Customer Liquidity Provision:
Implications for Corporate Bond Transaction Costs*

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Abstract

The convention in calculating corporate bond trading costs is to estimate bid-ask spreads that customers pay, implicitly assuming that dealers always provide liquidity to customers. We show that, contrary to this assumption, customers increasingly provide liquidity after the post-2008 banking regulations were adopted and, thus, conventional bid-ask spread measures underestimate the cost of dealers’ liquidity provision to customers. Among large trades wherein dealers use inventory capacity, customers pay 35 to 60 percent wider spreads than before the crisis. Our results help explain the puzzling finding in the literature that transaction costs remain low despite the decrease in dealers’ risk capacity.

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1 Introduction

How have new banking regulations imposed following the 2008 financial crisis, such as stricter capital requirements and the Volcker Rule, affected U.S. corporate bond market liquidity? This topic has been hotly debated among both practitioners and academics. On the one hand, inventory costs for dealers have increased following the stricter banking regulations, which should lead to lower risk capacity and liquidity provision. Bessembinder, Jacobsen, Maxwell and Venkataraman (2018), Bao, O’Hara and Zhou (2018), and Schultz (2017), for example, show that dealers have reduced their capital commitments and liquidity provision. On the other hand, this decline has not had an impact on broad priced-based measures of liquidity,\(^1\) except during specific market stress or liquidity events, such as rating downgrades or index rebalancing (Bao et al., 2018; Dick-Nielsen and Rossi, 2019). These findings seem puzzling; given that corporate bond markets are dealer-intermediated, we would expect overall market liquidity to worsen when dealers reduce their risk capacity.

We revisit this question using the regulatory version of the Trade Reporting and Compliance Engine (TRACE) database of U.S. corporate bond transactions from 2006 through 2015. We show that customers, rather than dealers, increasingly provide liquidity to other customers and fill the liquidity gap arising from weaker liquidity provision by dealers. Moreover, conventional liquidity measures place a high weight on trades in which customers provide liquidity and, as a result, these measures do not show deterioration in the dealer cost of liquidity provision despite the decreased inventory capacity. In fact, the cost of liquidity paid to dealers has increased substantially, as we find that trades in which dealers provide liquidity using their inventory capacity incur up to 60% higher transaction costs than before the crisis, consistent with the notion that the regulations have had a negative impact on dealer liquidity provision. Thus, our results can help explain why studies so far have found that bid-ask spreads in the post-regulation periods are not wider despite decreased risk capacity on the part of dealers.

The key advantage of our paper over prior studies is that we are able to identify those who demand liquidity by exploiting the unique regulatory TRACE database that provides the identities

\(^1\)See, e.g., Trebbi and Xiao (2017), Adrian, Fleming, Shachar and Vogt (2017), Anderson and Stulz (2017).
of corporate bond dealers. In the equity market, it has long been the case that non-dealers provide liquidity by placing limit orders, and researchers typically use algorithms such as those presented in Lee and Ready (1991) to distinguish between liquidity demanders and providers. Somewhat surprisingly, the implicit assumption in the corporate bond literature is often that customers initiate trades and dealers are the sole liquidity providers, perhaps due to the over-the-counter nature of the market structure. For example, two of the most commonly used liquidity measures are dealers’ average round-trip profit for positions held for a short period of time (Feldhütter, 2012) and the difference between customer buy and sell prices, which aims to calculate average trading costs that customers pay dealers (Hong and Warga, 2000, Chakravarty and Sarkar, 2003). We argue that this is not always a reliable way of identifying those who demand liquidity, particularly because of the decline in liquidity provision by dealers in the post-regulation period. When a substantial fraction of liquidity is provided by customers instead of dealers, there is a conceptual mismatch between the usual market liquidity measures and the liquidity provision capacity of dealers. Moreover, the conventional measures encounter an underestimation problem because they treat liquidity-providing trades from customers as liquidity-demanding and such liquidity-providing trades have much lower spreads. We find that this emergence of customer liquidity provision drives the low liquidity costs documented in Bessembinder et al. (2018) and Trebbi and Xiao (2017), thus reconciling the puzzling findings in the literature.

Using dealer identifiers and counterparty pair types in our unique regulatory TRACE data, we separate out trades in which customers provide liquidity from trades in which dealers use their inventory capacity. We conjecture that a dealer-to-customer (DC) trade that is subsequently matched within a short period of time with another DC trade of the same dealer is likely a trade in which the first customer is demanding liquidity while the second customer is providing liquidity. In such cases, the dealer does not use his inventory capacity and is only an agent. Consistent with our conjecture, we observe that the first customer pays a wide spread (transaction fee), while the second customer tends to pay a negative spread (compensation for providing liquidity). We also find this effect to be asymmetric and stronger when liquidity-providing customers buy, as large
asset managers are increasingly stepping in to provide liquidity in the post-regulation period. It is relatively easier for such asset managers to provide liquidity on their long positions, as they typically hold net long positions and also have been receiving substantial investor flows during the post-crisis period.

Building on these findings, we develop a transaction cost measure for trades in which dealers use inventory capacity for liquidity-demanding customers. In particular, we calculate bond transaction costs by focusing only on DC trades that are not matched subsequently (i.e., DC trades that stay in dealer inventories for longer than 15 minutes or “invt>15min” trades), because in such trades dealers use their inventory capacity for customers demanding liquidity. This measure more closely resembles those used in equity markets; we isolate a large subset of trades about which we know with high confidence who initiated the trade and measure the trading costs for those trades.

With our measure of transaction costs in hand, in our main analyses we revisit the question of whether trading costs have increased following the post-crisis regulations. We find that the cost of immediacy paid to dealers has substantially increased. For example, trading costs after July 2012 for large DC trades that are not subsequently matched increase by 35–60% compared with trades in the pre-crisis period and by 10–20% compared with trades in the 2009–2012 period. In contrast, we show that the Implied Round-trip Cost (IRC) or the difference between customer buy and sell prices, which are often used in the literature, do not show decreases in liquidity or show only mild decreases following the implementation of the post-crisis regulations. This is because these measures treat trades in which customers provide liquidity as trades in which customers demand liquidity. Thus, these measures underestimate the true liquidity costs, as the trades in which customers provide liquidity tend to have negative spreads.

In the next set of results, we exploit dealer identities reported in our data, a unique feature of our dataset, which allows us to examine cross-sectional variation in the impact of the banking regulations. We show that, in a substantially higher fraction of trades, customers provide liquidity

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2For example, BlackRock, a large institutional asset manager, commented that it is not only a price taker, but now also acts as a “price maker” that “expresses a price at which he or she is willing to buy (or sell) a particular security at a given time” (BlackRock, 2015). A recent Wall Street Journal article also mentions that “giant bond firms increasingly are taking on a price setting role in global debt markets, elbowing aside big banks facing tighter post-crisis regulation” (https://www.wsj.com/articles/in-the-new-bond-market-bigger-is-better-1498046401)

3We focus on customer trades of $1 million or larger because regulations should primarily affect large trades.
in place of dealers after the regulations took effect. More importantly, the fraction of trades that are associated with customer liquidity provision has increased for dealers that are affected by the Volcker Rule and banking regulations. For example, the fraction of such trades in high-yield bonds increased by 6.2 percentage points for Volcker-affected dealers compared with the pre-crisis period, whereas it decreased by 6.8 percentage points for non-Volcker dealers. These results, combined with our finding that customer liquidity provision drives down overall trading costs, suggest an answer to the puzzle in the literature that trading costs remain low despite decreased dealer risk capacity.

Our results show that trading costs for liquidity-demanding customers, as measured by invt>15min spreads, have increased substantially. Note that we do not argue that the increase in customer liquidity provision causes the increase in the cost of immediacy. Rather, the decrease in dealer liquidity provision leads to an increase in trading costs, and without customers absorbing liquidity demand, trading costs would have increased further. We show that customer liquidity provision gives rise to a measurement problem with the conventional trading cost measures and that this measurement problem becomes more severe in the post-regulation period.

Our results have broad implications for how to measure the cost of immediacy for illiquid markets using trade data. Because of customer liquidity provision, a bid-ask spread measure would understate the cost of immediacy to the extent that it puts more weight on trades that remained in dealers’ inventories for a short period of time (short-horizon trades). At the same time, a bid-ask measure should employ more instances of these trades, as noise in spread estimates increases with time between consecutive trades. Although these opposing effects exist in almost all trading-cost measures used in the corporate bond literature, the first channel has not been recognized before. Hence, most studies have put high weights on short-horizon trades, underestimating the cost of immediacy paid to dealers.

This paper makes important contributions to the growing empirical literature that studies the impact of post-crisis regulations on corporate bond market liquidity. Prior studies in the literature

\footnote{Several theoretical papers also examine the effects of regulations on market liquidity. Cimon and Garriott (2016) argue that the Volcker Rule and capital regulations motivate dealers to switch to trading on an agency basis. Uslu (2016) finds that the welfare impact of the Volcker Rule is not clear.}
find that dealers have reduced capital committed to market-making and inventory provision in recent years. Bessembinder et al. (2018), for example, show that dealers commit less capital in the post-regulation period and that this reduction in committed capital is driven mainly by bank-affiliated dealers. Bao et al. (2018) find that dealers that are affected by the Volcker Rule provide less liquidity during downgrade events. What is largely missing from these studies is the potentially important role that customers play in filling the void in liquidity. We thus contribute to this literature by investigating the customer side and show that customers increasingly provide liquidity, particularly on the buy side of trades.

We also reconcile the seemingly contrasting findings in the literature by showing that customer liquidity provision can help explain why bid-ask spread measurements may seem low despite dealers' committing less capital and maintaining smaller inventories. Trebbi and Xiao (2017), for example, test whether there is a discontinuity in bid-ask spreads around the time when post-crisis regulations were introduced and find no evidence of liquidity deterioration. Bessembinder et al. (2018) find that although dealers commit less capital, average trading costs remain largely similar to pre-crisis levels. Anderson and Stulz (2017) and Adrian, Fleming, Shachar and Vogt (2017) find similar results. We provide a potential explanation for these puzzling findings in the literature by pointing out that conventional liquidity measures can understate the cost of immediacy paid to dealers. We also propose a method for measuring the costs of demanding liquidity without using specific market stress or liquidity events and show that liquidity has worsened broadly.

Several recent papers examine the inventory management behaviors of dealers and institutional investors in the corporate bond market. Goldstein and Hotchkiss (2019), for example, show that dealers have a high propensity to offset trades for riskier and less actively traded bonds and optimally adjust their inventory management behaviors. Schultz (2017) also shows that dealers frequently avoid using inventory capacity but instead offset trades by prearranging them, indicating that dealer liquidity provision and prearranging trades are essentially substitutes. Zitzewitz (2010), Harris (2015), and Ederington et al. (2014) study prearranged trades explicitly. Our paper differs in that we focus on the customer side of liquidity provision, and we complement the findings reported in these studies by analyzing the impact of increasing customer liquidity provision on
common measures of liquidity. Moreover, these studies implicitly assume that a set of matched customer trades consists of two customers that demand liquidity in the opposite direction, whereas we show that these types of trades contain a high fraction of customer liquidity provision where the first customer demands liquidity and the second customer provides it. Another related study is Anand, Jotikasthira and Venkataraman (2017), who show that mutual funds providing liquidity in the corporate bond market exhibit superior performance, while our focus is to examine the transaction cost implications of customer liquidity provision.

2 Data and Variable Construction

2.1 Data Description

The main data source is the regulatory TRACE feed for U.S. corporate bond trades. The database includes dealer identities for each trade, while customers are identified as the counterparty code “C” only.\(^5\) The database also includes trade information such as trade date and time, volume, price, trading capacity (principal or agent), and trade direction. Trades in the database are categorized as taking place either between dealers (interdealer trades) or between a dealer and a customer (customer trades). We exclude trades between dealers and their affiliates, as described in Appendix A and Figure 1.\(^6\)

We use the Mergent Fixed Income Securities Database (FISD) to obtain bond characteristics such as size, offering date, maturity, and rating. Corporate bond market volatilities are calculated using returns on the Bank of America Merrill Lynch U.S. Corporate Master Index (for investment grade bonds) and High Yield Master II Index (for high-yield bonds).

