weights. 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. P&L is computed by compounding the daily return on dealers' position, which combines the bond return, the borrowing fee, and the half spread revenue earned at the opening ($t = 1$) and closing ($t = K$) legs of the dealer's round-trip short position. We decompose the terminal P&L by recomputing the full path three times, each time setting one component to zero. The contribution of each component is the difference between the full path and the corresponding zeroed-out path. Spread is the P&L attributed to the opening half spread at $t = 1$ plus the closing half spread at $t = K$, Fee is the cumulative borrowing fee, and Return is the cumulative bond return. The interaction residual is below 2 basis points in all cases and is omitted for clarity. Panel A covers all bonds. Panel B separates bonds by credit rating. Panel C splits bonds by collateral specialness: a bond is classified as special (SP) if its borrowing fee on the settlement date d is in the top decile of the cross-sectional fee distribution, and as general collateral (GC) otherwise. Panel D separates the sample into crisis and non-crisis periods, where crisis periods comprise the 2008–2009 Global Financial Crisis (January 2008–June 2009) and the 2020 COVID-19 market turmoil (March–April 2020). Panel E groups bonds by time to maturity: short-term (ST, less than 5 years), medium-term (MT, 5–10 years), and long-term (LT, more than 10 years). Panel F splits bonds by issue size relative to the cross-sectional median of amounts outstanding into large and small. Newey and West (1987) t-statistics with lag length equal to the horizon K are reported in parentheses below *Total*. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$K = 5$				$K = 10$				$K = 20$			
	Total	Spread	Fee	Return	Total	Spread	Fee	Return	Total	Spread	Fee	Return
Panel A: All Bonds												
All	0.475***	0.603	−0.007	−0.121	0.357***	0.609	−0.015	−0.239	0.147	0.595	−0.030	−0.421
	(15.67)				(6.58)				(1.41)			
Panel B: By Credit Rating												
IG	0.463***	0.581	−0.007	−0.112	0.352***	0.584	−0.014	−0.220	0.138	0.570	−0.028	−0.407
	(15.49)				(6.70)				(1.37)			
HY	0.517***	0.716	−0.010	−0.191	0.330**	0.733	−0.021	−0.390	0.126	0.742	−0.041	−0.560
	(9.03)				(2.44)				(0.72)			

Table 3, Continued.

	$K=5$				$K=10$				$K=20$			
	Total	Spread	Fee	Return	Total	Spread	Fee	Return	Total	Spread	Fee	Return
					Panel C: By Collateral Specialness							
GC	0.465***	0.592	−0.007	−0.122	0.344***	0.598	−0.014	−0.242	0.136	0.583	−0.027	−0.424
	(15.36)				(6.41)				(1.31)			
SP	0.736***	0.860	−0.026	−0.101	0.660***	0.874	−0.051	−0.164	0.425**	0.866	−0.102	−0.352
	(14.51)				(6.54)				(2.15)			
					Panel D: By Business Cycle							
Crisis	1.241***	1.356	−0.007	−0.109	0.956***	1.339	−0.015	−0.375	0.467	1.302	−0.030	−0.816
	(5.92)				(2.66)				(0.77)			
Non-crisis	0.387***	0.517	−0.007	−0.123	0.288***	0.525	−0.015	−0.224	0.111	0.513	−0.030	−0.375
	(18.38)				(7.14)				(1.26)			
					Panel E: By Maturity							
ST	0.364***	0.452	−0.008	−0.081	0.285***	0.458	−0.015	−0.159	0.112	0.445	−0.030	−0.306
	(17.03)				(7.34)				(1.63)			
MT	0.495***	0.631	−0.008	−0.129	0.352***	0.629	−0.015	−0.265	0.121	0.625	−0.031	−0.478
	(14.73)				(6.02)				(1.08)			
LT	0.736***	0.955	−0.007	−0.214	0.470***	0.975	−0.014	−0.507	0.347*	0.972	−0.028	−0.597
	(10.86)				(2.58)				(1.67)			
					Panel F: By Issuance Size							
Large	0.446***	0.574	−0.007	−0.121	0.328***	0.581	−0.014	−0.240	0.123	0.566	−0.029	−0.418
	(14.68)				(6.05)				(1.18)			
Small	0.961***	1.093	−0.012	−0.121	0.868***	1.103	−0.023	−0.212	0.641***	1.095	−0.046	−0.411
	(25.44)				(11.75)				(4.76)			

Table 4: Panel Regression of Daily Changes in Quantity on Loan

This table reports estimates from panel regressions of daily changes in the quantity on loan for all bonds of public firms. The dependent variable is the daily change in loan quantity dQ scaled by amount outstanding. Columns (1) and (2) report the linear specification in equation (8), using continuous customer buy and sell volumes, $Vol_{d^*,Buy}$ and $Vol_{d^*,Sell}$, as the regressors. Columns (3) and (4) replace continuous volumes with volume tercile indicators. Buy_{High} (Buy_{Med}) equals one if the customer's buy volume falls in the top (middle) tercile of the cross-sectional distribution on that date; the bottom tercile is the omitted category. $Sell_{High}$ and $Sell_{Med}$ are defined analogously for customer sell volume. Columns (5) and (6) augment the tercile specification with block trade interactions. Following Jacobsen and Venkataraman (2025), a trade is classified as a block trade if its par value is at least \$15 million. $Block_{Buy}$ ($Block_{Sell}$) equals one if at least one customer buys (sells) a block trade of that size on that day, and zero otherwise. The medium-tercile interaction terms and the main effects $Block_{Buy}$ and $Block_{Sell}$ are omitted. Odd-numbered columns include no controls beyond the reported regressors. Even-numbered columns add the full set of controls $Ctrl_{i,d}$ from equation (8). All continuous explanatory variables are standardized to have a mean of zero and a standard deviation of one. 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. All specifications include bond and date fixed effects. Standard errors are 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. The number of observations is 10,447,842.

	Linear Volume		Volume Terciles		Terciles × Block Trades	
	(1)	(2)	(3)	(4)	(5)	(6)
$Vol_{d^*,Buy}$	0.0548***	0.0566***				
	(130.87)	(132.98)				
$Vol_{d^*,Sell}$	−0.0445***	−0.0439***				
	(−130.69)	(−129.84)				
Buy_{High}			0.0570***	0.0590***	0.0550***	0.0571***
			(122.38)	(124.95)	(121.82)	(124.46)
Buy_{Med}			0.0056***	0.0058***	0.0059***	0.0062***
			(32.59)	(33.49)	(34.31)	(35.36)
$Sell_{High}$			−0.0402***	−0.0392***	−0.0387***	−0.0378***
			(−117.20)	(−115.59)	(−115.08)	(−113.35)
$Sell_{Med}$			−0.0037***	−0.0038***	−0.0039***	−0.0040***
			(−22.66)	(−23.03)	(−24.22)	(−24.52)
$Buy_{High} \times Block_{Buy}$					0.2031***	0.2094***
					(71.27)	(72.63)
$Sell_{High} \times Block_{Sell}$					−0.1445***	−0.1429***
					(−74.96)	(−74.38)
Controls	No	Yes	No	Yes	No	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.072	0.083	0.029	0.038	0.036	0.046

Table 5: 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 a rating between AAA and BBB-, while high-yield (HY) bonds have ratings below BBB-. 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 SP1 (90th–95th percentile), SP2 (95th–99th percentile), and SP3 (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 credit spreads and the average spread of bonds with the same notch-level rating. 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	−0.128	0.250	−0.377	0.311	0.689	11,341,920
	(−44.97)	(60.66)	(−59.02)	(97.52)	(215.56)	
Panel B: By Credit Rating						
IG	−0.148	0.278	−0.426	0.287	0.713	8,809,552
	(−44.16)	(55.56)	(−55.08)	(74.37)	(184.53)	
HY	−0.093	0.200	−0.293	0.354	0.646	2,532,363
	(−26.19)	(45.15)	(−42.45)	(102.55)	(187.44)	
Panel C: By Collateral Specialness						
GC	−0.137	0.275	−0.412	0.294	0.706	10,543,952
	(−46.25)	(62.70)	(−60.97)	(86.91)	(208.85)	
SP1	−0.064	0.150	−0.214	0.393	0.607	389,276
	(−12.43)	(25.58)	(−28.08)	(103.00)	(159.16)	
SP2	−0.064	0.072	−0.136	0.432	0.568	329,085
	(−11.44)	(14.48)	(−22.57)	(143.60)	(188.74)	
SP3	−0.089	−0.015	−0.073	0.463	0.537	77,668
	(−8.26)	(−1.84)	(−8.18)	(103.35)	(119.71)	

Table 5, Continued.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel D: By Public Status						
Public Firm	−0.129	0.252	−0.381	0.310	0.690	10,657,983
	(−45.42)	(61.67)	(−60.04)	(97.55)	(217.62)	
Private Firm	−0.102	0.219	−0.321	0.340	0.660	683,852
	(−15.17)	(24.50)	(−23.86)	(50.52)	(98.24)	
Panel E: By CDS Coverage						
Yes	−0.126	0.250	−0.376	0.312	0.688	6,050,571
	(−37.79)	(51.71)	(−50.27)	(83.40)	(183.95)	
No	−0.129	0.249	−0.378	0.311	0.689	5,291,333
	(−39.44)	(58.45)	(−56.10)	(92.13)	(204.33)	
Panel F: By Expensiveness						
Overvalued	−0.168	0.253	−0.421	0.289	0.711	6,088,535
	(−48.80)	(60.19)	(−60.85)	(83.58)	(205.29)	
Undervalued	−0.099	0.246	−0.345	0.327	0.673	5,224,909
	(−34.26)	(52.04)	(−50.65)	(96.15)	(197.46)	
Panel G: By Issuance Size						
Large	−0.130	0.261	−0.391	0.305	0.695	6,981,983
	(−41.74)	(57.36)	(−55.39)	(86.29)	(197.07)	
Small	−0.123	0.228	−0.351	0.325	0.675	4,359,912
	(−32.66)	(47.16)	(−45.91)	(84.97)	(176.79)	
Panel H: By Bid-ask Spread						
Illiquid	−0.111	0.226	−0.336	0.332	0.668	6,040,507
	(−36.90)	(49.74)	(−49.08)	(96.79)	(194.94)	
Liquid	−0.148	0.279	−0.427	0.286	0.714	5,133,221
	(−45.90)	(68.40)	(−66.44)	(89.07)	(221.94)	

Table 6: 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					
−0.016	0.199	−0.215	0.393	0.607	26,563
(−0.81)	(10.77)	(−11.25)	(41.07)	(63.57)	
Other Downgrades					
−0.042	0.159	−0.201	0.399	0.601	273,462
(−6.91)	(18.82)	(−22.67)	(90.11)	(135.46)	
Upgrade Crossing IG/HY Threshold					
−0.168	0.306	−0.473	0.263	0.737	20,793
(−6.62)	(13.30)	(−16.11)	(17.92)	(50.13)	
Other Upgrades					
−0.122	0.255	−0.377	0.312	0.688	184,345
(−13.34)	(30.02)	(−32.46)	(53.73)	(118.66)	
Panel B: 21 Trading Days Before Earnings News					
Very Bad News					
−0.071	0.195	−0.266	0.367	0.633	288,086
(−9.76)	(21.66)	(−21.80)	(60.15)	(103.75)	
Bad News					
−0.130	0.270	−0.400	0.300	0.700	775,612
(−22.33)	(36.83)	(−37.42)	(56.09)	(130.93)	
Around Expectation News					
−0.154	0.283	−0.437	0.282	0.718	1,053,228
(−33.35)	(49.22)	(−54.25)	(70.04)	(178.55)	
Good News					
−0.144	0.275	−0.419	0.291	0.709	760,107
(−28.68)	(45.01)	(−50.34)	(69.83)	(170.51)	
Very Good News					
−0.112	0.228	−0.340	0.330	0.670	425,723
(−19.66)	(32.27)	(−35.04)	(67.99)	(138.06)	

