Investors as a Liquidity Backstop in Corporate Bond Markets

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ABSTRACT

Investors act as a liquidity back-stop in the corporate bond market. By providing liquidity, investors help ease dealers' balance sheet constraints, especially during market stress. During the March 2020 Dash-for-Cash, in bonds where investors stopped providing liquidity, transaction costs rose by 38%. We find the composition of types of liquidity providers — rather than just their presence — shapes trading costs. Dealers relying on flexible-mandate investors, such as hedge funds, are more resilient to liquidity shocks. Dealers offer discounts to investors for past liquidity services to maintain liquidity provider networks. These discounts represent two-thirds of relationship discounts.

Keywords: Bond Markets, Liquidity, Clients-sourced liquidity, Balance sheet cost.

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I. Introduction

Concerns about declining bond market liquidity have occupied the media, industry participants, policymakers, and academics for several years.[1] Stricter regulatory requirements following the financial crisis (e.g., Basel 2.5, Basel III and the Volcker Rule) have significantly increased the balance sheet costs of market-making for banks, raising concerns about their ability to provide liquidity in times of stress[2]. Events such as the 2020 "Dash-for-Cash" episode have further highlighted how strains on dealers' balance sheet capacity could trigger large increases in illiquidity (Duffie et al., 2023).

Understanding how dealers can ease constraints on their balance sheet capacity is therefore important. One option for dealers is to source liquidity directly from their clients—investment funds, hedge funds, insurers, and other market participants. How frequently do dealers use their clients as a liquidity backstop? Does this practice leave a footprint on prices? And does it make dealers' liquidity provision more robust? The goal of this paper is to answer these questions.

To this end, we analyze granular transaction-level data from the UK corporate bond market, obtained under MiFID II, which allows us to track the identities of trade counterparties. This unique feature enables us to directly observe when investors provide liquidity to dealers and examine how the characteristics of liquidity suppliers impact market outcomes.[3] We define client sourced liquidity (CSL) trades as instances where a dealer buys from one client and sells to another within the same day, without an interim trade occurring in the interdealer market. We interpret the second trade as signalling a dealer's demand for liquidity from the second client.[4]

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[1]See, for example, *"People are worried about bond market liquidity,"* by Matt Levine, Bloomberg, June 4, 2015; *The bond market trilemma"* by Robin Wigglesworth, Financial Times, May 10, 2024; *"Why Market Liquidity has Deteriorated, Global Macro Research,"* Top of Mind, Goldman Sachs, (Aug. 2, 2015); and "Examination of Liquidity of the Secondary Corporate Bond Markets," IOSCO 2017.

[2]See CGFS (2014) and Adrian et al. (2017), who show that measures of dealers' balance sheet constraints (e.g., their leverage) become positively related to illiquidity of U.S corporate bonds after the crisis.

[3]Unlike enhanced Trade Reporting and Compliance Engine (TRACE) data typically used in bond market studies, our data includes customer names. This feature allows us to identify the types of clients that provide liquidity to dealers, which is crucial for many of our tests.

[4]CSL trades are similar to "paired roundtrip trades" in Goldstein and Hotchkiss (2020). In contrast to Goldstein and Hotchkiss (2020), we study how each leg of CSL trades are priced or how the network

All our analysis focuses on trades between dealers and their clients ("DtC trades").[5] CSL trades comprise approximately 17% of total "DtC trades", with a subset of fast CSL trades (where the second leg occurs within 15 minutes) making up 5% of volume. Importantly, fast CSL trades are distinct from Matched trades, where a dealer executes a buy and a sell order from two different clients in the same bond at the same time.[6] The latter account for 19% of trading volume and unlike CSL trades, entail no risk for dealers. Remaining trades ("Deal"), which include trades that take more than one day to unwind, account for the remaining 64% of trading volume. The ability to distinguish between CSL and matched trades is a unique feature of our dataset offering additional insights.

We find that the use of CSL trades increases with risk. Their share of trading volume during the Dash-for-Cash period in March 2020, increased by three percentage points and 43% of CSL trades are in high-yield bonds, and 15% in block volume, compared to just 33% (30%) and 8% (6%) in Deal (Match) trades, respectively.[7] As balance sheet costs are larger for riskier bonds, the positive association between CSL share and risk is consistent with dealers using client liquidity provision to reduce these costs.

To understand how the ability of dealers to obtain liquidity from their clients affects liquidity, we consider an extension of Saar et al. (2022). In this model, dealers can act either as market-makers or matchmakers. In the first case, they offer immediacy to their clients but they bear a balance sheet cost.[8] In the second case, dealers bear no balance sheet cost but incur a cost to find a suitable counterparty for their client. In choosing between these two possibilities, clients face a trade-off between waiting costs (which are

of liquidity supplying clients in a bond affects trading costs for that bond.

[5]We use the prices of interdealer trades to measure clients' trading costs; see below.

[6]Matched trades are pre-arranged trades in which a dealer acts as a matchmaker between two clients. In such trades, the dealer does not commit capital nor take on any inventory risk. Bao et al. (2018) find, using TRACE data, that the share of matched trades in U.S. corporate bonds has increased following the financial crisis. Choi et al. (2024) show that matched trades are more frequent across dealers affected by post-crisis regulation.

[7]Blocks are defined as trades over £2.5 million. Jacobsen and Venkataraman (2023) studies block trades in the U.S corporate bond markets. They find that "receivers" in these trades pay smaller markups than initiators, on average, which is consistent with our findings (see below). However, we find that CSL trades exist across all trade sizes. Thus, they are not a phenomenon specific to block trading.

[8]This cost represents the cost of using the dealers' balance sheet capacity, which increases the likelihood that the dealer might have to raise capital to satisfy capital constraints, for instance.

larger with matchmaking) and trading costs (which are larger with market-making).

In this model, we add the possibility for a dealer to rely on a pool of clients that she uses as a liquidity backstop. More specifically, after executing a market making trade, a dealer has the option to contact clients in this pool and make them offers to unwind the position she took with the first client. If a client accepts the dealer's offer, the dealer avoids the balance sheet cost—freeing up capacity for another market-making trade. Therefore, in equilibrium, there is room for the three types of DtC trades observed in our data: (i) Matched trades, (ii) CSL trades and (iii) Deal trades.[9]

We obtain three testable hypotheses. First, when a CSL trade occurs, the second client receives a price improvement relative to the first. Second, a dealer's clients receive better prices when the dealer is more likely to obtain liquidity from other clients, either because the size of her liquidity supply network is larger or because clients in this network are more likely to be able to trade the bond. Third, the negative effect of an increase in a dealer's balance sheet cost on liquidity is dampened when the dealer is more likely to obtain liquidity from other clients.

