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Customer Liquidity Provision: Implications for Corporate Bond Transaction Costs*

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Abstract

The convention when 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 following the adoption of post-2008 banking regulations and, thus, conventional bid-ask spread measures underestimate the cost of dealers' liquidity provision. Among large trades wherein dealers use inventory capacity, customers pay 40 to 60 percent wider spreads than before the crisis. Customers' balance-sheet capacity and their trading relationships with dealers are important determinants of customer liquidity provision.

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1 Introduction

The banking regulations imposed following the 2008 financial crisis, such as stricter capital requirements and the Volcker Rule, have increased inventory costs for dealers in the corporate bond market. Dealers that experienced a decline in their risk-bearing capacity have reduced liquidity provision to customers.[1] Instead, dealers increasingly prearrange customer trades in so-called riskless principal trades (RPTs), wherein dealers almost simultaneously match customers who trade in opposite directions, thus avoiding taking customer orders on their inventories.[2] Nevertheless, broad priced-based measures of transaction costs do not show liquidity deterioration despite weaker liquidity provision to customers.[3] If dealers reduce liquidity provision, do customers then fill this gap in market liquidity? What explains liquidity provision by customers and what are the implications for transaction costs in the corporate bond market? These are fundamental issues that must be considered if we are to understand the transitioning nature of liquidity in the post-crisis corporate bond market.

We show that customers, rather than dealers, increasingly provide liquidity to other customers and thus fill the liquidity gap arising from weaker liquidity provision by dealers. Customer liquidity provision (CLP) is concentrated in short-horizon paired trades that dealers match without using their inventory capacities. In these trades the customers in the second leg of the paired trades provide liquidity to customers in the first leg who demand liquidity. Moreover, conventional transaction-cost measures place heavy weight on trades in which customers provide liquidity and, as a result, these measures understate the cost of immediacy. In fact, the cost of immediacy 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. These results can also help explain why studies so far have found that bid-ask spreads in

[1] Bessembinder, Jacobsen, Maxwell and Venkataraman (2018) and Bao, O'Hara and Zhou (2018), for example, show that dealers commit less capital and provide weaker liquidity in the post-crisis period.

[2] Previous studies that examine prearranged trades include Zitzewitz (2010), Harris (2015), Ederington et al. (2014), and Schultz (2017).

[3] Trebbi and Xiao (2017) and Anderson and Stulz (2017), for example, show that bid-ask spreads has not widened under the new banking regulations.

the post-regulation periods are not wider despite dealers' lower risk capacity.

Once we show the importance of CLP in post-regulation market liquidity, we directly examine which economic forces drive CLP. Our results provide insights into when and why customers provide liquidity. Customers that face lower capital constraints and customers with ample liquidity reserves provide more liquidity. Trading relationships also matter; dealers tend to ask relationship customers for liquidity provision when they face incoming liquidity-demanding trades. These results are novel and new to the literature, which can also serve as a useful guidance to future studies.

The key advantage of our paper is that we are able to identify those who demand liquidity by exploiting the unique regulatory Trade Reporting and Compliance Engine (TRACE) database that provides the identities of corporate bond dealers. It has been the case in the equity market 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 reflecting the over-the-counter nature of the market.[4] We argue that this is not always a reliable way of identifying those who demand immediacy, particularly because of the decline in liquidity provision by dealers in the post-regulation period. The usual market liquidity measures encounter an underestimation problem because they treat liquidity-providing trades from customers as liquidity-demanding and such liquidity-providing trades involve much narrower spreads.

Using dealer identifiers and counterparty pair types in our 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 customers in the latter trades provide liquidity. In such cases, the dealer does not use his inventory capacity and is only an agent. Consistent with our hypothesis, we observe that the liquidity-providing customers tend to pay much lower spread or even negative spreads. We also find this effect to be

[4]For example, two of the most commonly used liquidity measures are dealers' average round-trip profits for positions held over short periods 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).

stronger when liquidity-providing customers buy, consistent with the post-crisis trend that large asset managers are increasingly stepping in to provide liquidity.[5]

Building on these findings, we develop a transaction-cost measure for trades in which dealers use inventory capacity for customers who demand immediacy from dealers. In particular, we calculate transaction costs by focusing only on DC trades that are not matched with another DC trades within the next 15 minutes, because in such trades dealers use their inventory capacity for customers who demand immediacy. 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 each trade and measure the trading costs for those trades.

With our measures of transaction costs in hand, we examine the extent to which trading costs have increased following the post-crisis regulations. We find that the cost of immediacy paid to dealers has risen substantially. For example, trading costs after July 2012 for large DC trades that are not subsequently matched increase by 40%–60% compared with trades in the pre-crisis period and by 10%–30% compared with trades in the 2009–2012 period.[6] 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 reductions in liquidity or show only mild reductions following the implementation of the post-crisis regulations. This is because these measures treat CLP trades as trades in which customers demand liquidity and thus underestimate liquidity costs.

Next, we examine how CLP is associated with dealers' inventory capacity by exploiting dealer identities reported in our data, enabling us to examine cross-sectional and time-series variation in CLP in response to the differential impacts of the banking regulations across dealers. We show that, in a substantially higher fraction of trades, customers provide liquidity in place of dealers after the regulations took effect. More importantly, the fraction of trades that are associated with CLP 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 5.6 percentage points for

[5]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). 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`)

[6]We focus on customer trades of $1 million or larger because regulations should affect primarily large trades.

Volcker-affected dealers, whereas it decreased by 7.7 percentage points for non-Volcker dealers. These results show that customers increasingly fill the liquidity gap, complementing the previous results that trading costs remain low despite lower dealer risk capacity.

Finally, to further understand the underlying economic drivers, we examine what explains CLP by exploiting insurers' trade- and balance-sheet-level information obtained from National Association of Insurance Commissioners (NAIC) data, which we carefully match with our TRACE data on a transaction-by-transaction basis to identify CLP by insurance companies. We find that the regulatory capital constraints that insurance companies face are strongly and negatively associated with CLP, suggesting that capital capacity is an important driver of liquidity provision for customers. We also find that dealers tend to ask their relationship customers for liquidity provision, as evidenced by the importance of dealer-customer trading links in explaining CLP. Customers manage inventories of their bonds when providing liquidity, as we find that customers tend to buy (sell) more for liquidity provision when their inventories of the bonds are low (high). CLP is also stronger for illiquid bonds and also for bonds that experience fire-sale pressure from other customers. For bonds that are sold heavily following mutual fund outflows, we find stronger CLP by insurers. In comparison, when a bond is downgraded and insurers face pressure to meet higher capital requirements, we find weaker liquidity provision by insurers, which is consistent with the capital-capacity story of CLP.

Summing up the results, we find that customers are more likely to provide liquidity when they they are less capital-constrained, when they have higher liquidity reserves, when they trade with their relationship dealers, and when bonds that experience liquidity deterioration are involved. These results are all consistent with the notion that customers provide liquidity through matched trades wherein dealers play only the matching role without using their inventory capacity.

Related literature. This paper makes important contributions to the growing empirical literature that studies the impact of post-crisis regulations on corporate bond market liquidity.[7] Prior studies in the literature find that dealers have reduced capital committed to market-making

[7]Several theoretical papers also examine the effects of regulations on market liquidity. Cimon and Garriott (2019) argue that the Volcker Rule and capital regulations motivate dealers to switch to trading on an agency basis. Üslü (2019) finds that the welfare impact of the Volcker Rule is not clear.

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. These papers conclude that while non-bank dealers have increased their liquidity provision somewhat, overall liquidity provision has declined. 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.

Bao et al. (2018), Anderson and Stulz (2017), and Dick-Nielsen and Rossi (2019) focus on specific market-stress or liquidity events such as bond downgrades, extreme VIX increases, and index exclusions and show that liquidity during those events has worsened in the post-regulation period. While these results are certainly consistent with dealers' committing less capital, it is unclear why the effect on trading costs would only appear during such market stress or liquidity events while the reduction in dealers' capital commitment is not confined to those times. Our results show that the cost of immediacy has also increased during non-stress periods. Also, relying on market stress or liquidity events to measure the cost of immediacy is often not practical because they happen infrequently—for instance, in monitoring liquidity for regulatory purposes or in academic studies in which we need daily or more frequent liquidity measures. Hence, many recent academic papers still use IRC or differences between customer buy and sell prices as a measure of the cost of immediacy. We propose a high-frequency measure of the costs of demanding liquidity without using specific market stress or liquidity events that can be easily used.

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 strong propensity to offset trades for riskier and less actively traded bonds and optimally adjust their inventory. 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 CLP on common measures of liquidity. Moreover, the aforementioned studies implicitly assume that a set of matched customer trades consists of two customers that demand liquidity in opposite directions, whereas we show that these types of trades contain a high fraction of CLP where the first customer demands liquidity and the second customer provides it.

2 Data and Variable Construction

2.1 Data Description

Our 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 by the counterparty code "C" only.[8] 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 the Internet Appendix IA.1 and Figure IA.1.[9]

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 (IG) bonds and High Yield Master II Index for high-yield (HY) bonds.

