Customer Liquidity Provision: Implications for Corporate Bond Transaction Costs*

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Abstract

The convention in calculating trading costs in corporate bond markets is to assume that dealers provide liquidity to non-dealers (customers) and to calculate average bid-ask spreads that customers pay dealers. We show that customers often provide liquidity in corporate bond markets, and thus, average bid-ask spreads underestimate trading costs that customers demanding liquidity pay. Since the periods before the 2008 financial crisis, substantial amounts of liquidity provision have moved from the dealer sector to the non-dealer sector, consistent with decreased dealer risk capacity. Among trades where customers are demanding liquidity, we find that these customers pay 35 to 50 percent higher spreads than before the crisis. Our results indicate that liquidity decreased in corporate bond markets and can help explain why, despite the decrease in dealers' risk capacity, average bid-ask spread estimates remain low.

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1 Introduction

Whether corporate bond liquidity has deteriorated has been hotly debated amongst both practitioners and academics since the introduction of new bank regulations such as the Volcker Rule and more stringent capital regulations. Three broad findings have emerged from the academic literature. First, dealers—especially those more heavily affected by various bank regulations—have decreased capital commitment and liquidity provision (Bessembinder, Jacobsen, Maxwell and Venkataraman (2017), Bao, O'Hara and Zhou (2017), and Schultz (2017)). However, broad price-based measures of liquidity have not worsened (Trebbi and Xiao (2017), Adrian, Fleming, Shachar and Vogt (2017), Anderson and Stulz (2017)). Finally, liquidity during specific market stress or liquidity events, such as rating downgrades or index rebalancing, has worsened (Bao et al. (2017), Dick-Nielsen and Rossi (2016)).

These findings seem puzzling; given that corporate bond markets are dealer-intermediated, we would expect market liquidity to worsen if dealers decrease their risk capacity. In this paper, we provide an explanation that helps reconcile these findings: an increase in liquidity provision by customers. In particular, we argue that bid-ask spreads are seemingly low because average bid-ask spreads that customers pay are a biased measure of the true cost of demanding liquidity. Using the regulatory version of the Trade Reporting and Compliance Engine (TRACE) database of U.S. corporate bond transactions from 2006 to 2015, we show that buy-side investors ("customers") often provide liquidity and that this customer liquidity provision causes our usual estimates of bid-ask spreads to underestimate the trading costs paid by liquidity-demanding customers. Moreover, as dealers become less willing to take inventory risk in the post-regulation period, customer liquidity provision increases, which exacerbates the underestimation problem. Once we correct for this bias, the measured cost of demanding liquidity is substantially higher during the post-regulation period compared with the pre-crisis period. Thus, our results can help explain why the literature so far has found that bid-ask spreads in the post-regulation periods are not higher despite decreased dealer liquidity provision.

Liquidity provision by customers may cause observed bid-ask spreads to underestimate the true cost of liquidity demand. Suppose a customer (C1) wants to sell a bond and contacts a dealer. The dealer, due to limited risk-taking capacity, is willing to take inventory risk only by charging substantial spreads (for example, 30 basis points (bps)). Instead of finding someone with a liquidity need to buy the bond, the dealer might find a non-dealer (C2) who is willing to provide liquidity for a fee (i.e., buying at a lower price than the fundamental value of the bond) even without a strict liquidity need. In this scenario, C1 is demanding liquidity, and C2 is providing liquidity. Also, C1 sells at a higher price than she would without liquidity provision by C2, because the dealer is willing to charge a spread smaller than 30 bps as the dealer does not take on inventory risk. C2 pays an even smaller spread (a negative spread in this scenario), implying that the average bid-ask spread paid by the two customers is much lower than the spread that would be paid by a customer that demanded immediacy. For instance, if C1 pays the dealer 10 bps and the dealer pays 4 bps to C2 (i.e., dealer sells to C2 at 4 bps lower than the fundamental price), then the average bid-ask spread is $(10-4)/2 = 3$ bps, which is lower than the 30 bps that a customer demanding immediacy will pay and also lower than the 10 bps that C1 paid. Importantly, the transaction between a dealer and a liquidity-providing customer can occur at a lower price than the fundamental value, indicating that the spread can be *negative*. Furthermore, the amounts of customer liquidity provision can be measured by the fraction of two matched customer trades (DC-DC trades, henceforth).

To the extent that customers exploit increased spreads quoted by dealers, customer liquidity provision will become stronger and underestimation of the true cost of immediacy will be more severe as dealers face increased inventory costs. Suppose that dealers face higher inventory costs and increases the price for immediate execution to 40 bps. Some customers that would have traded immediately with a dealer (and paid 30 bps) decide to wait for the dealer to find a counterparty, and some other customers may decide not to trade altogether, because transaction costs would be too high. The dealer will actively search for liquidity-providing customers, as matching trades with a liquidity-providing customer is better than foregoing a transaction with a liquidity-seeking seller. Thus, the fraction of DC-DC matched trades increases, and a higher fraction of liquidity is essentially provided by non-dealers. Moreover, despite the increased cost of immediacy, the average bid-ask spread paid by all customers may remain similar or even decrease due to the shift in the composition of liquidity provision between dealers and customers. We also expect 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.[1] It is relatively easier for such asset managers to provide liquidity on their long positions, as they typically should hold net long positions and also have been receiving substantial amounts of investor flows during the post-crisis period.

Our main database, the regulatory TRACE, provides dealer identities for each reported trade, which allows us to identify DC-DC trades and thus measure the degrees of customer liquidity provision. In particular, we match a trade between a customer and dealer with an offsetting trade between the same dealer and another customer (i.e., matching a buy with a sell and vice versa), using a last-in-first-out (LIFO) algorithm. We categorize as a DC-DC trade a customer trade that is matched to another customer trade within the next 15 minutes. As outlined previously, we hypothesize that these trades are generally one customer demanding liquidity and another customer supplying liquidity. Similarly, we define DC-ID

[1]For 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)). Also, a recent *Wall Street Journal* article 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`)

trades, which are customer trades matched with offsetting interdealer trades within the 15 minute window. These DC-ID matches are likely driven by a customer demanding liquidity and the other matched dealer providing liquidity. Trades that remain in dealers' inventory for longer than 15 minutes are categorized as invt>15min trades.

We provide empirical evidence that is consistent with predictions implied by customer liquidity provision. First, we show that customer trades that are matched with other customer trades (i.e., DC-DC trades) have lower average spreads than customer trades that are not matched. We find that DC-DC trades have 20–40% lower bid-ask spreads compared with trades where customers are demanding liquidity, indicating that average bid-ask spreads underestimate trading costs for customers demanding liquidity. We find that 40% of DC-DC trades exhibit negative spreads, higher than that of DC-ID or invt>15min trades. Furthermore, DC-DC trades have lower bid-ask spreads and are more likely to have negative spreads particularly for customer buy trades, which is consistent with our prediction that customers have more capacity to provide liquidity on their long positions. For investment grade bonds, for example, DC-DC trades for customer buys (sells) are on average 42.6 (23.7) bps and 17.17 (6.6) bps lower than DC-ID and invt>15min customer buy (sell) trades, respectively. Also, we find that the bid-ask spreads for DC-DC trades are lower particularly for bonds that trade infrequently, consistent with our customer liquidity provision hypothesis in that liquidity-providing customers are compensated more for bonds with high dealer inventory risk.

Next, we also show that this underestimation problem is severe for commonly used measures of bid-ask spreads in the literature, namely, the implied roundtrip costs of Feldhütter (2012) and the bid-ask spread estimates based on differences in customer buy and sell prices used in Hong and Warga (2000) and Adrian, Fleming, Shachar and Vogt (2017). These measures implicitly treat DC-DC trades as customer trades seeking immediacy and also put higher weights on those trades. More generally, a bid-ask spread measure would tend to understate the true cost of liquidity demand to the extent that it puts more weight in short-horizon trades, as our results show that liquidity provision is concentrated the most in short-horizon customer trades.

Lastly, we examine the extent to which increasing customer liquidity provision as proxied by DC-DC matched trades can explain the seemingly low transaction costs in the corporate bond market. We show that in the post-regulation period, compared with the pre-crisis period, dealers match a higher fraction of customer trades with other customer trades. Thus, trading costs estimated based mainly on DC-DC matched trades are substantially low, as one customer in this transaction is compensated for liquidity provision. In contrast, we find that trading costs for unmatched trades have increased substantially. These results are consistent with liquidity being lower due to increased dealer inventory costs. The fractions of trades that are immediately offloaded from dealer inventories increased by 30–50% from the pre-crisis levels. When we restrict our sample to customer trades that are not matched, we find that trading costs in the post-regulation period are 10–13 bps higher than the trading costs in the pre-crisis period and that this estimated increase is 6–10 bps larger than when some of the other bid-ask spread measures from the literature are used. Given that average bid-ask spreads for trades above $1 million are approximately 25 bps for the non-crisis periods, the 10–13 bps overall increases are economically substantial, and the 6–10 bps differences in the estimated change in trading costs are quite significant. Thus, customer liquidity provision increased post-regulation, and this increase causes the trading cost measures that are often used in the literature to understate the change in true trading costs for liquidity-demanding customers.

Although we do not exactly pinpoint the causal link between the decrease in dealers' risk taking and the increase in customer liquidity provision, our results also show that large dealers, who generally are bank-affiliated dealers, drove the change, consistent with regulations having played a role. Moreover, the fact that dealers increased their offloadings to customers is consistent with their incentives to comply with the Volcker Rule. One of the key Volcker metrics that banks are required to report is the fraction of trades that are conducted with customers. Hence, offloading inventories to customers is more advantageous in terms of compliance with the Volcker Rule than trading with other dealers, which can explain our findings. However, the results may also be due to changes in either the risk-bearing capacities of large dealer banks or risk-management practices that may not be directly caused by regulations. Finally, given that the effect of regulations should matter most for large trades, for most of the paper, we focus our analyses on trades with a volume of $1 million and larger.

2 Literature Review

This paper is most closely related to a number of contemporaneous empirical papers that study the impact of regulations on corporate bond market liquidity.[2] Overall, there are three main findings that emerge from these papers. First, dealers have decreased capital committed to market-making and inventory provision in the recent years, and the dealers that are more affected by various bank regulations have done so to a greater extent. Bessembinder et al. (2017) show that dealers commit less capital in the post-regulation period, and this reduction in committed capital is driven mainly by bank-affiliated dealers. Bao et al. (2017) find that dealers that are affected by the Volcker Rule provide less inventory service during downgrade events after the Volcker Rule was implemented. Schultz (2017) shows that dealers are less likely to take bonds into inventory after the Volcker Rule.