We test these predictions, measuring the trading costs for a given trade as the log of the ratio of the transaction price to the closest interdealer price times the direction of the trade (Hendershott and Madhavan, 2015). We find that the first client in a CSL trade is executed at a markup relative to Deal trades, consistent with our conjecture that dealers seek liquidity from their clients when their balance sheet cost is higher. Furthermore, as predicted, we find that the second client in a CSL trade obtains price improvements relative to prices for the first client. This result holds after controlling for a range of fixed effects (dealer-day, client-month, bond-day) and various possible determinants of bond trading costs (in particular trade size and the trading venue), suggesting that this result is due to the nature of the trade rather than specific characteristics of the bond, the dealer or the client. The price improvement for the second client is significant for fast CSL trades (fCSL) but insignificant for slow CSL (sCSL) trades, maybe because fCSL trades better identify trades in which dealers need liquidity.

[9] In the model these trades arise when the dealer does not try to source liquidity from other clients or when she tries without success.

Our second prediction is that a dealer's trading costs in a given bond are inversely related to the size of her network of liquidity suppliers. To test this prediction, we use the Dash-for-Cash period to instrument the size of a dealer's network. Intuitively, during this period, some clients who usually could be liquidity suppliers need to liquidate their assets (e.g., due to margin calls) and are therefore unavailable for liquidity provision.

Accordingly, for each bond and each day during the Dash-for-Cash period, we identify clients who are exclusively selling on these days and are therefore not available to provide liquidity to dealers in any given bond (the Dash-for-Cash is characterized by a massive sale of bonds). We measure the share of fCSL trades of these clients in the six months preceding the Dash-for-Cash and use this share as a proxy for the drop in available liquidity for dealers during the Dash-for-Cash period. As predicted, we find that sell orders (those straining dealers' inventory during the Dash-for-Cash period) are significantly more expensive in bonds experiencing a larger drop in the pool of available liquidity suppliers for dealers.

To test our third prediction, we study the evolution of trading costs around downgrades for "fallen angels" (bonds that are downgraded from investment grade to high-yield). These events are interesting because the downgrade of a bond raises balance sheet costs for dealers active in this bond and results in a transient increase in liquidity demand as some institutions (e.g., investment grade index funds) are forced to liquidate their holdings of a bond.[10]

Consistent with the previous literature (e.g., Bao et al., 2018), we show that trading costs for fallen angels increase significantly around downgrades and that part of the increase reflects transient price pressure (due to a transient increase in dealers' inventory risk). More importantly, these effects vary across fallen angels, depending on the size and composition of dealers' network of liquidity suppliers before the fallen angels' downgrade.

Indeed, bonds in which hedge funds account for a larger fraction of liquidity supply to the dealer before their downgrade experience a significantly smaller increase in their trading cost. In contrast, bonds in which dealers rely more on insurance companies

[10] See Ellul et al. (2011) or Dick-Nielsen and Rossi (2018).

as a source of liquidity experience a significantly larger increase in their trading costs. Intuitively, following the downgrade of a bond, dealers can still rely on their network of liquidity suppliers in the first case while they cannot in the second case because insurance companies face regulatory constraints when investing in high-yield bonds (in contrast to hedge funds).[11] This finding highlights the importance of the composition of the dealers' network of liquidity suppliers in a bond to their ability to withstand large demand shocks.

Given this finding, in the last part of our paper, we study which types of institutions provide liquidity to dealers. The granularity of our data enables us to go further than existing studies on this topic which have typically focused, due to data limitations, on one type of institution in isolation (e.g., insurer, mutual fund, hedge fund). In contrast, we have the entire cross-section of client types interacting with dealers in the UK bond market. This rich data source enables us to assess the relative importance of each type of client in liquidity provision.

We find that hedge funds are the most valuable source of client sourced liquidity. They account for 17% of fCSL second leg trades, which is higher than their share of first leg fCSL trades and overall trading volume, which are 13% and 10%, respectively. They further increase their liquidity provision during periods of stress and when bonds are downgraded. In contrast to findings in the previous literature, insurance companies appear relatively less important as a source of client liquidity provision. Indeed, their share of fCSL trades is lower than their overall share of trading activity, and it declines further in fallen angel bonds. While asset managers account for the largest share of overall trading activity, their contribution to second leg fCSL trades is lower than their contribution to first leg fCSL trades and their overall share of trading.

Finally, we show that dealers reward their clients for providing liquidity. A client with one percentage point higher share in liquidity provision receives an additional 0.1 bps discount on all trades, including deal trades. This discount is economically and statistically significant after controlling for the client's share of the dealer's trading volume. Thus, the

[11] For example, the Solvency Capital Requirement set out under Solvency II regulation for EU and UK insurers requires insurers to hold more capital for high-yield bonds compared to investment grade bonds.

reward for liquidity provision is distinct from a relationship discount. Hedge funds are particularly well rewarded, receiving a discount twice as large as the next closest client type. In sum, our evidence suggests that dealers view client-sourced liquidity as an insurance policy. Although used relatively infrequently, it is valuable to dealers, especially during periods of stress.

Our findings contribute to the literature on OTC market liquidity by identifying a previously underexplored source of liquidity provision — investors supplying liquidity to dealers.[12] While prior studies (e.g., Bessembinder et al. (2018) or Adrian et al. (2017)) have examined dealer balance sheet constraints in shaping bond market liquidity, our work provides novel evidence on the role of client liquidity provision in sustaining trading activity, particularly in periods of stress.

We also contribute to research on financial intermediation by demonstrating how dealers actively cultivate and maintain liquidity networks through pricing incentives. Our results complement existing studies on bond market liquidity by highlighting the role of trade networks and institutional investors (mutual funds, insurance companies and hedge funds) in mitigating liquidity shortages (e.g., Anand et al. (2021), Giannetti et al. (2023), O'Hara et al. (2023), Kruttli et al. (2023) and Choi et al. (2024)). Research on inter-dealer markets has shown that dealers rely on trading relationships to manage liquidity risk (e.g., Di Maggio et al. (2017); Hollifield et al. (2017); Li and Schurhoff (2019)) but less attention has been given to the relationships between dealers and their clients. By examining CSL trades, we provide new evidence that dealers strategically cultivate relationships with liquidity-supplying investors to mitigate balance sheet constraints and maintain market stability. The value of these networks goes beyond the relationship discounts documented by Jurkatis et al. (2023). And we show that trading costs are impacted by the composition of the network, as well as its size.[13]

Beyond academic contributions, our results have important implications for policymakers and market participants. The increasing reliance on client sourced liquidity suggests

[12] See Bessembinder et al. (2020) for a survey of the empirical literature on the liquidity of fixed income markets.