\(^5\)Dealers are identified by Market Participant Identifiers (MPIDs). Dealers may have multiple MPIDs for subsidiaries or change MPIDs due to mergers and acquisitions (M&As). In these cases, we construct a new identifier, MPID2, which identifies the same dealers with multiple MPIDs and the surviving firms in M&As. We delete trades between the same MPID2.

\(^6\)Additionally, we exclude trades that are reported by client brokers and interdealer traders. As we exclude trades that are reported only by these dealers, our sample still includes interdealer trades reported by regular dealers (i.e., dealers who are not client brokers or interdealer traders) even when such trades are executed with client brokers or interdealer traders. This procedure ensures that regular dealers' inventory accumulation is correct. Section IA.2 of the Internet Appendix further details how we identify client brokers and interdealer traders and also provides robustness tests showing that our main results are qualitatively similar without the exclusion of trades by client brokers and interdealer traders.
Our sample period runs from January 2006 through June 2015.\textsuperscript{7} MTNs, 144As, exchangeable bonds, and bond-days that occur less than 30 days since issuance are excluded. We restrict the sample to secondary market trades that are marked as principal trades. Our final cleaned sample consists of 15,860 bonds with a total of 38,932,240 trades (including duplicate interdealer trades), of which 3,940,700 are customer trades at par value of $1 million or higher.

2.2 Customer Trade Classification

We match customer trades and calculate inventory holding periods using the last-in-first-out (LIFO) method, starting each trading day for each bond with an inventory of zero. Each incoming customer trade (e.g., a customer sell) to a dealer is accumulated in the dealer’s inventories and is matched later with outgoing trades (e.g., interdealer trades or customer buys) when it leaves the inventories. Inventory holding periods are calculated based on how long dealers hold customer trades on their inventories. A single trade may be matched against multiple trades or fractions of multiple trades.

Using trade-matching, we classify all customer trades into three types: DC-DC trades, which are matched with other customer trades within 15 minutes; DC-ID trades, which are matched with interdealer trades within 15 minutes; and invt$>$15min trades, which have inventory holding periods of greater than 15 minutes. Section B of the Appendix details the inventory holding period calculation and customer trade classification, and Table A.2 of the Appendix provides an example. We use 15 minutes because dealers are required to report trades to TRACE within 15 minutes. We refer to DC-DC trades and DC-ID trades as “short-holding trades.” In untabulated results, we replicate the main tests using a 1-minute cutoff, and the results remain qualitatively similar.

In Table 1(a) we report the fractions of DC-DC, DC-ID, and invt$>$15min trades by trade size. We find that among short-holding trades DC-DC trades are more prevalent in large trades, whereas DC-ID trades are more prevalent in small trades. For example, among high-yield bonds with trade volumes under $100,000, there are approximately seven times more DC-ID trades than DC-DC trades. Hence, earlier papers that have studied matched trades (Zitzewitz, 2010, Ederington, Guan

\textsuperscript{7}We start the sample period in 2006 because the dissemination of trade information was introduced in multiple phases from 2002 to 2005 (Goldstein, Hotchkiss and Sirri, 2007), and we want to avoid the effect of increasing transparency in our empirical exercises.
and Yadav, 2014) have concentrated mostly on DC-ID trades, as they do not condition on trade size. Among trades of $1 million or higher, however, there are approximately six times more DC-DC trades than DC-ID trades. Because we focus on large trades that are $1 million and above in our main empirical analyses, DC-DC trades account for the majority of the matched trades in our sample and thus are more important.

2.3 Bid-Ask Spread Estimation

Our main measure of bid-ask spreads, $spread_1$, is defined as follows:

$$spread_1 = 2Q \times \frac{\text{traded price} - \text{reference price}}{\text{reference price}}$$  \hspace{1cm} (1)$$

where $Q$ is +1 for a customer buy and −1 for a customer sell. For each customer trade, we calculate its reference price as the volume-weighted average price of interdealer trades larger than $100,000 in the same bond-day, excluding interdealer trades executed within 15 minutes. Spread1 is calculated at the trade level for all customer trades and is also calculated at the bond-day level by taking the volume-weighted average of trade-level spreads.

The calculation of $spread_1$ can be sensitive to reference prices because interdealer trades may more likely to be missing for certain types of bonds or days. We perform a few robustness checks to show that our main results are not sensitive to the choice of reference prices. In the Internet Appendix, for instance, we employ as reference prices dealer quotes from the Merrill Lynch bond database, for which the quotes exist even on bond-days without trades, and show that our main results are qualitatively similar. In Tables 5 through 7 provided later in the paper, we perform additional robustness checks to show that our main results are not driven by sample selection based on the availability of interdealer prices.\textsuperscript{10}

\textsuperscript{8}Our construction of short-holding trades bear similarities to riskless principal trades (RPTs), which have been analyzed in previous papers (Zitzewitz, 2010, Harris, 2015, and Schultz, 2017). These papers identify RPTs as matched trades of the opposite direction that occur within one minute, which are most likely prearranged trades. The short-holding trades we construct in our paper include RPTs by construction. Section IA.1 of the Internet Appendix shows that among large trades of $1 million and above, more than half of DC-DC and DC-ID trades involve dealer holding periods of between 1 and 15 minutes (i.e., they are not classified as RPTs in the above papers).

\textsuperscript{9}Interdealer trades tend to be smaller and are less frequent; hence, we use the $100,000 cutoff instead of $1 million. The results are qualitatively similar if we do not exclude the 15 minutes before and after the trade.

\textsuperscript{10}Additionally, in the Internet Appendix, we employ reference prices based on weekly average interdealer prices.
To examine the extent to which customer liquidity provision affects spread estimation, we also calculate the following measures commonly used in the literature. The first is the implied round-trip cost (IRC) from Feldhütter (2012). IRC measures dealers’ round-trip costs for imputed round-trip trades (IRTs).\(^{11}\) If there are \(n\) sets of IRTs for bond \(i\) on day \(t\), IRC is calculated as

\[
IRC_{i,t} = \frac{1}{\sum_{l=1}^{n} \sum_{k=1}^{vol_{k}}\left(\frac{2(P_{\text{max},k} - P_{\text{min},k})}{P_{\text{max},k} + P_{\text{min},k}}\right)}.
\]

\(^{11}\)We use the IRT definition following Feldhütter (2012). Specifically, trades constitute IRTs if two or three trades of a given trade size are executed less than 15 minutes apart.

\(P_{\text{max},k}\) and \(P_{\text{min},k}\) are the maximum and minimum prices for the IRT set \(k\). \(vol_{k}\) is the volume for the IRT set \(k\). We also calculate \(IRC_{C}\), which we define as the implied round-trip cost based only on customer trades.

We also examine the same-day spread for bond \(i\) on day \(t\), defined as

\[
same\_day_{i,t} = \frac{2(vwavg(\text{customer buy})_{i,t} - vwavg(\text{customer sell})_{i,t})}{(vwavg(\text{customer buy})_{i,t} + vwavg(\text{customer sell})_{i,t})}.
\]

where \(vwavg\) stands for volume-weighted average. This measure is widely used in the literature, such as in Hong and Warga (2000) and Chakravarty and Sarkar (2003). All bid-ask spread measures are calculated using trades with par values of $1 million and above (except for the interdealer trades used in \(\text{spread1}\) calculations), are shown in basis points (bps), and are winsorized at the 1% level. We focus on trades of $1 million and above in par value because changes in dealers’ inventory costs should have the strongest effect on large trades.

It is important to note that the calculation of IRC and \(same\_day\) measures will include more instances of DC-DC trades. By construction, imputed round-trip trades (IRTs) used to calculate \(IRC_{C}\) and IRC will be mostly DC-DC trades. \(same\_day\) should also include disproportionately more DC-DC trades, because we need both customer-buy and customer-sell trades to be able to calculate \(same\_day\), implying that all DC-DC trades will be included while many invt>15min trades will be excluded from \(same\_day\) calculations. Table 1(b) presents the fraction of DC-DC, DC-ID, and obtain qualitatively similar results for our main analyses. \(\text{Spread1}\) can be calculated for approximately 40% of customer trades larger than $1 million when daily interdealer prices are used as reference prices, and using weekly interdealer prices substantially increases the sample size to approximately 75% of trades but potentially makes \(\text{spread1}\) noisier.
and invt>15min trades that are involved in calculating each of the four bid-ask spread measures. In IG bonds, for instance, DC-DC trades make up 82% of $IRC_C$ calculation, 62% of $IRC$ calculation, and 22% of $same\_day$ calculation, while it only accounts for 8% of $spread1$ calculation.

### 3 Customer Liquidity Provision

The main purpose of this paper is to show that customer liquidity provision, as measured by DC-DC trades, increased following the post-crisis regulations, leading to underestimation of transaction costs in conventional measures. In this section, we first establish that DC-DC trades are largely instances in which one customer demands liquidity and the other provides it. We also show that, in DC-ID trades, the second dealer generally provides liquidity to the customer, so these trades will have the lowest occurrences of customer liquidity provision.

Liquidity-providing customers are compensated by having to pay only a narrow or even negative spread (i.e., buying at a lower price or selling at a higher price than the fundamental value). Thus, to the extent that DC-DC trades are instances where one customer provides liquidity, DC-DC trades will have the narrowest average bid-ask spreads and the largest fraction of negative spreads. Alternatively, if neither customers are providing liquidity in DC-DC trades, they will not necessarily involve more instances of negative spreads and their average spreads will not be any narrower than those of DC-ID trades.\footnote{Appendix C provides additional evidence against this alternative proposition by showing that dealer profits from DC-DC trades are smaller than those from DC-ID trades. If DC-DC trades are instances in which a dealer matches two customers with opposite liquidity needs while DC-ID trades are cases where the second dealer provides liquidity, dealer profits should be larger for DC-DC trades.} Relatedly, to the extent that DC-ID trades are cases where the customer demands liquidity and the second dealer provides liquidity, the customer trade in DC-ID trades will have wider spreads.

We begin by examining average customer spreads and the fraction of negative-spread trades for each trade type. Table 1(c) clearly shows that average spreads are narrowest for DC-DC trades and widest for DC-ID trades. In IG bonds, for example, the average $spread1$ estimates for DC-DC, invt>15min, and DC-ID trades are 16.26 bps, 32.97 bps, and 58.56 bps, respectively. DC-DC trades also involve the largest fractions of negative spreads, as shown in Table 1(d). Moreover,
within DC-DC trades, customer buys include a higher fraction of negative spreads than customer sells do: 43.1% of DC-DC customer buys have negative spreads, while only 34.3% of customer sells are negative-spread trades. This result is consistent with the notion that typical customers have net long positions and, hence, will more likely provide liquidity by buying than by selling. These results strongly suggest that DC-DC trades are driven mainly by customer liquidity provision.

In Panel (a) of Table 2, we formally examine whether DC-DC trades have narrower spreads than the other trade types in a regression setting. We run the following model:

\[
\text{spread}^{1}_{i,j,t,k} = \alpha + \beta_{1}(\text{DC-DC})_{k} + \gamma_{1}(\text{DC-ID})_{k} + \epsilon_{i,j,t,k} \tag{4}
\]

where \(\text{spread}^{1}_{i,j,t,k}\) is the spread1, defined in (1), of trade \(k\) between dealer \(j\) and a customer for bond \(i\) on day \(t\). \(1(\text{DC-DC})_{k}\) and \(1(\text{DC-ID})_{k}\) are dummy variables indicating whether trade \(k\) is a DC-DC trade or a DC-ID trade, and invt>15min is the omitted category and thus forms the base level. We include control variables that are known to be associated with bond transaction costs such as trade size, bond age, and time-to-maturity, as well as bond, dealer, and time fixed effects.