Second, however, these studies find that broad price-based measures of liquidity such as average bid-ask spreads have not worsened. Trebbi and Xiao (2017) test whether there is a discontinuity in liquidity around the time when regulations were introduced and find

[2] A few theoretical papers also examine the effect of regulations on market liquidity. Cimon and Garriott (2016) argue that the Volcker Rule and capital regulations motivate dealers to switch to trading in an agency basis. Uslu (2016) finds that the welfare impact of the Volcker Rule is not clear.

no evidence of liquidity deterioration. Bessembinder et al. (2017) find that although dealers commit less capital, average trading costs remain largely similar to pre-crisis levels. Anderson and Stulz (2017) find similar results.

Lastly, a number of papers look at specific market stress or liquidity events and find that liquidity during these times have deteriorated in the post-regulation period. Bao et al. (2017) study bond downgrade events and find that liquidity during these events is worse than it was before the crisis. Anderson and Stulz (2017) find that liquidity is worse in the post-regulation period when the VIX spikes up but not during bond idiosyncratic events.

Our paper adds to this literature in a few ways. We bridge the seemingly contrasting findings 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. We also propose a method for measuring the costs for demanding liquidity without using specific market stress or liquidity events and show that liquidity has worsened broadly.

Paired trades where a dealer effectively act as an agent is fairly common in corporate bond markets. Zitzewitz (2010), for example, show that this type of trade happens frequently in small trades and is much more common than a dealer-customer trade paired with another dealer-customer trade. In contrast, in the large trade size that we focus on, paired trades are more likely to be between dealer-customer trades, consistent with the results in Harris (2015), who study the relationship between paired trades and trade-throughs. Goldstein and Hotchkiss (2017) also show that dealers actively manage inventories by pre-arranging trades or offsetting trades during the same day.

3 Data and Variable Construction

3.1 Data Description

The main data source is the regulatory TRACE feed. The database includes dealer identities for each trade, while customers are identified as the counterparty code "C" only. 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 either between dealers (interdealer trades) or between a dealer and a customer (customer trades).

Dealers in the TRACE data are identified by Market Participant Identifiers (MPIDs). Some dealers may have multiple MPIDs (they can be different subsidiaries or due to mergers and acquisitions) or shift MPIDs over time. Thus, we construct a new identifier, MPID2, in which MPIDs from the same dealers have the same MPID2. When two dealers merge, we attribute the acquired dealer's MPID to acquiring dealer's MPID2 after the merger. We delete trades between the same MPID2.

We exclude dealers that almost exclusively engage in agency or riskless principal trades,[3] such as trading platforms or interdealer brokers, as they are different in nature from typical dealers that perform a conventional role as market makers.[4] Because we are interested in trading costs that clients face, we also exclude dealers that almost exclusively engage in interdealer trades. We exclude trades between dealers and their affiliates, as described in Appendix A and Figure 1.

[3]If two trades by the same dealer for the same bond have the same quantities with opposite trade directions and occur less than one minute apart, then they are most certainly pre-arranged, where the dealer acted as an agent. As shown in Bessembinder et al. (2017) and Zitzewitz (2010), these trades are fairly common and are not always marked as agency trades (as opposed to principal trades) in TRACE.

[4]To identify such dealers, we first calculate the fractions of the numbers of trades and trading volumes that are paired. We mark as paired trades if two trades within one minute apart by the same dealer for the same bond have the same quantities with opposite trade directions. If more than half of trades and volumes are paired or if more than three-fourths of trades or volumes are paired for a dealer, then we exclude the dealer.

We use the Mergent Fixed Income Database (FISD) to get corporate bond characteristics such as size, offering date, maturity, and rating. We calculate corporate bond market volatility from returns on the Bank of America Merrill Lynch U.S. Corporate Master Index (for investment grade) and High Yield Master II Index (for high-yield).

Our sample period is January 2006 to June 2015. We start the sample period in 2006 as the trade information dissemination was introduced in multiple phases from 2002 to 2005, and we want to avoid the effect of increasing transparency in our empirical exercises (Goldstein, Hotchkiss and Sirri (2007)). We exclude MTNs, 144As, and exchangeable bonds, and bond-days with less than 30 days since issuance. We only include secondary market trades that are marked as principal trades. Our final cleaned sample consists of 15,860 bonds with total 38,932,240 trades (including duplicate interdealer trades), of which 3,940,700 are customer trades with par value $1 million or larger.

3.2 Matching Customer Trades

We classify customer trades by their inventory holding periods and which trades they are matched with. We first calculate dealers' inventory holding periods using the last-in-first-out (LIFO) method, starting each trading day with an inventory of zero, and define short-holding-period trades as those that dealers hold on to for less than 15 minutes.[5] Short-holding-period trades proxy for those that dealers pre-arrange and do not take on risk.

Table 1 gives a simple example of holding period calculation in Panel B, using fictitious trading data in Panel A. An inventory of –200 accumulated from trade number 1 will leave the inventory when trade number 2 arrives five seconds later. We match trade 1 with trade 2 with an inventory holding period of 5 seconds. Trades may not always be exactly matched by volume. 350 out of 500 in trade 4 is matched against trade 5 within 15 minutes, 100 is

[5]We use 15 minutes because dealers are required to report trades to TRACE within 15 minutes. Results remain similar when we use cutoffs shorter than 15 minutes.

matched against trade 6 but with a 40 minute holding period, and 50 remains unmatched. All of trade 1 and a portion of trade 4 have short holding periods.

We classify all customer trades into three types: DC-DC trades, which are matched with other customer trades; DC-ID, which are matched with interdealer trades; and invt>15min trades, which have inventory holding periods greater than 15 minutes. Specifically, trades in which 50% or more of the volume remains in the inventory for longer than 15 minutes are classified as invt>15min trades. The remaining trades (which we will refer to as "short-holding trades") are further divided into DC-DC and DC-ID, depending on whether there was a higher fraction of DC-DC or DC-ID volume. Table 2 presents the fraction of DC-DC, DC-ID, and invt>15min trades by trade size, dealer size, and bond trading frequency. For the trades $1 million and larger that we focus on, DC-DC trades are almost twice as more likely than DC-ID trades for investment grade bonds, and 6 times more likely for high-yield bonds.

3.3 Bid-Ask Spread Estimation

Our main measure of bid-ask spreads, *spread1*, is defined as follows:

$$\textit{spread1} = 2Q \times \frac{\text{traded price} - \text{reference price}}{\text{reference price}} \tag{1}$$

where Q is $+1$ for customer buy and -1 for customer sell. We multiply by 2 to get the full spread. For each customer trade, we calculate its reference price as the volume-weighted average price of the interdealer trades larger than $100,000 in the same bond-day, excluding interdealer trades within 15 minutes.[6] As a robustness check, we employ reference prices based on weekly average interdealer prices and obtain qualitatively similar results for our main analyses (results not shown). *spread1* is calculated at the trade level for all customer

[6]Interdealer trades tend to be smaller and are less frequent, hence we use the $100,000 cutoff instead of $1 million. Results are qualitatively similar if we do not exclude 15 minutes surrounding the trade.

trades and is also calculated at the bond-day level by taking the volume-weighted average of trade level spreads.

To examine underestimation of spreads due to customer liquidity provision, we also calculate the following measures commonly used in the literature. The first is the implied roundtrip cost (IRC) from Feldhütter (2012). IRC measures dealers' round-trip cost for imputed roundtrip trades (IRTs).[7] If there are n sets of IRTs for bond i on day t, IRC is calculated as

$$IRC_{i,t} = \sum_{k=1}^{n} \frac{vol_k}{\sum_{l=1}^{n} vol_l} \frac{2(P_{max,k} - P_{min,k})}{P_{max,k} + P_{min,k}}. \tag{2}$$

$P_{max,k}$ and $P_{min,k}$ are the maximum and the minimum prices for the IRT set k. vol_k is the volume for the IRT set k. We also use IRC_C, which we define as the implied roundtrip cost based only on customer trades.

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

$$SameDay_{i,t} = \frac{2(vwavg(\text{customer buy})_{i,t} - vwavg(\text{customer sell})_{i,t})}{(vwavg(\text{customer buy})_{i,t} + vwavg(\text{customer sell})_{i,t})} \tag{3}$$

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 larger than \$1 million par value (except for the interdealer trades used in *spread1* calculation) and are in basis points (bps), winsorized at 1% level.

Table 2(d) presents the summary statistics for the four spread measures. IRC_C is the smallest, followed by IRC and same-day spread, and finally, spread1 measure is the largest.

[7] We use the IRT definition following Feldhütter (2012). Specifically, trades constitute IRTs if two or three trades for a given trade size are less than 15 minutes apart.

4 Customer Liquidity Provision

4.1 Do DC-DC Trades Have Lower Average Spreads?

We hypothesize that, among short-holding trades, DC-DC trades are largely instances where one customer demands liquidity and the other provides liquidity. In contrast, DC-ID trades are generally driven by a customer who is demanding liquidity and the second dealer providing liquidity, so these trades will have the lowest occurrences of customer liquidity provision. Although some long-horizon trades (i.e., invt>15min trades) can be associated with customer liquidity provision, dealers tend to use inventory capacity in invt>15min trades and thus such trades are less likely driven by customer liquidity provision.

As outlined in the introduction, liquidity-providing customers are compensated with only having to pay a small or even negative spread (i.e., buying at a lower price or selling at a higher price than the fundamental value). Thus, our predictions are that DC-DC trades will have the lowest average bid-ask spreads and the most occurrences of negative spreads. DC-ID trades, in comparison, are the least likely to be driven by customer liquidity provision and will have higher average spreads and fewer instances of negative spreads.[8] An alternative hypothesis is that matched trades are largely driven by matching two sides with opposite liquidity needs and that neither side is providing liquidity. In this case, DC-DC trades will not necessarily have more instances of negative spreads, since customers do not need to be compensated. Moreover, the average spread of DC-DC trades will not be any smaller than the average spread of DC-ID trades.[9]

In Table 2 Panels (d) and (e), we begin by examining average spreads and the fraction of negative spread trades for DC-DC, DC-ID, and long-horizon (invt>15min) trades. Table 2(d) clearly shows that average spreads are smallest for DC-DC trades and largest for DC-

[8]We calculate bid-ask spreads for customer trades only, so for DC-ID trades, we are only using the customer trade and not the interdealer trades to calculate the average bid-ask spreads.

[9]Appendix B provides additional evidence against this alternative hypothesis.