[13] Hendershott et al. (2020) show that the size of a client's dealer network affects the price she receives from dealers. Instead we focus on dealers' liquidity networks.

that as traditional dealer intermediation declines, the stability of corporate bond markets will depend more on the composition and diversity of dealers' liquidity networks. Policies affecting the participation of hedge funds and other non-traditional liquidity providers could therefore have significant consequences for market resilience. Additionally, our findings highlight the potential risks associated with market structures that rely too heavily on constrained institutional investors, such as insurers, to provide liquidity in times of stress.

II. Data

A. Transaction data

Our main data are transaction reports in corporate bonds submitted to regulatory authorities under the Markets in Financial Instruments Directive (MiFID) II, which took effect on 3 January 2018. The same data are used in Jurkatis et al. (2023) and are described in detail in Jurkatis (2024).

Investment firms and other trading institutions are mandated to submit reports for their trades in debt instruments that are eligible to trade on a venue — which includes Regulated Markets, such as the London Stock Exchange, Multilateral Trading Facilities, such as request-for-quotes platforms (RFQ), and Organised Trading Facilities (OTF), such as inter-dealer broker platforms. In addition, all trades in instruments that are eligible to trade on a venue must be reported irrespective of whether or not they are executed on a venue. This means that the data also capture trades executed on Systematic Internalisers (SIs) and OTC.[14]

The data are made available by the Financial Conduct Authority (FCA), the United Kingdom (UK) financial markets regulator. The FCA receives reports for all transactions in reportable financial instruments involving at least one UK investment firm or executed

[14] An SI is an investment firm which executes client orders over-the-counter (OTC) on its own account on a frequent, systematic and substantial basis, as defined in Article 4(1)(20) of Directive 2014/65/EU (MiFID II).

on a UK trading venue.[15] Each report includes information on the International Securities Identification Number (ISIN) of the instrument traded, the time of the transaction (time-stamped to at least the nearest second), the price and the quantity as well as other trade characteristics such as details of how and where trades are executed.

One advantage of our data is that they identify both counterparties of a trade, the buyer and the seller, irrespective of whether the counterparty is a dealer or client. Each counterparty is identified via their Legal Entity Identifier (LEI) and name. This feature sets the dataset apart from other transaction datasets for OTC markets, such as TRACE for US corporate bonds, and allows us to analyse trader behavior at a more granular level than otherwise possible and to better understand the roles of different types of traders in this market.

B. *Auxiliary data*

To obtain more information on the characteristics of the traded bonds, such as maturity and credit ratings, we complement our transaction data with data from S&P Capital IQ, Refinitiv and the European Securities and Markets Authority's (ESMA's) Financial Instruments Reference Database System (FIRDS). To obtain more information on trading firms, we use the publicly available GLEIF Level 2 (Who Owns Whom) data on the parent-child relationships between companies and the Bank of England's (BoE) internal mapping between a firm's Legal Entity Identifier (LEI) and its sector assignment (dealer, asset manager, pension fund etc.). The mapping is constructed from public data, such as the ECB's list of financial institutions, BoE lists of its regulated and supervised entities, as well as tediously hand-mapped entities.

C. *Data filtering and cleaning*

The data pre-processing and cleaning precisely follows Jurkatis (2024). The steps consist of selecting corporate bond transactions, identifying duplicates, and subsequently correct-

[15] Prior to 1 January 2021, when the UK left the European Union (EU), the data include trades in UK regulated bonds executed on EU venues. We retain these trades in our sample.

ing price and quantity outliers and erroneous counterparty reports (i.e. a firm reporting an incorrect LEI of the firm it traded with). We refer the reader to Jurkatis (2024) for the details of each of these steps.

We supplement the cleaning approach by winsorizing reported quantities in terms of their nominal values in their respective denominated currency. We use reports in bonds denominated in United States dollars (USD), Euros (EUR) and Great British Pounds (GBP), which account for around 60%, 30% and 10% respectively amongst the bonds in those three currencies. All reported quantities are subsequently converted to GBP. We also drop the 2% most extreme reports according to their transaction costs (i.e. the 1% lowest and highest transaction costs), the computation of which we outline below. We also drop trades executed on a weekend or English public holiday, trades with counterparties that do not have an LEI (such as natural persons), trades involving governmental or state-like entities such as central banks, and trades between dealers and clients that have the same ultimate parent. Finally, while the BoE's mapping contains over 130 dealers due to their role in other markets such as the UK's government market or the derivative market, we filter out dealers less relevant for the corporate bond market by focusing on dealers that account for at least 0.1% of total trading volume over the entire sample period.

Table I shows the main descriptive statistics of our sample post cleaning and filtering. The table shows that we have a rich cross-section in all three main dimensions of our data: dealer, clients, and bonds. We have almost 18,000 clients, 40,000 bonds, 6.6 million trades and 52 dealers in our data — the latter being comparable to the number of core dealers in TRACE (see Bessembinder et al., 2018, 2020; Colliard et al., 2021). Panels B to D of the table also show that we have a reasonable amount of heterogeneity in each of these dimensions, with more and less active dealers/clients, and more and less liquid bonds.

The average dealer executes 127,000 trades. In 25% of the cases, a dealer executes not more than seven trades per day or, at the other extreme, at least 150 trades. On average, a dealer trades with 46 different clients and trades 70 different bonds on a given day. Clients, on the other hand, trade 365 times on average over the entire sample and, conditional on observing a client trading on a given day, it trades five times in four different bonds with three different dealers per day. All of these statistics show significant variation between different clients and days. Similarly, the average bond trades only 165 times over the entire sample and, conditional on being traded on a given day, is traded twice by two different clients and dealers.

[Insert Table I about here]

III. Main Variables: Client-Sourced Liquidity (CSL) Trades and Transaction Costs

A. Classifying Trades: CSL, Matched, and Deal Trades

In this section, we outline the procedure we use to identify client-sourced liquidity (CSL) trades. We define such trades as those in which a dealer executes two trades in opposite directions (e.g., a client's buy followed by a client's sell) in the same bond, with two different clients within the same day.

[Insert Figure 1 about here]

Figure 1 provides a graphical illustration of the procedure we follow to identify CSL trades in the data. At time t_1, a client C_1 buys or sells the bond to dealer D. Now suppose that within the same day, this trade is followed by a trade in the same bond at time $t_2 > t_1$ by the same dealer, with another client C_2. If this second trade is (a) in the opposite direction as the first trade and (b) there is no trade by the same dealer (including inter-dealer trades) in the same bond, we classify the pair of trades occurring at dates t_1 and t_2, a CSL trade. In this case, we refer to the trade at t_1 as the first leg, and the trade in t_2 as the second leg. We allow both the first and the second leg to include more than one client if the dealer happens to trade with more than one client in the same direction at the same time (same millisecond or second depending on the timestamp precision). Further, a particular trade cannot belong to more than one CSL trade, that is, a second leg of one CSL trade cannot be the first leg of another CSL trade. We also partition CSL trades into two subgroups: (i) fast CSL (fCSL) trades, that is, those for which $0 < t_2 - t_1 \leq 15$ mins and (ii) slow CSL (sCSL) trades. As shown below, the data suggest that fCSL trades are those in which dealers deliberately seek liquidity from clients in the second leg (C_2).