Results reported in Table 2(a) show that DC-DC trades have the narrowest spreads. In column (1), for example, the spreads of DC-DC trades for IG bonds are approximately 13.3 bps lower than invt>15min spreads. DC-ID spreads, in comparison, are 21.2 bps higher. In columns (2), (3), (5), and (6), we run the regressions separately for customer buy and sell trades. If DC-DC trades reflect customer liquidity provision, it would more likely be associated with buy trades as customers can more easily provide liquidity by buying than by selling because of short-selling costs. The results are consistent with this hypothesis. In IG bond regressions, for example, the difference in spreads for invt>15min trades and DC-DC trades are 17.2 bps and 6.6 bps for customer buys and sells, respectively.\(^{13}\)

In Table 2(b), we provide further evidence that DC-DC trades involve one customer who demands liquidity and another who provides liquidity by exploiting the order and trade direction in a matched pair of DC-DC trades. Among DC-DC trades, ‘in’ trades are defined as trades that

\(^{13}\)In Section IA.1 of the Internet Appendix, we separate out DC-DC trades into those held in dealers’ inventories for less than one minute and those held for periods between one and fifteen minutes and show that both types of DC-DC trades have high amounts of customer liquidity provision.
arrive first, while ‘out’ trades are defined as those that occur next. We hypothesize that among DC-DC trades, ‘in’ trades tend to demand liquidity, while ‘out’ trades provide liquidity. We regress DC-DC spreads on dummy variables indicating ‘out’ trades and customer buy trades, and present the results in Panel (b) of Table 2. Spreads are narrower for ‘out’ and customer buy trades, further supporting the notion that DC-DC trades include a large fraction of trades in which customers provide liquidity.\textsuperscript{14}

What would be the implication of increased customer liquidity provision for bid-ask spread measures? Because IRC and same-day spread calculations include high fractions of DC-DC trades as shown in Table 1(b), these measures will underestimate the cost of immediacy paid by customers. In general, variation in the fraction of DC-DC trades should be related to the differences in spreads across the measures reported in Table 1(c). When the cost of immediacy changes over time, spread measures with high fractions of DC-DC trades may not properly reflect the change. We will show this empirically in the next section.

4 Customer Liquidity Provision and Trading Costs After the Implementation of Banking Regulations

In this section, we examine the impact of the banking regulations on customer liquidity provision. First, we show that customers provide liquidity to a greater extent during the post-regulation period, particularly in place of dealers who are heavily affected by the regulations. Next, we examine the extent to which customer liquidity provision affects bid-ask spread estimates in the post-regulation period, thus reconciling the puzzling findings reported in the previous literature indicating that bond market liquidity based on price-based measures did not deteriorate after the regulations went into effect.

\textsuperscript{14}Results also hold when we look at DC-DC trades matched within 1 minute and those matched between 1 and 15 minutes separately.
4.1 The Impact of Banking Regulations on Customer Liquidity Provision

We begin by examining the extent to which customer liquidity provision increased in the post-regulation period, using the DC-DC trade volume scaled by customer trade volume ("DC-DC fraction") as a measure of customer liquidity provision. We then exploit our rich data at the dealer level, which enables us to identify which dealers are affected heavily by the banking regulations, and examine differential responses of dealer liquidity provision to the regulation changes.

In Figure 2, we first plot the fractions of customer trades that are DC-DC or DC-ID trades over time. The DC-DC fractions increased in the post-regulation period, while the DC-ID fractions remained similar or decreased. These plots are consistent with the notion that there has been a shift from principal trading by dealers to a pre-arranged, search-and-match trading model, as shown by Schultz (2017) and Bessembinder et al. (2018). Moreover, this increase in prearranged trades are primarily driven by increase in customer liquidity provision rather than offloading to other dealers.

In Table 3, we examine whether customer liquidity provision increases following the introduction of banking regulations. In Panel (a), we first regress the DC-DC fractions on the dummy variables indicating four subperiods:

\[ y_t = \alpha + \sum_{l=2}^{4} \beta_l 1(t \in T_l) + \epsilon_t \]  

(5)

\[ y_{j,t} = \alpha_j + \sum_{l=2}^{4} \beta_l 1(t \in T_l) + \epsilon_{j,t} \]  

(6)

The aggregate DC-DC fraction, \( y_t \), is calculated as the daily volume-weighted average of DC-DC fractions across bonds and dealers. The individual dealer DC-DC fraction, \( y_{j,t} \), is the volume of DC-DC trades executed by dealer \( j \) on day \( t \) divided by the customer trade volume of that dealer on that day.\footnote{To consider individual dealer level, we use the 15 dealers that are classified as large dealers. For each month, we first find the top ten dealers by customer trading volume. Using the full sample, we define large dealers as those that appear in the top ten for a total of ten months or more. Large dealers account for 70% or more of the volume in trades larger than $1 million.}

\( T_l \) \((l = 1, \ldots, 4)\) are the four subperiods: the pre-crisis (Jan 2006 to Jun 2007), financial crisis (Jul 2007 to Apr 2009), post-crisis (May 2009 to Jun 2012), and post-regulation (Jul 2012 to Jun 2015) periods.\footnote{The Dodd-Frank Act, of which the Volcker Rule is a part of, was signed into law in July 2010, and the
The results reported in Table 3(a) indicate that customer liquidity provision increased in the post-regulation period compared with what occurred during the pre-crisis and the post-crisis periods. As shown in column (4) for HY bonds, for example, the coefficient on the post-regulation dummy is 7.5% and is statistically significant at the 1% level, showing that the fraction of DC-DC trades is 7.5 percentage points higher in the post-regulation period compared with the pre-crisis levels, which forms the base level in our regressions. Also in column (4), the fraction of DC-DC trades during post-regulation period is higher than it is during the post-crisis period, as the difference between the coefficients on the post-regulation dummy and the post-crisis dummy (row $\beta_4 - \beta_3$ near the bottom) is 4.1% and statistically significant at the 1% level. Given that the DC-DC trades account for 24% of customer trades in HY bonds, these increases in customer liquidity provision are economically large. We report similar results for IG bonds in column (1). Moreover, the dealer-level mean and median regressions reported in columns (2), (3), (5), and (6) yield similar results, showing that our results are not driven by a single large dealer.

Interestingly, the results reported in Table 3(a) also suggest that dealers pull back during times of market stress, while customers tend to fill in. Note that customer liquidity provision is higher in the crisis period than in the pre-crisis period, as evidenced by the coefficients on the crisis period dummy. We also find that the coefficients on market volatility are positive, showing higher customer liquidity provision during uncertain times. While these results are interesting, we concentrate on the comparison between the post-regulation and pre-regulation periods, as the focus of the paper is on the effects of the regulations.

In Table 3(b), we further examine the impact of the regulations by isolating the responses of dealers who are heavily affected by the regulations. In particular, we employ a difference-in-differences-style regression approach and compare the changes in fractions of DC-DC trades for

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Volcker Rule was originally scheduled to be implemented by July 2012. The rule eventually went into effect in July 2015. The Basel III capital requirements were first agreed upon in 2010 and were phased in gradually over multiple years starting in 2013. Most banks adopted regulations in advance of the implementation deadlines. For instance, a recent Wall Street Journal article noted that the Volcker Rule kicked in “with little fanfare” because most big banks had “already fallen in line” (https://www.wsj.com/articles/volcker-bank-risk-rule-set-to-start-with-little-fanfare-1437517061). For these reasons, we choose July 2012 as the beginning of the post-regulation period, but the choice of July 2012 is not crucial to our results.
dealers that are affected by the regulations with those that are not, using the following regression:

\[ y_{m,t} = \alpha_1 + \alpha_2 \mathbb{1}(unaff)_m + \sum_{l=2}^{4} \mathbb{1}(aff)_m \beta_a,l \mathbb{1}(t \in T_l) + \sum_{l=2}^{4} \mathbb{1}(unaff)_m \beta_u,l \mathbb{1}(t \in T_l) + \epsilon_{m,t}. \]  

(7)

The dependent variable, \( y_{m,t} \), is the fraction of DC-DC trades at the dealer group level \((m = aff \text{ or } m = unaff)\), calculated separately for the group of dealers that are affected by the regulations \((m = aff)\) and for another group of dealers that are not \((m = unaff)\). The dummy variables, \( \mathbb{1}(aff)_m \) and \( \mathbb{1}(unaff)_m \), are indicators of dealer group \( m \). We use two proxies for whether a dealer is affected by the regulations. The first proxy is whether the dealer is affected by the Volcker Rule.\(^{17}\) The second is the size of the dealer, because most large dealers are affiliated with banks and thus are affected by various banking regulations, whereas small dealers are a mix of bank-affiliated and non-bank dealers and will be affected less severely by the banking regulations.\(^{18}\)

Regression results reported in Table 3(b) show that increases in customer liquidity provision and decreases in dealer risk-taking are driven mainly by dealers who are affected by the bank regulations. Column (2), for instance, reports that in HY bonds, the fraction of DC-DC trades for Volcker-affected dealers is 6.2 percentage points higher in the post-regulation period than in the pre-crisis period. In contrast, DC-DC trades decrease by 6.8 percentage points for dealers who are not affected by the Volcker Rule. The differences between the post-regulation period and the post-crisis period are 6.3 percentage points and –6.8 percentage points for Volcker-affected dealers and non-Volcker-affected dealers, respectively. We find similar results for IG bonds, albeit with smaller differences between Volcker-affected and non-Volcker-affected dealers. In columns (3) and (4), we report largely similar results, both qualitatively and quantitatively, when dealer size is employed as a proxy for whether a dealer is affected by regulations.

Overall, the results presented in this section show that customer liquidity provision is higher in the post-regulation period than in the pre-crisis and post-crisis periods. This increase is driven mostly by dealers who are affected more severely by the banking regulations, showing the impact of the regulations on customer liquidity provision.

\(^{17}\)We base our identification of Volcker-affected dealers on Bao et al. (2018). We thank Jack Bao and Alex Zhou for sharing the data with us.

\(^{18}\)Small banks are also exempt from many bank regulations. For large/small dealer classifications, see footnote 15.
4.2 Banking Regulations and Trading Costs: The Effects of Customer Liquidity Provision

In this section, we show that the usual bid-ask spread measures employed in the literature that include liquidity-providing customer trades in calculations would underestimate what liquidity-demanding customers would pay to dealers who use their inventory capacity particularly during the post-regulation period, and document the magnitude of such underestimation. Two factors contribute to this underestimation. First, as shown in Section 4.1, customer liquidity provision, as measured by the fraction of customer trades that are DC-DC trades, has increased in the post-regulation period. Hence, more DC-DC trades will be included in bid-ask spread calculations in the post-regulation period, further reducing the bid-ask spread measure. Second, bid-ask spread measures that contain a low fraction of invt>15min trades (for instance, the IRC measure) may not properly capture the change in the cost of immediacy after the regulations went into effect. These two mechanisms also explain why trading-cost measures containing higher fractions of DC-DC trades are subject to more severe underestimation.

Our preferred measure is trading costs of invt>15min, as dealers tend to use their inventory capacity for such trades, so we calculate the average spread1 for invt>15min trades at the bond-day level (“invt>15min spreads”). Even though DC-DC trades account for larger fractions in the post-regulation period, invt>15min trades still account for more than half of all trades, and thus we are still capturing the majority of the customer trades.

In Figure 3, we plot the monthly time series of IRC_C, same_day, and invt>15min spreads. The figure shows that for both investment-grade and high-yield bonds the spreads estimated for IRC_C and same_day are substantially lower than invt>15min spreads particularly in the post-regulation period. For instance, for investment grade bonds, the gap between invt>15min spreads and IRC_C spreads is much wider in 2014 than in 2007 or 2011. We also find that during the peak of the financial crisis the two measures diverge significantly, which might also reflect higher levels of customer liquidity provision as dealers’ balance-sheet capacity was significantly weaker during that period.

In Table 4, we examine how this underestimation of the common bid-ask spread measures
influences our inference regarding the cost of immediacy paid to dealers in the post-regulation period. We study five bid-ask spread measures—IRC\textsubscript{C}, IRC, same\textsubscript{day}, spread1, and invt>15min spreads—to compare our preferred measure (invt>15min spreads) with the other four measures. We estimate the following model for each spread measure:

\[
\text{spread}_{i,t} = \alpha + \sum_{l=2}^{4} \beta_l 1(t \in T_l) + \epsilon_{i,t}
\]

where \(\text{spread}_{i,t}\) is one of the trading cost measures for bond \(i\) on day \(t\). Dummy variables \(1(t \in T_l)\) \((l = 1, \ldots, 4)\) are indicators of the four subperiods and \(T_1\) is omitted to avoid multicollinearity. Control variables include bond characteristics such as outstanding amount, ratings, age, and time-to-maturity and market-level variables such as bond index volatility and the VIX, as well as the average customer trade size for bond \(i\) on day \(t\). We also perform a statistical test for \(\beta_4 - \beta_3\), the difference between the coefficient of the post-regulation dummy and the coefficient of the post-crisis dummy.