ID trades, for both investment-grade (IG) and high-yield (HY) bonds. 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. Also consistent with our hypothesis, DC-DC trades have the highest fractions of negative spreads, as shown in Table 2(e). More importantly, within DC-DC trades, customer buys have 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 that provide liquidity in the corporate bond market have net long positions and, hence, will be more likely to provide liquidity by buying than by selling. Among DC-ID trades, in contrast, customer sells have a higher fraction of negative spreads (15.3%) than customer buys (14.6%). Although it is possible that some of these negative spread trades are due to noise in reference prices, these results strongly suggest that DC-DC trades are driven mainly by customer liquidity provision.

In Table 3, we formally examine whether DC-DC trades have lower spreads relative to the other trade types in a regression setting. We run the following model:

$$\textit{spread1}_{i,j,t,k} = \alpha + \beta_2 \mathbb{1}(\text{DC-ID})_k + \beta_3 \mathbb{1}(\text{invt>15min})_k + \epsilon_{i,j,t,k} \tag{4}$$

where $\textit{spread1}_{i,j,t,k}$ is the *spread1*, defined in (1), of trade k between dealer j and a customer for bond i on day t. $\mathbb{1}(\text{DC-ID})_k$ and $\mathbb{1}(\text{invt>15min})_k$ are dummy variables indicating whether trade k is a DC-ID trade or a invt>15min trade. The dummy variable for DC-DC trades is omitted due to multicollinearity and thus forms the base level. We also include control variables that are known to be associated with bond transaction costs as well as bond, dealer, and time fixed effects.

Table 3 provides the results from the regression model in (4). The results show that DC-DC trades have the lowest spreads and that DC-ID trades have the highest spreads, consistent with our hypothesis. For example, compared with DC-DC spreads (i.e, the base level), the spreads of DC-ID trades are approximately 34.2 bps higher for IG bonds in column (1) and 38.3 bps higher for HY bonds in column (3), as can be seen from the coefficient estimates on $\mathbb{1}$(DC-ID). The spreads of invt>15min trades are also higher by 11.4 bps (IG) and 6.13 bps (HY) than those of DC-DC trades. The difference between the coefficient estimates on the indicator variables for DC-ID and invt>15min trades are positive and statistically significant across all columns (see the row for $\beta_2 - \beta_3$). Overall, the results show that DC-DC spreads are the lowest among all three trade types. The economic magnitudes of differences in spreads between non-DC-DC trades and DC-DC trades are substantial, given that the average spread for trades $1 million and above is approximately 35 bps.

In Table 4, we run the regression (4) separately for customer buy and sell trades to examine whether customers tend to provide liquidity more on buy trades. We find that the results are consistent with our 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. The difference between the coefficients on DC-ID and invt>15min trades (i.e., $\beta_2 - \beta_3$) are also larger for customer buys (25.4 bps) than for customer sells (17.1 bps). These results show that customer liquidity provision is more pronounced among customer buy trades.

In Table 5, we run the regression (4) separately for three subsamples based on the number of customer trades that are $1 million or larger in the past year. For bonds that trade infrequently, dealers face higher inventory risk and thus compensation to liquidity-providing customers should be higher. Thus, if the lower spreads on DC-DC trades are driven by having to compensate the customers that provide liquidity, the difference between DC-DC spreads and invt>15min spreads should be greater particularly for bonds traded infrequently.

Table 5 provides the regression results. For IG bonds, DC-DC spreads are 32 bps lower than invt>15min spreads for bonds with 50 or fewer customer trades in the past year, 22 bps lower for bonds with 50 to 100 trades, and 10 bps lower for bonds with more than 100 trades. Results are similar for HY bonds. These results are consistent with the idea that bid-ask spreads for DC-DC trades are lower because of customer liquidity provision, especially for the less active bonds.

Overall, our results show that DC-DC trades have the highest instances of customer liquidity provision, suggesting that the higher the customer liquidity provision, the more likely average bid-ask spreads underestimate the cost of demanding liquidity. We examine this underestimation issue in the next section.

4.2 The Effect of Customer Liquidity Provision on Trading Cost Measures

In this section, we examine the extent to which various existing bid-ask spread measures in the literature might underestimate the true cost of immediacy, given substantial amounts of customer liquidity provision as proxied by DC-DC trades.

Table 2(d) provides summary statistics of various bid-ask spread estimates provided in Section 3.3—namely, IRC, IRC_C, and same-day spread as well as *spread*1. We find wide dispersion in average bid-ask spread estimates across the measures. For example, the average bid-ask spread estimates for IG bonds are 16.7 bps, 17.3 bps, 25.6 bps, and 34.1 bps for IRC_C, IRC, same-day spread, and *spread1*, respectively.

This dispersion in bid-ask spread estimates across these measures can be explained by the differences in the fraction of trades used in the calculation of each measure that are DC-DC trades. IRC_C, by construction, is calculated using DC-DC trades almost exclusively and will understate the cost of demanding immediacy the most. IRC also overweights DC-DC trades and will understate the cost of liquidity demand. DC-DC trades will also affect same-day spread estimates, because same-day spread calculation requires both customer buys and sells.

In Table 6, we examine the extent to which DC-DC trades affect the average spread estimates from these spread measures. The table presents the fractions of DC-DC, DC-ID, and invt>15min trades for the full sample and the samples that we use to calculate each of IRC_C, IRC, same-day, and *spread1* estimates. We find that the IRC_C calculation requires a sample with the highest fraction of DC-DC trades, followed by IRC, same-day spread, and *spread*1 calculations. For IG bonds, for example, 82.2%, 61.6%, 21.5%, and 8.2% of the IRC_C, IRC, same-day, and *spread1* samples consist of DC-DC trades, respectively. We find even higher fractions of DC-DC trades in the HY bond samples, suggesting that the effect of customer liquidity provision in spread estimation is stronger for HY bonds. To the extent that DC-DC trades are driven by customer liquidity provision, IRC_C will understate the cost of demanding liquidity the most, followed by IRC, same-day spreads, and *spread1*.[10] These results are consistent with the empirical statistics in Table 2(d).

In general, a bid-ask spread measure would understate the cost of immediacy as long as it puts more weight in short-horizon trades. This poses a conundrum to most spread measures in the literature. On the one hand, a bid-ask measure should employ more instances of short-horizon trades, as noise in spread estimates increase with time between consecutive trades. On the other hand, the measure will more likely underestimate the cost of demanding immediacy as it places higher weight on short-horizon trades. These opposing effects will also exist in the weighted-regression-based methods of bid-ask spread estimates in Edwards, Harris and Piwowar (2007) and Bessembinder et al. (2006). Focusing more on short-horizon trades will reduce estimation errors, but it will also underestimate the true cost of immediacy

[10]Because IRC calculations overweight DC-ID trades, one might conclude that this channel will translate into IRCs being higher. However, this is not necessarily the case because in a DC-ID trade, the customer pays a high spread, of which a large fraction is paid to the second dealer. For example, in a DC-ID trade, if the customer pays 30 bps to the first dealer, and if the first dealer passes 20 bps to the second dealer, the average customer spread is 30 bps, but the IRC is 10 bps. Table A.2 in Appendix B shows that the profit that the first dealer makes is similar in DC-DC and DC-ID trades.

for customers.

5 Customer Liquidity Provision and Trading Costs Before and After the Banking Regulations

5.1 Overview of the Recent Banking Regulation Changes

In this section, we briefly discuss the potential impact of the Volcker Rule and capital regulations on corporate bond liquidity. The Volcker Rule prohibits banks from engaging in proprietary trading, except when making markets. As Duffie (2012) argues, however, the Rule may also discourage banks from market-making and providing liquidity. For example, the Volcker Rule specifies seven quantitative metrics to be reported for certain banks at the trading desk level, including inventory turnover and inventory aging metrics as well as customer-facing trade ratios. These requirements may discourage dealers from taking on inventory and incentivize dealers to offload inventories to customers rather than in the interdealer market, which is consistent with the rise in customer liquidity provision that we document in this paper.

Basel III establishes tougher capital rules through increases in the minimum capital ratio, among many other changes. Stricter capital regulations increase the cost of financing inventories for dealers. This could lead banks to decrease liquidity provision, especially in trades that take up large amounts of space in the inventories and are expected to remain longer.

Since the 2008 financial crisis, corporate bond holdings of banks and broker-dealers have decreased. Instead, asset managers, especially mutual funds, have increasingly been holding a larger fraction of outstanding corporate bonds. This has prompted some concerns about outflow risk (Feroli, Kashyap, Schoenholtz and Shin (2014)). On the other hand, market commentary indicates that these changes have pushed buy-side investors to increasingly be liquidity providers and price setters in the corporate bond market. For instance, a recent Bloomberg article documents the increasingly active role that buy-side investors play, and argues that they have gone from being price takers to price makers.[11]

5.2 Customer Liquidity Provision Over Time

In this section, we examine the extent to which customer liquidity provision increased in the post-regulation period using the fraction of DC-DC trades as a measure of customer liquidity provision. An increase in the fraction of DC-DC trades in the sample will lead to more severe underestimation in liquidity costs in the corporate bond market.

In Figure 2, we first examine the time series of the fractions of DC-DC and DC-ID trades. Figure 2 shows that the fractions of DC-DC trades indeed increased in the post-regulation period, while the fractions of DC-ID trades 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-arraged, search-and-match trading model and that with this change, increasing fractions of trades are associated with customer liquidity provision.

While these time series plots hint at regulations playing a role, other changes in the market may also be driving the results. Thus, we examine how the fractions of DC-DC trades change differentially for large and small dealers.[12] Most large dealers are affiliated with banks and thus are affected by various bank regulations. In comparison, small dealers are a mix of bank-affiliated and non-bank dealers and will be less affected by the banking regulations. In Figure 3, we plot the fractions of DC-DC trades separately for large and small dealers. Fractions of DC-DC trades increase for large dealers, while there is no distinct

[11] See `https://www.bloomberg.com/news/features/2016-08-15/the-rise-of-the-buy-side`

[12] 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 trading in trades $1 million and larger, as shown in Table 2(b).

pattern for small dealers. These results are consistent with regulations having an effect on dealers' inventory holding periods and increasing customer liquidity provision.

To show the above results on DC-DC trades more formally in a regression setting, we first define the four subperiods: 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. The choice of July 2012 as the beginning of the post-regulation period is not crucial for our results. Most of our empirical analyses in this section and Section 5.3 will focus on comparing the post-regulation period with the pre-crisis and the post-crisis periods.