Importantly, trades involving two different clients trading the same bond in opposite directions at the same time ($t_1 = t_2$) are not included in our set of CSL trades. Instead, we refer to the former as riskless principal trades or simply as 'matched' trades. Matched trades are different from CSL trades because a dealer bears no inventory risk in the former while she may in the latter. Moreover, in CSL trades, clients in the first leg receive immediate execution while clients who initiate a matched trade do not. Indeed, matched trades are usually prearranged, which means that the client at the origin of the trade has to wait until the dealer finds a counterparty to take the other side of the trade. Our ability to differentiate matched trades from fast CSL trades is due to the granularity of our data. In contrast, due to data limitations, studies relying on TRACE have not made this distinction (e.g., Choi et al., 2024; Kargar et al., 2021).[16]

We are confident that matched trades are different from other trades for several reasons. First, MiFID regulation requires trades to be timestamped with the time of the execution, not the time when an order was received (see Section 5.2 and 5.13 of the ESMA MiFID II reporting guidelines).[17] Second, MiFID II transaction reports contain a trade capacity field in which reporting firms must indicate whether they executed a trade on their own account (such trades are flagged as "DEAL"), in a riskless principal capacity ("MTCH"), or in any other trading capacity ("AOTC") (see Section 5.2 of the ESMA

[16] Dealers in U.S. corporate bonds can report trades with the potential for a 15-minute delay, which means that agency trades cannot be clearly distinguished from fast CSL trades. In contrast, trades for the bonds in our data must be reported with the timestamp of the execution, which allows us to separate matched trades from fast CSL trades.

[17] Special attention must be given to trade reports where several client orders are filled with more than one market side trade (see Section 5.23 of the ESMA guidelines). If these trades are not executed using the dealer's own account, the client trades receive the timestamp of the first market side transaction. We capture these trades as well as matched trades using the so-called "internal account" flag which must be used in such cases.

reporting guidelines).

In Table A.II in the Appendix, we present how our trade classifications overlap with dealers' self-reported trade capacity flags. This table shows that 90% of trades are reported as "DEAL" by dealers and that 96% of our "CSL" trades are reported as "DEAL". This shows that dealers view CSL trades as distinct from matched trades. Second, only 2% of all trades are flagged as "MTCH" by dealers and 5% of the trades that we classify as "matched trades" are indeed reported as "MTCH" by dealers. Others are reported either as "AOTC" (8%) or as "DEAL" (87%).[18][19] Therefore, some of our matched trades may indeed belong to fCSL trades. However, the fact that both sides of matched trades are executed contemporaneously means that they carry no economic risk for the dealer (other than maybe the risk of failed settlement on either side of the trade). This is the feature that matters for our analysis and interpretations.

[Insert Table II about here]

Moreover, we find striking differences between CSL and matched trades in terms of their trade and bond characteristics. Table II reports the share of total trading volume by trade type in different periods (normal vs crises period), and the distribution across bond ratings, maturities and trade sizes for each trade type. For the crisis period we use the "Dash-for-Cash" (DfC) of March 2020. The DfC period saw extreme selling pressure that occurred as investors tried to liquidate positions during the onset of the COVID pandemic. We define this period as 1 to 18 March.

CSL trades account for about 17% of total trading volume in normal times but their share increase during DfC (20%). They are also used more frequently when bond default risk increases or exposure to interest risk increases, which contrasts strongly with matched trades. For instance, trades in high yields bonds account for 48% of fCSL (41% of sCSL) trades compared to just 30% in matched trades, and trades in bonds with at least 15 years to maturity account for 22% of all CSL trades, compared to 20% for matched or

[18]Dealers can use the flag AOTC for matched trades because they allow the dealers to report two different prices for the two legs of a matched trade.

[19]For the remainder of the analysis, any trade flagged as MTCH but classified as 'deal' by our method, will be moved into our 'match' category.

deal trades. Even more distinct is the distribution of trade sizes across the different trade types. Around 15% of CSL trades are in the riskier block size (trades above £2.5m) compared to only 6% among matched trades and 8% in deal trades. The smallest and safer micro trades (trades of not more than £50,000) account for only around 9-12% of CSL trades compared to 25% in matched trades and 14% in deals. Overall, Table II shows that CSL trades, and especially fCSL trades, are more frequent when inventory risk and therefore inventory holding costs are large. This fact suggests that they are used as a tool for risk management for dealers.

[Insert Figure 2 about here]

Figure 2 shows that fCSL trades also have different dynamics compared to matched and deal trades. Fast CSL trades account for only around 5% of total trading volume, but regularly spike in stress episode such as the DfC-crisis, the invasion of Ukraine that precipitated a commodity market crisis, the LDI-crisis which mainly affected UK government bonds but also saw a sell-off of corporate bonds by LDIs and pension funds (Henning et al., 2023), and the banking crisis of March 2023 sparked by the failures of Silicon Valley Bank and Credit Suisse. This again confirms that fCSL trades are more frequent when balance sheet costs for dealers increase. In contrast, matched trades trend upward between 2019 and 2020 and then remain relatively stable at around 20% of trading volume. The upward trend in matched trades is mirrored by a downward trend in sCSL and deal trades, particularly pronounced around year end, when we see an increase in the former and decrease in the latter. Importantly, the dynamics of sCSL trades and matched trades are different from those fCSL trades during crises. None of the time-series show the same steep increase during these stress times. If anything, the share of matched trades seem to decrease in crises.

[Insert Figure 2 about here]

B. Transaction costs

We now turn to the measurement of our main dependent variable, namely transaction costs faced by clients in their corporate bond transactions. We define transaction costs following Hendershott and Madhavan (2015) and others as

$$tc_\tau := \log(p_\tau / p_\tau^*) \times D_\tau \times 10,000 \tag{1}$$

where p_τ is the clean price in transaction τ between a dealer d and client c at time t in bond b, p_τ^* is the benchmark price of the transaction which is the closest inter-dealer price in the same bond prior to the transaction but not older than 24 hours, and D_τ is the trade direction of the client (+1 for a client buy, -1 for a client sell). We multiply transaction costs by 10,000 to measure them in basis points (bps). Table II and Figure 3 provide some insights into overall transaction costs, split by trade type, and their dynamics.