Table 4(a) presents the estimation results for IG bonds. As the coefficient estimate on post-regulation reported in column (5) indicates, the invt>15min spreads are 12.7 bps higher in the post-regulation period than in the pre-crisis period (the base level). This difference is economically significant as the average of \(\text{spread1}\) is approximately 35 bps for the full sample and around 25 bps for the non-crisis periods. In contrast, using the IRC and same day spread measures in columns (1) through (3) underestimates this increase in trading costs during the post-regulation period. In column (1) when IRC\textsubscript{C} is used, for example, the estimated difference between post-regulation trading costs and pre-crisis trading costs is 0.9 bps (see the coefficient on post-regulation). Similarly, the coefficient estimates on post-regulation are 2.4 bps and 6.5 bps for IRC (see column 2) and same\textsubscript{day} (see column 3), respectively. Hence, using IRC\textsubscript{C} underestimates the post-regulation increase in bid-ask spreads to the greatest extent, followed by IRC and same\textsubscript{day}. Examining the differences between post-crisis and post-regulation trading costs (i.e., row \(\beta_4 - \beta_3\) at the bottom of the table) yields similar results: IRC\textsubscript{C} and IRC indicate that trading costs have not changed between the two periods, while invt>15min spreads show a 3.9 bps increase. We find qualitatively
similar and quantitatively stronger results for HY bonds in Panel (b).

Column (4) shows that the increase in trading costs estimated using spread1 is only slightly smaller than the increase in trading costs based on invt$>$15min spreads that is reported in column (5). For instance, the difference in trading costs between the post-regulation period and the post-crisis period, $\beta_4 - \beta_3$, is 3.85 bps using invt$>$15min spreads (column 5) and 3.05 bps using spread1 (column 4). In comparison, the increases in trading costs estimated using the other three measures are much smaller. These results are because spread1 contains a much smaller fraction of DC-DC trades than IRC or same day spread measures as shown in Table 1(b). While our preferred measure is the invt$>$15min spread measure, from a practical standpoint, accumulating dealer inventories requires data with dealer identifiers and may also be cumbersome to calculate. Thus, spread1 measure may work as a good alternative.

To provide additional evidence that the cost of immediacy paid to dealers who use their inventory capacities actually increased, in Table 5 we run a difference-in-differences-style test to examine whether differences in the coefficient estimates across trading-cost measures are statistically significant. Specifically, we compare each of the three trading-cost measures, $y_i$, with the benchmark measure, which is spread1 estimated using invt$>$15min only. We first define the difference between the trading-cost measure and the benchmark, $\text{diff}_{i,t}$, as:

$$\text{diff}_{i,t} = y_{i,t} - \text{(invt$>$15min spread)}_{i,t}$$

(9)

where $y_{i,t}$ is either IRC,C, IRC, or same_day for bond $i$ on day $t$. We then run the difference-in-differences regression as

$$\text{diff}_{i,t} = \alpha + \sum_{l=2}^{4} \beta_l 1(t \in T_l) + \epsilon_{i,t}.$$  

(10)

Note that $\text{diff}_{i,t}$ can be calculated only for bond-days where both $y$ and invt$>$15min spread exist.\(^{19}\)

Thus, this regression analysis mitigates the potential selection bias concern regarding our previous results reported in Table 4 insofar as certain spread measures are more likely to exist for certain bonds or days for reasons unrelated to customer liquidity provision. In this sense, this analysis

\(^{19}\)Thus, this regression analysis does not necessarily test the difference in estimates between using $y$ and invt$>$15min spreads from (8).
provides a nice robustness check on our results reported in Table 4.

Table 5 presents the results. Consistent with our prediction, \( IRC_C \) underestimates the change in trading costs to the greatest extent, followed by \( IRC \) and \( same\_day \). In column (4), for example, the coefficient on \( post\_regulation \) is \(-6.2 \text{ bps}\) and is statistically significant at the 1\% level, indicating that the estimated difference in \( IRC_C \) between post-regulation period and pre-crisis period is lower than the estimated difference in \( invt>15\text{min} \) spreads. We find similar results for the other spread measures reported in columns (5) and (6). These results confirm those reported in Table 4.

There are three main takeaways from this section. First, trading costs for liquidity-demanding customers, as measured by \( invt>15\text{min} \) spreads, have increased by 10–13 bps in the post-regulation period compared with the pre-crisis period and by 4–7 bps compared with the post-crisis period. Given that average bid-ask spreads during non-crisis times are around 25 bps, these increases are substantial. Moreover, because \( invt>15\text{min} \) trades do include trades where customers provide liquidity, these 10–13 bps increases are likely underestimates as well. Second, some liquidity measures that are commonly used in the literature underestimate this increase in costs for demanding liquidity. Using \( IRC \) and \( same\_day \), for instance, Anderson and Stulz (2017), Trebbi and Xiao (2017), and Adrian, Fleming, Shachar and Vogt (2017) conclude that price measures of liquidity have not worsened. Our results help explain why bid-ask spread estimates reported in previous studies did not increase in the post-regulation period despite financial intermediaries’ reduced inventory capacities. Lastly, we recommend using \( invt>15\text{min} \) spreads to proxy for cost of immediacy paid by customers but \( spread1 \) is a close alternative.

### 4.3 Additional Robustness Checks

We provide two robustness checks of the results that we report in Table 4. A potential concern is that the use of interdealer prices as reference prices in the \( spread1 \) calculation may somehow influence the results. To address this concern, in Table 6, we run the same regression (8) using the \( same\_day \) measure calculated only with \( invt>15\text{min} \) trades instead of using \( spread1 \). Consistent with the results reported in Table 4, we find that changes in trading costs are larger if we use \( invt>15\text{min} \) trades only. For instance, in IG bonds, if we use all trades, the \( same\_day \) is 6.5 bps...
higher in the post-regulation period than in the pre-crisis period, whereas it is 8.7 bps higher if we use invt$>$15min trades only.

In Table 7 we report the results of another robustness test to address the concern that bond characteristics such as rating, size, and age, rather than customer liquidity provision, drive our main results. That is, selection bias can occur because some spread measures are more likely to be available for particular types of bonds. For each rating category (IG, HY), we divide the sample into nine groups by bond size and age. Then, for each group, we run regression (8) for the four spread measures ($IRC_C$, $IRC$, same$_{\text{day}}$, and invt$>$15min spread). $\beta_4$, the difference between the post-regulation period and the pre-crisis period, and $\beta_4 - \beta_3$, the difference between the post-regulation period and the post-crisis period, are reported in Table 7. Because bond characteristics are roughly equal within each group, the potential selection bias concern should be mitigated. Consistent with the results reported in Table 4, for almost all groups, invt$>$15min spreads yield the largest $\beta_4$ and $\beta_4 - \beta_3$, followed by the same$_{\text{day}}$ and IRC, and finally, $IRC_C$ yield the smallest estimates. The Internet Appendix provides two additional robustness tests that address potential sources of selection bias due to the availability of the spread measures in our sample.

5 Conclusion

We show that substantial liquidity is provided by the non-dealer sector and that this provision of liquidity by non-dealers causes the average bid-ask spreads to underestimate the cost of immediacy paid by liquidity-demanding customers. Decreases in dealers’ willingness or ability to provide inventories have increasingly pushed liquidity provision to the non-dealer sector, which in turn has made the bias more severe. We show that these mechanisms lead to an underestimation of the impact of regulations on liquidity, and that, once we reduce this bias, the measured costs of demanding immediacy in U.S. corporate bond markets have increased post-regulation. This increase in transaction costs is consistent with the proposition that the Volcker Rule and more stringent capital requirements have affected liquidity in the over-the-counter markets.

The rise in customer liquidity provision in fixed income markets in some dimensions parallel the changes that the equity market underwent as it transitioned from floor trading to hybrid markets.
In modern-day equity markets, anyone can provide liquidity by placing a non-marketable limit order in the limit order book. Despite the move towards greater customer liquidity provision, however, the fixed income market structure is still markedly different from that of equity markets. All DC-DC trades that we identify go through dealers and, to some degree, are still at the discretion of dealers. With the tighter banking regulations, market power has shifted from dealers towards large asset managers who can now also provide liquidity with huge inventories of bonds. Smaller or less sophisticated investors may, however, find themselves at a relatively greater disadvantage. The cost of immediacy might have gone up for them as they still have to contact dealers when they seek liquidity. This new market landscape points to the increasing importance of all-to-all trading platforms, which have recently been gaining ground in corporate bond markets.\footnote{We exclude trading platforms from our sample, and thus our DC-DC trades do not include those executed through all-to-all trading platforms.}

Overall, the net effect of decreased dealer liquidity provision to customers may be ambiguous. Some buy-side investors who have enough liquidity and the expertise to provide liquidity may benefit from the reduced inventory capacity of the dealer sector. For other customers who generally demand liquidity only, both the cost of immediacy and the average waiting time have increased in the post-regulation period. Also, increased liquidity provision by the non-dealer sector may be unhealthy for financial market stability. Given that many non-dealers are likely buy-side participants subject to potential liquidity shocks from fund outflows, these shocks may have feedback effects. These potentially negative consequences should be weighed against the potentially positive impact that regulations have had on curbing systemic risk. We believe that it would be an interesting topic for future research to examine such welfare consequences of these regulations.\footnote{https://www.bloomberg.com/news/articles/2018-02-15/electronic-bond-trading-gains-ground-as-market-finally-matures}
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Figure 1: **Time-Series Plot of Fraction of Trades with Affiliates**
This figure plots the fraction of trades between dealers and their non-FINRA affiliates with respect to total customer trades. Appendix A explains the algorithm used to identify affiliate trades.
Figure 2: **Time Series Plot of the Fraction of DC-DC and DC-ID Trades**

This figure plots the monthly fraction of DC-DC (red solid line) and DC-ID trades (blue dotted line) with respect to total customer trade volumes over the sample period. Panel A plots IG bond trades, and Panel B plots HY bond trades.
Figure 3: Time Series Plot of Various Trading Cost Measures
This figure plots the monthly averages of IRC, $C$ (red solid line), same_day (green dotted line), and spread1 measured using invt>15min trades (blue dashed line) for IG (Panel A) and HY (Panel B) bonds.
Table 1: Summary Statistics

This table reports summary statistics on corporate bond trades and transaction cost estimates. Panel (a) reports the fractions of overnight, DC-DC, DC-ID, and invt>15min trades by rating (IG vs. HY) and trade size ($100K or less, $100K to $1 million, $1 million and larger) groups. We report the fractions of customer trades in columns 3 through 6, trade volume in billion USD in column 7, and trade count (the number of trades) in column 8. Panel (b) provides the fractions of DC-DC, DC-ID, and invt>15min trades (in terms of trade counts) used in the calculation of each bid-ask spread measure. Panel (c) displays the averages of trading costs estimated using IRC_C, IRC, same_day, and spread1 methods. Averages of spread1 estimates are reported for invt>15min, DC-DC, and DC-ID trades separately. Column marked #(bond-days) reports the number of bond-day observations. Panel (d) reports the fraction of customer trades with negative spread1 for DC-DC, DC-ID, and invt>15 min trades across rating groups (IG and HY) and trade directions (customer buy and sell). In Panel (a), we use all customer trades, while Panels (b) through (d) use customer trades of $1 million and above only. The sample period runs from 2006 through 2015.