In Table 7, we regress the daily fractions of DC-DC trades on dummy variables for each subperiod:

$$\text{Aggregate level}: y_t = \alpha + \sum_{l=2}^{4} \beta_l \mathbb{1}(t \in T_l) + \epsilon_t \tag{5}$$

$$\begin{aligned}\text{Dealer group level}: y_{m,t} = {} & \alpha_1 + \alpha_2 \mathbb{1}(small)_m + \sum_{l=2}^{4} \mathbb{1}(large)_m \beta_{large,l} \mathbb{1}(t \in T_l) \\ & + \sum_{l=2}^{4} \mathbb{1}(small)_m \beta_{small,l} \mathbb{1}(t \in T_l) + \epsilon_{m,t}\end{aligned} \tag{6}$$

$$\text{Individual dealer level}: y_{j,t} = \sum_j D_j + \sum_{l=2}^{4} \beta_l \mathbb{1}(t \in T_l) + \epsilon_{j,t}. \tag{7}$$

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. The dealer group level fraction of DC-DC trades, $y_{m,t}$, is the average fraction of DC-DC trades calculated separately for large and small dealers. The indicator variables, $\mathbb{1}(large)_m$ and $\mathbb{1}(small)_m$, are for large and small dealer groups, respectively. The individual dealer fraction of DC-DC trades, $y_{j,t}$, is the fraction of DC-DC trades for dealer j on day t. $T_l\,(l = 1, \ldots, 4)$ are the four subperiods (pre-crisis, financial crisis, post-crisis, post-regulation). We include the VIX and bond market volatility as control variables. For the individual dealer regression, we use only the 15 largest dealers and run both OLS and median regressions. The median regression is used to rule out the possibility that the results are driven by one or a few large dealers.[13]

Table 7 presents the regression results. Consistent with Figure 2, the results indicate that customers provide more liquidity and that dealers take on less risk in the post-regulation period compared with the pre-crisis and the post-crisis periods. In column (5) for HY bonds, for example, the coefficient on the post-regulation dummy is 7.5% and statistically significant at the 1% level, showing that the fraction of DC-DC trades are 7.5 percentage points higher in the post-regulation period compared with the pre-crisis levels, which forms the base level. Also in column (5), the fraction of DC-DC trades post-regulation is also higher than the post-crisis level as well, 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. We find similar results for IG bonds in column (1).

Table 7 also shows that these increases in customer liquidity provision and decreases in dealer risk taking are driven mainly by large dealers, consistent with regulations affecting bank-affiliated dealers. In the dealer group level regression for HY bonds in column (6), for instance, the coefficient estimate on the interaction between the large dealer dummy and post-regulation dummy is 8.4% and highly statistically significant, showing that large dealers increase the fraction of DC-DC trades in the post-regulation period compared to the pre-crisis period. Furthermore, the difference between the coefficient on *large* × *post-reg* and *large* × *post-crisis* is statistically significant at the 1% level (see row $\beta_{large,4} - \beta_{large,3}$ near the bottom), thus the faction of DC-DC trades in the post-regulation period is even higher than the post-crisis level for large dealers. In contrast, during the same period the small dealers decrease the fraction of DC-DC trades by 4.3%, as can be seen from the difference between the coefficients on *small* × *post-reg* and *small* × *post-crisis* also reported in row

[13]Given that some of the large dealers have a substantial fraction of the total trading volume, the increase in DC-DC trades can be due to one large dealer increasing the amounts of DC-DC trades substantially.

$\beta_{small,4} - \beta_{small,3}$. For IG bonds, both large and small dealers increase the fraction of DC-DC trades for investment grade bonds, as can be seen from the difference test on $\beta_{large,4} - \beta_{large,3}$ and $\beta_{small,4} - \beta_{small,3}$ reported in column (2). We also find that results for individual dealer level regressions in columns (3), (4), (7), and (8) are similar to that of the aggregate level regressions, and thus, these results are not driven by outliers.

Overall, the results in this section show that customer liquidity provision increased in the post-regulation period compared with the pre-crisis and the post-crisis periods. This increase is driven mostly by large dealers, which is consistent with bank regulations having had an impact.

5.3 Trading Costs Over Time

Our results thus far show that customer liquidity provision, as measured by the fractions of DC-DC trades, has increased in the post-regulation period. Thus, the usual bid-ask spread measures in the literature that are calculated using liquidity-providing customer trades would underestimate what liquidity-demanding customers would pay, particularly during the post-regulation period. In this section, we examine how severe underestimation in bid-ask spreads is during the post-regulation period.

In Table 8, we examine how this underestimation in the common bid-ask spread measures influences our inference on the liquidity of corporate bonds in the post-regulation period. We employ the previous three bid-ask spread measures, i.e., IRC_C, IRC, and same-day spreads as test cases. To the extent that DC-DC trades are used in the calculation of these measures, they will understate the true cost of immediacy. As a benchmark case with respect to these three measures, we also calculate bid-ask spreads based on the *spread*1 measure but using invt>15min trades only ("invt>15min spreads"). As invt>15min trades are largely trades where dealers provide immediacy to customers, focusing only on the invt>15min trades would alleviate the underestimation issue.[14] We compare post-regulation transaction costs across these four cases (i.e., the three common measures and the benchmark *spread*1 measure using invt>15min only).

We then estimate the following model for each of the four measures:

$$\text{spread}_{i,t} = \alpha + \sum_{l=2}^{4} \beta_l \mathbb{1}(t \in T_l) + \epsilon_{i,t} \tag{8}$$

where $\text{spread}_{i,t}$ is the trading cost measure for bond i on day t. T_l ($l = 1, \ldots, 4$) are the subperiod dummies, and T_1 is the omitted base level due to multicollinearity. We control for bond characteristics such as outstanding amount, ratings, age, and time-to-maturity and market-level variables such as the bond index volatility and 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 for post-regulation dummy and the coefficient for post-crisis dummy.

Table 8(a) presents the estimation results for investment grade bonds. As the coefficient estimate on *post-regulation* in column (4) indicates, the invt>15min spreads are 12.7 bps higher in the post-regulation period compared with the pre-crisis period (the base level). This difference is economically significant as the average of *spread1* is approximately 35 bps for the full sample, and around 25 bps for the non-crisis periods. In contrast, using the other trading cost measures in columns (1) through (3) underestimates this increase in trading costs during the post-regulation period. In column (1) when IRC_C is used, for example, the estimated difference in trading cost between the post-regulation period and pre-crisis period 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 (column 2) and same-day spreads (column 3), respectively. Hence, using IRC_C underestimates the post-regulation increase in bid-ask

[14] We also exclude DC-ID matched trades to focus on trades were dealers provided immediacy.

spreads the most, followed by IRC and same-day spreads. Looking at the differences between the post-crisis and the post-regulation periods (i.e., row $\beta_4 - \beta_3$ at the bottom of the table) yield similar results; IRC_C and IRC would 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 results for HY bonds in Panel (b) and also when we use regression specifications without bond-level controls in Panels (c) and (d). Overall, these results also show why using some of these other measures might result in the conclusion that trading costs have not increased post-regulation. For instance, Panel (d) indicates that trading costs for high-yield bonds are *lower* in the post-regulation period compared to the pre-crisis period if we use IRC_C, IRC, or same-day spreads, as can be seen from the coefficient estimates on *post-regulation*. In column (4), however, the same coefficient estimate shows that invt>15min spreads are 3.6 bps higher in the post-regulation period.

As a robustness check, in Table 9 we run a difference-in-differences-style test to examine whether differences in the coefficient estimates across samples are statistically signfiicant. Specifically, we compare each of the three trading cost measures, y, 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:

$$\text{diff}_{i,t} = y_{i,t} - (\text{invt>15min spread})_{i,t} \tag{9}$$

where $y_{i,t}$ is either IRC_C, IRC, or same-day spread for bond i on day t. Then, we run the difference-in-difference regression as

$$\text{diff}_{i,t} = \alpha + \sum_{l=2}^{4} \beta_l \mathbb{1}(t \in T_l)\epsilon_{i,t}. \tag{10}$$

Note that $\text{diff}_{i,t}$ can be calculated only for bond-days where both y and invt>15min spread exist, and thus this regression analysis does not necessarily test the difference in estimates between y and invt>15min spreads from (8).

Table 9 presents the regression in (10). Consistent with our prediction, IRC_C underestimates the change in trading costs the most, followed by IRC and same-day spreads. In column (4), for example, the coefficient on *post-regulation* is -6.2 bps and is statistically significant at 1% level, indicating that the bid-ask spread estimates using IRC_C is lower than the benchmark spread calculated using invt>15min trades. We find similar results for the other spread measures reported in columns (5) and (6). The results provided in Table Table 9 confirm those reported in Table 8.

There are two main takeaways from this section. First, trading costs for liquidity-demanding customers, as measured by invt>15min spreads, have increased by 10–13 bps in the post-regulation period compared with the pre-crisis period and 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, since invt>15min trades do contain trades where customers are providing liquidity, these 10–13 bps increases are likely underestimates as well.

Second, some of liquidity measures often used in the literature might understate this increase in costs for demanding liquidity. Using IRC and same-day spreads, for instance, Anderson and Stulz (2017), Trebbi and Xiao (2017), and Adrian, Fleming, Shachar and Vogt (2017) conclude that price measures of liquidity has not worsened. Our results help explain why bid-ask spread estimates reported in the previous studies did not increase in the post-regulation period despite reduction in the inventory capacity of financial intermediaries.

6 Conclusion

We show that substantial amounts of liquidity are 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 pushed more 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 once we reduce this bias, measured costs of demanding immediacy in the U.S. corporate bond markets have increased post-regulation. This increase in transaction costs are consistent with the Volcker Rule and more stringent capital regulations having affected liquidity in the OTC markets.

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 capabilities of the dealer sector in providing liquidity during the post-regulation period. For other customers that generally demand liquidity only, both the cost of immediacy and the average waiting time have increased in the post-regulation period. Also, the increased liquidity provision by the non-dealer sector may be unhealthy for the stability of financial markets. 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 potential negative consequences should be weighed against the potential positive impact that regulations have had on curbing systemic risk. We believe that it would be an interesting future research to examine such welfare consequences of these regulations.

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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.