Our sample period runs from January 2006 through December 2016.[10] MTNs, 144As, exchangeable bonds, and bond-days that occur less than 30 days since issuance are excluded. We restrict the

[8]Dealers are identified by Market Participant Identifiers (MPIDs). Dealers may have multiple MPIDs for subsidiaries or change MPIDs following 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 entities with the same MPID2.

[9]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.4 in 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 excluding trades by client brokers and interdealer traders.

[10]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.

sample to secondary-market trades that are marked as principal trades. Our final cleaned sample consists of 18,041 bonds with a total of 48,420,607 trades (including duplicate interdealer trades), of which 4,861,241 are customer trades at par values of $1 million or higher.

We also supplement TRACE data with NAIC insurance company data to obtain customer information, which we mainly utilize in Section 4. Specifically, we obtain insurance company transaction data from Schedule D filing, which captures variables such as customer (insurance company) identifier, date, volume, and transaction price. We also obtain annual balance-sheet items such as total assets, cash and cash-like security ratios, and risk-based capital (RBC) ratios from the NAIC. The NAIC-TRACE matching process is detailed in the Internet Appendix IA.2.

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-dealer with an inventory of zero. Each incoming customer trade (e.g., a customer sell) with a dealer is accumulated in the dealer's inventory and is matched later with outgoing trades (e.g., the dealer selling to another dealer or a customer) when it leaves the inventory. Inventory holding periods are calculated based on how long dealers hold 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 inventory trades, which have inventory holding periods of greater than 15 minutes.[11] Section A of the Appendix details the inventory holding period calculation and customer trade classification, and Table A.1 in the Appendix provides an example. We use 15 minutes as the holding-period cutoff 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

[11] Note that both customer trades that are matched in a trade pair are classified as DC-DC trades. A customer trade matched with an interdealer trade is classified as a DC-ID trade regardless of whether the customer trade occurs before or after the interdealer trade. See Figure 1 for an illustration of DC-DC and DC-ID trades.

qualitatively similar.[12]

In Table 1(a) we report the fractions of DC-DC, DC-ID, and inventory 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 HY bonds with trade volumes under \$100,000, there are approximately eight times more DC-ID trades than DC-DC trades. Hence, earlier papers that have studied matched trades (Zitzewitz, 2010, Ederington, Guan and Yadav, 2014) have concentrated mostly on DC-ID trades, as they do not condition on trade size.[13] 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*, is defined as follows for each trade:

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

where Q is $+1$ for a customer buy and -1 for a customer sell. For each customer trade (i.e., DC-DC, DC-ID, and inventory trades), we calculate its reference price as the volume-weighted average price of interdealer trades larger than \$100,000 in the same bond-day.[14] *Spread* is calculated at the trade level for all customer trades of \$1 million and larger and is also calculated at the bond-day level by taking the volume-weighted average of trade-level spreads.

The calculation of *Spread* relies on accurate estimation of reference prices, or the fundamental

[12] In Section IA.7 of the Internet Appendix, we show that trade classifications largely remain the same when we use longer inventory accumulation periods (5 days, 20 days, continuous) and when we accumulate the inventory in reverse direction.

[13] Our short-holding trades include RPTs in Harris (2015), which are defined as matched trades in opposite directions that occur within one minute. More than half of our short-holding trades, however, are not RPTs among large trades of \$1 million and above (e.g., their holding periods are longer than 1 minute). See Section IA.3 of the Internet Appendix for the details.

[14] Because interdealer trades tend to be smaller, we use the \$100,000 cutoff instead of \$1 million. We also exclude interdealer trades that occur within 15 minutes of the customer trades. The results are qualitatively similar if we do not exclude such interdealer trades.

values. While it is common to use midpoints from the best bid and ask quotes for the fundamental value of assets, the TRACE data provide only recorded transactions and midpoints of dealer bid and ask quotes are not readily available for assets traded in the OTC markets. Our approach is to proxy the reference prices using interdealer prices, as these prices are more likely to be stay within the bid-ask spreads than transactions involving customers and also they are more readily available from the TRACE data. Potential drawbacks of this approach, however, are that they may also deviate from the fundamental values and that interdealer prices can be missing for some days and bonds.

To address these potential issues in reference prices, we perform several robustness checks to show that our results involving *Spread* are not sensitive to our choice of reference prices. In our first set of robustness checks provided in Section IA.5 of the Internet Appendix, we employ as reference prices the midpoints of dealer bid-ask quotes from Thomson Reuters Datascope and Refinitive Eikon, which are often used as major sources of bond pricing by many Wall Street firms to mark their books to market, and show that our main results are qualitatively similar.[15] These robustness checks substantially alleviate the concern that our results are driven by measurement errors or sample bias involving reference prices, because the midpoints based on these quotes are affected to a lesser extent by price pressure in the inter-dealer market and also because these dealer quotes are largely available even for days when interdealer transaction prices are not available.

To examine the extent to which CLP affects spread estimation, we also calculate the following measures that are commonly used in the literature. The first is the IRC from Feldhütter (2012). *IRC* measures dealers' round-trip costs for imputed round-trip trades (IRTs).[16] 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 minimum prices for the IRT set k. vol_k is the volume for

[15] We also employ dealer quotes from the Merrill Lynch bond database and report similar results in the Internet Appendix. The coverage of the Merrill Lynch bond database is less extensive than that of Datascope and Refinitive.

[16] We define IRT following Feldhütter (2012). Specifically, trades constitute IRTs if two or three trades of a given trade size are executed less than 15 minutes apart.

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

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

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 with par values of $1 million and above (except for the interdealer trades used in *Spread* 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.

3 Customer Liquidity Provision

In this section we first establish that customers provide liquidity in DC-DC trades whereby the first customer in the matched DC-DC pair demands liquidity and the second customer in the pair provides it. In those trades, liquidity-providing customers tend to pay much lower spreads than liquidity-demanding customers. We then explore the implications of CLP for usual trading cost measures frequently employed in literature and show that, because of increased CLP in the post-crisis period, the usual measures can underestimate the cost of immediacy taken from dealers.

3.1 Do DC-DC Trades Have Narrower Average Spreads?

Liquidity-providing customers will be compensated by having to pay only small or even negative spreads. The chart provided in Figure 1 illustrates which customers provide liquidity in a matched DC-DC trade pair. In Panel A the selling customer (C1) in the first DC-DC trade demands liquidity, as she initiates the trade with the dealer (D), while buying customer (C2) in the second DC-DC trade provides liquidity.

When the liquidity-providing customer buys, she will tend to buy at lower prices than the fundamental value and pay negative spreads. Likewise, the liquidity-providing customer will tend to sell at higher prices and also pay negative spreads. Thus, to the extent that DC-DC trades are instances where one customer provides liquidity, we expect DC-DC trades to have narrowest average bid-ask spreads and the largest fraction of negative spreads. If neither customers provide liquidity in DC-DC trades, however, 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.[17] Relatedly, to the extent that DC-ID trades are cases where the customer demands liquidity and the second dealer provides liquidity as shown in Panel B of Figure 1, the DC-ID customer trades will have wider spreads.

3.1.1 Average Spreads: Simple Statistics

We begin by examining average customer spreads and the fraction of negative-spread trades for each trade type. Table 1(b) shows that average spreads are narrowest for DC-DC trades and widest for DC-ID trades. In IG bonds, for example, the average *Spread* estimates for DC-DC, inventory, and DC-ID trades are 16.33 bps, 32.38 bps, and 56.50 bps, respectively. DC-DC trades also involve the largest fractions of negative spreads, as shown in Table 1(c). Moreover, within DC-DC trades, customer buys include a higher fraction of negative spreads than customer sells do: 42.88% of DC-DC customer buys have negative spreads, while only 34.67% of customer sells are negative-spread trades. This result is consistent with the notion that typical customers find it costly to have net short positions and do not necessarily hold inventories in all outstanding bonds, hence, will be more likely to provide liquidity through buying than through selling.

3.1.2 Regression Analyses of Spreads

In Panel (a) of Table 2, we examine whether DC-DC trades have narrower spreads than the other trade types in a regression setting that includes control variables and fixed effects. We run the

[17] Section IA.8 of the Internet Appendix 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 higher for DC-DC trades.

following model:

$$Spread_{i,j,t,k} = \alpha + \beta \mathbb{1}(\text{DC-DC})_k + \gamma \mathbb{1}(\text{DC-ID})_k + \epsilon_{i,j,t,k} \tag{4}$$

where $Spread_{i,j,t,k}$ is the spread measure defined in (1), of trade k between dealer j and a customer for bond i on day t. $\mathbb{1}(\text{DC-DC})_k$ and $\mathbb{1}(\text{DC-ID})_k$ are dummy variables indicating whether customer trade k is a DC-DC trade or a DC-ID trade, and the dummy variable for inventory trades forms the base level. We include control variables that are known to be associated with transaction costs such as trade size, bond age, and time to maturity, as well as bond, dealer, and time fixed effects.