Table II shows that average transaction costs are around 10 bps, cheapest typically for matched trades (8.5 bps), followed by deal trades (9.5 bps), fCSL trades (10.9 bps) and sCSL trades (14 bps). Transaction costs increase markedly during the DfC, as was the case in the US corporate bond market (e.g. Kargar et al., 2021) and asymmetrically, more pronounced for client sells than for client buys which is expected since the crisis is characterized by large divestments by institutional investors. Average transaction costs across all trades increased to 22 bps, however, only to 13 bps for a client-buy compared to 29 bsp for client-sell. Slow CSL trades are the most expensive trades for both trade directions. Across client-buys fCSL trades are the cheapest (12 bps), while matched trades are the cheapest across client-sells (25 bps). Transaction costs also increase during other stress episodes, particularly for sCSL trades, as can be seen from Figure 3.

[Insert Table II about here]

The bottom panel of Figure 3 depicts transaction costs for the first and second leg of CSL trades separately. It shows that the first-leg trade is generally more expensive than the second leg. This is consistent with our interpretation that the second leg trade is initiated by the dealer. That is, the client in the second leg provides liquidity to the dealer acting in the first leg and the latter rewards the former for liquidity provision by trading at a discount. We study this point in more detail in subsequent sections.

[Insert Figure 3 about here]

Of course, these comparisons of average transaction costs across dealers, bonds, and clients do not account for the endogeneity of the various types of trades. For instance, Table II already suggests that CSL trades are more likely to be observed in riskier bonds and one naturally expects trading costs to be larger for such bonds (independent of the trade-type). In subsequent analyses, we therefore control for bond, dealer, client and time-fixed effects and other trade characteristics to measure the isolated effect of CSL trades on transaction costs. We will show that the second leg CSL trades are analogous to the exercise of an option for dealers. As Table II shows this option is used infrequently (because it is costly) but the possibility to exercise helps the dealer to manage her balance sheet cost more efficiently and therefore to reduce trading costs for all her clients.

IV. Hypotheses Development

We conjecture that CSL trades reflect dealers' use of clients as a liquidity backstop. Specifically, after executing trades that strain their balance sheet capacity — such as those involving riskier bonds or large block trades — dealers actively seek to transfer risk to other clients to restore balance sheet flexibility."

To better understand this mechanism and develop testable implications, we consider an extension of Saar et al. (2022). Saar et al. (2022) study how dealers' balance sheet costs affect the choice between riskless principal trades ("matchmaking") and risky principal trades ("market-making") by a dealer and her clients. To develop our testable hypotheses, we consider the possibility for dealers to source liquidity from other clients after a market-making trade, an option that is not available to dealers in Saar et al. (2022).

In this section, we outline the main ingredients of the model. Details and derivations are provided in Section *A* of the Appendix. Figure 4 offers a schematic overview of the model.

[Insert Figure 4 about here]

At time 1, a dealer is contacted by a client (C_1), who can be a buyer or a seller (with equal probabilities) of an asset with expected value v. If he executes his desired trade, the client obtains a private benefit, u_1, whose distribution is uniform over $[0, \bar{u}_1]$. The dealer offers two options for executing the client's trade: (i) the matchmaking option at price f or (ii) the market-making option at price S_1.[20] If he chooses the first option, the client pays f to the dealer and wait until the dealer finds a counterparty for his trade. In this case, the client's payoff is $(\delta \times u_1 - f)$, where $\delta < 1$ and the dealer's payoff is $f - I$. Parameter δ represents the cost of delay (the time of finding a counterparty) for the client while parameter I is the cost incurred by the dealer to find a suitable counterparty.[21] If instead the client chooses the market-making option, he pays a spread S_1 to the dealer and his order is immediately filled on the dealer's account. In this case, the client's payoff is $u_1 - S_1$. Finally, if the client rejects the dealer's offers, he obtains a payoff of zero.

When C_1 opts for the market-making option, the dealer faces a balance sheet cost B, unless she can offload her position quickly. To achieve this, the dealer depends on a network of clients, referred to as her liquidity supplier network.[22] This network has N clients, each with a probability $\pi < 1$ of being able to trade the bond.[23] Thus, the likelihood that the dealer finds at least one client who can trade the bond is $\alpha(\pi, N) = 1 - (1 - \pi)^N$. This likelihood increases with (i) the size (N) of the dealer's network and (ii) the likelihood (π) that a given client in this network is able to trade the bond.

The dealer contacts clients sequentially and stops canvassing her liquidity supply network at the first client (denoted C_2) who expresses interest. Then, the dealer offers C_2 the opportunity to buy the asset at price $(v + S_2)$ (if C_1 was a seller) or to sell the asset

[20] Prices f and S_1 cannot be contingent on u_1 because the client's private benefit is unobserved.

[21] In contrast to Saar et al. (2022), we assume that the client pays the fee when he contacts the dealer, not when he is matched. This simplifies the exposition without qualitatively affecting the results.

[22] For instance, Goldstein and Hotchkiss (2020) notes that dealers routinely signal their interest in unwinding positions by broadcasting bids and offers on a list of bonds in their inventory (called "runs"). See also Hendershott et al. (2024).

[23] In reality $\pi < 1$ because, for instance, clients are not allowed to trade some type of bond or because clients do not want to trade bonds on which they have no prior information (e.g., the bond is not already in their portfolios).

at price $(v - S_2)$ (if C_1 was a buyer). If C_2 accepts the offer, his payoff is $(u_2 - S_2)$, where u_2 is C_2's private benefit.[24] In this case, the dealer avoids the balance sheet cost triggered by the initial trade and earns a total profit (across both transactions) of $(S_1 + S_2)$. If C_2 rejects the offer, his payoff is zero, and the dealer's total profit is $(S_1 - B)$. That is, we assume the dealer does not attempt to contact another client in her network if negotiations fail with the first interested party.[25] If no client in the dealer's liquidity supply network expresses an interest for trading the asset (which happens with probability $(1 - \alpha(\pi, N))$, the dealer's total profit is $(S_1 - B)$ as well.[26]

We assume that C_2's private benefit, u_2, is uniformly distributed over $[-\bar{u}_2, \bar{u}_2]$, with $\bar{u}_2 < Min\{\bar{u}_1, \frac{\bar{u}_1}{2} + \frac{I}{2\delta}\}$. This condition is sufficient (see Appendix A) for C_2 to be worse off trading at date 1 (at the equilibrium values for f and S_1). In this sense, C_2 is a client who does not have a strong interest in the bond in the first place. However, he may be willing to trade opportunistically if the dealer offers a sufficiently attractive price (low S_2).

The dealer's choice variables are the matchmaking fee (f), the spread (S_1) charged to C_1, and the spread (S_2) offered to C_2. The dealer chooses these prices to maximize her expected profit and each client behaves optimally given these prices.[27] We solve for the dealer's equilibrium prices $(f^*, S_1^*, S_2^*))$ in Appendix A.