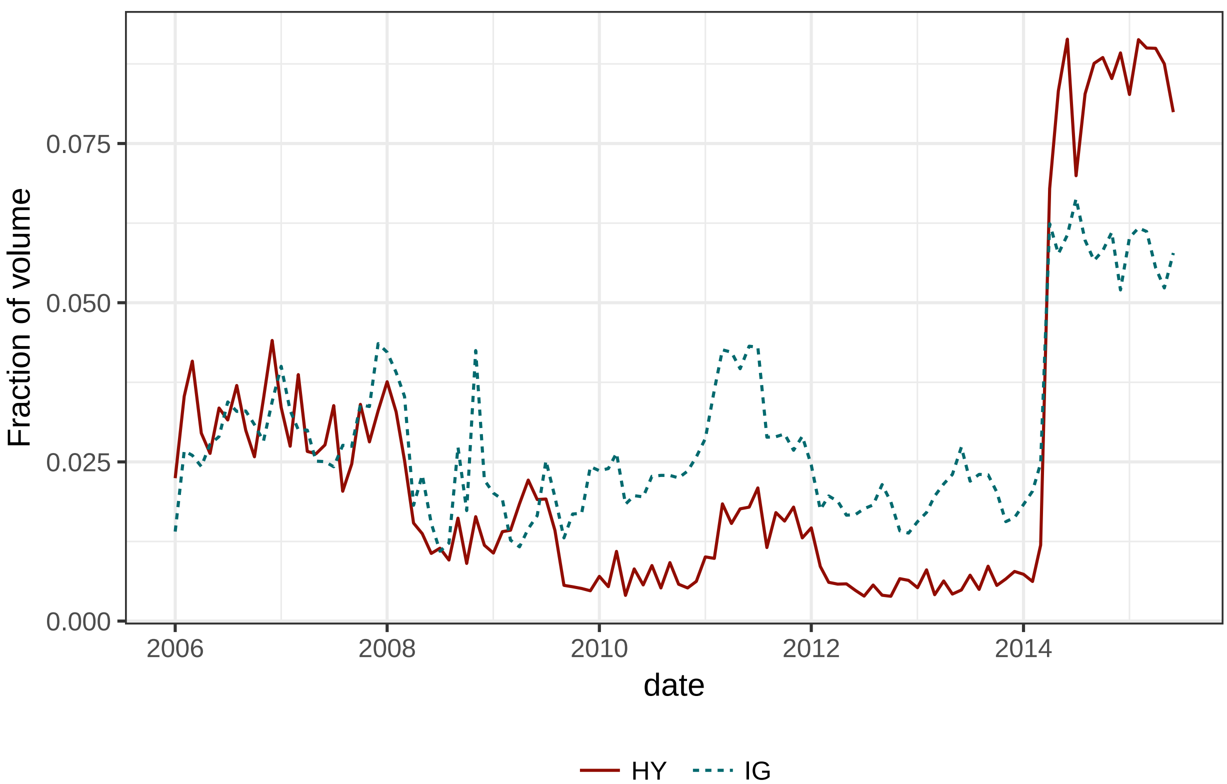

Figure 2: **Time Series Plot of the Fraction of DC-DC and DC-ID Trades**
This figure plots the monthly fraction of customer trades that are DC-DC (red solid line) and DC-ID trades (blue dotted line) with respect to total customer trade volumes over the sample period. Panel A plots IG bond trades, and Panel B plots HY bond trades.

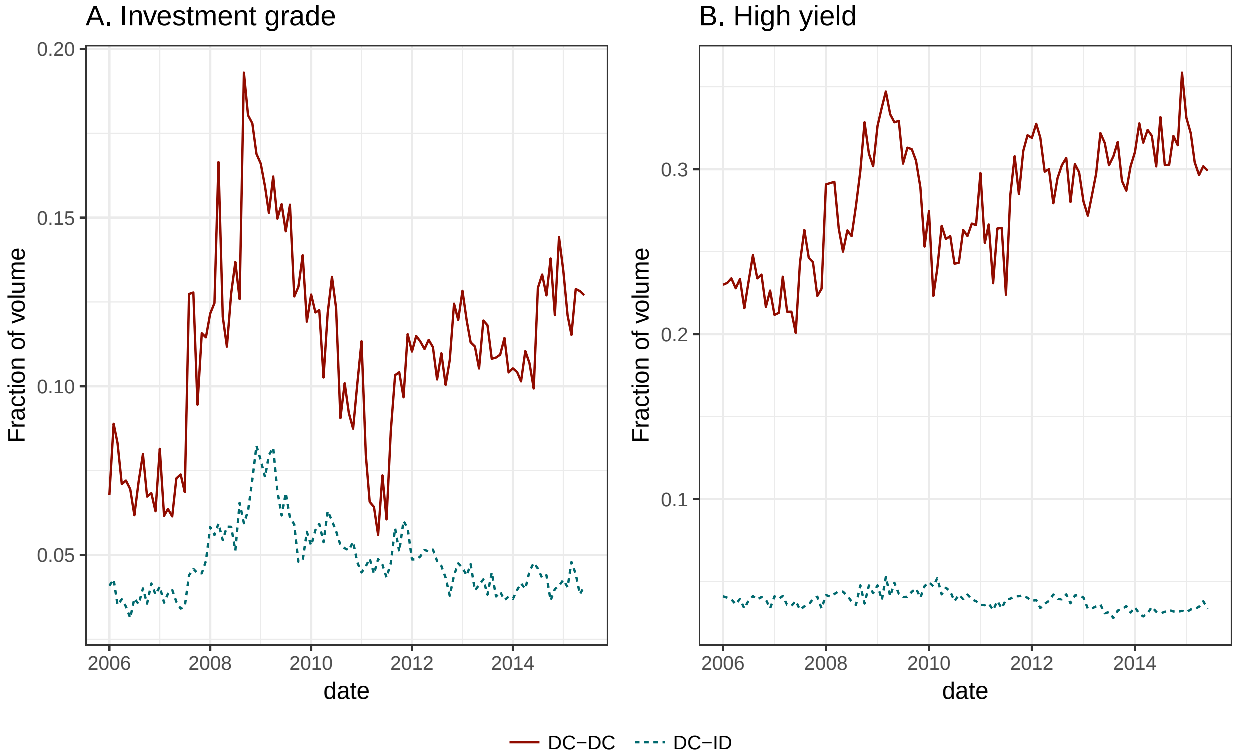

Figure 3: **Time Series Plot of the Fraction of DC-DC Trades by Dealer Size**
This figure plots the monthly volume of DC-DC trades as a fraction of total customer trade volume for large (red solid line) and small (blue dotted line) dealers. Panel A plots IG bond trades, and Panel B plots HY bond trades. Large dealers are defined as dealers that are in the top ten by customer trading volume for ten months or longer in the sample. The remaining dealers are defined as small dealers.

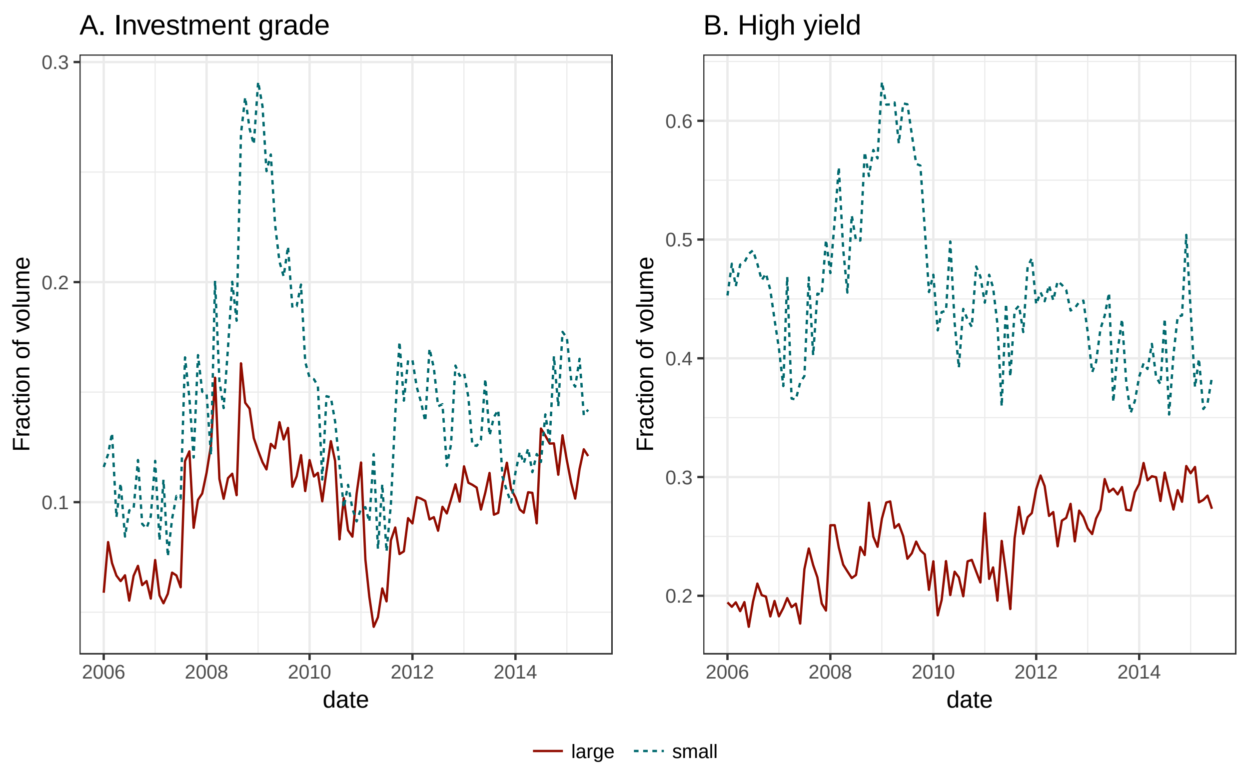

Figure 4: **Time Series Plot of Various Trading Cost Measures**
This figure plots the monthly time series of IRC_C (red solid line), same-day spreads (green dotted line), and *spread1* measured using invt>15min trades (blue dashed line) for IG (Panel A) and HY (Panel B) bonds.