The results reported in Table 2(a) show that DC-DC trades involve narrower spreads than DC-ID and inventory trades. As can be seen in column (1), for example, spreads of DC-DC trades for IG bonds are approximately 13.0 bps lower than spreads for inventory trades and approximately 34.1 bps lower than DC-ID spreads, confirming the previous results reported in Table 1(b). In comparison, the coefficient estimates for DC-ID trades indicates that spreads for DC-ID trades are higher than spreads for the other trade types. Note that DC-ID trades have the widest spreads, suggesting that customers in these trades likely take liquidity while the matching dealers pass the trades on to the second dealers, who provide liquidity. In fact, Appendix IA.8 shows that the matching dealers in DC-ID pairs actually do not earn higher profits than matching dealers in DC-DC trades.

We run the regressions separately for customer buy and sell trades and report the results in columns (2), (3), (5), and (6). If DC-DC trades reflect customer liquidity provision, they would more likely be associated with buy trades, as customers are more likely to provide liquidity on the buy side than on the sell side. In IG bond regressions, for example, the difference in spreads for inventory trades and DC-DC trades are 17.1 bps and 6.1 bps for customer buys and sells, respectively. The differences between DC-ID and DC-DC trades are also larger for customer buys (42.2 bps) than for customer sells (23.2 bps).

In the Internet Appendix we present several robustness checks of the results provided in Table 2. First, we use mid-points from dealer bid-ask quotes obtained from the Datascope and Eikon databases as reference prices to alleviate the concern that measurement errors in interdealer prices as reference prices drive the results. The mid-points based on dealer quotes are available for a larger set of bond-days than interdealer prices, further alleviating sample selection concerns associated with the limited availability of interdealer prices. Second, in Section IA.3 of the Internet Appendix, we also address the concern that there might be false-positive categorizations of matched trades in our trade-classification algorithm. Specifically, we separate out DC-DC trades into those held in dealers' inventories for less than one minute and those held for periods of between one and fifteen minutes and show that both types of DC-DC trades involve high fractions of CLP. Since DC-DC trades matched within one minute are less likely to mis-matched, this robustness check alleviates the concern that trade mis-classification might drive our results.[18]

3.1.3 Regression Analysis: Liquidity-Demanding Versus Liquidity-Providing Trades

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 order and trade direction in matched pairs of DC-DC trades. In-trades are defined as the first legs of a DC-DC trade pairs (i.e., the trades that arrive first), while out-trades are those in the second legs of the trade pairs (i.e., the trades that occur next). We expect to find that DC-DC in-trades tend to demand liquidity while DC-DC out-trades provide liquidity. We thus regress DC-DC spreads on dummy variables indicating out-trades while controlling for customer buy trades, and present the results in Panel (b) of Table 2.

The results reported in Table 2(b) show that spreads are narrower for DC-DC out-trades, further indicating that DC-DC out-trades include large fractions of trades in which customers provide liquidity. In column (1) for IG bonds, for example, we find that the coefficient estimate for the DC-DC out-trade indicator is -8.6 and statistically significant at the 1% level, showing that spreads are lower for the second legs of DC-DC pairs. In columns (3) through (6), we provide the results of subsample analyses for DC-DC trade pairs matched within one minute and those matched between one and fifteen minutes. While the results are qualitatively similar across these

[18] Another alternative hypothesis is that the greater bargaining power of large customers might drive the results that we document in Table 2. In Table IA.19 of the Internet Appendix, we show that the spreads of large customers' DC-DC trades are not particularly narrower than those of other customer trades, using the NAIC insurance company data.

two subsamples, we find that the economic magnitudes of the coefficient estimates for the out-trade indicators tend to be smaller for trades matched in short time horizons (i.e., matched within one minute), perhaps because the orders of trades that are matched within one minute can be noisy.[19]

3.1.4 Implications of CLP for Trading Cost Measures

What would be the implications of the results documented so far for bid-ask spread measures commonly used in the literature? Because DC-DC trades include higher fractions of CLP trades, bid-ask measures that include disproportionately high fractions of DC-DC trades can underestimate the cost of immediacy paid by customers. To examine this issue, we examine the fractions of DC-DC, DC-ID, and inventory trades that are involved in calculating *IRC_C*, *IRC*, *same_day*, and *Spread*.

Table 3 shows the results. In IG bonds, for instance, DC-DC trades make up 83% of the *IRC_C* calculation, 62% of the *IRC* calculation, and 21% of the *same_day* calculation, while they account for only 8% of the *Spread* calculation. By construction, IRTs used to calculate *IRC_C* and *IRC* are mostly DC-DC trades. *Same_day* also includes disproportionately more DC-DC trades, because both customer-buy and customer-sell trades are necessary to calculate *same_day*, implying that all DC-DC trades will be included while many inventory trades will be excluded from *same_day* calculations.

These results suggest that commonly-used bid-ask spread measures underestimate the cost of immediacy paid by customers. Moreover, even when the cost of liquidity increases over time, spread measures involving high fractions of DC-DC trades may not properly reflect the increases if CLP has also increased.

[19] The results also hold when we consider DC-DC trades matched within 1 minute and those matched between 1 and 15 minutes separately. Also, the criticism in Hu (2009) that market movements may dominate bid-ask spread measures is irrelevant here because our reference price is neither a pre-trade nor a post-trade price but is a 'during-trade' price. Hu (2009) shows that bid-ask spread measures based on 'during-trade' reference prices are neutral to market movements. In Tables IA.14 and IA.15 of the Internet Appendix, we perform additional tests by calculating reference prices in two separate ways, using interdealer trades within one hour around the trade and excluding one hour around the trade, and replicate Table 2. We find similar results in both of the tests.

3.2 The Effects of Customer Liquidity Provision on Trading-Cost Measures: Evidence from the Post-Crisis Banking Regulations

The post-crisis banking regulations have reduced the balance-sheet capacities and capital commitments of dealers. The implementation of those regulations provides us with a nice setting in which to examine variations in CLP in both the time series and cross section and its impact on trading-cost measures. Dealers who are affected heavily by the regulations may prefer matching customer trades over using up their balance-sheet capacities, which could provide customers with additional opportunities to provide liquidity. In this section we thus examine CLP and bond-transaction costs, focusing on time periods around the implementations of the post-crisis banking regulations.

3.2.1 Customer Liquidity Provision Has Increased Following the Regulations

Figure 2 plots fractions of DC-DC and DC-ID customer trades over time. For both IG and HY bonds, the DC-DC fractions have been rising since around 2011, which coincides with the post-regulation period, while the DC-ID fractions remain similar or declined. These patterns reveal a shift in the market trend from principal trading by dealers to a pre-arranged, search-and-match trading model, driven primarily by increases in CLP.

In Table 4(a), we examine the extent to which CLP rises following the introduction of banking regulations. For a sharper test of the regulatory effects, we isolate the responses of dealers who are affected by the regulations, using difference-in-differences-style regressions. The dependent variable is the daily fractions of DC-DC trades at the dealer level, which are regressed on indicator variables for the treated dealers, indicator variables for four separate stages of the crisis and regulations, and the interactions between these indicators. Our treated group of dealers are defined in two ways—the first based on whether dealers are affected by the Volcker Rule,[20] and the second based on dealer size, because most large dealers are affiliated with banks and thus are affected to a greater extent by banking regulations.[21] The four subperiods are pre-crisis (Jan 2006 to Jun 2007), financial crisis

[20]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.

[21]Small banks are also exempt from many bank regulations. For large/small dealer classifications, we first find the top ten dealers by customer trading volume for each month. 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

(Jul 2007 to Apr 2009), post-crisis (May 2009 to Jun 2012), and post-regulation (Jul 2012 to Dec 2016) periods.[22]

The results reported in Table 4(a) show that CLP has increased in the post-regulation period for dealers affected by the bank regulations. In column (2), for instance, we report that the fraction of DC-DC trades in HY bonds for Volcker-affected dealers is 5.6 percentage points higher in the post-regulation period than in the pre-crisis period. The differences in DC-DC fractions between the post-regulation and post-crisis periods are 5.8 percentage points and –7.9 percentage points for Volcker-affected dealers and non-Volcker-affected dealers, respectively. Given that the DC-DC trades account for 24% of customer trades in HY bonds, this increase in CLP for Volcker-affected dealers is economically large. 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.

Interestingly, the results also suggest that dealers pull back from liquidity provision during times of market stress, while customers tend to fill in. Note that CLP 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 CLP during uncertain times.

3.2.2 Transaction Costs Following the Banking Regulations

We would expect usual bid-ask spread measures that overweight DC-DC trades in calculations to underestimate what customers would pay for liquidity, particularly during the post-regulation period. Two factors contribute to this underestimation. First, as shown in Section 3.2.1, CLP has increased and more DC-DC trades will be included in bid-ask spread calculations. Second, bid-ask spread measures that capture a higher fraction of DC-DC trades may not properly capture the cost

in trades larger than $1 million.

[22] The Dodd-Frank Act, of which the Volcker Rule is a part of, was signed into law in July 2010, while the 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.

of immediacy from dealers.