We show that the dealer offers a price improvement to C_2 relative to C_1 ($S_2^* < S_1^*$). Moreover, this improvement increases with the dealer's balance sheet cost. This reflects the fact that the dealer is willing to offer an even more attractive price to C_2 when her balance sheet cost increases ($\frac{\partial S_2^*}{\partial B} < 0$), to avoid this cost while, in contrast, her cost of market making for C_1 increase ($\frac{\partial S_1^*}{\partial B} > 0$). These effects combined with the condition $\bar{u}_2 < \bar{u}_1$ imply that $S_2^* < S_1^*$ for all values of B.[28]

Our first testable hypothesis is therefore:

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[24]For instance, if C_2 buys the asset, he pays $v + S_2$ for an asset that he values at $v + u_2$. Thus, C_2's payoff is $(v + u_2) - (v + S_2) = u_2 - S_2$.

[25]This assumption is not key. It just simplifies the exposition. What is important is that the dealer's offer might be rejected so that the dealer is not able to avoid the balance sheet cost with certainty.

[26]When $\alpha = 0$, the model is identical to Saar et al. (2022).

[27]In particular, C_1 optimally chooses between market making or matchmaking.

[28]The condition $\bar{u}_2 < \bar{u}_1$ is sufficient to guarantee $S_2^* < S_1^*$ for all values of B, including $B = 0$. However as B increases, one can relax the condition.

HYPOTHESIS 1 (H1). *The first leg of a CSL trade is more expensive than the second leg:* $S_2^* < S_1^*$.

The second implication of the model is that a drop in α leads to an increase in trading costs for C_1 (S_1^*) and an increase in average transaction costs across all clients for the dealer. This yields our second testable hypothesis.

HYPOTHESIS 2 (H2). *When the size (N) of a dealer's liquidity supplier network decreases or when clients in the dealer's network becomes less able to trade a bond (π decreases), the trading costs for the dealers' clients increase.*

Third, we show that when a dealer's balance sheet cost increases, she offers larger discounts on second leg trades and charges larger spreads on first leg trades. The net effect on average transaction costs for the dealer's clients is always positive but it is dampened when α is larger. This leads to our third testable hypothesis.

HYPOTHESIS 3 (H3). *The positive effect of an increase in dealer's balance sheet costs on trading costs for her clients is smaller when the size (N) of a dealer's liquidity supply network is larger or when clients in the dealer's network are more able to trade a bond (π increases).*

We test these implications in the next section.

V. Empirical Findings

A. Liquidity Discounts

Based on Hypothesis H1 we expect the first leg of CSL trades to be more expensive than the second leg since the dealer has to price in the risk of not being able to unwind the first leg trade despite her intention and effort to do so. We expect the second leg to trade at a discount relative to deal trades (trades that the dealer intends to keep on her book). Indeed, this discount reflects the price concession that the dealer pays to obtain liquidity from the second leg client.

To test this hypothesis, we regress transaction costs on the first and second leg of CSL trades controlling for other trade characteristics:

$$tc_\tau = \sum_{j=1,2} \gamma_j \, CSL_\tau^{(j)} + x_\tau' \beta + \mathbf{1}' \mu + \varepsilon_\tau, \tag{2}$$

where tc_τ are the transaction costs in transaction τ, and $CSL_\tau^{(j)}$ is a dummy capturing if the transaction is the 1st ($j = 1$) or second ($j = 2$) leg of a CSL trade. Controls x_τ include the trade size (in log), a dummy capturing if the client is selling, a dummy for matched trades, and a dummy for trades that are algorithmically executed. Each transaction is executed at a given time (t) between a dealer (d) and client (c) in a given bond (b) on a given venue, such as an MTF, OTF or RM, or bilaterally with an SI or over-the-counter.[29] We use these dimensions of a trade to include dealer-day, client-month, bond-day and venue-type (incl. OTC) fixed effects (μ). We have already established that CSL trades are related to risk management being more frequent in riskier trades. As such the inclusion of dealer-time, client-time, bond-time and venue-type fixed effects ensures that any premium or discount relative to deal and matched trades are not driven by CSL trades being related to dealer, client, bond, time or execution venue specific risk concerns or other such characteristics that would simultaneously affect transaction costs. Standard errors are double clustered by dealer and bond.

[Insert Table III about here]

Table III presents the results. The first column is similar to the specification in Choi et al. (2024). The difference here is that we separate matched trades, where the dealer matches clients instantaneously acting only on a riskless principal basis, from those trades where the dealer provides immediacy to one counterparty to then unwind the trade with another counterparty, using its own balance sheet throughout the process. In columns (1), we find that the second leg in CSL trades receives a discount of three bps relative to the average of deal and first leg trades which form the baseline of this regression. The discount is similar to that of matched trades.

[29]In the following, for ease of exposition, we will include SIs and OTC trades in the venue terminology.

In column (2) we include the first leg of CSL trades as a separate dummy — which leaves deal trades as the baseline category. We find that the first leg trades at a premium of four bps relative to the transaction costs of a deal trade. This is in line with CSL trades being trades that the dealer is more reluctant to execute in the first place. The dealer therefore charges a higher spread to compensate for the risk of having to book the trade on her own account. Interestingly, the discount on the second leg becomes small and insignificant, which is explained by the next column.

In column (3) we split CSL trades by the time between the first and second leg: $fCSL$ trades where the second leg follows within 15 minutes of the first leg, $CSL_{(15,30]}$ where the second leg follows within 15 to 30 minutes, $CSL_{(30,60]}$ where the second leg follows within 30 to 60 minutes, and $CSL_{(60,\infty)}$ where the second leg follows within the same day but not earlier than 60 minutes after the first leg.

We find that discounts in the second leg are reserved exclusively for $fCSL$ trades. This indicates that the second leg in $sCSL$ trades (which follow more than 15 minutes of their first leg) are trades with clients that arrive randomly and, by chance, want to trade in the opposite direction of the previous client, rather than being trades in which dealers intentionally seek client liquidity. Interestingly, the first leg of CSL trades are generally more expensive than regular deal trades and increase in the time-distance to their second leg. This may again be related to the previous finding in that sCSL may be executed by the dealer in the expectation of not being able find an offsetting trade (or only with greater difficulty).

Finally, column (4) groups CSL trades into fast and slow ones. This specification provides the baseline for our remaining analyses.

In sum, the negative (positive) estimates for the second (first) leg of CSL trades justify our interpretation that second leg clients receive compensation for providing liquidity to dealers in circumstances where the dealer had provided immediacy to a different client in the previous trade, but where she is reluctant to keep the inventory on her books. The dealer pays the second client compensation to allow her to unwind the position quickly. The discount on the second leg then raises the question of why the dealer does not trade in the inter-dealer market instead? The answer is that despite the discount, the average transaction costs for second-leg trades are still positive (see Figure 3). To the extent that our benchmark price to measure transaction costs reflects the price a dealer would obtain in the inter-dealer market, the fact that second-leg transaction costs are positive imply that the dealer fares better trading with a client than with another dealer.