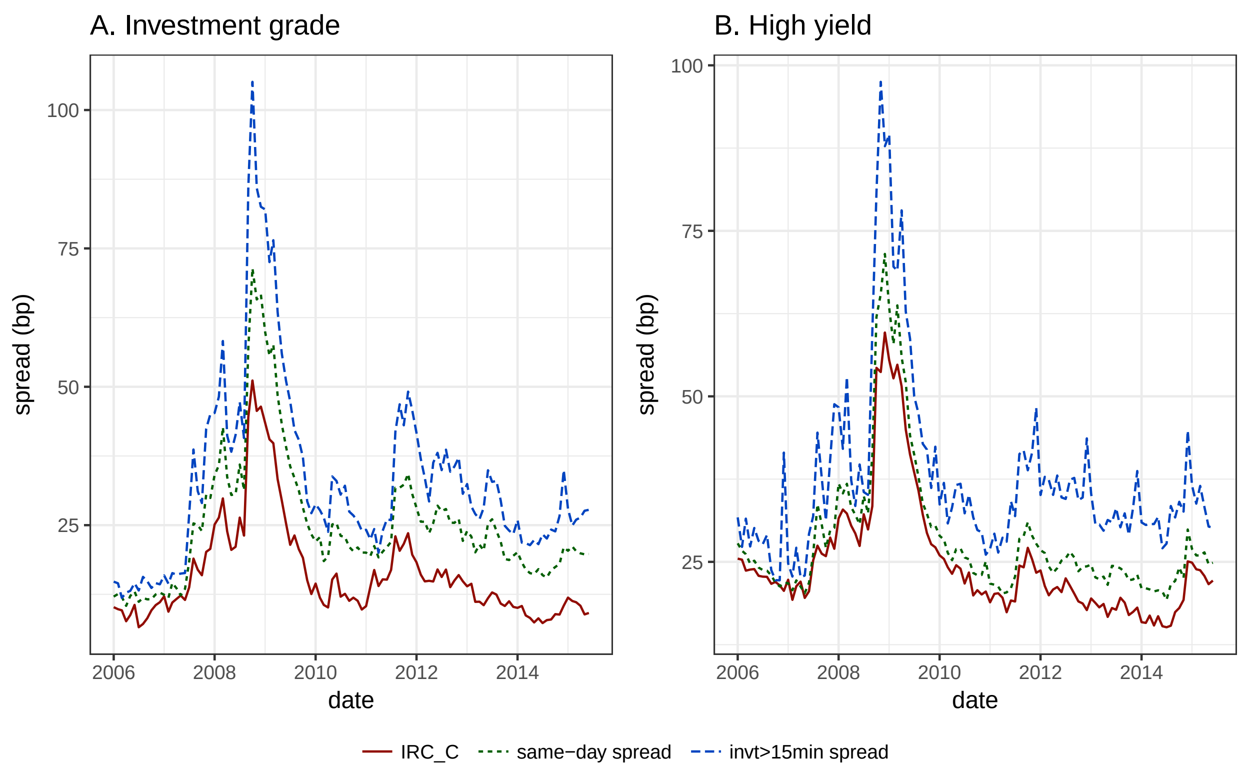

Table 1: **An Example of Matching Customer Trades**

Panel A: Sample (Ficticious) 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

Panel 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

Panel 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

Table 2: **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 trades in columns 3 through 6, trade volume in billion USD in column 7, and trade count (the number of trades) in column 8. Panels (b) and (c) reports the same statistics as Panel (a) but by rating (IG vs. HY) and dealer size groups in Panel (b) and by rating (IG vs. HY) and trade count groups in Panel (c). Panel (d) reports the averages of trading costs estimated using IRC_C, IRC, same-day spread, and *spread*1 methods. We also report average *spread1* for DC-DC, DC-ID, and invt>15min trades separately. Column *#(bond-days)* reports the number of bond-day observations. Panel (e) 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 (e) use customer trades $1 million and larger only. The sample period is from 2006 to 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) Fractions of Customer Trades by Rating and Dealer Size

rating	dealer size	overnight	DC-DC	DC-ID	invt>15min	volume	trade count
IG	large	71.42%	8.20%	2.69%	89.11%	8,104	1,555,775
IG	small	53.75%	12.81%	10.99%	76.20%	2,472	677,748
HY	large	55.43%	19.40%	2.63%	77.97%	4,893	1,381,711
HY	small	21.92%	42.96%	9.97%	47.06%	943	325,466

(c) Fractions of Customer Trades by Rating and Trade Count Per Year

rating	# trade/year	overnight	DC-DC	DC-ID	invt>15min	volume	trade count
IG	(0,20]	59.66%	14.41%	6.41%	79.19%	748	182,018
IG	(20,50]	65.77%	10.85%	5.27%	83.88%	1,676	392,599
IG	(50,100]	68.13%	9.35%	5.17%	85.47%	2,398	527,197
IG	(100,Inf]	66.23%	8.50%	5.01%	86.49%	5,753	1,131,709
HY	(0,20]	39.57%	38.47%	4.54%	56.99%	166	42,834
HY	(20,50]	42.96%	34.44%	3.41%	62.15%	495	142,783
HY	(50,100]	47.92%	28.71%	3.41%	67.88%	920	280,064
HY	(100,Inf]	50.32%	21.09%	4.22%	74.69%	4,254	1,241,496

(d) 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
spread1	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

(e) 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 3: **Regressions of Bid-Ask Spreads on Customer Trade Types**
This table presents the results from the following panel regression for IG (columns 1 and 2) and HY bonds (columns 3 and 4)

$$\textit{spread1}_{i,j,t,k} = \alpha + \beta_2 \mathbb{1}(\text{DC-ID})_k + \beta_3 \mathbb{1}(\text{invt>15min})_k + \epsilon_{i,j,t,k}$$

where $\textit{spread1}_{i,j,t,k}$ is the *spread1* for customer trade k of bond i on day t with dealer j. $\mathbb{1}(\text{DC-ID})_k$ and $\mathbb{1}(\text{invt>15min})_k$ are dummy variables for DC-ID and invt>15min trades, respectively. We omit the dummy variable for DC-DC trades. Control variables are log amount outstanding of bond i, log trading volume, bond rating, both age and log age of the bond, log time-to-maturity of the bond, volatility of bond index returns, and the VIX. We also include bond and time fixed effects as well as dealer fixed effects. Row $\beta_2 - \beta_3$ reports the coefficient difference between β_2 and β_3 and its statistical significance. The sample period is from 2006 to 2015, and we restrict the sample to trades over $1 million. Standard errors are double clustered by bond and date. *, **, and *** denote statistical significant at the 10%, 5%, and 1% levels, respectively.

	IG		HY	
	(1)	(2)	(3)	(4)
$\mathbb{1}$(DC-ID)	34.234***	34.494***	38.266***	38.107***
	(0.721)	(0.695)	(0.876)	(0.863)
$\mathbb{1}$(invt>15min)	11.441***	13.301***	6.126***	6.631***
	(0.434)	(0.432)	(0.447)	(0.457)
log(outstanding)	−7.550***		−6.960***	
	(0.424)		(0.562)	
log(volume)	−0.331**	0.387**	1.340***	1.503***
	(0.160)	(0.154)	(0.335)	(0.329)
rating	0.057		0.728***	
	(0.105)		(0.138)	
age	0.016		0.074***	
	(0.012)		(0.024)	
log(age)	5.884***	6.766***	0.579	0.948
	(0.360)	(0.392)	(0.545)	(0.592)
time-to-maturity	−0.011***		0.032***	
	(0.004)		(0.007)	
log(time-to-maturity)	12.854***	14.078***	2.052**	11.979***
	(0.433)	(0.535)	(0.893)	(1.357)
index volatility	171.356***		110.326***	
	(18.888)		(16.350)	
VIX	1.048***		0.702***	
	(0.040)		(0.062)	
$\beta_2 - \beta_3$	22.793***	21.193***	32.14***	31.476***
dealer f.e.	Yes	Yes	Yes	Yes
cusip, date f.e.	No	Yes	No	Yes
Observations	879,095	879,095	689,376	689,376
R^2	0.052	0.082	0.019	0.035

Table 4: **Regressions of Bid-Ask Spreads on Customer Trade Types: Buy versus Sell Trades**

This table presents the results from the following panel regressions separately for customer buy and customer sell trades:

$$\mathit{spread1}_{i,j,t,k} = \alpha + \beta_2 \mathbb{1}(\text{DC-ID})_k + \beta_3 \mathbb{1}(\text{invt}>15\text{min})_k + \epsilon_{i,j,t,k}$$

where $\mathit{spread1}_{i,j,t,k}$ is the *spread1* for customer trade k of bond i on day t with dealer j. $\mathbb{1}(\text{DC-ID})_k$ and $\mathbb{1}(\text{invt}>15\text{min})_k$ are dummy variables for DC-ID and invt>15min trades, respectively. We omit a dummy variable for DC-DC trades. Control variables are log trading volume, log age of the bond, and log time-to-maturity of the bond. We also include bond and time fixed effects as well as dealer fixed effects. We report esimtation results separately for customer buy and sell trades in IG bonds in columns (1) and (2), respectively, and also for customer buy and sell trades in HY bonds in columns (3) and (4), respectively. Row $\beta_2 - \beta_3$ reports the coefficient difference between β_2 and β_3 and its statistical significance. The sample period is from 2006 to 2015, and we restrict the sample to trades over $1 million. Standard errors are double clustered by bond and date. *, **, and *** denote statistical significant at the 10%, 5%, and 1% levels, respectively.

	IG		HY	
	buy	sell	buy	sell
$\mathbb{1}$(DC-ID)	42.573***	23.715***	43.413***	29.138***
	(1.188)	(1.126)	(1.315)	(1.166)
$\mathbb{1}$(invt>15min)	17.168***	6.621***	9.859***	1.550**
	(0.895)	(0.896)	(0.830)	(0.782)
log(volume)	−4.138***	2.936***	−1.748***	3.080***
	(0.246)	(0.218)	(0.431)	(0.451)
log(age)	6.102***	6.881***	2.401**	−0.574
	(0.510)	(0.708)	(1.131)	(1.088)
log(time-to-maturity)	11.739***	15.672***	12.104***	11.713***
	(0.687)	(0.970)	(2.954)	(2.656)
$\beta_2 - \beta_3$	25.405***	17.094***	33.554***	27.588***
dealer, cusip, date f.e.	Yes	Yes	Yes	Yes
Observations	466,351	412,744	351,528	337,848
R^2	0.106	0.154	0.072	0.070

Table 5: **Regressions of Bid-Ask Spreads on Customer Trade Types: By Trade Counts**

This table presents the estimation results from the following panel regressions for the three subsamples of bonds based on the number of customer trades in the past year:

$$spread1_{i,j,t,k} = \alpha + \beta_2 \mathbb{1}(\text{DC-ID})_k + \beta_3 \mathbb{1}(\text{invt>15min})_k + \epsilon_{i,j,t,k}$$

where $spread1_{i,j,t,k}$ is the *spread1* for customer trade k of bond i on day t with dealer j. $\mathbb{1}(\text{DC-ID})_k$ and $\mathbb{1}(\text{invt>15min})_k$ are dummy variables for DC-ID and invt>15min trades, respectively. We omit the dummy variable for DC-DC trades. Control variables are log trading volume, log age of the bond, and log time-to-maturity of the bond. We also include bond and time fixed effects as well as dealer fixed effects. For both IG and HY bonds, we group bonds into three subsamples based on the number of customer trades in the past year: [0,50] (from zero to 50 trades), (50,100] (from 50 to 100 trades), and >100 (more than 100 trades). Row $\beta_2 - \beta_3$ reports the coefficient difference between β_2 and β_3 and its statistical significance. The sample period is from 2006 to 2015, and we restrict the sample to trades over $1 million. Standard errors are double clustered by bond and date. *, **, and *** denote statistical significant at the 10%, 5%, and 1% levels, respectively.