Our measure of the cost of immediacy is the spread of inventory trades, as dealers provide immediacy to customers in these trades, so we calculate average *Spread* for inventory trades at the bond-day level ("*invcost*"). We also measure the overall liquidity cost paid by liquidity-demanding customers as the combined trading costs of inventory trades and DC-DC in-trades, as customers tend to demand liquidity in both types of trades. Specifically, we calculate the volume-weighted average *Spread* of inventory trades and DC-DC in-trades at the bond-day level. We call this measure the liquidity cost, or *liqcost*.

Figure 3 plots the spreads of inventory trades (*invcost*) as well as *IRC_C* and *same_day* spreads over time. The figure shows that the spreads estimated for *IRC_C* and *same_day* are substantially narrower, making them lower than the spreads of inventory trades, particularly in the post-regulation period. For IG bonds, for example, the gap between *invcost* and *IRC_C* 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 reflects higher levels of CLP as dealers' balance-sheet capacity was significantly weaker.

We also examine how the underestimation of the common bid-ask spread measures influences our inference regarding market liquidity and report the results in Panels (b) and (c) of Table 4. We consider five transaction-cost measures—*IRC_C*, *IRC*, *same_day*, *invcost*, and *liqcost*—to compare our preferred measures (the inventory and liquidity costs) with the other three measures. In particular, we regress each of the five cost measures on the four indicators for the same subperiods as in Table 4(a).

Table 4(b) presents the estimation results for IG bonds. In column (5) we find that the liquidity costs are 12.4 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 *liqcost* is 21.0 bps in the pre-crisis period (see the estimate for the constant). We report similar results in column (4) based on *invcost*, showing that the cost of immediacy provided by dealers has also increased significantly. In contrast, using the IRC and same-day spread measures, as can be seen in columns (1) through (3), underestimates this increase in trading costs. The results reported in column (1) for *IRC_C*, for example, show that the difference in trading costs between post-regulation and pre-crisis is 1.3 bps (see the coefficient on *post-regulation*). We find similar results for the differences in coefficients (see rows $\beta_4 - \beta_3$): the results for *IRC_C* and *IRC* indicate that trading costs have not changed between the two periods (less than 1 bps), while *invtcost* and *liqcost* show 4.1 bps and 3.8 bps increases, respectively. We find qualitatively similar and quantitatively stronger results for HY bonds in Panel (c).[23]

3.2.3 Discussion: Customer Liquidity Provision and Bond Market Liquidity

Our results thus far show that CLP has been increasing, offsetting decreased liquidity provision from dealers. In this section, we examine time-series variation in trading volumes of CLP trades, which will be informative of the overall net effect of shift in liquidity provision on market liquidity. Figure 4 plots the average trade sizes of DC-DC, DC-ID, and inventory trades.[24] A couple of observations are in order. First, DC-DC trades are larger on average, indicating that customers provide liquidity for larger trades, while dealers handle smaller-sized trades. Second, and more importantly, inventory-trade sizes have been declining, consistent with the reduced capacity of dealers. At the same time, the volumes of DC-DC trades tend to increase over our sample period. This result suggests that customers wanting to liquidate larger trades have to wait for longer as such trades tend to involve matching trades, because dealers can be unwilling to provide liquidity for large trades.

The results in Figure 4 suggest that dealers are less willing to take on large trades, while customers provide liquidity using those trades. On the one hand, this increase in DC-DC trades can imply larger volumes of liquidity provision, but on the other hand it can also lead to an implicit increase in the cost of immediacy for large trades if CLP involves longer waiting times for liquidity demanders.

[23] Because not all measures are available for all bond-day pairs, as evidenced by the different sample sizes, differences in bond characteristics may drive the results. In Tables IA.8 and IA.9 of the Internet Appendix, we show that this is not the case.

[24] We thank the anonymous referee for the suggestion.

4 What Explains Customer Liquidity Provision? Evidence from Insurance Company Trades

We have so far documented evidence consistent with CLP, using data on the broad TRACE universe. In this section, we focus on bond transactions involving insurance companies, one of the largest groups of customers in the U.S. corporate bond market. We employ customer-level data that are available in the matched NAIC-TRACE dataset, which provides detailed information on insurance companies' balance sheets and bond transactions, enabling us to provide more direct evidence for CLP and examine which economic drivers are at work behind liquidity provision by customers.

We provide the descriptive statistics for the matched trade sample in Table 5, including the fractions of DC-DC trades, average spread estimates, and the fractions of trades with negative spreads. The results show that the main findings that we document for the main TRACE sample also hold in this matched subsample. We find that, for example, average spreads reported in Panel (b) are lower for DC-DC trades than for DC-ID or inventory trades. The results reported in Panel (c) indicate that the fractions of negative-spread trades are also higher for DC-DC trades than for DC-ID trades, particularly for customer buy trades.

4.1 Which Insurance Companies Provide More Liquidity?

We examine which characteristics can explain liquidity provision in the cross section of insurance companies. We estimate the following regression of CLP for insurer v in year t:

$$CLP_{v,t}^{Buy} = \alpha + \beta X_{v,t-1} + \epsilon_{v,t}. \tag{5}$$

where the dependent variable, $CLP_{v,t}^{Buy}$, is the fraction of customer v's DC-DC buy out-trade volumes in year t with respect to the total trade volumes of that customer in that year. This measure of CLP is based on our previous results indicating that DC-DC buy out-trades largely comprise instances of CLP. We also consider $CLP_{v,t}^{Sell}$ based on DC-DC sell out-trades as an additional dependent variable.

The explanatory variables, $X_{v,t-1}$, include insurer-level variables that represent economic factors that are expected to drive CLP. We first consider insurers' balance-sheet capacities and capital constraints. Funding constraints are widely shown to be an important factor in liquidity provision for dealers,[25] and likewise we expect insurers that are better capitalized and less financially constrained to provide more liquidity. We thus include insurer size (as measured by log total assets), cash and cash-like securities ratio (i.e., holdings scaled by total assets), and risk-based capital (RBC) ratio.[26]

We also consider trading relationships, as they are important determinants of liquidity provision in over-the-counter markets (Di Maggio et al. 2017, Hendershott et al. 2020*a*, and Li and Schürhoff 2019). In particular, we include concentration in trading relationships for each insurer, measured as the Herfindahl–Hirschman index of the fractions of trading volumes of that insurer with dealers. Insurers that concentrate their trades with a few dealers can be contacted repeatedly from their go-to dealers seeking liquidity provision.[27] Additionally, we employ the volume of DC-DC out-trades by a given insurer in the previous year, which can capture any unobservable persistent tendency to provide liquidity that its dealers might know about through their past trading relationships. We look at which of these variables matter for CLP empirically.

Table 6 provides the regression results. We first find that CLP tends to be negatively associated with capital constraints that insurers face. In column (1), for example, the coefficient estimate on the indicator for low RBC ratios (*Low RBC*) is –0.66 and statistically significant at the 5% level, showing that on average, insurers with RBC ratios lower than the regulatory level (250%) have about 0.66 percentage points lower CLP-buy fraction of total trading volumes, which is about 41% of the average CLP-buy fraction (1.634%). Insurers with low cash ratios also provide less liquidity, as can be seen from the coefficient estimate of 0.28, which is also statistically significant at the 5% level. We also find that large insurers provide more liquidity. While this result is also consistent with the capital-capacity story, it can also suggest other possibilities, for example, that larger customers are asked more often by dealers to provide liquidity.

[25]For example, see Brunnermeier and Pedersen (2009), Duffie (2010), Comerton-Forde et al. (2010), and Choi, Shachar and Shin (2019)

[26]The NAIC takes regulatory action against insurance companies when their RBC ratios fall below 250%.

[27]Hendershott, Li, Livdan and Schürhoff (2020*a*) show that insurers can get better bargaining and terms by repeatedly using a smaller concentrated set of dealers. In untabulated results, we also employ the number of dealers for each insurer instead of the trading concentration measure and find qualitatively similar reseults.

We also find that trading relationships involving insurance companies can also explain liquidity provision. The coefficient estimate on *HHI* reported in column (1) is positive and statistically significant, suggesting that customers with trading relationships that are concentrated in a smaller set of dealers tend to be contacted more often by dealers for liquidity provision. We also find that CLP tends to be persistent at the insurer level, as can be seen from the positive coefficient estimate of *Past CLP* reported in the same column. Note that we include time fixed effects in the regressions, so that the estimation suggests cross-sectional associations between our variables and liquidity provision. These findings also are concentrated in buy-side liquidity provision (column 1), while the results reported in column (2) show that most of these explanatory variables are not significantly associated with CLP sell trades. Thus, buy-side CLP is much more predictable systematically, while sell-side CLP does not tend to be associated with capital constraints or trading relationships. In Section IA.9 of the Internet Appendix, we further explore the trading relationship by examining insurers' relationship with Volcker-affected dealers. The results in Table IA.22 show that customers provide more liquidity in the post-regulation period when they have stronger connections to Volcker-affected dealers.