This in turn raises the question why clients trade in the second leg if they are still paying the transaction cost. One motive could be a pure co-incidence of needs. A dealer may contact clients who she knows to have an interest in the bond and so the client, who potentially would have traded the bond in the near future anyway and simply waited for an opportune moment, agrees to the trade. In addition, informed clients can understand and take advantage of the opportunity to trade a bond below average transaction costs, irrespective of their prior inclination to trade the bond. From the dealer's perspective such a trade could fulfill two purposes: to avoid balance sheet costs and to learn from informed investors (Czech and Monroe, 2025; Pintér et al., 2022). Lastly, certain clients may be able to unwind the trade quickly so that they earn the spread due to the discount they obtained in the CSL trade. We intend to investigate these motives in future research.

B. *Losing Liquidity Providers*

Table II shows fast CSL trades account for only 5% of overall trading volume. However, the model in Appendix *A* suggests that this does not undermine the importance of liquidity provision by dealers' clients. Indeed, the dealer prices in the option to contact liquidity providers, even if this option is not exercised. As shown by our hypothesis H2, this option results in lower average transaction costs for the dealer's client than when the option is not present (the average transaction costs are maximal when $\alpha = 0$ in the model since they decline with α). One implication is that dealers with a larger network of liquidity providers should charge lower transaction costs, all else equal (H2). In this section, we test this hypothesis.

We examine situations when the usual liquidity suppliers are unwilling or unable to provide that service. We do so by focusing on the DfC stress episode which saw a global sell-off of corporate and government bonds that eventually led to world-wide central bank and government interventions to stabilize markets. Asset managers faced historical outflows, UK pension funds faced margin calls on their US dollar (USD) hedges and hedge funds on their basis trades (Czech et al., 2021, 2022; Ma et al., 2022). During this episode, some clients, who would usually be liquidity suppliers, liquidated their assets which reduced the potential pool of liquidity supplying clients.

First, for each day during the DfC we identify clients that are not available for liquidity provision as they are exclusively selling on that day.[30] Second, for each bond we measure its share of fCSL trades in total trading volume over the 180 days prior to the DfC, $LPshare_b$. Finally, we measure the share of client-sourced liquidity that is unavailable or 'blocked' on a given bond day, $BlockedLP_{bt}$, by the share in $fCSL^{(2)}$ volume over those 180 days accounted for by clients that are not available for liquidity provision.

We interpret $BlockedLP_{bt}$ as a negative shock to the potential network of client liquidity support for a bond (α). We measure the impact of that shock on average transaction costs by regressing

$$\begin{aligned} tc_\tau = {} & \gamma_0 \, LPshare_\tau + \gamma_1 \, BlockedLP_\tau + \gamma_2 \, BlockedLP_\tau \times clientsell_\tau + \gamma_3 clientsell_\tau \\ & + x_\tau' \beta + \mathbf{1}' \mu + \varepsilon_\tau \end{aligned} \tag{3}$$

where, as previously, tc_τ is the transaction cost of a given trade τ (between dealer d and client c at time t on a given venue) and x_τ includes the previous variables $iCSL^{(j)}$ for $i = f, s$ and $j = 1, 2$, 'match', 'algo', and 'logQ', and μ are fixed effects (refer to Table A.I in the Appendix for the variable definitions). Since trades in which clients want to sell are generally more expensive than trades in which clients want to buy during the crisis, we test the asymmetric impact of a reduction in the potential client-liquidity network for a bond on the ability to buy or sell the bond by interacting $BlockedLP$ with the $clientsell$ dummy.

Including the overall share of fCSL trades for a bond before the DfC period ($LPshare$)

[30] Given that DfC was marked by significant selling pressure (as opposed to buying), we assume that dealers demanded liquidity from clients that were able to buy.

in the regression is not strictly necessary as our main focus is on the effect of unavailable liquidity supply ($BlockedLP$). However, it may be interesting to see if a bond's share of liquidity provision prior to the crisis relates to transaction costs during the crisis. To include $LPshare$, however, we cannot include bond fixed effects. At the same time, bond risk characteristics simultaneously influence the share of client-sourced liquidity and transaction costs (as in high-yield bonds). Similarly, such characteristics may be simultaneously associated with a higher share of blocked liquidity supply and higher transaction costs. Therefore, to ensure that our results are not confounded by bond riskiness in the absence of bond-fixed effects, we include time-to-maturity (in years) and rating fixed effects to account for a bond's duration and credit risk in the regression.

We also include dealer and client fixed effects to ensure that the results are not driven by dealers or clients that are simultaneously associated with trading bonds that have a higher share of blocked liquidity supply and higher transaction costs. For example, including dealer fixed effects means that we are utilizing within dealer variation of bonds with more and less blocked liquidity support. As before, we also include venue-type fixed effects to account for cases where different bonds are systematically traded on different platform types that face different transaction costs during the crisis.

Finally, we have to avoid that our $BlockedLP$ variable simply captures selling pressure which would be the case if the clients identified as not being available for liquidity provision are selling the same bonds in which they used to provide liquidity. To avoid these concerns we exclude such bonds from the sample. Table IV presents the results.

[Insert Table IV about here]

Column (1) of Table IV shows that transaction costs in bonds whose entire network of liquidity supplying clients is unavailable ($BlockedLP = 1$) increases by 11 bps for a client sell ($\gamma_2 - \gamma_1$) compared to a bond whose network of liquidity support is not impacted ($BlockedLP = 0$). This constitutes an increase of 38% relative to the 29 bps transaction costs of an average sell during DfC (see Table II). Put differently, the 11 bps surcharge for a client sell during the crisis doubles in bonds with entirely blocked liquidity supply. At the same time, a client buy is 11 bps cheaper in bonds with blocked liquidity supply.

We also find that the discount on liquidity providing trades doubles from four bps over the entire sample (see Table III) to around eight bps during the crisis. We do not find evidence that a premium is charged on the liquidity-demanding first legs. This is explained by the correlation of the trade direction of the first leg with client sells during the crisis. There is no additional premium that is not already captured by the client sell dummy.

The results are remarkably robust to including more granular fixed effects, notably the inclusion of bond and dealer-day fixed effects in columns (3)-(4). In column (5) we even include bond-day fixed effects, which eliminates the possibility of including $BlockedLP_{bt}$ which is measured at the bond-day level. As such, the interaction of $BlockedLP$ with the client-sell dummy captures the additional premium on a client sell compared to a client buy for an increase in the share of unavailable client liquidity support.