	IG			HY		
	[0,50]	(50,100]	>100	[0,50]	(50,100]	>100
$\mathbb{1}$(DC-ID)	47.279***	40.417***	32.669***	59.657***	51.223***	40.138***
	(1.973)	(1.687)	(1.131)	(5.457)	(3.132)	(1.138)
$\mathbb{1}$(invt>15min)	32.384***	22.045***	10.028***	31.292***	21.407***	6.630***
	(1.484)	(1.280)	(0.607)	(4.009)	(1.881)	(0.612)
log(volume)	−2.918***	−0.357	0.348	−0.516	1.139	2.062***
	(0.624)	(0.479)	(0.249)	(2.668)	(1.158)	(0.445)
log(age)	7.273*	4.153	8.667***	3.320	6.917	6.641**
	(4.240)	(3.820)	(2.007)	(15.646)	(7.801)	(2.887)
log(time-to-maturity)	15.209***	11.284***	10.817***	20.241***	20.870***	9.198***
	(1.668)	(1.636)	(0.905)	(7.811)	(6.457)	(2.037)
$\beta_2 - \beta_3$	14.896***	18.372***	22.64***	28.365***	29.816***	33.507***
dealer/cusip/date f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	71,724	95,471	347,642	16,342	36,792	378,042
R^2	0.188	0.130	0.072	0.221	0.125	0.034

Table 6: **Fractions of DC-DC, DC-ID, and invt>15min Trades in Trading Cost Calculations**

This table provides the fractions of DC-DC, DC-ID, and invt>15min trades (in terms of trade counts) used in the calculations of the bid-ask spread measures. We report for the following bid-ask spread measures: IRC_C, IRC, same-day spread, and *spread*1. Row *full* reports the fraction of trade counts for each trade type for the full sample of customer trades. We report for IG and HY bonds separately, using only customer trades larger than $1 million. The sample period is from 2006 to 2015.

	IG			HY		
sample	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%

Table 7: **Regression of the Fraction of DC-DC trades on Pre- and Post-Regulation Dummy Variables**

This table provides the estimation results from the following regressions at the aggregate, dealer group, and individual dealer levels:

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

$$\text{Dealer group level}: y_{m,t} = \alpha_1 + \alpha_2 \mathbb{1}(small)_m + \sum_{l=2}^{4} \mathbb{1}(large)_m \beta_{large,l} \mathbb{1}(t \in T_l) + \sum_{l=2}^{4} \mathbb{1}(small)_m \beta_{small,l} \mathbb{1}(t \in T_l) + \epsilon_{m,t}$$

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

where the dependent variables, y_t, $y_{m,t}$, and $y_{j,t}$, are the fractions of daily DC-DC trade volumes at the aggregate, dealer group, 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, $\mathbb{1}(t \in T_l)$, indicate the four subperiods. $\mathbb{1}(T_1)$ is the omitted dummy, and thus, forms the base level. We report the aggregate (*agg*), dealer group (*group*), and individual dealer (*ind*) level regressions for IG bonds in columns (1), (2), and (3), respectively. Column (4) (*ind med*) reports the median regression of IG bonds at the individual dealer level. Columns (5) through (8) report the same set of regressions for HY bonds. The dealer group level fraction of DC-DC trades, $y_{m,t}$, is the average fraction of DC-DC trades calculated separately for large and small dealers, where the large dealer group consists of 15 largest dealers and the small dealer group consists of the rest. The indicator variables, $\mathbb{1}(large)_m$ and $\mathbb{1}(small)_m$, are for large and small dealer groups, respectively. The individual dealer fraction of DC-DC trades, $y_{j,t}$, is the fraction of DC-DC trades for dealer j on day t. We include the VIX and bond market volatility as control variables. We also report the differences in coefficients and their statistical significance in the five rows at the bottom of the table. We use Newey-West standard errors with 20 lags for the aggregate level regression and use standard errors clustered by date for the dealer group and individual dealer regressions. We calculate standard errors for the individual dealer level median regression based on 2,000 bootstraps. The sample period is from 2006 to 2015. *, **, and *** denote statistical significant at the 10%, 5%, and 1% levels, respectively.

	IG				HY			
	agg (1)	group (2)	ind OLS (3)	ind med (4)	agg (5)	group (6)	ind OLS (7)	ind med (8)
crisis	0.032***		0.059***	0.031***	0.023***		0.032***	0.035***
	(0.007)		(0.004)	(0.003)	(0.007)		(0.004)	(0.004)
post-crisis	0.019***		0.038***	0.009***	0.034***		0.023***	0.030***
	(0.005)		(0.002)	(0.002)	(0.007)		(0.003)	(0.003)
post-regulation	0.042***		0.070***	0.031***	0.075***		0.057***	0.074***
	(0.003)		(0.002)	(0.002)	(0.004)		(0.003)	(0.003)
index volatility	0.334**	0.332***	0.219***	0.096*	0.049	0.024	−0.007	−0.049
	(0.133)	(0.075)	(0.066)	(0.057)	(0.127)	(0.086)	(0.058)	(0.066)
VIX	0.001***	0.002***	0.001***	0.001***	0.002***	0.002***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.001)	(0.0003)	(0.0002)	(0.0002)
small		0.033***				0.251***		
		(0.003)				(0.005)		
large × crisis		0.008**				0.005		
		(0.004)				(0.004)		
small × crisis		0.053***				0.036***		
		(0.006)				(0.008)		
large × post-crisis		0.008***				0.020***		
		(0.003)				(0.004)		
small × post-crisis		0.020***				−0.0005		
		(0.004)				(0.007)		
large × post-reg		0.039***				0.084***		
		(0.002)				(0.003)		
small × post-reg		0.034***				−0.044***		
		(0.004)				(0.006)		
Constant	0.044***	0.031***	0.007**	0.016***	0.200***	0.161***	0.178***	0.157***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.007)	(0.004)	(0.004)	(0.004)
dealer f.e.			Yes	Yes			Yes	Yes
$\beta_4 - \beta_3$	0.022***		0.032***	0.022***	0.041***		0.034***	0.044***
$\beta_{large,4} - \beta_{large,3}$		0.03***				0.064***		
$\beta_{small,4} - \beta_{small,3}$		0.014***				-0.043***		
Observations	2,300	4,600	25,149	25,149	2,300	4,600	26,282	26,282
R^2	0.305	0.341	0.658		0.263	0.673	0.470	

Table 8: **Regression of Bid-Ask Spreads on Pre- and Post-Regulation Dummy Variables**

This table provides the estimation results from the following regressions:

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

where $spread_{i,t}$ is one of the following four trading cost measures for bond i on day t: the IRC_C, the IRC, the same-day spread, and *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, $\mathbb{1}(t \in T_l)$, indicate the four subperiods. $\mathbb{1}(T_1)$ 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. Panel (a) and (c) present the results for investment grade bonds, and Panel (b) and (d) present the results for high-yield bonds. Panel (c) and (d) regressions do not control for bond characteristics. In each panel, we report $\beta_4 - \beta_3$, which is the difference between the coefficient for post-regulation dummy and the coefficient for post-crisis dummy. The sample period is from 2006 to 2015 and we restrict the sample to trades over $1 million. Standard errors are double clustered by bond and date. *, **, and *** denote statistical significant at the 10%, 5%, and 1% levels, respectively.

(a) **Investment Grade Bonds**

	IRC_C (1)	IRC (2)	same-day (3)	invt>15min (4)
crisis	8.201***	7.917***	12.170***	18.316***
	(0.658)	(0.497)	(0.680)	(1.207)
post-crisis	0.510	2.352***	4.414***	8.829***
	(0.421)	(0.326)	(0.412)	(0.739)
post-regulation	0.853***	2.370***	6.501***	12.678***
	(0.329)	(0.260)	(0.328)	(0.571)
log(avg size)	−0.752***	−2.456***	−1.826***	−0.775***
	(0.109)	(0.091)	(0.106)	(0.200)
log(outstanding)	−5.727***	−4.249***	−3.170***	−10.465***
	(0.215)	(0.198)	(0.258)	(0.408)
rating	0.131**	0.105**	−0.179***	−0.137
	(0.063)	(0.054)	(0.065)	(0.106)
age	0.018***	0.016***	0.010*	0.033***
	(0.006)	(0.005)	(0.005)	(0.013)
log(age)	2.041***	1.680***	2.706***	6.655***
	(0.232)	(0.186)	(0.195)	(0.373)
time-to-maturity	0.010***	0.003	0.010***	−0.008*
	(0.003)	(0.002)	(0.003)	(0.004)
log(time-to-maturity)	4.991***	5.558***	8.636***	14.392***
	(0.209)	(0.171)	(0.212)	(0.419)
index volatility	63.350***	62.700***	88.419***	141.560***
	(11.527)	(9.407)	(11.360)	(20.797)
VIX	0.561***	0.475***	0.803***	1.145***
	(0.027)	(0.023)	(0.027)	(0.051)
Constant	52.631***	48.325***	11.513***	62.928***
	(3.251)	(2.939)	(3.951)	(6.087)
$\beta_4 - \beta_3$	0.343	0.018	2.087***	3.85***
Observations	84,293	152,113	344,359	429,682
R^2	0.267	0.211	0.180	0.064

(b) **High Yield Bonds**

	IRC_C (1)	IRC (2)	same-day (3)	invt>15min (4)
crisis	3.668***	3.600***	4.898***	9.634***
	(0.618)	(0.588)	(0.631)	(1.386)
post-crisis	−2.056***	−1.097**	−1.905***	3.514***
	(0.528)	(0.501)	(0.516)	(1.111)
post-regulation	−0.980**	0.307	1.159***	10.199***
	(0.438)	(0.427)	(0.419)	(0.943)
log(avg size)	0.920***	0.099	−0.098	0.185
	(0.138)	(0.133)	(0.163)	(0.437)
log(outstanding)	−3.581***	−3.414***	−2.641***	−10.097***
	(0.252)	(0.242)	(0.294)	(0.623)
rating	2.250***	2.063***	1.412***	0.884***
	(0.088)	(0.084)	(0.092)	(0.165)
age	0.006	0.018**	0.008	0.096***
	(0.008)	(0.008)	(0.009)	(0.025)
log(age)	1.008***	0.969***	0.977***	0.902
	(0.257)	(0.249)	(0.256)	(0.591)
time-to-maturity	0.017***	0.018***	0.029***	0.039***
	(0.003)	(0.003)	(0.005)	(0.008)
log(time-to-maturity)	3.288***	3.110***	2.781***	3.502***
	(0.369)	(0.340)	(0.442)	(0.925)
index volatility	44.630***	43.191***	61.018***	73.687***
	(11.705)	(11.110)	(10.463)	(22.060)
VIX	0.623***	0.623***	0.682***	0.935***
	(0.045)	(0.043)	(0.042)	(0.083)
Constant	−1.483	5.731	9.373*	106.696***
	(4.371)	(4.233)	(5.183)	(10.112)
$\beta_4 - \beta_3$	1.076**	1.404***	3.064***	6.685***
Observations	107,794	130,186	333,476	224,427
R^2	0.199	0.178	0.094	0.022