(a) Fractions of Customer Trades by Rating and Trade Size

| rating | trade size | overnight | DC-DC | DC-ID | invt>15min | volume | trade count |
|--------|------------|-----------|-------|-------|------------|--------|-------------|
| IG     | ≤100K      | 49.25%    | 3.31% | 27.25%| 69.44%     | 284    | 9,697,291   |
| IG     | 100K-1mil  | 71.16%    | 4.60% | 10.43%| 84.97%     | 961    | 2,747,612   |
| IG     | ≥ 1mil     | 66.06%    | 9.60% | 5.21% | 85.19%     | 10,576 | 2,233,523   |
| HY     | ≤100K      | 47.01%    | 3.65% | 25.35%| 71.00%     | 98     | 3,354,601   |
| HY     | 100K-1mil  | 60.75%    | 11.33%| 9.26% | 79.41%     | 394    | 1,041,394   |
| HY     | ≥ 1mil     | 49.04%    | 23.89%| 4.03% | 72.08%     | 5,835  | 1,707,177   |

(b) Fraction of DC-DC, DC-ID, and Invt>15min Trades

| sample  | IG      | HY      |
|---------|---------|---------|
|         | DC-DC   | DC-ID   | invt>15min | DC-DC   | DC-ID   | invt>15min |
| full    | 9.60%   | 5.21%   | 85.19%     | 23.89%  | 4.03%   | 72.08%     |
| IRC_C   | 82.20%  | 4.99%   | 12.81%     | 84.84%  | 1.88%   | 13.28%     |
| IRC     | 61.58%  | 27.69%  | 10.74%     | 78.30%  | 8.94%   | 12.76%     |
| same_day| 21.51%  | 4.90%   | 73.59%     | 35.44%  | 3.79%   | 60.78%     |
| spread1 | 8.24%   | 7.36%   | 84.40%     | 18.92%  | 7.01%   | 74.07%     |
(c) Average Bid-Ask Spreads Across Various Estimation Methods

|                | IG   | HY   |
|----------------|------|------|
|                | average spread (bps) | # (bond-days) | average spread (bps) | # (bond-days) |
| IRC_C          | 16.65 | 84,374 | 25.60 | 107,866 |
| IRC            | 17.25 | 152,243 | 25.68 | 130,264 |
| same day       | 25.59 | 344,645 | 28.59 | 333,690 |
| spread 1       | 34.14 | 464,825 | 37.80 | 248,368 |
| DC-DC          | 16.26 | 34,043 | 25.80 | 52,222 |
| DC-ID          | 58.56 | 54,097 | 68.78 | 37,158 |
| invt > 15min   | 32.97 | 430,008 | 36.06 | 224,532 |

(d) Fractions of Negative Spread Trades

|                | DC-DC | DC-ID | invt > 15min |
|----------------|-------|-------|--------------|
| rating         |       |       |              |
| IG             | 41.59% | 13.93% | 31.17%     |
| HY             | 37.26% | 16.19% | 32.75%     |
| trade direction|       |       |              |
| customer buy   | 43.08% | 14.63% | 34.45%     |
| customer sell  | 34.30% | 15.27% | 28.99%     |
Table 2: Regressions of Bid-Ask Spreads on Customer Trade Types and Trade Order
Panel (a) presents the results of the following panel regression for IG (columns 1 through 3) and HY bonds (columns 4 through 6):

\[ \text{spread1}_{i,j,t,k} = \alpha + \beta_1 \mathbb{1}(\text{DC-DC})_k + \gamma \mathbb{1}(\text{DC-ID})_k + \epsilon_{i,j,t,k} \]

where \( \text{spread1}_{i,j,t,k} \) is the spread1 for customer trade \( k \) of bond \( i \) on day \( t \) with dealer \( j \). \( \mathbb{1}(\text{DC-DC})_k \) and \( \mathbb{1}(\text{DC-ID})_k \) are dummy variables for DC-DC and DC-ID trades, respectively. We omit the dummy variable for invt>15min trades. Control variables are the log trade size, log age of the bond, and log time-to-maturity. Control variables are standardized to have means of zero and standard deviations of one. We also include bond and time fixed effects as well as dealer fixed effects. Row marked \( \gamma - \beta \) reports the coefficient differences between \( \beta \) and \( \gamma \) and their statistical significance. In columns 2 and 5 we restrict the sample to customer-buy trades, and in columns 3 and 6 we restrict the sample to customer-sell trades.

Panel (b) presents the results derived from the following regression:

\[ \text{spread1}_{i,j,t,k} = \alpha + \beta_2 \mathbb{1}(\text{out})_k + \beta_3 \mathbb{1}(\text{cust buy})_k + \epsilon_{i,j,t,k} \]

where the sample consists of DC-DC trades only. \( \mathbb{1}(\text{out})_k \) is the indicator variable that equals one when trade \( k \) is an ‘out’ trade. ‘In’ trades are those that arrive at inventory and increase its size (in absolute value terms). ‘Out’ trades are trades that arrive later and match with the earlier trade, thereby decreasing inventory size. We omit the dummy variable for ‘in’ trades. We also include bond, dealer, and time fixed effects. Columns 1 and 2 use all DC-DC trades, columns 3 and 4 use DC-DC trades with holding period of one minute or shorter, and columns 5 and 6 use DC-DC trades with holding period longer than a minute. We look at the DC-DC trades with holding periods of one minute or shorter and longer than one minute separately in case determining which trade arrived first is difficult for trades with very short holding periods.

The sample period for both panels runs from 2006 to 2015, and we restrict the sample to customer trades of $1 million and above. Row marked ‘avg f.e.’ reports the value-weighted average of fixed effects, which can be interpreted as the average value of the dependent variable for the omitted category. Standard errors for the average fixed effect are not calculated. Standard errors are double clustered by bond and date. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.
(a) Regression of Spreads on DC-DC and DC-ID Dummies

|                | IG | HY |
|----------------|----|----|
|                | (1) | (2) | (3) | (4) | (5) | (6) |
| $1$(DC-DC)    | $-13.301^{***}$ | $-17.168^{***}$ | $-6.621^{***}$ | $-6.631^{***}$ | $-9.859^{***}$ | $-1.550^{**}$ |
|                | $(0.432)$ | $(0.895)$ | $(0.896)$ | $(0.457)$ | $(0.830)$ | $(0.782)$ |
| $1$(DC-ID)    | $21.193^{***}$ | $25.405^{***}$ | $17.094^{***}$ | $31.476^{***}$ | $33.554^{***}$ | $27.588^{***}$ |
|                | $(0.575)$ | $(0.745)$ | $(0.906)$ | $(0.737)$ | $(1.068)$ | $(1.002)$ |
| log(trade size) | $0.344^{**}$ | $-3.603^{***}$ | $2.645^{***}$ | $1.095^{***}$ | $-1.267^{**}$ | $2.254^{***}$ |
|                | $(0.137)$ | $(0.214)$ | $(0.197)$ | $(0.240)$ | $(0.313)$ | $(0.330)$ |
| log(age)       | $7.639^{***}$ | $6.952^{***}$ | $7.688^{***}$ | $0.932$ | $2.364^{**}$ | $-0.563$ |
|                | $(0.443)$ | $(0.581)$ | $(0.791)$ | $(0.582)$ | $(1.114)$ | $(1.069)$ |
| log(time-to-maturity) | $15.033^{***}$ | $12.638^{***}$ | $16.576^{***}$ | $8.127^{***}$ | $8.257^{***}$ | $7.900^{***}$ |
|                | $(0.572)$ | $(0.739)$ | $(1.026)$ | $(0.921)$ | $(2.015)$ | $(1.791)$ |
| avg f.e.       | $30.229$ | $22.944$ | $38.06$ | $31.381$ | $26.868$ | $35.879$ |
| $\gamma - \beta$ | $34.494^{***}$ | $42.573^{***}$ | $23.715^{***}$ | $38.107^{***}$ | $43.413^{***}$ | $29.138^{***}$ |
| dealer, cusip, date f.e. | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations   | $879,095$ | $466,351$ | $412,744$ | $689,376$ | $351,528$ | $337,848$ |
| $R^2$          | $0.082$ | $0.106$ | $0.154$ | $0.035$ | $0.072$ | $0.070$ |

(b) Bid-Ask Spreads of DC-DC Trades by Trade Order

|                | IG | HY |
|----------------|----|----|
|                | (1) | (2) |
| $1$(out)      | $-10.148^{***}$ | $-11.086^{***}$ |
|                | $(1.341)$ | $(1.364)$ |
| $1$(cust buy) | $-27.222^{***}$ | $-15.053^{***}$ |
|                | $(1.972)$ | $(1.670)$ |
| avg f.e.      | $34.995$ | $38.589$ |
| dealer, cusip, date f.e. | Yes | Yes |
| Observations  | $72,213$ | $129,390$ |
| $R^2$         | $0.054$ | $0.023$ |
Table 3: Regression of the Fraction of DC-DC Trades on Pre- and Post-Regulation Dummy Variables

Panel (a) provides the estimation results derived from the following regressions using aggregate and individual dealer data:

Aggregate : \( y_t = \alpha + \sum_{l=2}^{4} \beta_l 1(t \in T_l) + \epsilon_t \)

Individual dealer : \( y_{j,t} = \alpha_j + \sum_{l=2}^{4} \beta_l 1(t \in T_l) + \epsilon_{j,t} \)

where the dependent variables, \( y_t \) and \( y_{j,t} \) are the fractions of daily DC-DC trade volumes at the aggregate and individual dealer levels, respectively. The aggregate-level fraction of DC-DC trades, \( y_t \), is calculated as the daily volume-weighted average of DC-DC fractions across bonds and dealers. \( T_l (l = 1, \ldots, 4) \) are the four subperiods (pre-crisis, financial crisis, post-crisis, post-regulation) and the dummy variables, \( 1(t \in T_l) \), indicate the four subperiods. \( 1(t \in T_1) \) is the omitted dummy, and thus, forms the base level. We report the estimates for the aggregate (agg) and individual-dealer (ind OLS) level OLS regressions and for the individual-dealer median regression (ind med). We use Newey-West standard errors with 20 lags for the aggregate-level regression and use standard errors clustered by date for the individual-dealer OLS regressions. We calculate standard errors for the individual-dealer-level median regression based on 2,000 bootstraps.

Panel (b) reports the results of regressions studying how dealers who are affected and unaffected by regulations have changed the fractions of DC-DC trades differentially.

\[ y_{m,t} = \alpha_1 + \alpha_2 1(\text{unaff})_m + \sum_{l=2}^{4} 1(\text{aff})_m \beta_{a,l} 1(t \in T_l) + \sum_{l=2}^{4} 1(\text{unaff})_m \beta_{u,l} 1(t \in T_l) + \epsilon_{m,t} \]

We use two proxies for whether a dealer is affected by regulations. The first proxy is whether a dealer is affected by the Volcker Rule, and uses the classification from Bao et al. (2018). The second proxy is the size of the dealer, where the large dealer group consists of 15 largest dealers, and the small dealer group consists of the rest. The dependent variable, \( y_{m,t} \), is the average fraction of DC-DC trades calculated separately for affected and unaffected dealers. The indicator variables, \( 1(\text{aff}) \) and \( 1(\text{unaff}) \), represent affected and unaffected dealer groups, respectively. Standard errors are clustered by date.