Table 7: 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. Dealer refers to the liquidity provider, and Customer refers to the liquidity taker. Following Diether, Lee, and Werner (2009b), 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 (SP) 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	0.054	0.053	0.001	0.500	0.500	14,431,379
	(11.78)	(23.26)	(0.21)	(274.31)	(273.89)	
			Panel B: By Market Capitalization			
Micro	0.069	0.081	−0.011	0.494	0.506	7,273,330
	(6.56)	(18.95)	(−1.21)	(105.34)	(107.76)	
Small	0.050	0.034	0.016	0.508	0.492	3,499,712
	(9.88)	(13.91)	(4.71)	(295.32)	(285.90)	
Large	0.034	0.034	0.000	0.500	0.500	3,658,255
	(8.58)	(13.20)	(−0.13)	(499.37)	(499.63)	
			Panel C: By Collateral Specialness			
GC	0.048	0.042	0.006	0.503	0.497	11,233,450
	(15.72)	(24.26)	(3.20)	(524.33)	(517.93)	
SP	0.079	0.091	−0.012	0.494	0.506	3,197,254
	(7.11)	(15.83)	(−1.24)	(103.90)	(106.37)	
			Panel D: By Bond Issuance			
Issuer	0.035	0.035	0.000	0.500	0.500	3,981,086
	(13.58)	(18.20)	(−0.22)	(658.58)	(659.03)	
Non-Issuer	0.063	0.062	0.001	0.501	0.499	10,450,257
	(10.31)	(21.18)	(0.29)	(203.34)	(202.76)	
			Panel E: By CDS Coverage			
Yes	0.037	0.034	0.003	0.502	0.498	1,711,900
	(11.16)	(13.01)	(1.84)	(589.07)	(585.39)	
No	0.056	0.055	0.000	0.500	0.500	12,719,469
	(11.32)	(22.72)	(0.10)	(251.31)	(251.10)	

Table 8: Long-Short Portfolio Sorts on the Dealer Share: Bond Liquidity

This table reports the time-series average of the long-short value-weighted average of ten bond liquidity measures across quintile portfolios formed on the dealer share. Each calendar month, bonds with non-missing dealer shares are sorted into quintiles, with $Q1$ holding the lowest shares and $Q5$ the highest. Within each portfolio, bonds are weighted by their lagged market capitalization. The long-short series is $Q5$ minus $Q1$ in each month. The ten liquidity outcomes follow Schestag, Schuster, and Uhrig-Homburg (2016). *AvgBidAsk_All* and *AvgBidAsk_Inst* are volume-weighted average bid-ask spreads (in percent) constructed from customer buy and sell prices, using all customer trades and institutional-size customer trades ($100,000 par value or larger), respectively. *IQR_All* and *IQR_Inst* are interquartile-range spread proxies constructed from all TRACE trades and institutional-size trades, respectively. *HighLow* is the Corwin and Schultz (2012) estimator based on high and low prices. *Gibbs* is twice the posterior mean of the effective cost from the Hasbrouck (2009) Bayesian Gibbs sampler on daily TRACE prices. *Roll* is the Roll (1984) estimator on autocovariance of trade-active daily returns. *FHT* is the Fong, Holden, and Trzcinka (2017) estimator on continuous TRACE-fill daily returns. *ZeroTrade* is the fraction of business days with no TRACE trade. *Log DollarVolume* is the natural logarithm of average daily dollar trading volume in a month. All refers to portfolios using all bonds. IG and HY restrict to investment-grade and high-yield bonds, and non-rated bonds enter only All. The t-statistics in parentheses are Newey and West (1987)-adjusted with 12 lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) AvgBid Ask_All	(2) AvgBid Ask_Inst	(3) IQR_All	(4) IQR_Inst	(5) HighLow	(6) Gibbs	(7) Roll	(8) FHT	(9) Zero Trade	(10) Log Dollar Volume
All	−0.210***	−0.091***	−0.145***	−0.106***	−0.158***	−0.164***	−0.311***	−0.135***	−0.026	0.120*
	(−5.80)	(−6.58)	(−9.43)	(−8.82)	(−8.26)	(−16.74)	(−7.00)	(−3.48)	(−1.53)	(1.81)
IG	−0.163***	−0.076***	−0.088***	−0.069***	−0.103***	−0.129***	−0.208***	−0.097***	−0.033*	0.166***
	(−4.80)	(−5.01)	(−7.30)	(−7.20)	(−5.52)	(−11.71)	(−5.85)	(−2.77)	(−1.90)	(2.89)
HY	−0.350***	−0.134***	−0.321***	−0.209***	−0.350***	−0.268***	−0.671***	−0.307***	−0.018	0.108
	(−8.15)	(−9.91)	(−7.42)	(−7.57)	(−9.70)	(−13.35)	(−5.18)	(−2.87)	(−0.97)	(1.44)

Table 9: Fama-MacBeth Regression of Bond Liquidity on the Dealer Share

This table reports estimates of Fama and MacBeth (1973) regressions of bond liquidity outcomes in month $t+1$ on the bond-level dealer share in month t. Variable definitions and the sample are in Table IA11. All right-hand-side variables are winsorized at the 1st and 99th percentiles within each calendar month and then standardized to mean zero and unit standard deviation. The t-statistics in parentheses are based on Newey and West (1987) standard errors with 12 lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) AvgBid Ask_All	(2) AvgBid Ask_Inst	(3) IQR_All	(4) IQR_Inst	(5) HighLow	(6) Gibbs	(7) Roll	(8) FHT	(9) Zero Trade	(10) Log Dollar Volume
Dealer Share	−0.0625***	−0.0325***	−0.0442***	−0.0378***	−0.0543***	−0.0350***	−0.1074***	−0.0353	0.0057*	−0.0001
	(−3.45)	(−3.71)	(−3.06)	(−3.10)	(−4.48)	(−7.85)	(−2.75)	(−1.37)	(1.72)	(−0.01)
Log Amount	−0.1320***	−0.0255***	−0.0487***	−0.0309***	0.0300	−0.0931***	−0.1523***	−0.2668***	−0.1620***	0.7301***
	(−20.90)	(−3.77)	(−3.69)	(−4.15)	(1.40)	(−20.03)	(−13.70)	(−8.11)	(−55.27)	(97.56)
Age	0.1764***	0.0462***	0.0738***	0.0358***	0.0723***	0.1089***	0.1647***	0.0553***	0.0095	−0.2631***
	(8.74)	(8.51)	(10.14)	(9.17)	(9.84)	(19.81)	(9.62)	(10.05)	(1.63)	(−22.91)
Maturity	0.2173***	0.1070***	0.2198***	0.1382***	0.1500***	0.2489***	0.3569***	0.2956***	0.0642***	0.0638***
	(9.19)	(16.87)	(12.75)	(18.35)	(10.72)	(26.61)	(9.52)	(10.61)	(20.51)	(3.19)
Rating	0.0636***	0.0242**	0.1367***	0.0803***	0.1177***	0.0705***	0.2200***	0.1006***	−0.0341***	0.2977***
	(3.29)	(2.28)	(6.55)	(6.51)	(11.87)	(5.87)	(6.98)	(2.68)	(−5.93)	(34.04)
Observations	635,793	520,639	664,443	541,756	605,216	605,216	605,216	605,216	717,608	605,216
Avg. R^2	0.206	0.118	0.289	0.215	0.170	0.258	0.202	0.415	0.417	0.426

Table 10: Monthly Portfolio Returns Sorted by Equity Characteristics

This table reports value-weighted returns to corporate bond portfolios sorted on 13 characteristics of the issuing firm, for the pooled sample and separately for investment-grade (IG) and high-yield (HY) bonds. Each month, bonds are sorted into quintiles for each characteristic, with breakpoints computed separately within each sample across the cross-section of bonds with nonmissing values for the characteristic, lending fee, next-month return, and bond market capitalization. Characteristics are signed so that higher values predict higher returns, so Q1 is the short leg and Q5 the long leg. Portfolios are value-weighted using lagged bond market capitalization and held for one month. Panel A reports the equal-weighted average of the 13 characteristics from past stock and option returns used in Dickerson, Nozawa, and Robotti (2025). Adjusted returns subtract from each bond return the value-weighted return of bonds in the same credit rating group and time-to-maturity tercile. Duration-adjusted alphas are the intercepts from time-series regressions of portfolio returns on the duration and credit factors of van Binsbergen, Nozawa, and Schwert (2025). Panel B counts, out of the 13 characteristics, those with an absolute t-statistic of at least 1.96 in that column. Returns and alphas are in percent per month, and the sample period is September 2006 to November 2022 (195 months). The t-statistics in parentheses are Newey and West (1987)-adjusted with 12 lags. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Adjusted Return			Duration-Adjusted Alpha		
	All	IG	HY	All	IG	HY
Panel A: Average Across 13 Factors						
Q1 (short leg)	-0.117^{***}	-0.100^{***}	-0.178^{***}	-0.152^{***}	-0.136^{***}	-0.073
	(-2.93)	(-2.77)	(-2.63)	(-3.31)	(-3.04)	(-0.94)
Q5 (long leg)	0.079^{***}	0.070^{***}	0.102^{***}	0.117^{***}	0.067^{*}	0.276^{***}
	(3.86)	(3.52)	(3.19)	(3.15)	(1.86)	(4.12)
Q5 − Q1	0.195^{***}	0.170^{***}	0.280^{***}	0.268^{***}	0.203^{***}	0.350^{***}
	(3.46)	(3.18)	(4.29)	(3.72)	(3.71)	(4.62)
Q5 + Q1	-0.038	-0.030	-0.076	-0.035	-0.070	0.203
	(-1.34)	(-1.30)	(-0.92)	(-0.84)	(-1.16)	(1.62)
Panel B: Number of Significant Factors (of 13)						
Q1 (short leg)	8	6	7	8	7	3
Q5 (long leg)	8	7	3	9	4	10
Q5 − Q1	8	8	6	11	8	7
Q5 + Q1	1	1	1	1	1	5

Appendix

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

TRACE data contains transaction prices and volume, trade direction, and the 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 2023b; 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;[21] (2) bonds that are U.S. Government, private placements,[22] equity-linked,[23] mortgage-backed, asset-backed, agency-backed, trust-preferred capital securities, corporate pay-in-kind bonds, corporate pass-through trusts, municipal issues, or preferred securities;[24] (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 or more than 30 years to maturity; (5) bond transactions that TRACE does not report as regular trades, including when-issued trades, locked-in trades, trades executed at a special price, trades reported at a weighted average price, and trades reported outside normal market hours or reported late;[25] (6) transaction records with trade

[21] We require the FISD issuer's country of domicile to be the United States and the issue's currency to be U.S. dollars.

[22] `PRIVATE_PLACEMENT='N'`

[23] 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: "`EQUITY-LINKED`," "`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.

[24] In FISD, these correspond to the `BOND_TYPE` codes `TPCS`, `CPIK`, `CPAS`, `TXMU`, and `PS`.

[25] Following Augustin, Cong, Lopez A., and Tédongap (2025), we retain only regular trades. In TRACE data files before February 6, 2012, we require "`SALE_CNDTN_CD`" to equal "`@`," which identifies a regular trade rather than a cash sale, next-day settlement, seller's option settlement, weighted average price, or a trade sold out of sequence, and we require "`SALE_CNDTN2_CD`" to be blank, indicating that no second sale condition applies. For data from February 6, 2012 onward, we exclude trades reported outside normal market hours or reported late ("`TRD_MOD_3`" equals "`Z`," "`T`," or "`U`") and trades reported at a weighted average price ("`TRD_MOD_4`" equals "`W`"). We do not impose any filters on days to settlement.

size larger than issue size or trade size is not an integer; (7) bonds that do not have a principal value of $1,000; (8) bonds with incomplete issuance information (offering date, offering amount, maturity, coupon rate, coupon frequency, and first interest payment date), bonds whose offering date falls after the first interest payment date, or bonds with a non-positive historical amount outstanding (e.g., bonds that are called); and (9) bond-days on which the bond carries no credit rating.