4.2 What Explains Customer Liquidity Provision? Transaction-Level Evidence

Having shown which insurers provide more liquidity, we now conduct micro-level analyses to explain CLP using the matched NAIC-TRACE data that enable us to identify DC-DC out-trades at the insurer-trade level. Specifically, we estimate the following trade-level regression model for trade k of bond i between dealer j and customer v on day t:

$$\mathbb{1}(\text{CLP})_{i,j,v,t,k} = \alpha + \beta X_{i,j,v,t,k} + \epsilon_{i,j,v,t,k} \tag{6}$$

where the dependent variables are indicator variables that equal one for customer *buy* DC-DC out-trade, $\mathbb{1}(\text{CLP}_{Buy})$, and zero otherwise; and that equal one for customer *sell* DC-DC out-trade, $\mathbb{1}(\text{CLP}_{Sell})$, and zero otherwise. The regressions include insurer fixed effects to absorb insurer-level cross-sectional variation so that we can focus on the more micro-level effects.

We consider the following explanatory variables to investigate the determinants of CLP through several channels. The first set of variables focuses on customer-dealer-level channels to fully utilize the advantages of our data. In particular, we include an indicator variable that indicates whether an insurer has executed DC-DC out-trades with the same dealer during the past year, as customers are more likely to provide liquidity to their relationship dealers. We also include the inventories of a given bond held by an insurer. The underlying idea behind this variable is that inventory management should be important for insurers who provide liquidity. We also consider dealer-specific variables such as dealer size and centrality in dealer networks to examine the extent to which the small and peripheral dealers ask their customers to provide liquidity.

The next set of variables focuses on bond-level liquidity events to examine whether CLP increases when liquidity provision is needed. We consider Coval and Stafford (2007) measure of flow-driven fire-sale (and fire-purchase) pressures from mutual funds, which are also among the largest corporate bond investors in the U.S., to examine whether insurers lean against the wind during such episodes.[28] We also consider bond downgrades from IG to HY ratings, as insurers are less likely to provide liquidity because of the stricter capital requirements they must meet to hold HY bonds.[29] Lastly, we also control for bond-level illiquidity measures, including the Amihud (2002) measure, the fraction of no trading days in the past quarter, and bond age, as well as trade volume and time to maturity.

Table 7 provides the estimation results of Equation (6). We find that DC-DC out-trades involving insurers tend to occur with the same dealers with whom the insurers had executed DC-DC out-trades in the past year, suggesting that dealers tend to ask their relationship customers to provide liquidity. This result holds for both buy (column 1) and sell (column 2) DC-DC out-trades, as shown by positive and statistically significant coefficients on *Prev CLP*

We next move on to the coefficient estimates of dealer size and network centrality. We find that larger dealers tend to ask for liquidity less frequently (i.e., execute fewer DC-DC out-trades) but instead take inventory positions with insurers more often (execute more inventory trades). We find similar results for dealer network centrality; more central dealers tend to execute fewer DC-DC

[28] Choi, Hoseinzade, Shin and Tehranian (2020) and Falato, Hortacsu, Li and Shin (2020) examine price impacts from flow-driven fire sales by bond mutual funds.

[29] Ambrose, Cai and Helwege (2008) and Ellul, Jotikasthira and Lundblad (2011) show that when a bond is downgraded to high yield, insurance companies engage in fire sales due to capital regulations.

out-trades with insurers while executing more inventory trades. These results suggest that smaller and more peripheral dealers tend to ask insurers for liquidity provision because these dealers might lack inventory capacity or access to deep interdealer networks.

The results reported in Table 7 also show how insurers' liquidity provision responds to selling and buying pressure from mutual funds as well as to bond downgrades. Focusing on the coefficient estimates of mutual fund buy pressure, we find that insurer liquidity provision responds positively to buy pressure from mutual fund demand, as can be seen by the positive and significant coefficient reported in column (2). We also find that, given mutual fund fire-sale pressure, insurers provide more liquidity (see column 1). Focusing next on the coefficient estimates of the rating downgrade dummy, we find that insurers tend to reduce liquidity provision in buy transactions during downgrade events, which is consistent with the stricter capital requirements for holding HY bonds that discourage liquidity provision. In comparison, they still prefer to provide liquidity on the sell side (as can be seen column 2), which is also advantageous to them because sales of downgraded bonds will free them from meeting regulatory capital requirements.

Lastly, the results reported in Table 7 also show that illiquid bonds tend to be associated with more frequent DC-DC out trades, suggesting that illiquid bonds and bonds that dealers are less willing to take into inventory are associated to a greater extent with CLP. As can be seen in column (1), for example, the coefficient estimate of the zero-trading day measure is positive (0.679) and statistically significant at the 1% level.

To summarize, the results provided in Table 7 show that the customer-, dealer-, and bond-level factors that we consider help us better understand the underlying drivers of CLP. First, we find that customer-dealer trading networks are important. Dealers contact their relationship customers for liquidity provision. Small and peripheral dealers often ask customers to provide liquidity instead of handling orders in their inventories. Second, insurers respond to increased liquidity demand from flow-driven mutual fund trading. In contrast, insurer liquidity provision decreases following bond downgrades. Insurers' tendency to provide liquidity also depends on their inventory holding levels. Lastly, illiquid bonds that dealers are less likely to take on their inventories are associated with more CLP.

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. Using NAIC data, we also examine liquidity provision by insurance companies and find that financial constraints and customer-dealer trading relationships are important variables that help explain CLP.

Our results also have broad implications for measuring the cost of immediacy for illiquid markets using trade data. We show that CLP gives rise to a *measurement problem* with conventional trading-cost measures and that this measurement problem becomes more severe in the post-regulation period. Because of CLP, a bid-ask spread measure would understate the cost of immediacy to the extent that it puts more weight on DC-DC trades.

The rise in CLP in fixed-income markets parallel the changes that the equity market experienced 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 CLP, 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 executed at the discretion of dealers. This gives dealers an advantage in providing liquidity and makes the relationship between dealers and customers important. With 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 must still 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.[30]

[30] https://www.bloomberg.com/news/articles/2018-02-15/electronic-bond-trading-gains-ground-as-market-finally-

What would be the overall net effect of shift in liquidity provision on market liquidity? Market liquidity might not necessarily improve with CLP if customers have to wait longer to be matched with another customer (see, e.g., Saar et al., 2020 and Kargar et al., 2020) or some trades fail to execute (Hendershott et al. 2020*b*). Such implicit costs can be greater for larger trades if dealers are unwilling to handle such trades because of higher inventory costs.

The net effect of this shift in liquidity provision is ambiguous and beyond the scope of our empirical framework. Dealers appear less willing to take on large trades, while customers provide liquidity using those trades. On the one hand, this increase in DC-DC trades can imply larger volumes of liquidity provision, but on the other hand it can also lead to an implicit increase in the cost of immediacy for large trades if CLP involves longer waiting times for liquidity demanders. Moreover, our measure is based on realized transactions and does not necessarily reflect implicit costs associated with execution delays in matching trades (Saar et al., 2020). It would be an interesting future research topic to provide more definitive empirical evidence regarding the overall impacts of this paradigm shift in liquidity provision and also its effects on overall economic welfare.

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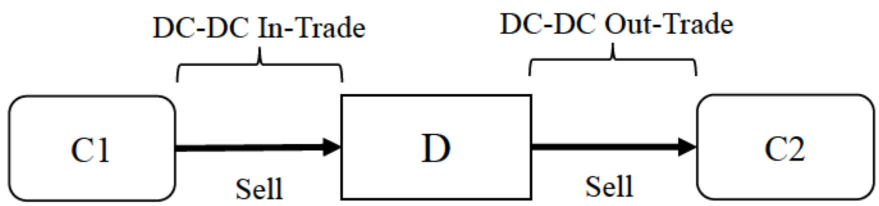
Figure 1: **Illustration of Matched Trades**

This figure shows two examples of matched trades. Panel A illustrates DC-DC trades where a customer (C1) demands liquidity to sell a bond to a dealer (D) and another customer (C2) provides the liquidity by purchasing the bond from the dealer (D). A DC-DC trade refers to each node of these two trades between the dealer and customers. Within a matched DC-DC trade pair, we define the earlier trade as an in-trade and later trade as an out-trade. Panel B illustrates a DC-ID trade and an interdealer trade. In DC-ID trade, a customer (C) demands liquidity by selling a bond to a dealer (D1) and another dealer (D2) provides liquidity to the dealer (D1). A DC-ID trade refers to the first node between dealer D1 and customer C.

Panel A. C2 Providing Liquidity to C1 (DC-DC pair)



Panel B. D2 Providing Liquidity to C (DC-ID pair)

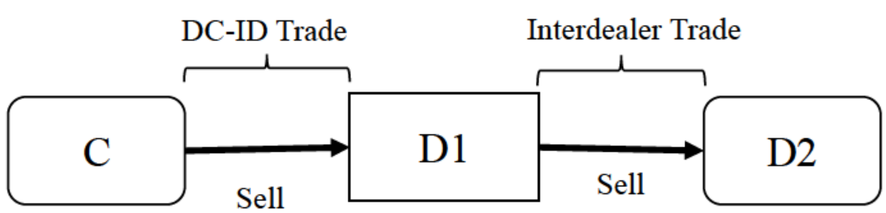


Figure 2: **Time Series Plot of the Fractions of DC-DC and DC-ID Trades**
This figure plots the monthly fractions of DC-DC (red solid line) and DC-ID trades (green dotted line) with respect to total customer trade volumes. Panel A plots IG bond trades and Panel B plots HY bond trades.