For all regressions, we include the VIX and bond market volatility as control variables, and they are standardized to have means of zero and standard deviations of one. We also report the differences between coefficients on the post-regulation and post-crisis dummies. The sample period runs from 2006 to 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Electronic copy available at: https://ssrn.com/abstract=2848344
(a) Aggregate and Individual-Dealer regressions

|                | IG                  |             | HY                  |             |
|----------------|---------------------|-------------|---------------------|-------------|
|                | agg (1)             | ind OLS (2) | ind med (3)         | agg (4)     | ind OLS (5) | ind med (6) |
| crisis         | 0.033*** (0.007)    | 0.059*** (0.004) | 0.031*** (0.003) | 0.023*** (0.007) | 0.032*** (0.004) | 0.035*** (0.004) |
| post-crisis    | 0.019*** (0.005)    | 0.038*** (0.002) | 0.009*** (0.002) | 0.034*** (0.007) | 0.023*** (0.003) | 0.030*** (0.003) |
| post-regulation| 0.042*** (0.003)    | 0.070*** (0.002) | 0.031*** (0.002) | 0.075*** (0.004) | 0.057*** (0.003) | 0.074*** (0.003) |
| index volatility| 0.006** (0.002)    | 0.004*** (0.001) | 0.002* (0.001) | 0.002 (0.004) | −0.0002 (0.002) | −0.001 (0.002) |
| VIX            | 0.012*** (0.002)    | 0.008*** (0.001) | 0.009*** (0.001) | 0.018*** (0.005) | 0.011*** (0.002) | 0.011*** (0.002) |
| Constant       | 0.084*** (0.003)    | 0.083*** (0.002) | 0.086*** (0.001) | 0.238*** (0.004) | 0.226*** (0.002) | 0.206*** (0.002) |
| dealer f.e.    | Yes                 | Yes         | Yes                | Yes         | Yes         | Yes         |
| $\beta_4 - \beta_3$ | 0.022*** (0.032*** | 0.022*** (0.022*** | 0.041*** (0.034*** | 0.044*** (0.0263) | 0.263 (0.470) |
| Observations   | 2,301               | 25,161      | 25,161              | 2,301       | 26,293      | 26,293      |
| $R^2$          | 0.305               | 0.658       | 0.263               | 0.470       |             |             |

Electronic copy available at: https://ssrn.com/abstract=2848344
(b) Dealers Affected By/Unaffected By Regulations

|                      | Volcker/nonVolcker | Large/Small |
|----------------------|--------------------|-------------|
|                      | IG (1)             | HY (2)      | IG (3) | HY (4) |
| index volatility     | 0.006*** (0.002)   | 0.002 (0.003) | 0.006*** (0.001) | 0.001 (0.003) |
| VIX                  | 0.019*** (0.002)   | 0.014*** (0.003) | 0.017*** (0.002) | 0.022*** (0.003) |
| unaffected           | 0.056*** (0.006)   | 0.287*** (0.008) | 0.033*** (0.003) | 0.251*** (0.005) |
| unaffected×crisis    | 0.010*** (0.004)   | 0.004 (0.004) | 0.008** (0.004) | 0.005 (0.004) |
| affected×crisis      | 0.062*** (0.009)   | 0.037*** (0.011) | 0.053*** (0.006) | 0.036*** (0.008) |
| affected×post-crisis | 0.003 (0.003)      | -0.001 (0.004) | 0.008** (0.003) | 0.020*** (0.004) |
| unaffected×post-crisis | 0.027*** (0.007)  | -0.0004 (0.009) | 0.020*** (0.004) | -0.0005 (0.007) |
| affected×post-regulation | 0.034*** (0.002) | 0.062*** (0.003) | 0.039*** (0.002) | 0.084*** (0.003) |
| unaffected×post-regulation | 0.025*** (0.006) | -0.068*** (0.008) | 0.034*** (0.004) | -0.044*** (0.006) |
| Constant             | 0.086*** (0.002)   | 0.224*** (0.002) | 0.081*** (0.002) | 0.207*** (0.002) |

|                      |                      |             |
|                      | β_{a,4} - β_{a,3}   | 0.031***    | 0.063***    | 0.03***    | 0.064***    |
|                      | β_{u,4} - β_{u,3}   | -0.002      | -0.068***   | 0.014***   | -0.043***   |
| Observations         | 4,596                | 4,602       | 4,602       | 4,602       |
| R^2                  | 0.338                | 0.689       | 0.341       | 0.673       |
Table 4: Regression of Bid-Ask Spreads on Pre- and Post-Regulation Dummy Variables

This table provides the estimation results from the following regressions:

\[ spread_{i,t} = \alpha + \sum_{l=2}^{4} \beta_l 1(t \in T_l) + \epsilon_{i,t} \]

where \( spread_{i,t} \) is one of the following five trading cost measures for bond \( i \) on day \( t \): \( IRC, IRC, same\_day, spread1, or spread1 \) using invt\(>\)15min trades only. \( T_l (l = 1, \ldots, 4) \) are the four subperiods (pre-crisis, financial crisis, post-crisis, post-regulation) and the dummy variables, \( 1(t \in T_l) \), indicate the four subperiods. \( 1(t \in T_1) \) is the omitted dummy, and thus, forms the base level.

\( \log(\text{trade size})_{i,t} \) is the log of the average customer trade size used in calculating \( spread_{i,t} \). Other bond-level controls include amounts outstanding, rating, age, and time to maturity. As market-level controls, we include the volatility of bond index returns and the VIX. All control variables are standardized to have means of zero and standard deviations of one. Panel (a) presents the results for investment grade bonds, and Panel (b) presents the results for high-yield bonds. In each panel, we report \( \beta_4 - \beta_3 \), which is the difference between the coefficient of the post-regulation dummy and the coefficient of the post-crisis dummy. The sample period runs from 2006 to 2015, and we restrict the sample to customer trades $1 million and above. Standard errors are double clustered by bond and date. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.
### (a) Investment Grade Bonds

|                | IRC, C | IRC | same_day | spread1 | invt > 15min |
|----------------|--------|-----|----------|---------|--------------|
| crisis         | 8.201*** | 7.917*** | 12.170*** | 18.861*** | 18.316***   |
|                | (0.658)  | (0.497)  | (0.680)  | (1.153)  | (1.207)     |
| post-crisis    | 0.510   | 2.357*** | 4.144*** | 9.013*** | 8.829***    |
|                | (0.421)  | (0.326)  | (0.412)  | (0.714)  | (0.739)     |
| post-regulation| 0.853*** | 2.370*** | 6.501*** | 12.061*** | 12.678***   |
|                | (0.329)  | (0.260)  | (0.328)  | (0.553)  | (0.571)     |
| log(trade size)| −0.662***| −2.094***| −1.401***| −2.103***| −0.632***   |
|                | (0.096)  | (0.077)  | (0.081)  | (0.162)  | (0.163)     |
| log(outstanding)| −4.681***| −3.440***| −2.514***| −7.428***| −7.493***   |
|                | (0.176)  | (0.160)  | (0.205)  | (0.304)  | (0.292)     |
| rating         | 0.289**  | 0.240**  | −0.397***| −0.371   | −0.308      |
|                | (0.141)  | (0.122)  | (0.144)  | (0.240)  | (0.238)     |
| age            | 0.817*** | 0.700*** | 0.393*   | 1.240*** | 1.166***    |
|                | (0.281)  | (0.212)  | (0.212)  | (0.474)  | (0.450)     |
| log(age)       | 2.235*** | 1.830**  | 3.032*** | 7.185*** | 7.285***    |
|                | (0.254)  | (0.203)  | (0.218)  | (0.417)  | (0.408)     |
| time-to-maturity| 1.266***| 0.402   | 1.300*** | −1.264** | −0.920*     |
|                | (0.331)  | (0.268)  | (0.329)  | (0.502)  | (0.505)     |
| log(time-to-maturity)| 6.092***| 6.663***| 10.062***| 15.658***| 15.341***   |
|                | (0.255)  | (0.206)  | (0.247)  | (0.451)  | (0.447)     |
| index volatility| 1.256***| 1.215***| 1.665*** | 2.475*** | 2.569***    |
|                | (0.229)  | (0.182)  | (0.214)  | (0.363)  | (0.377)     |
| VIX            | 6.010*** | 4.990*** | 8.018*** | 10.863***| 10.949***   |
|                | (0.285)  | (0.239)  | (0.273)  | (0.490)  | (0.491)     |
| Constant       | 14.733***| 14.183***| 19.597***| 23.511***| 22.268***   |
|                | (0.343)  | (0.260)  | (0.332)  | (0.561)  | (0.582)     |

|                |        |        |        |        |        |
| β₄ − β₃         | 0.343  | 0.018  | 2.087***| 3.049***| 3.85***  |
| Observations    | 84,293 | 152,113| 344,359 | 464,465 | 429,682  |
| R²              | 0.267  | 0.211  | 0.180  | 0.070  | 0.064    |
(b) High Yield Bonds

|                | IRC, C | IRC | same_day | spread | invt>15min |
|----------------|--------|-----|----------|--------|------------|
| crisis         | 3.668*** | 3.600*** | 4.898*** | 9.713*** | 9.634*** |
|                | (0.618) | (0.588) | (0.631)  | (1.263) | (1.386)   |
| post-crisis    | -2.056*** | -1.097*** | -1.905*** | 2.758*** | 3.514*** |
|                | (0.528) | (0.501) | (0.516)  | (1.020) | (1.111)   |
| post-regulation| -0.980**  | 0.307 | 1.159*** | 8.833*** | 10.199*** |
|                | (0.438) | (0.427) | (0.419)  | (0.891) | (0.943)   |
| log(trade size)| 0.680*** | 0.072 | -0.062   | -1.767*** | 0.117     |
|                | (0.102) | (0.098) | (0.104)  | (0.247) | (0.277)   |
| log(outstanding)| -2.805*** | -2.707*** | -2.097*** | -7.204*** | -7.547*** |
|                | (0.197) | (0.192) | (0.233)  | (0.443) | (0.466)   |
| rating         | 5.351*** | 4.986*** | 3.356*** | 2.692*** | 2.164***  |
|                | (0.208) | (0.202) | (0.220)  | (0.383) | (0.404)   |
| age            | 0.210    | 0.653** | 0.257    | 4.235*** | 3.321***  |
|                | (0.289) | (0.289) | (0.309)  | (0.872) | (0.877)   |
| log(age)       | 0.958*** | 0.926*** | 0.942*** | 0.408    | 0.884     |
|                | (0.244) | (0.238) | (0.247)  | (0.567) | (0.579)   |
| time-to-maturity| 1.230*** | 1.397*** | 2.016*** | 3.214*** | 3.041***  |
|                | (0.236) | (0.244) | (0.326)  | (0.624) | (0.587)   |
| log(time-to-maturity)| 2.210*** | 2.154*** | 1.765*** | 2.285*** | 2.329***  |
|                 | (0.248) | (0.235) | (0.280)  | (0.596) | (0.615)   |
| index volatility| 1.461*** | 1.394*** | 1.937*** | 1.706*** | 2.135***  |
|                 | (0.383) | (0.359) | (0.332)  | (0.540) | (0.639)   |
| VIX            | 6.464*** | 6.391*** | 6.798*** | 9.204*** | 8.570***  |
|                | (0.471) | (0.439) | (0.421)  | (0.655) | (0.760)   |
| Constant       | 25.934*** | 25.291*** | 27.970*** | 32.099*** | 29.614*** |
|                | (0.422) | (0.408) | (0.419)  | (0.829) | (0.894)   |
| β₄ - β₃         | 1.076*** | 1.404*** | 3.064*** | 6.074*** | 6.685***  |
| Observations   | 107,794 | 130,186 | 333,476  | 248,246  | 224,427   |
| R²             | 0.199    | 0.178    | 0.094    | 0.029    | 0.022     |
Table 5: Regression of Spread Differences on Pre- and Post-Regulation Dummy Variables

This table presents the estimation results from the regression

\[ \text{diff}_{i,t} = \alpha + \sum_{l=2}^{4} \beta_l 1(t \in T_l) + \epsilon_{i,t} \]

where \( \text{diff}_{i,t} \) is the difference between \( y_{i,t} \) and \( \text{spread1} \) calculated using invt>15min trades only. \( y_{i,t} \) is one of the three trading-cost measures: IRC, IRC, or same_day. \( T_l \ (l = 1, \ldots, 4) \) are the four subperiods (pre-crisis, financial crisis, post-crisis, post-regulation) and the dummy variables, \( 1(t \in T_l) \), indicate the four subperiods. \( 1(t \in T_1) \) is the omitted dummy, and thus forms the base level. We also include the volatility of bond index returns and the VIX as control variables, and they are standardized to have means of zero and standard deviations of one. The sample period is from 2006 to 2015. We include in our sample only bond-day observations with available trading-cost measures. Standard errors are double clustered by bond and date. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

|                    | without controls | with controls |
|--------------------|------------------|---------------|
|                    | IRC, IRC, same_day | IRC, IRC, same_day |
| **crisis**         | IRC, IRC, same_day | IRC, IRC, same_day |
| IRC                | -13.629***       | -2.251        |
| (1)                | (2.183)          | (2.434)       |
| IRC                | -17.780***       | -3.667**      |
| (2)                | (1.521)          | (1.657)       |
| same_day IRC       | -4.673***        | -0.862        |
| (3)                | (0.562)          | (0.630)       |
| **post-crisis**    | IRC, IRC, same_day | IRC, IRC, same_day |
| IRC                | -7.465***        | -1.921        |
| (1)                | (1.462)          | (1.802)       |
| IRC                | -6.543***        | 0.443         |
| (2)                | (0.952)          | (1.140)       |
| same_day IRC       | -1.717***        | 0.201         |
| (3)                | (0.379)          | (0.429)       |
| **post-regulation** | IRC, IRC, same_day | IRC, IRC, same_day |
| IRC                | -7.846***        | -6.203***     |
| (1)                | (1.375)          | (1.404)       |
| IRC                | -5.329***        | -3.753***     |
| (2)                | (0.871)          | (0.885)       |
| same_day IRC       | -1.451***        | -1.007***     |
| (3)                | (0.346)          | (0.346)       |
| **index volatility** | IRC, IRC, same_day | IRC, IRC, same_day |
| IRC                | -3.231***        | -3.231***     |
| (4)                | (1.106)          | (1.061)       |
| IRC                | -1.637***        | -1.637***     |
| (5)                | (0.734)          | (0.734)       |
| same_day IRC       | -0.443*          | -0.443*       |
| (6)                | (0.263)          | (0.263)       |
| **VIX**            | IRC, IRC, same_day | IRC, IRC, same_day |
| IRC                | -2.674**         | -5.349***     |
| (4)                | (1.271)          | (0.849)       |
| IRC                | -5.349***        | -1.433***     |
| (5)                | (0.849)          | (0.849)       |
| same_day IRC       | -1.433***        | -1.433***     |
| (6)                | (0.307)          | (0.307)       |
| **Constant**       | IRC, IRC, same_day | IRC, IRC, same_day |
| IRC                | -4.535***        | -9.051***     |
| (4)                | (1.209)          | (1.523)       |
| IRC                | -5.480***        | -11.019***    |
| (5)                | (0.744)          | (0.945)       |
| same_day IRC       | -0.224           | -1.661***     |
| (6)                | (0.311)          | (0.364)       |

\[ \beta_4 - \beta_3 \]