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
$AbHS_{Buy}$ (%)	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
$AbHS_{Sell}$ (%)	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
$\overline{HS}_{d-5,d-1,Buy}$ (%)	Average daily abnormal half spread from the customer buy side over trading days $d-5$ to $d-1$	daily	Mergent FISD, TRACE
$\overline{HS}_{d-5,d-1,Sell}$ (%)	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	Markit, Mergent FISD
Lendable Supply (%)	Active lendable quantity from Markit divided by the amount outstanding	daily, monthly	Markit, Mergent FISD
Borrowing Fee (%)	Buy-side fee paid by the ultimate borrower ("IndicativeFee" in Markit)	daily, monthly	Markit
Amount ($ mil)	Amount of bonds outstanding in millions of dollars	daily, monthly	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	Mergent FISD
Age (years)	Age of a bond in years since issuance	daily, monthly	Mergent FISD
Maturity (years)	Time to maturity in years	daily, monthly	Mergent FISD
AvgBidAsk_All (%)	Volume-weighted bid-ask spread. On each bond-day with both customer buy and customer sell trades, $2\,(\bar{P}^{Buy} - \bar{P}^{Sell})/(\bar{P}^{Buy} + \bar{P}^{Sell})$, where $\bar{P}^{Buy}$ and $\bar{P}^{Sell}$ are the volume-weighted customer buy and sell prices. The monthly measure is the mean of the daily values.	monthly	TRACE
AvgBidAsk_Inst (%)	Same construction as *AvgBidAsk_All*, restricted to institutional-size trades (par value of $100,000 or larger).	monthly	TRACE
IQR_All (%)	Interquartile-range spread proxy. On each bond-day with at least three reported trades, $(P_{75} - P_{25})/\bar{P}$, the difference between the 75th and 25th percentiles of intraday trade prices divided by the average daily price. The monthly measure is the mean of the daily values.	monthly	TRACE

Table A1, Continued

Variable	Definition	Frequency	Data Source
IQR_Inst (%)	Same construction as *IQR_All*, restricted to institutional-size trades (par value of $100,000 or larger).	monthly	TRACE
HighLow (%)	High-low spread estimator of Corwin and Schultz (2012) from daily high and low trade prices, with their overnight and single-trade-day adjustments. Negative daily estimates are set to zero and averaged within the month.	monthly	TRACE
Gibbs (%)	Twice the posterior mean of the effective cost c from the Hasbrouck (2009) Bayesian Gibbs sampler, applied to close-to-close price changes across successive days on which the bond trades.	monthly	TRACE
Roll (%)	Effective-spread estimator of Roll (1984) computed each bond-month, equal to $2\sqrt{-\widehat{\mathrm{Cov}}(r_t, r_{t-1})}$ when the first-order autocovariance of returns between successive days on which the bond trades is negative, and zero otherwise.	monthly	TRACE
FHT (%)	Bid-ask spread proxy of Fong, Holden, and Trzcinka (2017), $2\,\sigma_R\,\Phi^{-1}((1+\mathit{Zeros})/2)$, where σ_R is the within-month standard deviation of daily returns computed from the last trade price and carried forward on days without a trade, *Zeros* is the fraction of zero-return days, and Φ^{-1} is the inverse standard normal CDF.	monthly	TRACE
ZeroTrade	Fraction of trading days in the month on which no trade is reported in TRACE, equal to the number of trading days in the month minus the number of days the bond trades, divided by the number of trading days in the month.	monthly	TRACE
Log DollarVolume	Natural logarithm of the bond's average daily dollar trading volume over the month, where daily dollar volume is the sum across trades of price (fraction of the par value) times par amount traded, averaged across days with at least one trade.	monthly	TRACE

Internet Appendix
"On the Drivers of Corporate Bond Lending"

This internet appendix gives additional results.

IA1 TRACE Return

We use daily bond returns constructed from Enhanced TRACE. For each bond-day, we compute volume-weighted bid and ask from customer-dealer transactions of at least \$100,000, classifying each trade as a customer sell (bid) or customer buy (ask). When both are available, the daily price is the bid-ask midpoint. When either is missing, the daily price is the volume-weighted interdealer price using transactions of at least \$100,000. When both are missing, the daily price is missing. Daily returns are computed as the change in dirty price (clean price plus accrued interest), plus any coupon paid over the day, divided by the dirty price on the prior trading day, expressed in percent. We run a panel regression of daily bond TRACE returns on changes in quantity on loan, akin to those in Figure 4, and report the results in Figure IA1. We recalculate portfolio returns following the same procedure as in Table 2, and report the results in Table IA1.

IA2 Level and Changes of Quantity on Loan

Given our interest in understanding the drivers of short selling, our main variable of interest is the *change* in short interest quantity. This focus is consistent with the suggestions of Boehmer, Jones, and Zhang (2008) and Diether, Lee, and Werner (2009b) who highlight the advantages of using flow rather than stock of short interest to understand short selling activity. In contrast, Hendershott, Kozhan, and Raman (2020) study the relation between the *level* of short interest and future bond returns. To better understand the differences, we decompose the level into changes and its lag,

$$Q_{i,d} = dQ_{i,d-1:d} + dQ_{i,d-5:d-1} + dQ_{i,d-21:d-5} + dQ_{i,d-252:d-21} + Q_{i,d-252}. \tag{IA1}$$

Thus, if the level of short sales predicts returns, then either past changes in loan quantity or the lagged level must predict them. Every business day, d, we sort bonds into terciles based on $Q_{i,d}$ or on its components.[26] We construct overlapping portfolios as in Section 3.3 and

[26] If the threshold between P1 and P2 and that between P2 and P3 coincide, we subtract 10^{-4} from the former and add 10^{-4} to the latter to ensure each tercile is populated.

hold the positions from $d^* + 4$ to $d^* + 23$. For this analysis, the sample starts in September 2007, roughly one year later than in the main results, because we require all predictors to be available.

Table IA2 reports the annualized average return (raw and rating-and-maturity-adjusted) difference, in percent, between bonds with a high loan amount and those with a low amount. For IG bonds, the level of quantity on loan insignificantly and positively predicts future bond returns. However, the three components of the quantity on loan, including one-day, one-week (skipping one day), and one-month (skipping one week) changes, all positively predict returns, with raw return differences of 0.51%, 0.48%, and 0.47% per year. The characteristic-adjusted return differences are slightly smaller, but display the same pattern.[27] Therefore, in IG bonds, intensified short selling signals an increase in bond values, consistent with our thesis that bond borrowing is motivated by customers' urgent buy orders. Results for the full sample are similar to those for IG bonds.

For HY bonds, the results are more nuanced. Consistent with Hendershott, Kozhan, and Raman (2020), we find that the level of quantity on loan (Q_d) negatively predicts corporate bond returns, with an average of -2.46% per year ($t = -2.44$). However, consistent with IG bonds, recent changes in loan quantity positively predict returns, with averages of 0.64%, 0.62%, and 0.36% for the one-day, one-week, and one-month horizons, respectively. This positive link between increased short sales and future returns is offset by the fact that one-year changes in loan quantity (skipping one month) significantly and negatively predict returns, with an average of -2.16% per year. These return differences change little for rating- and maturity-adjusted returns, with the one-year change remaining significantly negative (-1.61%, $t = -3.23$). The level of quantity on loan lagged one year does not significantly predict returns in either raw or adjusted terms.

These results suggest an interesting difference in the speed at which the information contained in short sales is disseminated. If speculative customers learn negative news about HY bonds and borrow them for short sales, their short positions accumulate slowly over time, and the negative information about the bonds is also impounded into prices with a lag of at least a month. In contrast, if customers have positive private information about a bond, their urgent buy orders force dealers to borrow bonds quickly, and this action helps bond prices rapidly reflect the information, pushing up bond prices within a month.

[27]The numbers in Table IA2 do not exactly match those in Panel C of Table 2 because of differences in how terciles are constructed.

IA3 Multivariate Analysis of Loan Quantity

In Section 3.6, we discuss the results of a multivariate analysis of loan quantity on trading volume. Table 4 in that section reports coefficients only on selected variables of interest. Table IA3 reports the full set of coefficient estimates corresponding to Table 4.

IA4 Availability of CDS

In Table IA4, 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 (8). We find that these additional terms have economically 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.

IA5 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 (8):

$$
\begin{aligned}
CumRet_{i,d^*+1,d^*+5} = {} & b_0 dQ_{i,d} + b_1 \overline{dQ}_{i,d-5,d-1} + b_2 \overline{Vol}_{i,d^*-5,d^*-1,Buy} \\
& + b_3 \overline{Vol}_{i,d^*-5,d^*-1,Sell} + b_4 \overline{HS}_{i,d^*-5,d^*-1,Buy} \\
& + b_5 \overline{HS}_{i,d^*-5,d^*-1,Sell} + b_6 \sigma_{i,d^*-5,d^*-1} + b_7 \bar{r}_{i,d^*-5,d^*-1} \\
& + b_8 dQ^{Stock}_{i,d} + b_9 \overline{dQ}^{Stock}_{i,d-5,d-1} + \gamma_d + \alpha_i + Ctrl_{i,d} + \varepsilon_{i,d}. \qquad \text{(IA2)}
\end{aligned}
$$

Table IA5 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 ($t = 11.17$) in Column (1). Across the five specifications, the estimates range from 1.41 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 (see, e.g., Boehmer, Jones, and Zhang 2008).

IA6 Multivariate Analysis of Bond Trading Volume

Table IA6 presents the results from estimating equation (17). The coefficients from this regression are used in Table 5.

IA7 Dealer Share from Univariate Regression Estimates

Table IA7 shows the estimated dealer share (similar to those in Table 5) when we estimate univariate regressions instead of equation (17). Figures IA3 and IA4 plot specification curves for the regression coefficients, b_ξ, showing they are stable across the $2^8 = 256$ specifications.

IA8 Sub-sample Results

Table IA8 presents the results of Table 5, splitting the sample before and after September 4, 2017.

IA9 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 IA9 and IA10 report the main results of Table 5 using these two approaches, respectively. We also replicate results in Figure 1 using the two interpolation methods and present these results in Figure IA5.

Figure IA1: Panel Regression of Daily Bond Returns on Changes in Quantity on Loan, Using TRACE-Based Returns

This figure replicates Figure 4 using daily bond returns constructed from Enhanced TRACE transaction data in place of ICE BAML quote prices. 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. Returns 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 vertical 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 $\mathbf{1}_{dQ>0}$ and $\mathbf{1}_{dQ=0}$, where $\mathbf{1}_{dQ>0}$ is an indicator equal to one if $dQ > 0$, and plots the coefficients on $\mathbf{1}_{dQ>0}$. Results are reported for investment-grade (IG), high-yield (HY), and all bonds.

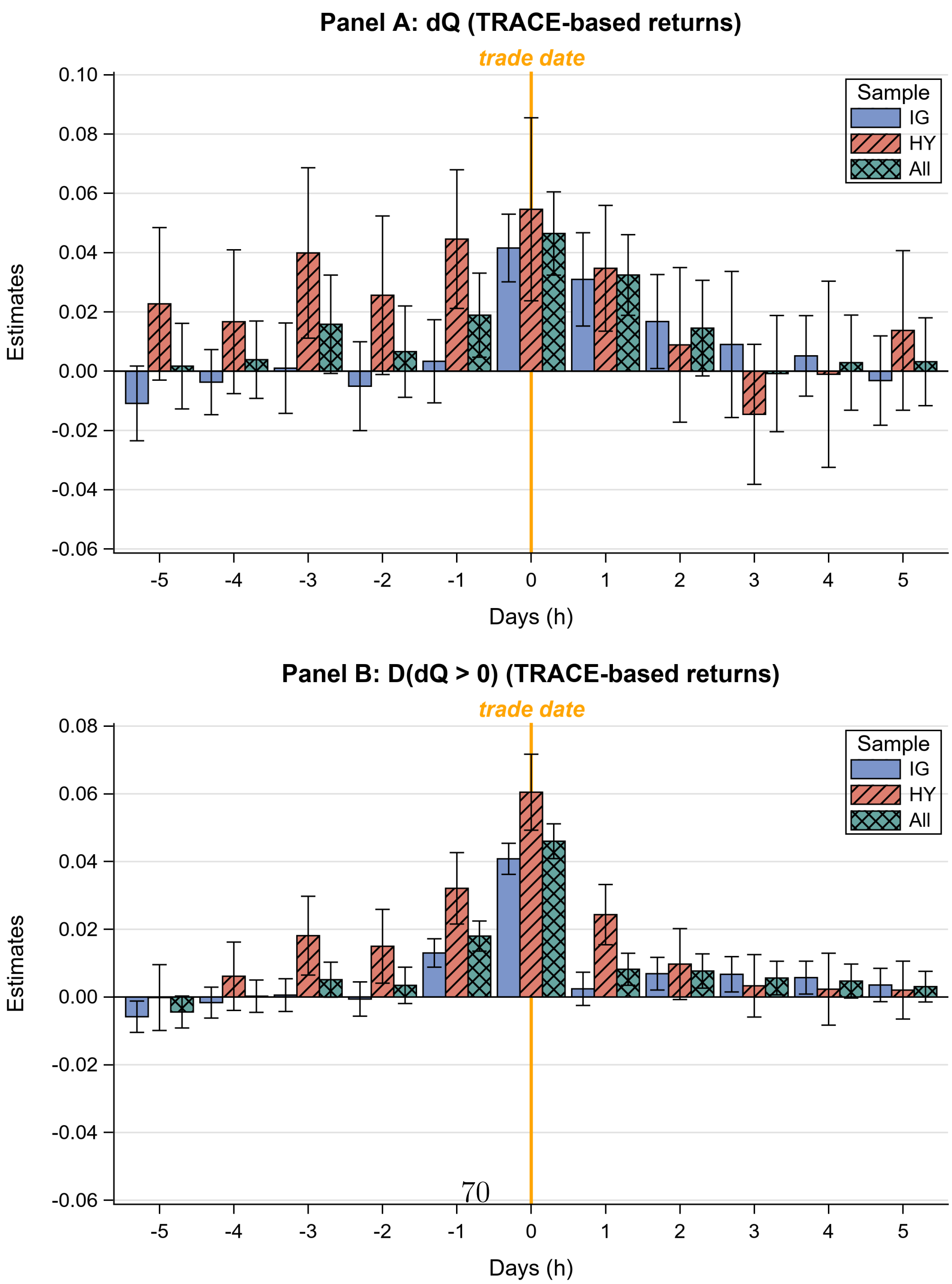


Figure IA2: Markit Loan Quantity and Short Interest

This figure plots the daily cross-sectional average of loan quantity and short interest for corporate bonds, both scaled by the bond's amount outstanding. Loan Quantity is "`QuantityOnLoan`" from Markit Securities Finance, the total quantity of the bond on loan net of double counting, scaled by the amount outstanding from Mergent FISD. Short Interest is "`ShortLoanQuantity`" from Markit, the quantity on loan remaining after Markit's proprietary filters remove financing, dividend, and nondirectional lending transactions, scaled by the same denominator. On each trading day, we winsorize both variables at the 1st and 99th percentiles across bonds, take the equal-weighted average across bonds, and smooth the resulting series with a five-trading-day moving average. The y-axis reports both series in percent of amount outstanding. The sample runs from September 15, 2006, the first date with a complete five-trading-day window, to December 30, 2022.