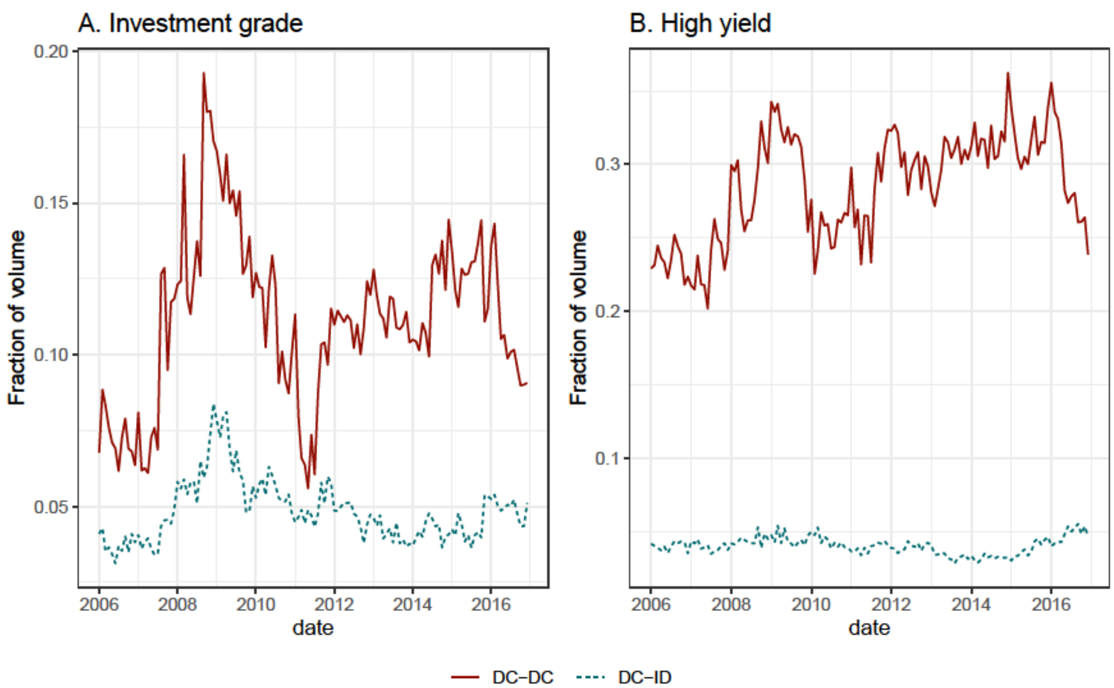


Figure 3: **Time Series Plot of Trading Cost Measures**
This figure plots the monthly averages of *IRC_C* (red solid line), *same_day* (green dotted line), and *invcost* (blue dashed line) for IG (Panel A) and HY (Panel B) bond trades.

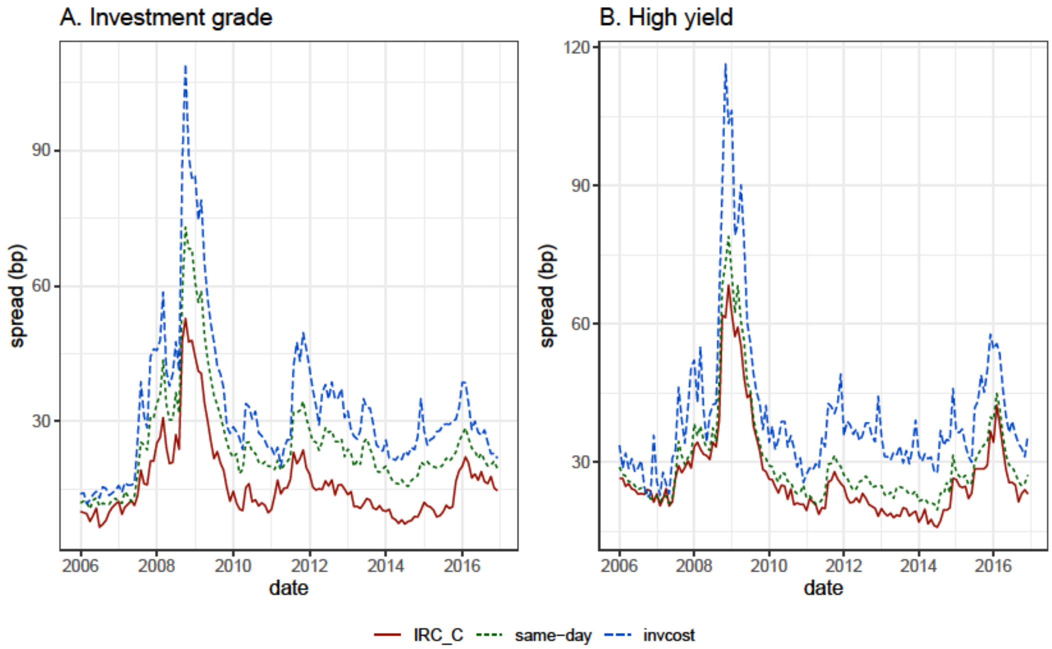


Figure 4: **Time Series Plot of Average Trade Volumes for DC-DC, DC-ID, and Inventory Trades**

This figure plots the monthly averages of trade volumes (in $1,000) in DC-DC, DC-ID, and inventory trades for IG (Panel A) and HY (Panel B) bonds. We first take monthly averages for each bond and then take averages across bonds for each month.

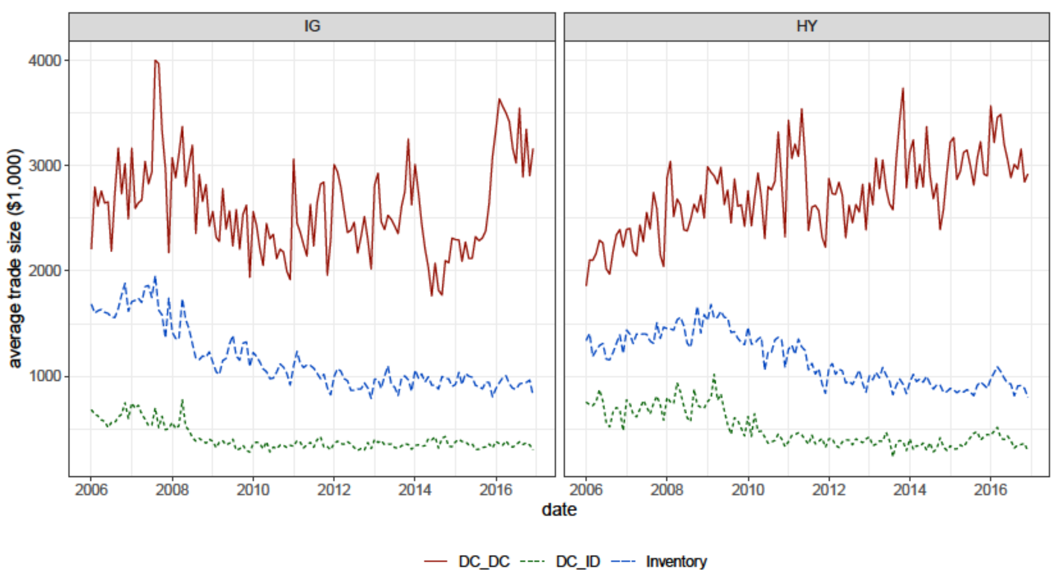


Table 1: **Summary Statistics**

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 inventory 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), total trade volumes in billion USD in column (7), and trade counts (the number of trades) in column (8). Panel (b) displays average trading costs estimated using *IRC_C*, *IRC*, *same_day*, and *Spread* methods. Averages of *Spread* estimates are reported for inventory, DC-DC, and DC-ID trades separately. Column marked *#(bond-days)* reports the number of bond-day observations on which the bid-ask spread measures can be calculated. Panel (c) reports the fractions of customer trades with negative *Spread* for DC-DC, DC-ID, and inventory 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) and (c) use customer trades of $1 million and above only. The sample period runs from 2006 through 2016.