(c) **Investment Grade Bonds: Without Bond Characteristics Controls**

	IRC_C (1)	IRC (2)	same-day (3)	invt>15min (4)
crisis	7.567***	7.547***	11.688***	16.534***
	(0.704)	(0.535)	(0.682)	(1.152)
post-crisis	−0.554	1.650***	3.597***	5.610***
	(0.467)	(0.352)	(0.439)	(0.735)
post-regulation	−0.571	1.603***	5.896***	10.120***
	(0.363)	(0.284)	(0.365)	(0.591)
log(avg size)	−1.273***	−2.939***	−2.209***	−2.037***
	(0.121)	(0.098)	(0.125)	(0.223)
index volatility	60.364***	63.131***	92.252***	124.279***
	(11.968)	(9.823)	(11.664)	(20.761)
VIX	0.562***	0.465***	0.779***	1.082***
	(0.028)	(0.024)	(0.028)	(0.051)
Constant	11.158***	25.207***	18.137***	13.441***
	(1.140)	(0.907)	(1.182)	(2.047)
$\beta_4 - \beta_3$	-0.017	-0.047	2.299***	4.51***
Observations	84,293	152,113	344,359	429,682
R^2	0.136	0.105	0.090	0.029

(d) **High Yield Bonds: Without Bond Characteristics Controls**

	IRC_C (1)	IRC (2)	same-day (3)	invt>15min (4)
crisis	2.445***	2.538***	3.817***	6.821***
	(0.638)	(0.618)	(0.630)	(1.343)
post-crisis	−4.250***	−3.134***	−3.481***	−0.451
	(0.569)	(0.547)	(0.520)	(1.045)
post-regulation	−4.973***	−3.448***	−1.574***	3.637***
	(0.507)	(0.497)	(0.439)	(0.874)
log(avg size)	0.148	−0.375**	−0.945***	−2.246***
	(0.156)	(0.146)	(0.174)	(0.444)
index volatility	40.242***	39.685***	57.614***	64.902***
	(11.784)	(11.174)	(10.522)	(22.211)
VIX	0.589***	0.596***	0.662***	0.891***
	(0.046)	(0.043)	(0.043)	(0.085)
Constant	13.196***	16.443***	21.585***	31.792***
	(1.444)	(1.352)	(1.618)	(3.841)
$\beta_4 - \beta_3$	-0.722	-0.314	1.907***	4.087***
Observations	107,794	130,186	333,476	224,427
R^2	0.130	0.114	0.074	0.012

Table 9: **Regression of Spread Differences on Pre- and Post-Regulation Dummy Variables**

This table presents the estimation results from the regression

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

where $\text{diff}_{i,t}$ is the difference between $y_{i,t}$ and *spread1* calculated using invt>15min trades only. $y_{i,t}$ is one of the three trading cost measures: IRC_C, IRC, or same-day spread. 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. $\mathbb{1}(T_1)$ 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. The sample period is from 2006 to 2015. We only include in our sample bond-day observations with available trading cost measures. Standard errors are double clustered by bond and date. *, **, and *** denote statistical significant at the 10%, 5%, and 1% levels, respectively.

	without controls			with controls		
	IRC_C	IRC	same-day	IRC_C	IRC	same-day
	(1)	(2)	(3)	(4)	(5)	(6)
crisis	−13.629***	−17.780***	−4.673***	−2.251	−3.667**	−0.862
	(2.183)	(1.521)	(0.562)	(2.434)	(1.657)	(0.630)
post-crisis	−7.465***	−6.543***	−1.717***	−1.921	0.443	0.201
	(1.462)	(0.952)	(0.379)	(1.802)	(1.140)	(0.429)
post-regulation	−7.846***	−5.329***	−1.451***	−6.203***	−3.753***	−1.007***
	(1.375)	(0.871)	(0.346)	(1.404)	(0.885)	(0.346)
index volatility				−116.329***	−63.085**	−17.040*
				(39.822)	(28.263)	(10.130)
VIX				−0.261**	−0.524***	−0.144***
				(0.124)	(0.083)	(0.031)
Constant	−4.535***	−5.480***	−0.224	1.262	2.724**	2.012***
	(1.209)	(0.744)	(0.311)	(1.834)	(1.203)	(0.465)
$\beta_4 - \beta_3$	-0.381	1.214*	0.266	-4.281***	-4.196***	-1.208***
Observations	39,107	76,493	247,655	39,107	76,493	247,655
R^2	0.002	0.004	0.001	0.004	0.007	0.001

Appendix

A Identifying Trades with Affiliates

Adrian, Boyarchenko and Shachar (2017) notes that there is an increasing practice of dealers transferring bonds to their non-FINRA affiliates for bookkeeping purposes. These trades usually appear as the dealer trading with a counterparty, and then trading with the 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 fraction of DC-DC or DC-ID trades. Moreover, Bessembinder et al. (2017) notes that there is one relatively large dealer that offloads most of its principal trades immediately to its affiliate starting in 2014.[15] This could appear as an increase in the fraction 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 from the data.

We assume that if there are two offsetting trades in the same bond by the same dealer with the same volume and price within one minute from each other, that one side is a 'bookkeeping' trade, or in other words, a trade with an affiliate. Unless one of the trades was internal or 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 to October 15, 2016, during which, 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

[15] Bessembinder et al. (2017) excludes this dealer. Adrian, Boyarchenko and Shachar (2017) writes that they use an algorithm to identify and clean affiliate trades.

one side is with an affiliate. We classify trades into three types: matched with another trade in the same second, matched with another trade within one minute but not the same second, and unmatched. Next, using the 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 $\mathbb{1}(A) = 1$ (0 otherwise). For each of the three categories, we calculate the average and value-weighted $\mathbb{1}(A)$.

Results are provided in Table A.1. Our algorithm performs with high accuracy, and allowing the time difference up to one minute seems reasonable, especially for the large trade category that we focus on in the paper. For example, for trades \$1 million and larger, 99% of trades identified as $\mathbb{1}(A) = 1$ using the same second criterion are classified correctly, and 80% of trades identified as $\mathbb{1}(A) = 1$ that are not in the same second but within one minute are classified correctly. Only about 5% of trades that are categorized as $\mathbb{1}(A) = 0$ 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 to find which side is with an affiliate. Hence, we delete both sides to be consistent. Figure 1 plots the fraction of volume that is identified as affiliate trades. (We divide the volume of trades that are identified as $\mathbb{1}(A) = 1$ by two in the figure, and thus, in cleaning the data, twice the volume plotted are deleted.) 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 mostly translate into an increase in DC-DC trades.

B Dealer Profit in Short-Holding Trades

In Table A.2, 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 mainly customers seeking liquidity and the second dealers providing liquidity, then dealer matching the trades should generally profit more from DC-DC trades. This is because dealers should be able to obtain spreads from both sides in DC-DC trades, but only from 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 difference in dealer sell prices and dealer buy prices. Unit is in basis points, per $100 par value. We also winsorize the profit at 1% level. We then run the regression

$$profit_{i,j,t,k} = \beta_2 \mathbb{1}(DC - ID)_k + \epsilon_{i,j,t,k} \tag{11}$$

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.

Results in Table A.2 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 of DC-DC trades mainly consisting of dealers matching liquidity-seeking buyers and liquidity-seeking sellers.

Additionally, these results help us understand why in Section 4.2, despite the fact that IRC calculations put a relatively high weight on DC-ID trades, IRC measures are low.

Comparing the results in Table 3 and Table A.2, DC-ID trades have approximately 35 bps higher average spreads than DC-DC trades, but the dealer that match the trades make only 1 bp more in the DC-ID trades. The second dealer that provides liquidity is receiving the rest. Because IRC measures the profits that dealers make on short-holding trades, IRC values are not higher despite the high weight on DC-ID trades.

Table A.1: **Performance of the Algorithm That Identifies Trades With Affiliates** This table presents the performance for 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, 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: matched with another trade in the same second, matched with another trade within one minute but not the same second, and unmatched. Next, using the 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 $\mathbb{1}(A) = 1$ (0 otherwise). For each of the three categories, we calculate the average and value-weighted $\mathbb{1}(A)$.

Algorithm classification	$avg(\mathbb{1}(A))$	$vwavg(\mathbb{1}(A))$	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 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: **Regressions of Dealer Profits for Short-Holding Trades**
Following table presents the results from the regression

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

where $profit_{i,j,t,k}$ 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 \$1 million and larger. $\mathbb{1}(\text{DC-ID})_k$ 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. Standard errors are double clustered by bond and date. *, **, and *** denote statistical significant at the 10%, 5%, and 1% levels, respectively.

	IG		HY	
	(1)	(2)	(3)	(4)
$\mathbb{1}$(DC-ID)	0.652***	0.761***	1.418***	1.060***
	(0.172)	(0.149)	(0.148)	(0.134)
log(outstanding)	−2.404***		−2.036***	
	(0.172)		(0.127)	
log(volume)	−1.737***	−1.702***	−1.308***	−1.236***
	(0.077)	(0.068)	(0.057)	(0.052)
rating	0.029		0.523***	
	(0.051)		(0.034)	
age	0.025***		0.012***	
	(0.005)		(0.004)	
log(age)	1.429***	1.962***	−0.087	0.126
	(0.167)	(0.156)	(0.128)	(0.128)
time-to-maturity	0.003		0.006***	
	(0.002)		(0.002)	
log(time-to-maturity)	6.780***	5.681***	2.048***	5.555***
	(0.182)	(0.191)	(0.241)	(0.330)
index volatility	75.775***		25.553***	
	(9.010)		(4.565)	
VIX	0.432***		0.266***	
	(0.018)		(0.014)	
dealer f.e.	Yes	Yes	Yes	Yes
cusip, date f.e.	No	Yes	No	Yes
Observations	330,366	330,366	476,358	476,358
R^2	0.352	0.461	0.183	0.267