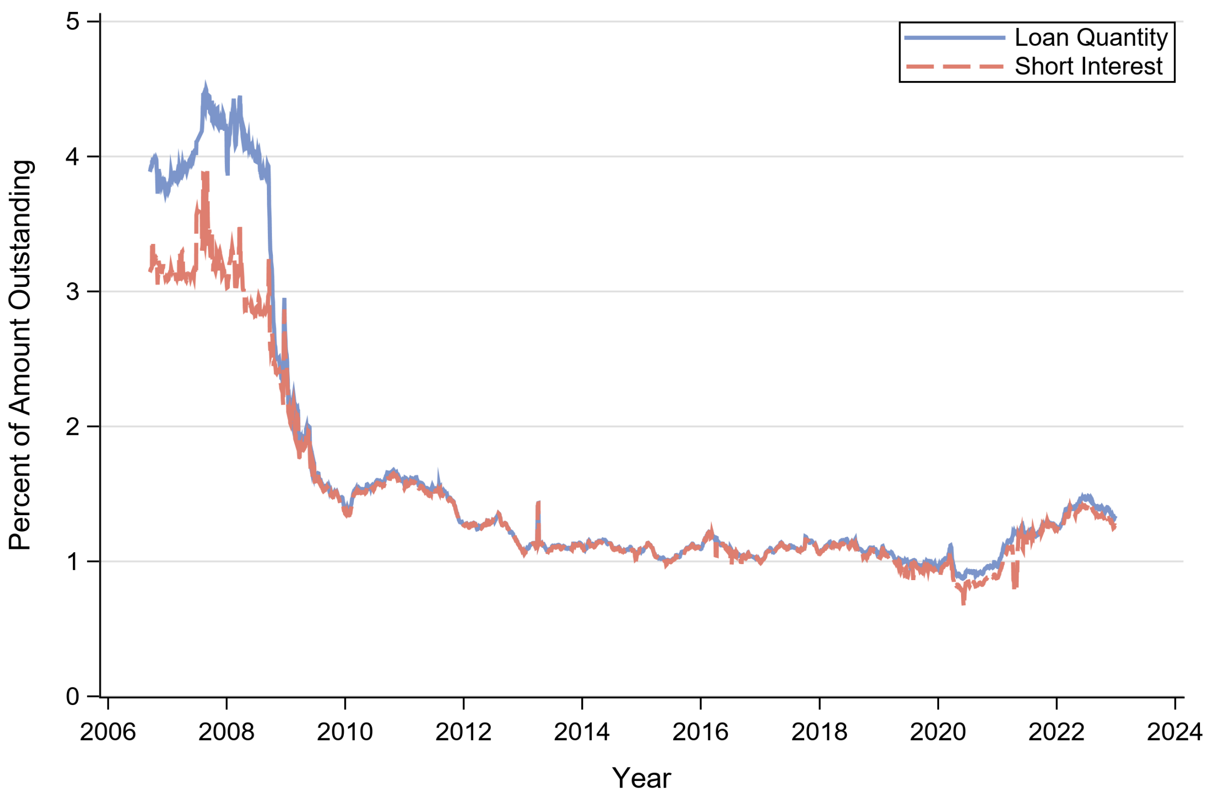


Figure IA3: Specification Curve Analysis: Customer Buy Volume

The figure shows the specification curve for the panel regression of customer buy volume on day d^* on change in quantity on loan on day d. Panel A plots the estimated coefficient on dQ_d from each of the 256 specifications. The specifications are ordered along the horizontal axis by the size of that estimate, from smallest to largest. The filled circle is the point estimate and the vertical line is the estimate plus or minus two standard errors. Panel B shows which control groups enter each specification. A mark in a row means that the group named at the left is included in the specification at that horizontal position. The two panels share the same horizontal ordering, so a vertical slice through both panels describes one regression.

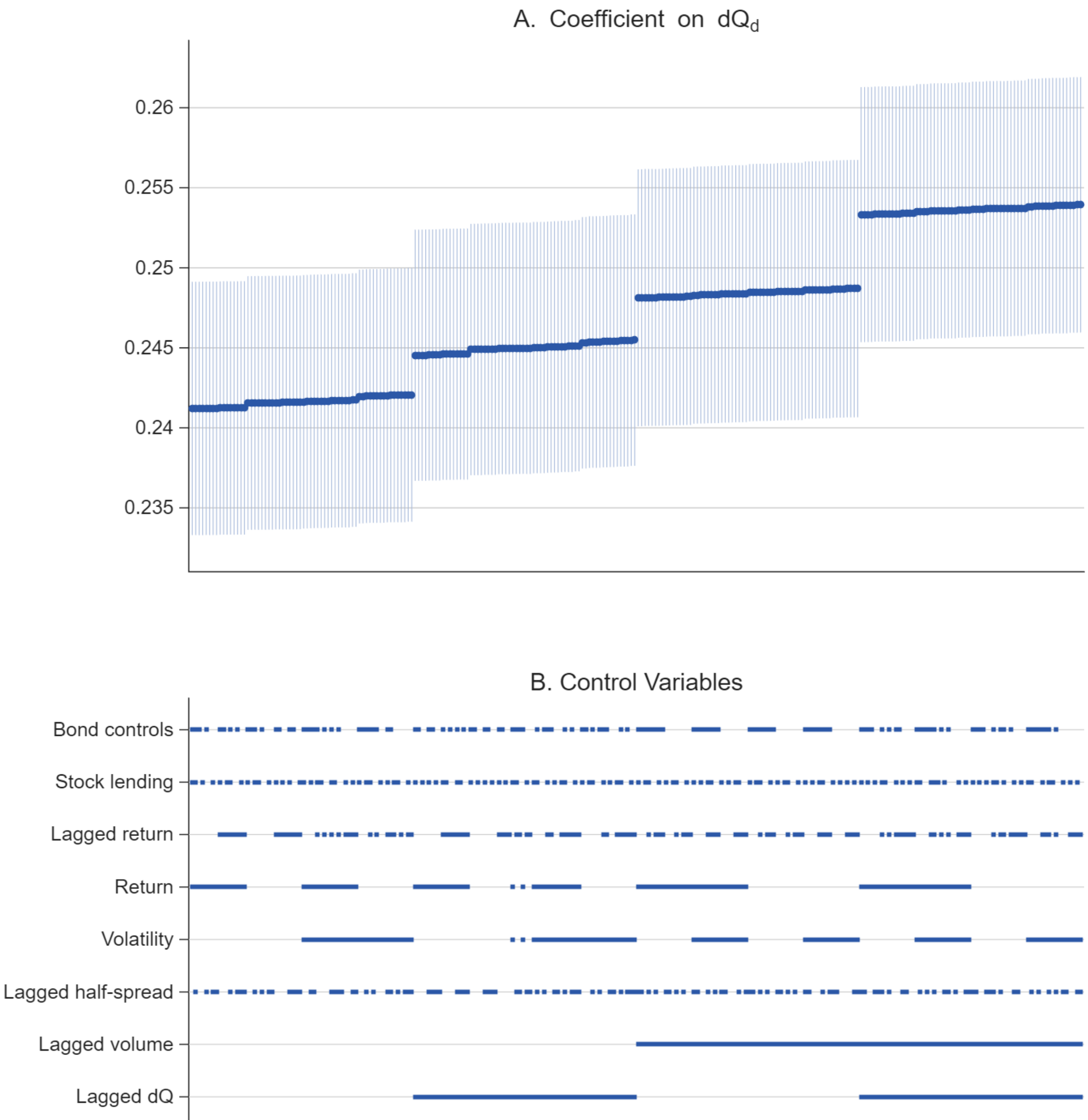


Figure IA4: Specification Curve Analysis: Customer Sell Volume

The figure shows the specification curve for the panel regression of customer sell volume on day d^* on change in quantity on loan on day d. Panel A plots the estimated coefficient on dQ_d from each of the 256 specifications. The specifications are ordered along the horizontal axis by the size of that estimate, from smallest to largest. The filled circle is the point estimate and the vertical line is the estimate plus or minus two standard errors. Panel B shows which control groups enter each specification. A mark in a row means that the group named at the left is included in the specification at that horizontal position. The two panels share the same horizontal ordering, so a vertical slice through both panels describes one regression.