-0.381  1.214*  0.266
(1.020) (0.744) (0.311)

Observations  39,107  76,493  247,655
R\(^2\)       0.002  0.004  0.001
Table 6: Regression of same\textit{\_day} on Pre- and Post-Regulation Dummy Variables

This table provides the estimation results from the following regressions:

\[ same_{\text{day}}_{i,t} = \alpha + \sum_{l=2}^{4} \beta_{l} \mathbb{1}(t \in T_{l}) + \epsilon_{i,t} \]

where same\textit{\_day}_{i,t} is the same\textit{\_day} for bond \( i \) on day \( t \) calculated using either all customer trades or invt>15min trades only. \( T_{l} (l = 1, \ldots, 4) \) are the four subperiods (pre-crisis, financial crisis, post-crisis, post-regulation) and the dummy variables, \( \mathbb{1}(t \in T_{l}) \), indicate the four subperiods. \( \mathbb{1}(t \in T_{1}) \) is the omitted dummy, and thus forms the base level. Columns (1) and (2) report the results for investment grade bonds, and columns (3) and (4) report those for high-yield bonds. Columns (1) and (3) use all customer trades to calculate the same\textit{\_day}, and columns (2) and (4) use invt>15min trades only. Coefficient estimates for the control variables (the log of average trade size, the log of outstanding amount, rating, bond age, the log of age, time-to-maturity, the log of time-to-maturity, index volatility, and the VIX) are not reported in the table. Control variables are standardized to have means of zero and standard deviations of one. We report \( \beta_{4} - \beta_{3} \), which is the difference between the coefficient of the post-regulation dummy and the coefficient of the post-crisis dummy. The sample period is from 2006 to 2015 and we restrict the sample to customer trades with par values of $1 million and above. Standard errors are double clustered by bond and date. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

|             | IG                |                     | HY                |                     |
|-------------|-------------------|---------------------|-------------------|---------------------|
|             | all invt>15min    | all invt>15min      | all invt>15min    |                     |
| crisis      | 12.170***         | 11.810***           | 4.898***          | 5.596***            |
|             | (0.680)           | (0.801)             | (0.631)           | (0.755)             |
| post-crisis | 4.414***          | 5.466***            | -1.905***         | -1.257**            |
|             | (0.412)           | (0.476)             | (0.516)           | (0.607)             |
| post-regulation | 6.501***       | 8.668***            | 1.159***          | 3.451***            |
|             | (0.328)           | (0.379)             | (0.419)           | (0.465)             |
| Constant    | 19.597***         | 18.946***           | 27.970***         | 25.758***           |
|             | (0.332)           | (0.388)             | (0.419)           | (0.486)             |
| \( \beta_{4} - \beta_{3} \) | 2.087***         | 3.202***            | 3.064***          | 4.708***            |
| Observations| 344,359           | 240,447             | 333,476           | 190,907             |
| \( R^{2} \) | 0.180             | 0.160               | 0.094             | 0.062               |
Table 7: Time-Series Regressions by Groups for Robustness Checks
For each rating group (IG, HY), we first divide the sample into nine groups by bond size (small, medium, and large) and bond age (young, medium, and old). We then run the following regression for each group:

\[ \text{spread}_{i,t} = \alpha + \sum_{l=2}^{4} \beta_l 1(t \in T_l) + \epsilon_{i,t} \]

where \( \text{spread}_{i,t} \) is one of the following four trading cost measures for bond \( i \) on day \( t \): IRC_C, IRC, same_day, or spread1 using invt>15min only. \( T_l (l = 1, \ldots, 4) \) are the four subperiods (pre-crisis, financial crisis, post-crisis, post-regulation) and the dummy variables, \( 1(t \in T_l) \), indicate the four subperiods. \( 1(t \in T_1) \) is the omitted dummy, and thus forms the base level. As bond-level control variables, we include amounts outstanding, rating, age, time to maturity, and average customer trade size. As market-level controls, we include the volatility of bond index returns and the VIX. We report the estimates and statistical significance of \( \beta_4 \) and \( \beta_4 - \beta_3 \) for investment grade bonds (Panel (a)) and high-yield bonds (Panel (b)). The sample period is from 2006 to 2015 and we restrict the sample to customer trades with par values of $1 million and above. Standard errors are double-clustered by bond and date. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.
(a) Investment Grade Bonds

| bond size | measure      | young | medium | old  |
|-----------|--------------|-------|--------|------|
|           |              | $\beta_4$ | $\beta_4 - \beta_3$ | N   | $\beta_4$ | $\beta_4 - \beta_3$ | N   | $\beta_4$ | $\beta_4 - \beta_3$ | N   |
| small     | IRC          | 2.468*** | 0.105  | 10362| 1.156*  | 1.126  | 13204| 2.435*** | -1.586** | 15687|
|           | IRC          | 3.446*** | 0.87   | 17504| 2.056***| 1.346**| 22066| 3.16***  | -1.014** | 26716|
|           | IRC          | 7.849*** | 2.719***| 41221| 4.763***| 2.191***| 41741| 6.419*** | 0.105   | 42437|
|           | invt>15min   | 12.828***| 3.606**| 40470| 15.275***| 7.692***| 35676| 19.016***| 1.959   | 31833|
| medium    | IRC          | 0.555   | 2.317***| 7420 | -0.321  | 0.08   | 8527 | -1.071  | -0.336  | 9065  |
|           | IRC          | 1.95***  | 1.156  | 13090| 1.485*  | 0.346  | 15372| 1.243**  | -1.247**| 17872|
|           | IRC          | 9.103*** | 3.477***| 37802| 7.057***| 2.508***| 36112| 4.164*** | 0.193   | 33332|
|           | invt>15min   | 11.559***| 5.95***| 52760| 12.677***| 4.732***| 48531| 10.172***| 4.408***| 47977|
| large     | IRC          | -0.553  | 2.039**| 7109 | -1.207  | 2.06** | 6099 | -0.585  | -0.715  | 6820  |
|           | IRC          | 1.507** | 1.557**| 12730| 1.207*  | 0.684  | 12374| 1.077*  | -1.554**| 14389|
|           | IRC          | 6.971***| 4.151***| 41979| 5.49*** | 4.392***| 35566| 7.311***| -0.807  | 34169|
|           | invt>15min   | 9.426***| 3.489***| 59883| 7.346***| 5.147***| 56699| 11.468***| -0.208  | 55853|
(b) High Yield Bonds

| bond size | measure     | young          | medium         | old              |
|-----------|-------------|----------------|----------------|------------------|
|           |             | $\beta_4$ | $\beta_4 - \beta_3$ | N | $\beta_4$ | $\beta_4 - \beta_3$ | N | $\beta_4$ | $\beta_4 - \beta_3$ | N |
| small     | IRC_C       | -1.424*    | 3.975***       | 16268          | -2.011***       | -1.35  | 18451          | -1.705*    | -0.821          | 17768          |
|           | IRC         | -0.477     | 3.768***       | 18320          | -1.225          | -1.219 | 20786          | -0.496     | -0.512          | 21067          |
|           | same_day    | -0.775     | 6.207***       | 42374          | -1.121          | 0.515  | 42069          | 0.246      | 0.339           | 39372          |
|           | invt>15min  | 16.831***  | 14.755***      | 14774          | 15.076***       | 13.601*** | 14143          | 21.291***  | 11.072***       | 16393          |
| medium    | IRC_C       | -0.412     | 3.238***       | 10597          | -1.765          | 0.38   | 10442          | 2.371      | 0.847           | 10651          |
|           | IRC         | 1.532      | 3.578***       | 12652          | 0.578           | 1.006  | 12822          | 3.352**    | 1.668           | 13552          |
|           | same_day    | 3.097***   | 5.177***       | 36557          | 1.104           | 1.732* | 35639          | 4.038***   | 1.919*          | 33047          |
|           | invt>15min  | 14.369***  | 9.063***       | 24588          | 9.955***        | 8.252***| 25180          | 11.6***    | 3.277           | 27090          |
| large     | IRC_C       | 0.02       | 0.84           | 7597           | 2.096           | 0.722  | 8200           | -2.581*    | 0.723           | 7820           |
|           | IRC         | 1.508      | 0.796          | 9877           | 3.719***        | 1.566  | 10408          | -1.451     | 1.044           | 10702          |
|           | same_day    | 3.849***   | 2.461***       | 36534          | 2.906**         | 3.127***| 35337          | 2.027      | 3.5***          | 32547          |
|           | invt>15min  | 6.621***   | 2.049          | 33691          | 6.929***        | 5.981***| 33092          | 3.264      | 6.387***        | 35476          |
Appendix

A Identifying Trades with Affiliates

Adrian, Boyarchenko and Shachar (2017) note that dealers increasingly transfer bonds to their non-FINRA affiliates for bookkeeping purposes. These trades usually appear individually as a dealer trading with a counterparty, and then trading with an affiliate at the same price within one minute or less. Before November 2015, non-FINRA affiliates were recorded as customers in the data, although the transfer between a dealer and its affiliate is not necessarily an actual risk transfer. Hence, not deleting these trades could artificially increase the fractions of DC-DC or DC-ID trades. Moreover, Bessembinder et al. (2018) notes that there is one relatively large dealer that offloads most of its principal trades immediately to its affiliate, starting in 2014.\footnote{Bessembinder et al. (2018) excludes this dealer. Adrian, Boyarchenko and Shachar (2017) writes that they use an algorithm to identify and clean affiliate trades.} This could appear as an increase in the fractions of DC-DC trades in the data even if there was no real increase in customer liquidity provision. Hence, we develop an algorithm to identify this type of trades, test the algorithm on 2016 data, and delete the trades that are identified as affiliate trades.

We assume that if two offsetting trades in the same bond by the same dealer at the same volume and price are executed within one minute of each other, one side is a ‘bookkeeping’ trade or, in other words, a trade with an affiliate. Unless one of the trades was internal or executed for bookkeeping purposes, it would be odd for the dealer to make exactly zero profit from matching two trades, as we would expect the dealer to be compensated for finding a counterparty. We test the accuracy of this algorithm using data from January 1 through October 15, 2016, during which time trades with affiliates were marked as counterparty ‘A’ (affiliate) instead of ‘C’ (customer). We match trades based on CUSIP, dealer, volume, price, (opposite) direction, and time within one minute. For matched pairs, we hypothesize that one side is with an affiliate. We classify trades into three types: trades matched with other trades in the same second, those matched with other trades within one minute but not in the same second, and unmatched trades. Next, using actual counterparty information, if the trade is with an affiliate, or if the trade is matched with a trade
with an affiliate, we classify that trade as having $1(A) = 1$ (0 otherwise). For each of the three categories, we calculate the average and value-weighted $1(A)$.