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

Rating	Trade size	Overnight	DC-DC	DC-ID	Inventory	Volume	Trade count
IG	≤100K	49.70%	3.14%	27.52%	69.34%	334	11,287,226
IG	100K-1mil	71.72%	4.42%	10.15%	85.44%	1,181	3,380,294
IG	≥ 1mil	65.49%	9.57%	5.21%	85.22%	12,715	2,705,836
HY	≤100K	46.86%	3.41%	25.92%	70.67%	125	4,220,018
HY	100K-1mil	60.38%	10.47%	9.85%	79.68%	496	1,322,653
HY	≥ 1mil	47.56%	24.13%	4.33%	71.54%	7,364	2,138,627

(b) Average Bid-Ask Spreads Across Various Estimation Methods

	IG		HY	
	average spread (bps)	#(bond-days)	average spread (bps)	#(bond-days)
IRC_C	16.72	99,582	27.78	133,379
IRC	17.15	181,940	27.54	163,789
same_day	25.26	421,560	30.47	416,653
Spread	33.44	580,215	40.87	330,703
DC_DC	16.33	41,830	28.41	71,148
DC_ID	56.50	65,551	73.03	49,874
Inventory	32.38	537,433	39.15	298,308

(c) Fractions of Negative Spread Trades

	DC-DC	DC-ID	Inventory
rating			
IG	41.33%	14.79%	31.12%
HY	37.70%	18.87%	32.86%
trade direction			
customer buy	42.88%	16.35%	34.55%
customer sell	34.67%	17.10%	29.00%

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):

$$\mathit{Spread}_{i,j,t,k} = \alpha + \beta \mathbb{1}(\text{DC-DC})_k + \gamma \mathbb{1}(\text{DC-ID})_k + \epsilon_{i,j,t,k}$$

where $\mathit{Spread}_{i,j,t,k}$ is the *Spread* measure 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 inventory 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 β and γ 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:

$$\mathit{Spread}_{i,j,t,k} = \alpha + \beta_1 \mathbb{1}(\text{out})_k + \beta_2 \mathbb{1}(\text{cust buy})_k + \epsilon_{i,j,t,k}$$

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 2016, and we restrict the sample to customer trades 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) Regression of Spreads on DC-DC and DC-ID Dummies

	IG			HY		
	all	cust buy	cust sell	all	cust buy	cust sell
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(DC-DC)	-12.985^{***}	-17.069^{***}	-6.073^{***}	-7.813^{***}	-10.235^{***}	-3.466^{***}
	(0.392)	(0.815)	(0.817)	(0.488)	(0.882)	(0.847)
$\mathbb{1}$(DC-ID)	21.077^{***}	25.107^{***}	17.149^{***}	33.413^{***}	34.958^{***}	29.436^{***}
	(0.522)	(0.662)	(0.850)	(0.809)	(1.127)	(1.076)
Trade size	0.513^{***}	-3.277^{***}	2.713^{***}	1.930^{***}	-0.801^{**}	3.574^{***}
	(0.122)	(0.193)	(0.175)	(0.238)	(0.341)	(0.343)
Age	7.302^{***}	6.615^{***}	7.295^{***}	0.860	1.902^{*}	-0.207
	(0.398)	(0.514)	(0.717)	(0.646)	(0.974)	(1.042)
TTM	15.367^{***}	12.379^{***}	17.629^{***}	7.751^{***}	6.180^{***}	9.370^{***}
	(0.512)	(0.633)	(0.939)	(1.263)	(2.059)	(2.084)
$\gamma - \beta$	34.061^{***}	42.177^{***}	23.223^{***}	41.226^{***}	45.192^{***}	32.901^{***}
dealer, cusip, date f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,088,873	574,768	514,105	926,628	472,077	454,551
R^2	0.076	0.101	0.144	0.034	0.070	0.066

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

	all		$\leq$ 1min		>1min	
	IG	HY	IG	HY	IG	HY
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(out)	-8.592^{***}	-10.109^{***}	-0.534	-9.813^{***}	-10.892^{***}	-10.245^{***}
	(1.220)	(1.324)	(2.522)	(1.829)	(1.316)	(1.841)
$\mathbb{1}$(cust buy)	-29.491^{***}	-10.337^{***}	-37.935^{***}	-10.343^{***}	-26.866^{***}	-10.298^{***}
	(1.739)	(1.817)	(2.927)	(2.299)	(1.730)	(2.151)
dealer, cusip, date f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	87,862	179,393	26,059	98,327	61,701	80,307
R^2	0.050	0.019	0.065	0.021	0.062	0.033

Table 3: **Fractions of DC-DC, DC-ID, and Inventory Trades**

This table provides the fractions of DC-DC, DC-ID, and inventory trades (in terms of trade counts) used in the calculation of each bid-ask spread measure. We use customer trades of $1 million and above only. The sample period runs from 2006 through 2016.

	IG			HY		
sample	DC-DC	DC-ID	Inventory	DC-DC	DC-ID	Inventory
full	9.57%	5.21%	85.22%	24.13%	4.33%	71.54%
IRC_C	82.97%	4.77%	12.27%	84.76%	1.97%	13.27%
IRC	61.78%	28.01%	10.21%	77.96%	9.38%	12.65%
same_day	21.28%	4.81%	73.91%	35.20%	4.06%	60.74%
Spread	8.09%	7.21%	84.70%	19.52%	7.21%	73.27%

Table 4: **Regression of the Fractions of DC-DC Trades and Bid-Ask Spreads on Pre- and Post-Regulation Indicator Variables**

Panel (a) reports the regression results of DC-DC trade fractions on indicators for dealers who are affected and unaffected by regulations, indicators for the four sub-periods, and the interactions of these indicators:

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

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, based on the classification from Bao et al. (2018). The second proxy is the size of the dealer, whereby we classify 15 largest dealers as affected by regulations. The dependent variable, $y_{m,t}$, is the average fraction of DC-DC trades calculated separately for affected and unaffected dealers. The indicator variables, $\mathbb{1}(\text{aff})$ and $\mathbb{1}(\text{unaff})$, represent affected and unaffected dealers, respectively. T_l $(l = 1, \ . \ . \ . \ , 4)$ 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. $\mathbb{1}(t \in T_l)$ is the omitted dummy variable, and thus, forms the base level. We include the bond market volatility and VIX 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 indicator variables. Standard errors are clustered by date.

Panels (b) and (c) provides the estimation results from the following regressions of trading cost estimates:

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

where $y_{i,t}$ is one of the following five trading cost measures for bond i on day t: IRC_C, IRC, *same_day*, *invcost*, or *liqcost*. *invcost* is calculated based on the *Spread* measure using inventory trades only. *liqcost* is calculated by volume-weighting *Spread* for inventory trades and *Spread* for the first legs of DC-DC trades. We include the following set of control variables: the log of the average customer trade size used in calculating $y_{i,t}$; the log of bond amounts outstanding; rating and the log of rating; age and the log of age; time to maturity and the log of time to maturity; the VIX; and bond market volatility. To save space, we do not report the coefficient estimates for the control variables. Panel (b) and (c) presents the estimation results for IG and HY bonds, respectively. 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 indicators. We restrict the sample to customer trades $1 million and above. Standard errors are double clustered by bond and date.

For all regressions, the sample period runs from 2006 to 2016. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

(a) Regressions of DC-DC fractions

	Volcker/nonVolcker		Large/Small	
	IG	HY	IG	HY
	(1)	(2)	(3)	(4)
Index Volatility	0.005***	0.002	0.006***	0.003
	(0.001)	(0.002)	(0.001)	(0.002)
VIX	0.019***	0.013***	0.017***	0.018***
	(0.002)	(0.002)	(0.001)	(0.002)
unaffected	0.059***	0.288***	0.033***	0.253***
	(0.006)	(0.007)	(0.004)	(0.005)
unaffected×crisis	0.064***	0.039***	0.052***	0.039***
	(0.009)	(0.010)	(0.005)	(0.008)
unaffected×post-crisis	0.025***	0.002	0.019***	0.001
	(0.007)	(0.009)	(0.004)	(0.006)
unaffected×post-regulation	0.028***	−0.077***	0.041***	−0.053***
	(0.006)	(0.008)	(0.003)	(0.006)
affected×crisis	0.011***	0.002	0.007*	0.006
	(0.004)	(0.004)	(0.004)	(0.004)
affected×post-crisis	0.003	−0.002	0.008***	0.021***
	(0.003)	(0.003)	(0.003)	(0.003)
affected×post-regulation	0.030***	0.056***	0.032***	0.076***
	(0.002)	(0.003)	(0.002)	(0.003)
Constant	0.085***	0.226***	0.081***	0.208***
	(0.002)	(0.002)	(0.002)	(0.002)
$\beta_{a,4} - \beta_{a,3}$	0.027***	0.058***	0.024***	0.055***
$\beta_{u,4} - \beta_{u,3}$	0.003	-0.079***	0.021***	-0.053***
Observations	5,332	5,339	5,338	5,339
R^2	0.343	0.687	0.347	0.666

(b) Spread Regressions for IG Bonds

	Dependent Variables:				
	IRC_C	*IRC*	*same_day*	*invcost*	*liqcost*
	(1)	(2)	(3)	(4)	(5)
crisis	9.007***	8.600***	13.278***	19.153***	19.079***
	(0.692)	(0.521)	(0.700)	(1.236)	(1.227)
post-crisis	0.402	2.403***	4.630***	8.829***	8.615***
	(0.431)	(0.333)	(0.413)	(0.752)	(0.741)
post-regulation	1.328***	2.776***	6.438***	12.940***	12.418***
	(0.328)	(0.253)	(0.312)	(0.552)	(0.542)
Constant	14.641***	13.888***	19.001***	21.061***	21.026***
	(0.343)	(0.258)	(0.322)	(0.569)	(0.560)
$\beta_4 - \beta_3$	0.926***	0.372	1.808***	4.111***	3.803***
Observations	99,501	181,811	421,281	537,117	551,790
R^2	0.251	0.195	0.176	0.062	0.060