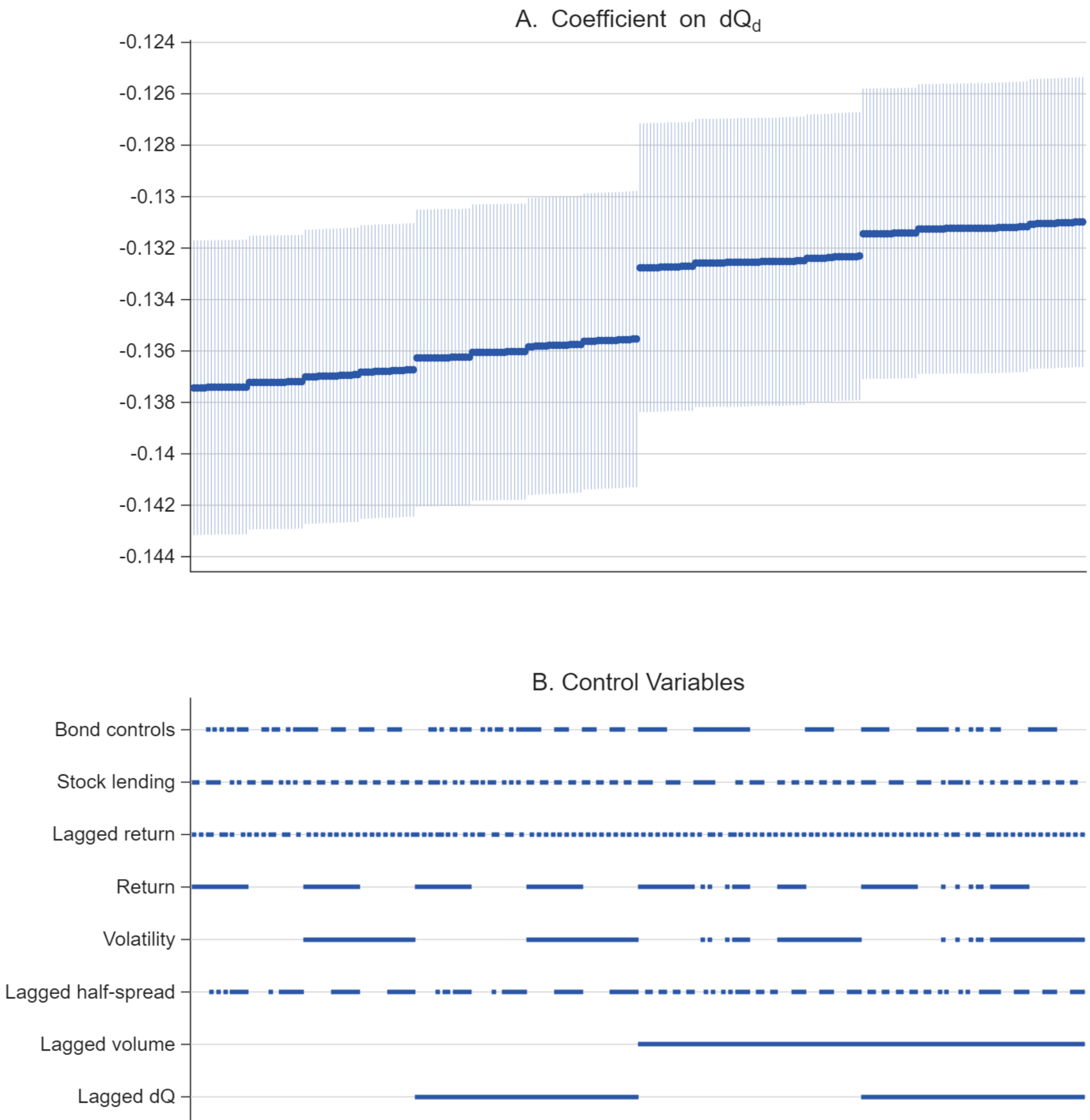
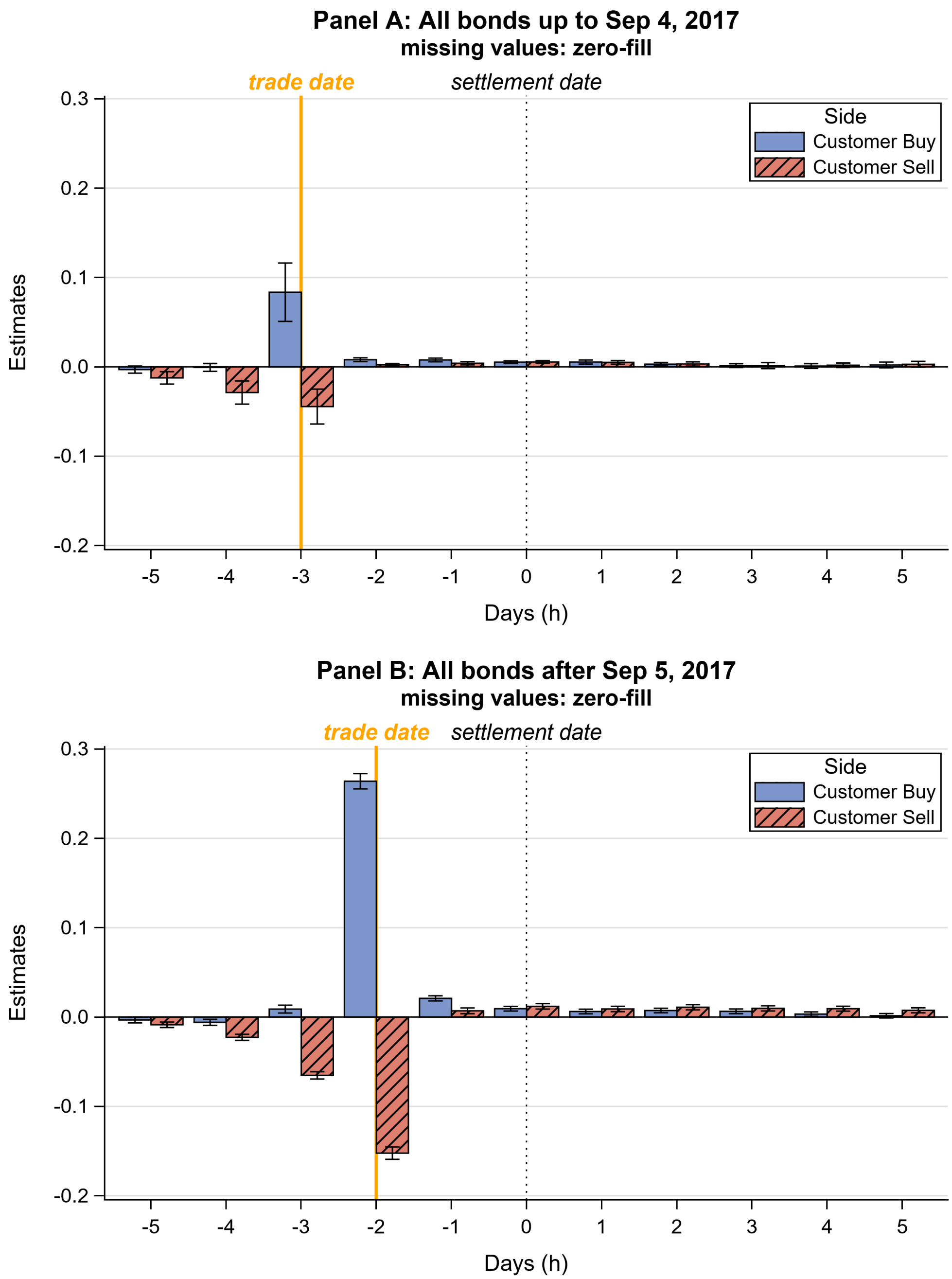
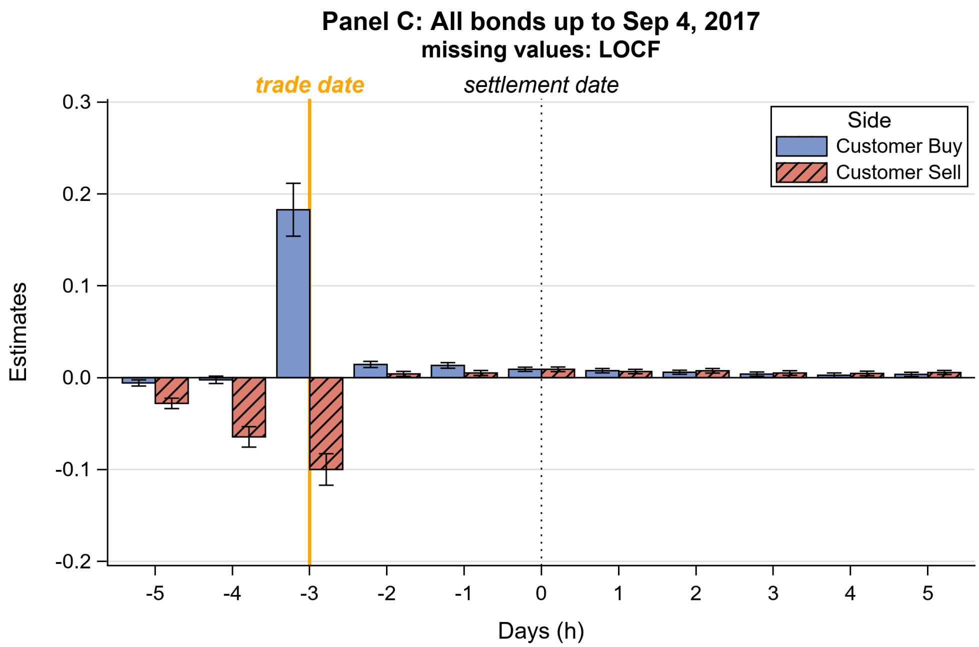


Figure IA5: Robustness of Panel Regression of Dollar Trading Volume on Changes in Quantity on Loan

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 A and B use zero-fill interpolation for missing loan quantities, while Panels C and D use last-observation-carried-forward (LOCF) interpolation. Panels A and C cover the period up to September 4, 2017, and Panels B and D cover the period from September 5, 2017 onward.




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)

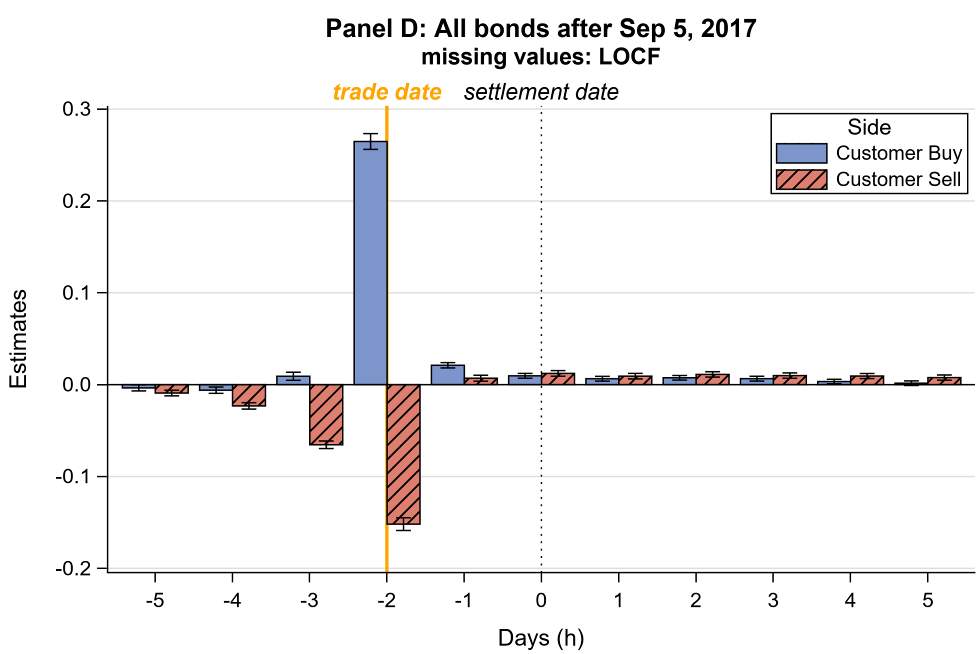

Panel D: All bonds after Sep 5, 2017
missing values: LOCF
trade date
settlement date
Side
Customer Buy
Customer Sell
Estimates
0.3
0.2
0.1
0.0
-0.1
-0.2
-5
-4
-3
-2
-1
0
1
2
3
4
5
Days (h)

Table IA1: Annualized Portfolio Returns (Percent) Sorted by Daily Changes in Quantity on Loan, Using TRACE-Based Returns

This table replicates Table 2 using daily bond returns constructed from Enhanced TRACE transaction data in place of ICE BAML quote prices. For each bond-day, we compute volume-weighted bid and ask from customer-dealer transactions of at least \$100,000, classifying each trade as a customer sell (bid) or customer buy (ask). When both are available, the daily price is the bid-ask midpoint. When either is missing, the daily price is the volume-weighted interdealer price using transactions of at least \$100,000. When both are missing, the daily price is missing. Daily returns are computed as the change in dirty price (clean price plus accrued interest), plus any coupon paid over the day, divided by the dirty price on the prior trading day, expressed in percent. The matched TRACE return panel covers 2,903,725 bond-days from September 12, 2006 through December 30, 2022. Portfolio construction, holding periods, weighting, adjusted return definitions, and significance conventions follow Table 2. Adjusted returns are computed as the difference between the raw bond returns and the value-weighted average return of bonds in the same credit rating group (AAA, AA, A, BBB, BB, B, and CCC-D) and time-to-maturity tercile on the same day.

	Raw Return				Adjusted Return			
	P1	P2	P3	P3 − P1	P1	P2	P3	P3 − P1
				Panel A: Return on Day d^*				
All	1.17	3.38	10.06***	8.64***	−3.91***	−2.70***	3.95***	7.88***
	(0.57)	(1.40)	(5.17)	(9.05)	(−14.33)	(−4.18)	(10.73)	(12.82)
IG	1.57	2.43	10.21***	8.36***	−3.17***	−2.50***	4.03***	7.22***
	(0.86)	(1.28)	(5.46)	(11.72)	(−8.04)	(−4.47)	(7.37)	(11.31)
HY	1.87	6.45	13.98***	11.99***	−7.23***	−2.29	4.57***	11.86***
	(0.47)	(1.22)	(3.60)	(7.65)	(−6.16)	(−1.06)	(5.61)	(10.18)
				Panel B: Return Window $[d^* + 1,\ d^* + 3]$				
All	4.49**	5.89**	6.15***	1.64**	−1.26***	−0.21	0.52***	1.78***
	(2.18)	(2.43)	(3.13)	(2.50)	(−10.02)	(−0.32)	(4.17)	(8.25)
IG	5.51**	4.65**	5.68***	0.38	−0.74***	−0.52	0.32**	1.07***
	(2.37)	(2.19)	(2.97)	(0.37)	(−6.30)	(−0.94)	(2.07)	(4.39)
HY	7.41*	12.66***	11.66***	6.58***	−4.00***	2.06	1.68***	5.69***
	(1.80)	(2.76)	(3.18)	(5.99)	(−7.79)	(1.39)	(3.02)	(6.46)
				Panel C: Return Window $[d^* + 4,\ d^* + 23]$				
All	4.71**	8.20***	5.15***	0.41	−0.71***	0.88*	−0.35***	0.36***
	(2.42)	(2.99)	(2.73)	(1.23)	(−8.56)	(1.75)	(−2.61)	(3.04)
IG	5.01**	4.87**	5.08***	0.07	−0.55***	0.28	−0.14	0.42***
	(2.45)	(2.03)	(2.73)	(0.18)	(−7.26)	(0.46)	(−1.27)	(3.25)
HY	7.51**	16.22***	8.54**	1.04*	−1.58***	2.72*	−1.54***	0.04
	(2.14)	(4.21)	(2.45)	(1.87)	(−5.36)	(1.76)	(−4.16)	(0.19)

Table IA2: Average Returns (Annualized Percent) on Long-Short Portfolios Sorted by Levels and Changes in Quantity on Loan

Every trade day d^*, bonds are sorted into tercile portfolios based on either the quantity on loan (Q) or the changes in quantity on loan (dQ). The level and the changes are measured over the intervals indicated in the subscripts. The rest of the procedure is the same as that in Table 2. The table reports the difference in raw and adjusted annualized returns of terciles P3−P1 over window $d^* + 4$ to $d^* + 23$. 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.