The results are reported in Table A.1. Our algorithm performs with high accuracy, and allowing a time difference of up to one minute seems reasonable, especially for the large trade category on which we focus in the paper. For example, for trades with par values of $1$ million and above, 99% of trades identified as $1(A) = 1$ using the same-second criterion are classified correctly, and 80% of trades identified as $1(A) = 1$ that are not in the same second but are executed within one minute are classified correctly. Only about 5% of trades that are categorized as $1(A) = 0$ in the algorithm are identified incorrectly.

We use this algorithm to identify and delete trades with affiliates. When both trades are with customers, there does not seem to be a reliable method for determining which side is with an affiliate. Hence, to be consistent, we delete both sides. Figure 1 plots the fraction of volume that is identified as affiliate trades. (We divide the volume of trades that are identified as $1(A) = 1$ by 2 in the figure.) As is evident in the graph, there is a large increase in affiliate trades in early 2014. Without deleting these trades, a large fraction of this increase would be misidentified as an increase in DC-DC trades.

Key results are similar qualitatively and, if anything, stronger quantitatively when affiliate trades are not deleted. There are two factors in play. First, DC-DC trades in which one side is with an affiliate have an average spread of zero, which is lower than the average spread for DC-DC trades. Therefore, the differences in spreads between DC-DC trades and other trades will be exaggerated. Second, the sharp increase in trades with affiliates in 2014 would translate mostly into an increase in DC-DC trades.

B Customer Trade Classification: Details

We match customer trades and calculate inventory holding periods using the last-in-first-out (LIFO) method, starting each trading day for each bond with an inventory of zero. Each incoming customer trade (e.g., a customer sell) to a dealer is accumulated in the dealer’s inventories and is matched later with outgoing trades (e.g., interdealer trades or customer buys) when it leaves the inventories.
Inventory holding periods are calculated based on how long dealers hold customer trades on their inventories. In Panel (b) of Table A.2 we provide a simple example of matching trades, using fictitious data shown in Panel (a). An inventory of −200 accumulated from trade 1 leaves the inventory when trade 2 arrives five seconds later. Trade 1 is matched with trade 2. A single trade may be matched with multiple trades if their volumes are different. Three hundred fifty out of 500 in trade 4 is matched with trade 5, 100 is matched with trade 6, and 50 remains unmatched. Trades do not have to be exactly matched by volume, and a single trade may be matched against multiple trades.

Using the inventory holding periods and matches, we then classify all customer trades. Customer trades in which 50% or more of the volume remains in inventory for longer than 15 minutes are classified first as invt>15min trades. The remaining trades (to which we refer as “short-holding trades”) are further divided into DC-DC trades and DC-ID trades, depending on whether there was a higher fraction of DC-DC trading volume or DC-ID trading volume. Panel (c) provides the trade classification for the fictitious sample.

C Dealer Profits in Short-Holding Trades

In Table A.3, we provide an additional test to rule out the possibility that DC-DC trades are generally driven by dealers matching liquidity-seeking buyers with liquidity-seeking sellers. If it was the case that DC-DC trades were mainly dealers matching liquidity-seeking buyers with liquidity-seeking sellers, but DC-ID trades were executed mainly by customers seeking liquidity and the second dealers providing liquidity, then dealers matching the trades should generally reap higher profits from DC-DC trades. This is because dealers should be able to obtain spreads from both sides in DC-DC trades, but from only one side in DC-ID trades.

To test this possibility, we first calculate the round-trip profit that dealers make in DC-DC and DC-ID trades. Round-trip profits for these short-holding trades are calculated as the differences between dealer-sell prices and dealer-buy prices. The unit is shown in basis points, per $100 of par
value. We also winsorize the profit at the 1% level. We then run the following regression:

\[
profit_{i,j,t,k} = \beta_2 \mathbb{1}(\text{DC-ID})_k + \epsilon_{i,j,t,k}
\]

(11)

where \(profit_{i,j,t,k}\) is the round-trip profit for trade \(k\) in bond \(i\) on day \(t\) between dealer \(j\) and a client. DC-DC matched trades are the omitted category. We include bond, day, and dealer fixed effects as well as other control variables.

The results provided in Table A.3 indicate that dealer profits are about 1 bp higher for DC-ID trades than for DC-DC trades. This contradicts the predictions for the scenario in which DC-DC trades consist mainly of dealers matching liquidity-seeking buyers and liquidity-seeking sellers.

Additionally, these results help us understand why, as reported in Table 1(c), even though \(IRC\) calculations put a relatively high weight on DC-ID trades, \(IRC\) measures are low. Comparing the results in Table 2 and Table A.3, DC-ID trades have approximately 35 bps wider average spreads than DC-DC trades, but the dealers that match the trades make only 1 bp more in the DC-ID trades. The second dealer who provides liquidity receives the rest. Because \(IRC\) measures the profits that dealers make on short-holding trades, \(IRC\) values are not higher despite the heavy weight on DC-ID trades.
Table A.1: Performance of the Algorithm That Identifies Trades With Affiliates
This table presents the performance of the algorithm, described in Appendix A, that identifies trades between dealers and their non-FINRA affiliates. The sample period is from January 1 to October 15, 2016, during which time trades with affiliates were marked as counterparty ‘A’ (affiliate) instead of ‘C’ (customer). We match trades based on bond, dealer, volume, price, (opposite) direction, and time within one minute. For matched pairs, we hypothesize that one side is with an affiliate. We classify trades into three types: trades matched with other trades in the same second, those matched with other trades within one minute but not in the same second, and unmatched trades. Next, using actual counterparty information, if the trade is with an affiliate, or, if the trade is matched with a trade with an affiliate, we classify that trade as having $1(A) = 1$ (0 otherwise). For each of the three categories, we calculate the average and value-weighted $1(A)$.

| Algorithm classification | $\text{avg}(1(A))$ | $\text{vwavg}(1(A))$ | N     | volume (mil USD) |
|--------------------------|---------------------|----------------------|-------|-----------------|
| All trades               |                     |                      |       |                 |
| same price & same second | 90.89%              | 99.32%               | 494,674 | 662,928.32     |
| same price & 2s – 1min   | 38.58%              | 78.40%               | 32,646  | 23,547.78      |
| others                   | 4.23%               | 5.60%                | 6,335,734 | 4,163,985.60  |
| $1\text{ million and above}$ |                     |                      |       |                 |
| same price & same second | 99.37%              | 99.54%               | 164,214 | 600,141.22     |
| same price & 2s – 1min   | 79.73%              | 80.75%               | 6,098  | 20,415.02      |
| others                   | 5.16%               | 5.54%                | 1,003,649 | 3,592,423.36  |
Table A.2: An Example of Matching Customer Trades

(a) Sample (Fictitious) Trading Data

| trade num | time        | trade type | dealer buy/dealer sell | quantity |
|-----------|-------------|------------|------------------------|----------|
| 1         | 10:00:00 AM | DC         | S                      | 200      |
| 2         | 10:00:05 AM | DC         | B                      | 200      |
| 3         | 11:20:07 AM | DC         | B                      | 400      |
| 4         | 11:50:00 AM | DC         | B                      | 500      |
| 5         | 12:02:03 PM | ID         | S                      | 350      |
| 6         | 12:30:00 PM | DC         | S                      | 100      |
| 7         | 1:00:00 PM  | DC         | B                      | 550      |
| 8         | 1:00:03 PM  | DC         | S                      | 100      |
| 9         | 1:00:05 PM  | ID         | S                      | 400      |

(b) Trade Matching and Holding Period Calculation

| trade num | other side | holding period | volume | short holding | short type | overnight |
|-----------|------------|----------------|--------|---------------|------------|-----------|
| 1         | 2          | 00:00:05       | 200    | 1             | DC-DC      | 0         |
| 2         | 1          | 00:00:05       | 200    | 1             | DC-DC      | 0         |
| 3         | NA         | NA             | 400    | 0             |            | 1         |
| 4         | 5          | 00:12:03       | 350    | 1             | DC-ID      | 0         |
| 4         | 6          | 00:40:00       | 100    | 0             |            | 0         |
| 4         | NA         | NA             | 50     | 0             |            | 1         |
| 6         | 4          | 00:40:00       | 100    | 0             |            | 0         |
| 7         | 8          | 00:00:03       | 100    | 1             | DC-DC      | 0         |
| 7         | 9          | 00:00:05       | 400    | 1             | DC-ID      | 0         |
| 7         | NA         | NA             | 50     | 0             |            | 1         |
| 8         | 7          | 00:00:03       | 100    | 1             | DC-DC      | 0         |

(c) Trade Classification

| trade num | vwavg(short) | vwavg(DC-DC | short) | vwavg(DC-ID | short) | trade type    |
|-----------|--------------|-------------|---------|-------------|---------|---------------|
| 1         | 1            | 1           | 0       | DC-DC       |         |
| 2         | 1            | 1           | 0       | DC-DC       |         |
| 3         | 0            |             |         |             |         | invt>15min    |
| 4         | 0.7          | 0           | 1       | DC-ID       |         |
| 6         | 0            | 0           | 0       |             |         | invt>15min    |
| 7         | 0.91         | 0.2         | 0.8     | DC-ID       |         |
| 8         | 1            | 1           | 0       | DC-DC       |         |

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Table A.3: Regressions of Dealer Profits for Short-Holding Trades
Following table presents the results from the following regression:

\[ \text{profit}_{i,j,t,k} = \beta_2 \mathbb{1}(\text{DC-ID})_k + \epsilon_{i,j,t,k} \]

where \( \text{profit}_{i,j,t,k} \) is the round-trip profit for customer trade \( k \) of bond \( i \) on day \( t \) with dealer \( j \). We restrict the sample to DC-DC and DC-ID customer trades with par values of $1 million or above. \( \mathbb{1}(\text{DC-ID})_k \) is the dummy variable for DC-ID trades, and the dummy variable for DC-DC trades is omitted. The sample period is from 2006 to 2015. All control variables are standardized to have means of zero and standard deviations of one. Row marked ‘avg f.e.’ reports the value-weighted averages of fixed effects, which can be interpreted as the average values of the dependent variable for the omitted category. Standard errors for the average fixed effects are not calculated. Standard errors are double clustered by bond and date. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

|                  | IG   |      | HY   |      |
|------------------|------|------|------|------|
|                  | (1)  | (2)  | (3)  | (4)  |
| \( \mathbb{1}(\text{DC-ID}) \) | 0.652*** | 0.761*** | 1.418*** | 1.060*** |
|                  | (0.172) | (0.149) | (0.148) | (0.134) |
| log(outstanding) | −1.957*** |      | −1.643*** |      |
|                  | (0.140) |      | (0.103) |      |
| log(trade size)  | −1.552*** | −1.520*** | −1.011*** | −0.956*** |
|                  | (0.069) | (0.061) | (0.044) | (0.040) |
| rating           | 0.065  |      | 1.260*** |      |
|                  | (0.115) |      | (0.082) |      |
| age              | 1.093*** |      | 0.404*** |      |
|                  | (0.203) |      | (0.144) |      |
| log(age)         | 1.577*** | 2.164*** | −0.083  | 0.120 |
|                  | (0.185) | (0.172) | (0.121) | (0.121) |
| time-to-maturity | 0.421  |      | 0.412*** |      |
|                  | (0.261) |      | (0.132) |      |
| log(time-to-maturity) | 8.155*** | 6.833*** | 1.347*** | 3.655*** |
|                  | (0.218) | (0.230) | (0.158) | (0.217) |
| index volatility | 1.509*** |      | 0.839*** |      |
|                  | (0.179) |      | (0.150) |      |
| VIX              | 4.652*** |      | 2.755*** |      |
|                  | (0.190) |      | (0.146) |      |
| avg f.e.         | 19.499 | 19.461 | 24.061 | 24.113 |
| dealer f.e.      | Yes   | Yes   | Yes   | Yes   |
| cusip, date f.e. | No    | Yes   | No    | Yes   |
| Observations     | 330,366 | 330,366 | 476,358 | 476,358 |
| R²               | 0.352  | 0.461 | 0.183 | 0.267 |