(c) Spread Regressions for HY Bonds

	Dependent Variables:				
	IRC_C	*IRC*	*same_day*	*invcost*	*liqcost*
	(1)	(2)	(3)	(4)	(5)
crisis	3.859***	3.727***	5.187***	10.315***	10.381***
	(0.687)	(0.653)	(0.703)	(1.536)	(1.485)
post-crisis	−1.915***	−0.880	−1.726***	3.922***	3.349***
	(0.603)	(0.579)	(0.594)	(1.287)	(1.227)
post-regulation	1.599***	2.583***	3.327***	14.219***	13.073***
	(0.534)	(0.522)	(0.511)	(1.117)	(1.061)
Constant	27.026***	26.084***	28.685***	29.722***	30.418***
	(0.473)	(0.456)	(0.469)	(1.018)	(0.959)
$\beta_4 - \beta_3$	3.515***	3.464***	5.053***	10.297***	9.724***
Observations	133,308	163,712	416,442	298,199	317,046
R^2	0.205	0.192	0.101	0.024	0.022

Table 5: **Summary Statistics of the NAIC-TRACE Sample**

This table reports summary statistics on corporate bond trades and transaction cost estimates for the NAIC and TRACE matched (NAIC-TRACE) sample. The construction of the NAIC-TRACE sample is detailed in Section IA.2 of the Internet Appendix. Panel (a) reports the fractions of overnight, DC-DC, DC-ID, and inventory 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) displays the averages of *Spread*, separately reported for all, DC-DC, DC-ID, and inventory trades. Column marked *#(bond-days with Spread)* reports the number of bond-day observations that have estimates of *Spread* available. Column marked *#(bond-days all)* reports the number of bond-day observations. Panel (c) reports the fractions of customer trades with negative *Spread* for DC-DC, DC-ID, and inventory 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) and (c) use customer trades of $1 million and above only. The sample period runs from 2006 through 2016.

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

Rating	Trade size	Overnight	DC-DC	DC-ID	Inventory	Volume	Trade count
IG	$\leq$100K	71.20%	3.12%	11.93%	84.95%	1.86	27,973
IG	100K-1mil	74.34%	3.77%	9.03%	87.20%	39.55	99,134
IG	$\geq$ 1mil	66.68%	9.20%	5.74%	85.07%	711.60	166,370
HY	$\leq$100K	74.57%	4.31%	6.03%	89.66%	0.33	5,435
HY	100K-1mil	71.30%	7.63%	4.99%	87.38%	6.37	15,990
HY	$\geq$ 1mil	53.49%	20.40%	4.50%	75.10%	70.79	21,498

(b) Average *Spread* Estimates

	average spread (bps)	#(bond-days with *Spread*)	#(bond-days all)
Spread	40.42	56,135	179,537
DC-DC	30.39	4,097	18,258
DC-ID	74.06	4,703	10,214
Inventory	38.06	48,027	152,445

(c) Fractions of Negative Spreads Trades

	DC-DC	DC-ID	Inventory
rating			
IG	36.53%	10.78%	27.14%
HY	32.29%	9.97%	26.90%
trade direction			
customer buy	43.26%	11.81%	29.92%
customer sell	28.33%	8.60%	24.64%

Table 6: **Regression of Insurer-Level Customer Liquidity Provision**

This table reports the estimation results from panel regressions of insurer-level DC-DC out-trade fractions, using the following model for customer v and year t:

$$\text{CLP}_{v,t} = \alpha + \beta X_{v,t-1} + \epsilon_{v,t}$$

where the dependent variables are fractions of DC-DC out-trade volumes that are customer buys (CLP_{Buy}) in column (1) and customer sells (CLP_{Sell}) in column (2), calculated based on par-value dollar trade volumes using all customer trades in the NAIC-TRACE matched sample. The fractions are in the percentage scale. The explanatory variables (X) are log total assets of the insurer ($Size$); the ratio of cash, cash equivalents, and short-term investment securities to total assets ($Cash$); an indicator variable for whether the risk-based capital ratio of the insurer is lower than 250% ($Low\ RBC$); log of Herfindahl–Hirschman index of trade volumes between the insurer and its dealers (HHI); and log of DC-DC out-trade volumes of the customer ($Past\ CLP$). All explanatory variables are measured at $t-1$. All explanatory variables except for $Low\ RBC$ are standardized by subtracting their respective means and dividing by their respective standard deviations. We also include the year fixed effect. The sample period runs from 2006 through 2016. Standard errors are two-way clustered by customer and year. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variables:	
	CLP_{Buy} (1)	CLP_{Sell} (2)
Size	0.559***	0.344***
	(0.163)	(0.063)
Cash	0.280**	−0.029
	(0.111)	(0.030)
Low RBC	−0.662**	0.291
	(0.238)	(0.223)
HHI	0.316***	−0.069
	(0.090)	(0.059)
Past CLP	1.065***	0.243***
	(0.130)	(0.043)
year f.e.	Yes	Yes
Observations	6,574	6,574
R^2	0.089	0.082

Table 7: **Regression of Transaction-Level Customer Liquidity Provision from Insurance Companies**

This table reports the estimation results from the panel regressions of DC-DC out-trades of insurance companies in the NAIC-TRACE sample, using the following model for trade k of bond i between dealer j and customer v on day t:

$$\mathbb{1}(\text{CLP})_{i,j,v,t,k} = \alpha + \beta X_{i,j,v,t,k} + \epsilon_{i,j,v,t,k}$$

where the dependent variable in column (1), $\mathbb{1}(\text{CLP}_{Buy})$, is an indicator variable that equals one if a trade is a DC-DC buy out-trade and zero otherwise. Likewise, we define the dependent variable in column (2), $\mathbb{1}(\text{CLP}_{Sell})$, for DC-DC sell out-trades. The explanatory variables (X) are an indicator variable that indicates whether the insurer has executed previous DC-DC out-trades with dealer j during the past year (*Prev CLP*); the inventories of the bond held by the insurer, measured as the log of par-value amounts of the bond at the end of previous year (*Inventory*); dealer size, as measured by log trading volumes of dealer j during the previous year (*Dealer Size*); the interdealer network centrality of the dealer, calculated as the eigenvector centrality of interdealer trades in the previous year, following Friewald and Nagler (2019) (*Dealer Centrality*); fire-purchase and fire-sales pressures on the bond from mutual fund (*MF Buy Pressure* and *MF Sell Pressure*). Specifically, we calculate flow-induced trading measures, *Pressure*, for bond i during the contemporaneous quarter following Coval and Stafford (2007) and Choi et al. (2020), and define *MF Buy Pressure MF Sell Pressure* as max(*Pressure*,0) and max($-$*Pressure*,0), respectively.; an indicator variable for credit rating downgrade from IG to HY during 180 days before or after day t (*Downgrade*); the illiquidity measure based on Amihud (2002) (*Amihud*), calculated as the median of daily Amihud illiquidity during past 90 days following Dick-Nielsen et al. (2012); and the ratio of zero trading days, calculated as a fraction of zero-trading days of the bond during past 90 days (*ZTD*). We also add the log age, log trading size, and log time to maturity as in Table 2. All explanatory variables except for *Prev CLP* and *Downgrade* are standardized using their means and standard deviations. We scale all coefficient estimates by multiplying 100 to the original estimates. The regressions include insurer, rating, and date fixed effects. The sample period runs from 2006 through 2016, and we restrict the sample to customer trades of $1 million and above in the NAIC-TRACE sample. Standard errors are double clustered by bond and date. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variables:	
	$\mathbb{1}(\text{CLP}_{Buy})$	$\mathbb{1}(\text{CLP}_{Sell})$
	(1)	(2)
Prev CLP	1.857***	0.689***
	(0.142)	(0.094)
Inventory	−1.316***	0.789***
	(0.071)	(0.033)
Dealer Size	−2.778***	−1.041***
	(0.184)	(0.130)
Dealer Centrality	−0.393***	−0.201***
	(0.066)	(0.046)
MF Buy Pressure	0.036	0.100***
	(0.052)	(0.039)
MF Sell Pressure	0.191***	−0.033
	(0.048)	(0.033)
Downgrade	−1.962***	2.558***
	(0.367)	(0.464)
Amihud	0.018	0.104**
	(0.055)	(0.043)
ZTD	0.679***	0.455***
	(0.050)	(0.036)
Age	0.720***	0.153***
	(0.060)	(0.034)
Trade size	0.617***	0.662***
	(0.064)	(0.045)
TTM	0.558***	−0.139***
	(0.048)	(0.042)
customer, rating, date f.e.	Yes	Yes
Observations	161,426	161,426
R^2	0.068	0.035

Appendix

A 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 buy) to a dealer is accumulated in the dealer's inventories and is matched later with outgoing trades (e.g., interdealer trades or customer sells) 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.1 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 inventory 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.

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

(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

(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

(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			Inventory
4	0.7	0	1	DC-ID
6	0	0	0	Inventory