	All	IG	HY	All	IG	HY
	Raw Return			Adjusted Return		
Q_d	0.63	0.83	−2.46**	−0.18	0.31	−2.45***
	(0.97)	(1.46)	(−2.44)	(−0.48)	(0.87)	(−3.50)
Decomposition of Q_d:						
$dQ_{d-1:d}$	0.60***	0.51***	0.64***	0.46***	0.43***	0.60***
	(5.19)	(4.66)	(3.48)	(4.78)	(4.32)	(4.24)
$dQ_{d-5:d-1}$	0.55***	0.48***	0.62*	0.41***	0.36***	0.52*
	(3.29)	(2.84)	(1.73)	(2.96)	(2.60)	(1.83)
$dQ_{d-21:d-5}$	0.41**	0.47***	0.36	0.29*	0.33**	0.16
	(1.97)	(2.67)	(0.80)	(1.96)	(2.20)	(0.45)
$dQ_{d-252:d-21}$	−0.33	−0.07	−2.16***	−0.20	0.11	−1.61***
	(−0.99)	(−0.22)	(−3.12)	(−0.90)	(0.48)	(−3.23)
Q_{d-252}	0.48	0.35	−0.50	−0.25	−0.11	−1.00
	(0.96)	(0.71)	(−0.51)	(−0.92)	(−0.41)	(−1.58)

Table IA3: Panel Regression of dQ: Full Coefficients

This table reports the full set of coefficient estimates corresponding to Table 4. The number of observations is 10,447,842.

	Linear volume		Volume terciles		Terciles $\times$ block trades	
	(1)	(2)	(3)	(4)	(5)	(6)
$Vol_{d^*,Buy}$	0.0548***	0.0566***				
	(130.87)	(132.98)				
$Vol_{d^*,Sell}$	−0.0445***	−0.0439***				
	(−130.69)	(−129.84)				
Buy_{High}			0.0570***	0.0590***	0.0550***	0.0571***
			(122.38)	(124.95)	(121.82)	(124.46)
Buy_{Med}			0.0056***	0.0058***	0.0059***	0.0062***
			(32.59)	(33.49)	(34.31)	(35.36)
$Sell_{High}$			−0.0402***	−0.0392***	−0.0387***	−0.0378***
			(−117.20)	(−115.59)	(−115.08)	(−113.35)
$Sell_{Med}$			−0.0037***	−0.0038***	−0.0039***	−0.0040***
			(−22.66)	(−23.03)	(−24.22)	(−24.52)
$Buy_{High} \times Block_{Buy}$					0.2031***	0.2094***
					(71.27)	(72.63)
$Sell_{High} \times Block_{Sell}$					−0.1445***	−0.1429***
					(−74.96)	(−74.38)
$\overline{dQ}_{d-5,d-1}$		−0.0186***		−0.0181***		−0.0182***
		(−30.04)		(−29.16)		(−29.35)
$\overline{Vol}_{d^*-5,d^*-1,Buy}$		0.0140***		0.0136***		0.0138***
		(40.38)		(39.07)		(39.71)
$\overline{Vol}_{d^*-5,d^*-1,Sell}$		−0.0222***		−0.0195***		−0.0201***
		(−64.26)		(−57.40)		(−58.88)
$\overline{HS}_{d^*-5,d^*-1,Buy}$		0.0003***		0.0003**		0.0002**
		(3.04)		(2.53)		(2.38)
$\overline{HS}_{d^*-5,d^*-1,Sell}$		0.0004***		0.0003***		0.0003***
		(4.49)		(3.28)		(3.07)
σ_{d^*-5,d^*-1}		−0.0016***		−0.0013***		−0.0014***
		(−7.75)		(−6.42)		(−6.54)
r_{d^*}		0.0011***		0.0015***		0.0015***
		(6.49)		(8.01)		(8.00)
$\bar{r}_{d^*-5,d^*-1}$		0.0013***		0.0008***		0.0009***
		(7.07)		(4.37)		(4.51)
dQ_d^{Stock}		0.0006***		0.0006***		0.0006***
		(3.13)		(3.01)		(3.03)
$\overline{dQ}_{d-5,d-1}^{Stock}$		0.0002**		0.0002**		0.0002**
		(2.22)		(2.05)		(2.03)
Log Amount		−0.0006		−0.0017***		−0.0019***
		(−1.34)		(−4.02)		(−4.35)
Rating		−0.0024***		−0.0004		−0.0004
		(−6.05)		(−0.88)		(−1.08)
Maturity		−0.0811***		−0.0929***		−0.0929***
		(−3.02)		(−3.37)		(−3.39)
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.072	0.083	0.029	0.038	0.036	0.046

Table IA4: 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 4 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 4, 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. The number of observations is 11,341,920.

	(1)	(2)	(3)	(4)	(5)	(6)
$Vol_{d^*,Buy}$	0.0536^{***}	0.0554^{***}	0.0553^{***}	0.0494^{***}	0.0509^{***}	0.0508^{***}
	(105.93)	(108.33)	(107.36)	(41.41)	(42.14)	(41.41)
$Vol_{d^*,Sell}$	-0.0446^{***}	-0.0440^{***}	-0.0440^{***}	-0.0424^{***}	-0.0413^{***}	-0.0415^{***}
	(−102.11)	(−101.18)	(−101.41)	(−40.81)	(−39.58)	(−40.06)
$CDS \times Vol_{d^*,Buy}$	0.0019^{***}	0.0019^{***}	0.0021^{***}			
	(3.16)	(3.13)	(3.38)			
$CDS \times Vol_{d^*,Sell}$	0.0004	0.0004	0.0005			
	(0.69)	(0.81)	(0.99)			
CDS	0.0001	0.0001	0.0002			
	(0.33)	(0.18)	(0.42)			
$PUB \times Vol_{d^*,Buy}$				0.0055^{***}	0.0058^{***}	0.0060^{***}
				(4.58)	(4.80)	(4.82)
$PUB \times Vol_{d^*,Sell}$				-0.0022^{**}	-0.0026^{**}	-0.0025^{**}
				(−2.08)	(−2.45)	(−2.34)
PUB				0.0005	0.0004	0.0006
				(1.38)	(1.04)	(1.48)
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
Adjusted R^2	0.071	0.082	0.082	0.071	0.082	0.082

Table IA5: 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 bonds of public firms, as specified in equation (IA2). The explanatory variables include the daily change in quantity on loan, dQ_d, and the same set of control variables as in Table 4. 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. The number of observations is 10,409,033.

	(1)	(2)	(3)	(4)	(5)
dQ_d	0.0142***	0.0149***	0.0141***	0.0142***	0.0141***
	(11.17)	(11.28)	(10.59)	(11.26)	(10.66)
$\overline{dQ}_{d-5,d-1}$		0.0109***	0.0022		0.0021
		(6.71)	(1.29)		(1.21)
$\overline{Vol}_{d^*-5,d^*-1,Buy}$			0.0361***		0.0356***
			(14.55)		(13.72)
$\overline{Vol}_{d^*-5,d^*-1,Sell}$			−0.0304***		−0.0301***
			(−13.55)		(−12.92)
$\overline{HS}_{d^*-5,d^*-1,Buy}$			0.0267***		0.0247***
			(3.96)		(4.09)
$\overline{HS}_{d^*-5,d^*-1,Sell}$			0.0135**		0.0163***
			(2.08)		(3.02)
σ_{d^*-5,d^*-1}			0.1004***		0.0993***
			(4.07)		(3.92)
$\bar{r}_{d^*-5,d^*-1}$				0.0223	0.0169
				(0.99)	(0.73)
dQ_d^{Stock}				−0.0160***	−0.0151***
				(−3.75)	(−3.56)
$\overline{dQ}_{d-5,d-1}^{Stock}$				−0.0073	−0.0067
				(−1.26)	(−1.16)
Bond Controls	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.232	0.232	0.234	0.232	0.234

Table IA6: 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 5. 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. The number of observations is 11,341,920.

	$Vol_{d^*,Buy}$				$Vol_{d^*,Sell}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
dQ_d	0.237***	0.241***	0.250***	0.250***	−0.134***	−0.133***	−0.128***	−0.128***
	(58.03)	(59.43)	(60.58)	(60.66)	(−46.59)	(−45.83)	(−45.06)	(−44.97)
$\overline{dQ}_{d-5,d-1}$		0.102***	0.136***	0.137***		0.036***	0.036***	0.036***
		(40.10)	(51.95)	(52.31)		(14.14)	(15.16)	(15.36)
$\overline{Vol}_{d^*-5,d^*-1,Buy}$			0.073***	0.073***			0.110***	0.110***
			(36.37)	(36.35)			(64.73)	(64.81)
$\overline{Vol}_{d^*-5,d^*-1,Sell}$			0.237***	0.236***			0.146***	0.146***
			(117.92)	(118.97)			(77.46)	(78.72)
$\overline{HS}_{d^*-5,d^*-1,Buy}$			−0.003***	−0.003***			−0.002***	−0.001***
			(−11.89)	(−10.56)			(−6.33)	(−5.01)
$\overline{HS}_{d^*-5,d^*-1,Sell}$			0.001*	−0.001***			−0.002***	−0.003***
			(1.65)	(−3.76)			(−5.09)	(−9.50)
σ_{d^*-5,d^*-1}			0.004**	0.008***			0.005**	0.008***
			(2.07)	(6.75)			(2.29)	(4.87)
r_{d^*}				0.003				0.002
				(1.51)				(1.34)
$\bar{r}_{d^*-5,d^*-1}$				−0.015***				−0.009***
				(−11.34)				(−5.24)
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
Adjusted R^2	0.091	0.092	0.138	0.138	0.066	0.066	0.088	0.088

Table IA7: 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 5, 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 5, 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	−0.117	0.213	−0.330	0.335	0.665	19,760,034
	(−20.07)	(20.77)	(−20.75)	(42.07)	(83.56)	
Panel B: By Credit Rating						
IG	−0.126	0.228	−0.354	0.323	0.677	15,838,352
	(−15.69)	(15.95)	(−15.96)	(29.12)	(61.04)	
HY	−0.099	0.184	−0.283	0.358	0.642	3,849,648
	(−27.78)	(39.92)	(−38.40)	(97.08)	(173.89)	
Panel C: By Collateral Specialness						
GC	−0.122	0.231	−0.354	0.323	0.677	18,078,629
	(−18.77)	(19.35)	(−19.32)	(35.31)	(73.95)	
SP1	−0.075	0.141	−0.216	0.392	0.608	778,714
	(−15.60)	(23.89)	(−26.59)	(96.58)	(149.75)	
SP2	−0.069	0.059	−0.129	0.436	0.564	726,986
	(−13.18)	(12.53)	(−19.57)	(132.70)	(171.85)	
SP3	−0.090	−0.015	−0.075	0.462	0.538	173,108
	(−9.15)	(−2.00)	(−9.45)	(116.28)	(135.19)	
Panel D: By Public Status						
Public Firm	−0.119	0.218	−0.337	0.331	0.669	18,329,519
	(−20.17)	(20.90)	(−20.87)	(41.03)	(82.77)	
Private Firm	−0.087	0.160	−0.248	0.376	0.624	1,429,753
	(−13.67)	(15.55)	(−15.80)	(47.95)	(79.54)	

Table IA7, Continued.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel E: By CDS Coverage						
Yes	−0.115	0.214	−0.329	0.335	0.665	10,063,075
	(−18.87)	(19.72)	(−19.69)	(40.08)	(79.46)	
No	−0.119	0.212	−0.331	0.334	0.666	9,696,927
	(−20.33)	(21.32)	(−21.30)	(42.96)	(85.56)	
Panel F: By Expensiveness						
Overvalued	−0.154	0.216	−0.370	0.315	0.685	8,507,915
	(−22.75)	(23.67)	(−23.64)	(40.28)	(87.57)	
Undervalued	−0.107	0.223	−0.330	0.335	0.665	8,491,168
	(−22.76)	(24.51)	(−24.54)	(49.76)	(98.84)	
Panel G: By Issuance Size						
Large	−0.125	0.242	−0.367	0.316	0.684	9,251,999
	(−27.79)	(30.12)	(−30.09)	(51.81)	(112.00)	
Small	−0.108	0.179	−0.287	0.357	0.643	10,507,961
	(−14.35)	(14.79)	(−14.76)	(36.70)	(66.23)	
Panel H: By Bid-ask Spread						
Illiquid	−0.117	0.209	−0.326	0.337	0.663	8,437,110
	(−24.88)	(26.34)	(−26.50)	(54.85)	(107.84)	
Liquid	−0.135	0.257	−0.392	0.304	0.696	8,426,329
	(−33.12)	(38.30)	(−38.11)	(59.23)	(135.45)	

Table IA8: 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 5 except that we present results for two subperiods: September 13, 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: 2006.09.13 – 2017.09.04						
Panel A1: Whole Sample						
All	−0.120	0.242	−0.362	0.319	0.681	6,272,861
	(−30.35)	(40.44)	(−38.98)	(68.82)	(146.77)	
Panel B1: By Credit Rating						
IG	−0.139	0.274	−0.413	0.293	0.707	4,643,612
	(−28.15)	(34.58)	(−33.96)	(48.22)	(116.14)	
HY	−0.093	0.193	−0.286	0.357	0.643	1,629,246
	(−19.91)	(33.72)	(−31.57)	(78.90)	(142.04)	
Panel C1: By Collateral Specialness						
GC	−0.130	0.270	−0.400	0.300	0.700	5,819,184
	(−30.78)	(41.06)	(−39.55)	(59.40)	(138.50)	
SP1	−0.069	0.131	−0.200	0.400	0.600	180,516
	(−9.03)	(14.97)	(−17.13)	(68.59)	(102.85)	
SP2	−0.063	0.074	−0.137	0.432	0.568	220,474
	(−9.27)	(12.09)	(−18.19)	(114.68)	(151.06)	
SP3	−0.082	−0.021	−0.061	0.470	0.530	51,179
	(−6.02)	(−1.98)	(−5.78)	(89.37)	(100.93)	
Panel D1: By Public Status						
Public Firm	−0.123	0.245	−0.368	0.316	0.684	5,890,280
	(−30.61)	(40.86)	(−39.38)	(67.77)	(146.52)	
Private Firm	−0.086	0.204	−0.290	0.355	0.645	382,547
	(−10.80)	(18.73)	(−18.30)	(44.71)	(81.31)	

Table IA8, Continued.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Period 1: 2006.09.13 – 2017.09.04						
Panel E1: By CDS Coverage						
Yes	−0.120	0.241	−0.360	0.320	0.680	3,471,926
	(−26.30)	(35.23)	(−34.09)	(60.51)	(128.69)	
No	−0.121	0.243	−0.364	0.318	0.682	2,800,926
	(−26.26)	(38.77)	(−37.02)	(64.80)	(138.84)	
Panel F1: By Expensiveness						
Overvalued	−0.160	0.246	−0.406	0.297	0.703	3,192,947
	(−31.84)	(39.58)	(−39.21)	(57.35)	(135.77)	
Undervalued	−0.094	0.238	−0.332	0.334	0.666	3,055,248
	(−23.96)	(35.39)	(−34.30)	(68.90)	(137.49)	
Panel G1: By Issuance Size						
Large	−0.123	0.255	−0.378	0.311	0.689	3,927,775
	(−28.69)	(38.67)	(−37.18)	(61.08)	(135.44)	
Small	−0.114	0.214	−0.328	0.336	0.664	2,345,066
	(−21.57)	(31.00)	(−29.96)	(61.31)	(121.23)	
Panel H1: By Bid-ask Spread						
Illiquid	−0.105	0.215	−0.319	0.340	0.660	3,432,475
	(−25.26)	(33.33)	(−32.68)	(69.61)	(134.98)	
Liquid	−0.139	0.275	−0.415	0.293	0.707	2,741,794
	(−30.69)	(45.82)	(−43.75)	(61.76)	(149.26)	

Table IA8, 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	−0.141	0.262	−0.403	0.299	0.701	5,069,054
	(−44.25)	(68.59)	(−72.36)	(107.30)	(252.02)	
Panel B2: By Credit Rating						
IG	−0.160	0.283	−0.443	0.278	0.722	4,165,935
	(−46.94)	(70.19)	(−76.41)	(96.03)	(248.85)	
HY	−0.095	0.214	−0.308	0.346	0.654	903,117
	(−20.17)	(39.51)	(−38.70)	(86.86)	(164.26)	
Panel C2: By Collateral Specialness						
GC	−0.151	0.282	−0.433	0.284	0.716	4,724,757
	(−47.16)	(73.07)	(−78.52)	(102.96)	(260.00)	
SP1	−0.060	0.170	−0.230	0.385	0.615	208,300
	(−8.82)	(25.57)	(−26.51)	(88.51)	(141.53)	
SP2	−0.064	0.068	−0.132	0.434	0.566	108,180
	(−7.46)	(8.86)	(−15.40)	(101.48)	(132.28)	
SP3	−0.108	−0.001	−0.107	0.446	0.554	26,469
	(−7.64)	(−0.08)	(−8.11)	(67.32)	(83.53)	
Panel D2: By Public Status						
Public Firm	−0.141	0.262	−0.403	0.299	0.701	4,767,691
	(−43.52)	(68.10)	(−71.56)	(106.08)	(249.20)	
Private Firm	−0.144	0.258	−0.402	0.299	0.701	301,300
	(−17.13)	(22.46)	(−24.29)	(36.17)	(84.75)	

Table IA8, 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	−0.140	0.265	−0.405	0.298	0.702	2,578,643
	(−36.46)	(61.76)	(−63.47)	(93.32)	(220.26)	
No	−0.142	0.259	−0.401	0.300	0.700	2,490,404
	(−35.96)	(57.10)	(−56.92)	(85.20)	(199.04)	
			Panel F2: By Expensiveness			
Overvalued	−0.180	0.264	−0.444	0.278	0.722	2,895,524
	(−48.85)	(59.99)	(−68.33)	(85.59)	(222.25)	
Undervalued	−0.109	0.259	−0.368	0.316	0.684	2,169,582
	(−30.55)	(60.20)	(−60.85)	(104.59)	(226.29)	
			Panel G2: By Issuance Size			
Large	−0.143	0.270	−0.413	0.293	0.707	3,054,208
	(−40.76)	(66.94)	(−68.45)	(97.27)	(234.17)	
Small	−0.137	0.248	−0.385	0.308	0.692	2,014,839
	(−30.33)	(49.05)	(−49.54)	(79.24)	(178.33)	
			Panel H2: By Bid-ask Spread			
Illiquid	−0.121	0.244	−0.365	0.318	0.682	2,607,998
	(−33.90)	(56.78)	(−58.25)	(101.42)	(217.92)	
Liquid	−0.164	0.284	−0.448	0.276	0.724	2,391,398
	(−45.32)	(69.75)	(−77.61)	(95.68)	(250.90)	

Table IA9: 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 5, 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 13, 2006 to December 30, 2022.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel A: Whole Sample						
All	−0.098	0.199	−0.298	0.351	0.649	11,703,646
	(−9.29)	(10.15)	(−9.88)	(23.30)	(43.06)	
Panel B: By Credit Rating						
IG	−0.118	0.226	−0.344	0.328	0.672	9,092,875
	(−12.96)	(13.40)	(−13.31)	(25.43)	(52.06)	
HY	−0.069	0.157	−0.226	0.387	0.613	2,610,766
	(−6.39)	(7.38)	(−7.09)	(24.28)	(38.47)	
Panel C: By Collateral Specialness						
GC	−0.108	0.223	−0.332	0.334	0.666	10,885,383
	(−11.25)	(12.21)	(−11.93)	(24.02)	(47.89)	
SP1	−0.051	0.117	−0.168	0.416	0.584	397,413
	(−6.40)	(5.17)	(−5.68)	(28.13)	(39.49)	
SP2	−0.049	0.059	−0.108	0.446	0.554	338,973
	(−6.29)	(6.99)	(−7.29)	(60.11)	(74.68)	
SP3	−0.064	−0.008	−0.056	0.472	0.528	79,942
	(−4.33)	(−0.99)	(−5.05)	(84.41)	(94.50)	
Panel D: By Public Status						
Public Firm	−0.101	0.202	−0.302	0.349	0.651	10,991,233
	(−9.51)	(10.37)	(−10.10)	(23.30)	(43.50)	
Private Firm	−0.073	0.165	−0.238	0.381	0.619	712,329
	(−6.27)	(7.33)	(−7.12)	(22.81)	(37.04)	

Table IA9, Continued.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel E: By CDS Coverage						
Yes	−0.094	0.193	−0.287	0.356	0.644	6,232,798
	(−7.80)	(8.66)	(−8.39)	(20.81)	(37.60)	
No	−0.105	0.208	−0.313	0.343	0.657	5,470,832
	(−12.23)	(13.12)	(−12.91)	(28.34)	(54.17)	
Panel F: By Expensiveness						
Overvalued	−0.142	0.218	−0.360	0.320	0.680	6,279,272
	(−17.16)	(17.64)	(−17.62)	(31.36)	(66.60)	
Undervalued	−0.072	0.188	−0.260	0.370	0.630	5,394,514
	(−7.18)	(8.10)	(−7.85)	(22.35)	(38.06)	
Panel G: By Issuance Size						
Large	−0.102	0.212	−0.314	0.343	0.657	7,194,439
	(−9.98)	(11.07)	(−10.74)	(23.45)	(44.92)	
Small	−0.093	0.177	−0.270	0.365	0.635	4,509,190
	(−8.32)	(8.76)	(−8.66)	(23.44)	(40.75)	
Panel H: By Bid-ask Spread						
Illiquid	−0.083	0.176	−0.258	0.371	0.629	6,254,877
	(−8.47)	(9.24)	(−9.02)	(25.90)	(43.93)	
Liquid	−0.120	0.232	−0.353	0.324	0.676	5,270,006
	(−10.42)	(11.53)	(−11.19)	(20.53)	(42.90)	

Table IA10: 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 5 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 13, 2006 to December 30, 2022.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel A: Whole Sample						
All	−0.125	0.250	−0.375	0.313	0.687	11,703,646
	(−39.43)	(55.11)	(−52.08)	(86.81)	(190.97)	
Panel B: By Credit Rating						
IG	−0.145	0.279	−0.423	0.288	0.712	9,092,875
	(−40.37)	(51.58)	(−50.31)	(68.59)	(169.21)	
HY	−0.091	0.201	−0.291	0.354	0.646	2,610,766
	(−23.87)	(41.84)	(−38.24)	(93.03)	(169.52)	
Panel C: By Collateral Specialness						
GC	−0.134	0.275	−0.410	0.295	0.705	10,885,383
	(−41.08)	(56.60)	(−53.87)	(77.66)	(185.40)	
SP1	−0.063	0.150	−0.213	0.394	0.606	397,413
	(−12.13)	(22.76)	(−26.01)	(96.14)	(148.15)	
SP2	−0.062	0.074	−0.136	0.432	0.568	338,973
	(−11.31)	(15.06)	(−22.83)	(144.50)	(190.16)	
SP3	−0.085	−0.012	−0.073	0.464	0.536	79,942
	(−7.20)	(−1.30)	(−8.08)	(103.12)	(119.28)	
Panel D: By Public Status						
Public Firm	−0.127	0.252	−0.379	0.311	0.689	10,991,233
	(−39.71)	(55.52)	(−52.49)	(86.09)	(191.07)	
Private Firm	−0.099	0.222	−0.321	0.340	0.660	712,329
	(−14.62)	(24.58)	(−23.93)	(50.69)	(98.55)	

Table IA10, Continued.

	Regression Coefficients			Variance Ratio		
	β_S	β_B	Diff.	Customer	Dealer	Observations
Panel E: By CDS Coverage						
Yes	−0.123	0.250	−0.374	0.313	0.687	6,232,798
	(−33.74)	(48.76)	(−45.89)	(76.82)	(168.61)	
No	−0.126	0.250	−0.376	0.312	0.688	5,470,832
	(−36.25)	(52.34)	(−49.85)	(82.59)	(182.30)	
Panel F: By Expensiveness						
Overvalued	−0.166	0.255	−0.420	0.290	0.710	6,279,272
	(−47.22)	(58.85)	(−58.88)	(81.16)	(198.92)	
Undervalued	−0.096	0.246	−0.342	0.329	0.671	5,394,514
	(−29.46)	(45.86)	(−43.21)	(83.01)	(169.42)	
Panel G: By Issuance Size						
Large	−0.127	0.261	−0.389	0.306	0.694	7,194,439
	(−37.30)	(53.50)	(−50.22)	(79.05)	(179.49)	
Small	−0.120	0.229	−0.349	0.326	0.674	4,509,190
	(−30.11)	(43.07)	(−41.45)	(77.42)	(160.32)	
Panel H: By Bid–Ask Spread						
Illiquid	−0.108	0.227	−0.335	0.333	0.667	6,254,877
	(−34.26)	(46.10)	(−44.98)	(89.31)	(179.27)	
Liquid	−0.145	0.279	−0.425	0.288	0.712	5,270,006
	(−38.95)	(61.09)	(−56.24)	(76.18)	(188.66)	

Table IA11: Descriptive Statistics: Dealer Share and Bond Liquidity

This table reports summary statistics for the variables used in the bond-level dealer share and liquidity analysis. *Minus Beta Diff* is $-(\beta_S - \beta_B)$ at month t, where β_S and β_B are the slope coefficients from rolling regressions of customer sell volume ($Vol_{i,d^*,Sell}$) and customer buy volume ($Vol_{i,d^*,Buy}$), respectively, on the daily change in loan quantity ($dQ_{i,d}$), all scaled by amount outstanding. The regressions are estimated over a trailing 252-trading-day window ending on the last valid trading day in month t. *Dealer Share* is the affine transform $D_{i,t} = \frac{1}{2} - \frac{1}{2}(\beta_S - \beta_B)$. The ten liquidity proxies are measured in month $m+1$ and follow Schestag, Schuster, and Uhrig-Homburg (2016). *AvgBidAsk_All* and *AvgBidAsk_Inst* are volume-weighted average bid-ask spreads (in percent) constructed from customer buy and sell prices, using all customer trades and institutional-size customer trades ($100,000 par value or larger), respectively. *IQR_All* and *IQR_Inst* are interquartile-range spread proxies constructed from all TRACE trades and institutional-size trades, respectively. *HighLow* is the Corwin and Schultz (2012) estimator based on high and low prices. *Gibbs* is twice the posterior mean of the effective cost from the Hasbrouck (2009) Bayesian Gibbs sampler on daily TRACE prices. *Roll* is the Roll (1984) estimator on autocovariance of trade-active daily returns. *FHT* is the Fong, Holden, and Trzcinka (2017) estimator on continuous TRACE-fill daily returns. *ZeroTrade* is the fraction of business days in a month with no TRACE trade. *Log DollarVolume* is the natural logarithm of average daily TRACE dollar trading volume in a month. *Log Amount*, the natural logarithm of the par amount outstanding. *Rating* is the numerical rating score (1 = AAA, 21 = C). *Age* is the years since issuance. *Maturity* is the time to maturity in years. All continuous variables are winsorized at the 1st and 99th percentiles within each calendar month. *Rating* is a bounded integer and is not winsorized. The sample period is from March 2007 to December 2022.

Variable	Mean	SD	P1	P25	P50	P75	P99	Obs
Minus Beta Diff	0.557	0.462	−0.407	0.230	0.512	0.812	2.031	836,261
Dealer Share	0.778	0.231	0.296	0.615	0.756	0.906	1.515	836,261
AvgBidAsk_All (%)	0.744	0.900	−0.065	0.239	0.462	0.918	4.113	636,165
AvgBidAsk_Inst (%)	0.383	0.501	−0.138	0.122	0.244	0.464	2.351	520,983
IQR_All (%)	0.633	0.728	0.050	0.233	0.429	0.778	3.320	664,824
IQR_Inst (%)	0.419	0.531	0.021	0.148	0.276	0.500	2.393	542,111
HighLow (%)	0.540	0.623	0.041	0.176	0.336	0.665	2.898	605,566
Gibbs (%)	0.904	0.634	0.098	0.410	0.752	1.252	2.834	605,566
Roll (%)	1.161	1.495	0.000	0.358	0.783	1.491	6.405	605,566
FHT (%)	0.550	0.879	0.000	0.101	0.289	0.694	3.684	605,566
ZeroTrade	0.324	0.271	0.000	0.091	0.250	0.524	0.955	718,019
Log DollarVolume	14.220	1.154	11.324	13.477	14.303	15.039	16.579	605,566
Log Amount	6.367	0.655	5.011	5.858	6.215	6.802	8.006	836,261
Rating	8.496	3.251	1.000	6.000	8.000	10.000	18.000	833,093
Age (years)	4.937	4.028	0.597	2.055	3.868	6.611	19.732	836,261
Maturity (years)	9.193	8.706	0.170	3.044	5.882	10.962	29.362	836,261

Table IA12: Definitions of the Equity Momentum and Equity Reversal Factors
This table defines the 13 equity signals from past stock and option returns used in Dickerson, Nozawa, and Robotti (2025). Panel A reports the nine signals assigned to the Equity Momentum group. Panel B reports the four signals assigned to the Equity Reversal group. Lowercase underscore codes, such as `ret_3_1` and `seas_2_5an`, follow the Jensen, Kelly, and Pedersen (JKP) Global Factor Data convention (jkpfactors.com), under which `ret_`a`_`b denotes the cumulative stock return from month $t-a$ to month $t-b$. Mixed-case acronyms, such as `TrendFactor` and `IndRetBig`, follow the Open Source Asset Pricing (OSAP) convention (openassetpricing.com).

Code	Name	Definition	Source
		Panel A: Equity Momentum	
`dVolCall`	Change in call implied vol	First difference of the 30-day, at-the-money ($\Delta \approx 0.5$) call-option implied volatility from the OptionMetrics surface.	An et al. (2014)
`dVolPut`	Change in put implied vol	First difference of the 30-day, at-the-money ($\Delta \approx 0.5$) put-option implied volatility.	An et al. (2014)
`TrendFactor`	Trend factor	Expected return from a cross-sectional regression of returns on price moving averages over short, intermediate, and long horizons.	Han et al. (2016)
`AnnouncementReturn`	Earnings-announcement return	Cumulative abnormal return over the window from one day before to two days after the most recent quarterly earnings announcement.	Chan et al. (1996)
`ret_3_1`	Price momentum, $t-3$ to $t-1$	Cumulative stock return over months $t-3$ through $t-1$, skipping the most recent month.	Jegadeesh and Titman (1993)
`seas_1_1na`	Seasonality, year 1, non-annual	Average monthly return over the past year, excluding the same-calendar-month observation.	Heston and Sadka (2008)
`seas_2_5an`	Seasonality, years 2–5, annual	Average return in the same calendar month over years $t-2$ to $t-5$.	Heston and Sadka (2008)
`seas_6_10an`	Seasonality, years 6–10, annual	Average return in the same calendar month over years $t-6$ to $t-10$.	Heston and Sadka (2008)
`MomSeason06YrPlus`	Seasonality, years 6–10	Average return in the same calendar month over the preceding 6–10 years (OSAP counterpart of `seas_6_10an`).	Heston and Sadka (2008)
		Panel B: Equity Reversal	
`ret_1_0`	Short-term reversal	Stock return over the most recent month ($t-1$ to t), with no skip.	Jegadeesh (1990)
`rmax5_21d`	Highest 5 days of return	Average of the five highest daily returns over the previous 21 trading days.	Bali et al. (2017)
`rmax5_rvol_21d`	Highest 5 days, vol-scaled	`rmax5_21d` divided by the standard deviation of daily returns over the previous 252 trading days.	Asness et al. (2020)
`IndRetBig`	Industry return of big firms	Lagged average return of the largest 30% of firms by market equity in the same Fama–French 48 industry.	Hou (2007)

Table IA13: Breakdown of Bond Factors: Q5 − Q1 Spreads

This table reports the Q5 − Q1 spread for each of the thirteen factors from past stock and option returns used in Dickerson, Nozawa, and Robotti (2025), for the pooled sample and separately for investment-grade (IG) and high-yield (HY) bonds. Portfolio formation, the adjusted-return benchmark, and the construction of the composite follow Table 10, and the composite row repeats the corresponding row of that table. Returns and alphas are in percent per month, and the sample period is September 2006 to November 2022 (195 months). The t-statistics in parentheses are Newey and West (1987) adjusted with a lag of 12. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Adjusted Return			Duration-Adjusted Alpha		
	All	IG	HY	All	IG	HY
AnnouncementReturn	0.144***	0.127***	0.258***	0.225***	0.183***	0.388***
	(4.29)	(4.76)	(3.85)	(5.10)	(4.52)	(4.73)
MomSeason06YrPlus	0.074	0.085*	0.033	0.200**	0.160*	0.065
	(1.64)	(1.74)	(0.20)	(1.97)	(1.78)	(0.51)
TrendFactor	0.236*	0.246*	0.205*	0.344**	0.314**	0.205*
	(1.85)	(1.76)	(1.86)	(2.39)	(2.19)	(1.69)
dVolCall	0.246***	0.233***	0.279**	0.267***	0.204***	0.348***
	(4.03)	(3.77)	(1.99)	(5.28)	(4.06)	(3.03)
dVolPut	0.201***	0.198***	0.151*	0.234***	0.172***	0.284***
	(4.24)	(4.27)	(1.67)	(4.66)	(3.69)	(2.95)
ret_1_0	0.477***	0.374**	0.974***	0.557***	0.418***	1.128***
	(2.71)	(2.55)	(2.93)	(2.94)	(2.90)	(3.64)
ret_3_1	0.182	0.179	0.008	0.352**	0.294*	0.076
	(1.54)	(1.61)	(0.03)	(2.27)	(1.93)	(0.33)
rmax5_21d	0.122	0.067	0.315	0.157*	0.052	0.189
	(1.08)	(0.63)	(1.38)	(1.71)	(0.71)	(0.88)
rmax5_rvol_21d	0.153**	0.108**	0.472**	0.186**	0.131*	0.429**
	(2.56)	(2.15)	(2.24)	(1.99)	(1.95)	(2.07)
seas_1_1na	0.274**	0.220**	0.577**	0.381***	0.270***	0.867***
	(2.22)	(2.04)	(2.57)	(3.85)	(3.32)	(3.86)
seas_2_5an	0.073**	0.086**	−0.005	0.140**	0.112**	0.088
	(2.08)	(2.23)	(−0.05)	(2.44)	(2.00)	(0.85)
seas_6_10an	0.063	0.071	−0.014	0.192*	0.157*	0.052
	(1.49)	(1.58)	(−0.11)	(1.86)	(1.67)	(0.68)
IndRetBig	0.294***	0.217**	0.381***	0.254**	0.169***	0.426***
	(2.90)	(2.24)	(2.78)	(2.39)	(2.73)	(2.70)
Composite	0.195***	0.170***	0.280***	0.268***	0.203***	0.350***
	(3.46)	(3.18)	(4.29)	(3.72)	(3.71)	(4.62)

Table IA14: Breakdown of Bond Factors: Q5 + Q1

This table reports the Q5 + Q1 sum for each of the thirteen factors from past stock and option returns used in Dickerson, Nozawa, and Robotti (2025), for the pooled sample and separately for investment-grade (IG) and high-yield (HY) bonds. Portfolio formation, the adjusted-return benchmark, and the construction of the composite follow Table 10, and the composite row repeats the corresponding row of that table. Returns and alphas are in percent per month, and the sample period is September 2006 to November 2022 (195 months). The t-statistics in parentheses are Newey and West (1987) adjusted with a lag of 12. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Adjusted Return			Duration-Adjusted Alpha		
	All	IG	HY	All	IG	HY
AnnouncementReturn	0.040	0.057	−0.113	0.082	0.052	0.132
	(1.27)	(1.56)	(−1.08)	(1.20)	(0.63)	(0.89)
MomSeason06YrPlus	−0.027	−0.031	0.018	−0.063	−0.084	0.324**
	(−1.15)	(−1.31)	(0.23)	(−1.24)	(−1.27)	(2.29)
TrendFactor	−0.041*	−0.026	−0.087	−0.029	−0.080	0.313***
	(−1.68)	(−1.10)	(−1.03)	(−0.64)	(−1.28)	(3.00)
dVolCall	−0.019	−0.025	−0.029	−0.014	−0.064	0.266**
	(−0.91)	(−1.02)	(−0.29)	(−0.31)	(−0.95)	(1.96)
dVolPut	−0.014	−0.024	−0.098	−0.019	−0.066	0.132
	(−0.49)	(−0.76)	(−0.65)	(−0.42)	(−1.06)	(0.81)
ret_1_0	−0.053	−0.029	−0.056	−0.034	−0.053	0.199
	(−1.18)	(−0.97)	(−0.36)	(−0.59)	(−0.69)	(1.17)
ret_3_1	−0.032	−0.029	0.003	−0.047	−0.080	0.266
	(−0.41)	(−0.48)	(0.02)	(−0.55)	(−1.00)	(1.55)
rmax5_21d	0.036	0.005	0.031	0.054	−0.033	0.300*
	(0.80)	(0.14)	(0.27)	(0.73)	(−0.43)	(1.77)
rmax5_rvol_21d	−0.008	0.002	−0.051	−0.024	−0.053	0.212**
	(−0.36)	(0.10)	(−0.97)	(−0.72)	(−0.96)	(2.13)
seas_1_1na	−0.075	−0.042	−0.263	−0.069	−0.097	0.031
	(−1.34)	(−1.05)	(−1.49)	(−1.12)	(−1.26)	(0.17)
seas_2_5an	0.010	0.000	−0.007	0.001	−0.053	0.262*
	(0.34)	(0.00)	(−0.07)	(0.03)	(−0.77)	(1.88)
seas_6_10an	−0.022	−0.038*	0.042	−0.046	−0.090	0.322**
	(−1.04)	(−1.68)	(0.47)	(−0.86)	(−1.31)	(2.19)
IndRetBig	−0.286***	−0.216**	−0.381**	−0.247***	−0.204***	−0.125
	(−2.82)	(−2.24)	(−2.56)	(−2.63)	(−2.97)	(−0.78)
Composite	−0.038	−0.030	−0.076	−0.035	−0.070	0.203
	(−1.34)	(−1.30)	(−0.92)	(−0.84)	(−1.16)	(1.62)