Taken together the results imply that dealers charge higher transaction costs for sells in bonds where the dealer expects it to be more difficult to find a client for an offsetting trade while providing discounts for client buys to manage the inventory against increased selling pressure during the crisis in the absence of the usual clients' liquidity support. The results also imply search frictions on the part of the dealers since clients that have previously supplied liquidity do not seem to be easily replaceable.

C. Liquidity-Providing Trades Dampen Shocks to Dealers' Balance Sheet Costs

Our third testable hypothesis (H3) implies that following an increase in the balance sheet cost of holding a bond (e.g., because the bond is downgraded), dealers should charge larger trading costs on average. However, the increase in trading costs should be smaller for bonds traded by dealers with a larger network of liquidity suppliers. In this section, we test this prediction.

C.1. Price impact and client-sourced liquidity around bond downgrades

To test the relevance of client liquidity support when dealers experience an increase in their balance sheet costs for specific bonds, we focus our analysis on *fallen angels* — bonds that are downgraded from investment grade (IG) to high-yield (HY). The downgrade represents a direct increase in the cost of holding that bond on a dealer's balance sheet due to the increase in capital requirements associated with holding an HY bond rather than an IG bond. Previous studies (e.g., Ellul et al. (2011)) have shown that downgrade events are associated with increased selling pressure driven by investors such as certain investment funds (e.g. investment-grade index tracking funds) whose mandates generally do not allow them to own HY bonds. This selling pressure has been shown to exert temporary price pressure, driving prices below their fundamentals around the downgrade event. This means that fallen angels present an ideal environment to test our model implication as the downgrade represents a sufficiently large increase in the cost of holding that bond on the balance sheet to test the dealers' balance sheet capacities.

We start our analysis by corroborating previous findings that downgrade events exert temporary price pressure. The left Panel of Figure 5 shows a moving average of daily transaction costs across fallen angels tracked relative to the date of the downgrade. It shows that in the period 300 to 100 days before the downgrade, the cost of trading fallen angel bonds falls between those for IG and HY bonds. At around 100 days prior to the downgrade, transaction costs start to increase above the overall HY average, peaking just after the day of the downgrade.[31] Transaction costs then converge back towards the HY average at around 300 days following the downgrade.

The right Panel of Figure 5 provides preliminary evidence of the use of client-sourced liquidity to alleviate the balance sheet pressure resulting from the downgrade event. It shows that the average daily share of trading volume in fCSL trades around the downgrade event follows closely the trajectory of transaction costs — increasing from around 2.3% 100 days prior to the downgrade to 4% just after the downgrade, before falling back to

[31] The increase in transaction costs in advance of the actual downgrade event is consistent with previous studies showing that downgrades are anticipated events.

the previous level between 100 and 200 days after the downgrade. This observation is consistent with the model. When the balance sheet cost of holding a bond increases, a dealer offers larger discounts to liquidity suppliers and as a result, other things equal, a liquidity supplier is more likely to accept a dealer's offer. Thus, the likelihood of observing CSL trades increases when the balance sheet cost of holding a bond increases.

C.2. The impact of client liquidity supply on the price impact of fallen angels

Next, we turn our analysis to the impact on transaction costs of fallen angels depending on client liquidity support, using a differences-in-differences (diff-in-diff) regression design. For each fallen angel we define two periods: a downgrade window and a post-downgrade window. Informed by our previous analysis on the price impact around the downgrade event, we define the downgrade window of a fallen angel to start 100 days before the downgrade and to end 300 days after the downgrade. The post-downgrade period is defined as the period starting 301 days after the downgrade. For each day over those two periods, we subtract from the transaction costs of a given trade in a fallen angel the average transaction costs across all HY bonds traded on the same day:

$$\Delta^{HY} tc_\tau := tc_\tau - \sum_{s \in \mathcal{T}_t^{HY,\neg FA}} tc_s / |\mathcal{T}_t^{HY,\neg FA}|, \tag{4}$$

where $\mathcal{T}_t^{HY,\neg FA}$ are all transactions in HY bonds on day t not including the set of fallen angels. The time windows and the transaction costs measured against average transaction costs of the HY peer group provide the two dimensions for the diff-in-diff design.

To analyse the importance of client sourced liquidity, for each fallen angel we compute the amount of client liquidity provision before the downgrade.[32] We do so by measuring the share of fCSL trades in total trading volume over the 100 days before the start of the

[32] Using contemporaneous client liquidity supply would raise concerns about liquidity supply reacting endogenously to the size of the price impact.

downgrade window, $LPshare_b$. We then regress:

$$\Delta^{HY} tc_\tau = \gamma_0 \, LPshare_\tau + \gamma_1 \, D_\tau + \gamma_2 \, LPshare_\tau \times D_\tau + x'_\tau \beta + \mathbf{1}'\mu + \varepsilon_\tau, \tag{5}$$

where D_τ takes the value 1 if the transaction falls into the downgrade window for the given bond and 0 otherwise. The idea is that $LPshare_\tau$ is a measure of the size of the network of liquidity suppliers, prior to the downgrade, for dealers active in bond b. A positive value for γ_1 means that fallen angels trade further away from their HY peers around the downgrade event than post-downgrade, which is expected given Figure 5.

To be able to attribute the price impact to the downgrade itself and not to changes in trading characteristics between the two periods that also affect transactions costs we include in x_τ the previous variables $iCSL^{(j)}$ for $i = f, s$ and $j = 1, 2$, 'clientsell', 'match', 'algo', and 'logQ' (refer to Table A.I in the Appendix for the variable definitions). For μ we include dealer, client, ratings and venue-type fixed effects which ensure that the results are not driven by, for example, dealers (or clients) that charge (or are being charged) larger transaction costs in general and trade fallen angels more frequently during the downgrade window than post-downgrade.

The inclusion of these fixed effects is also important for the interpretation of the estimate on the interaction term, γ_2. Our hypothesis H3 implies that we should observe a negative estimate for γ_2, that is, the price impact triggered by the downgrade is alleviated by dealers' access to client liquidity. However, if a higher share of liquidity provision is associated with riskier (and therefore less liquid) bonds and if such bonds experience larger price impacts, we will underestimate the benefit of accessing client liquidity if we do not control for ratings fixed effects. The same problem arises if a higher share of client liquidity provision is associated with dealers that are more constrained going into the downgrade period. The inclusion of dealer fixed effects addresses this concern. Regarding client fixed effects, on the other hand, if a higher $LPshare$ is associated with the absence of clients that typically exert selling pressure due to not having the mandate to hold HY bonds, not including client fixed effects will overestimate the beneficial impact of client liquidity support.

[Insert Table V about here]

Table Table V presents the results.[33] Column (1) shows that fallen angels trade at a 4 bps premium during the downgrade window compared to the post-downgrade period. This confirms our price impact analysis in the previous section. Column (2) shows that the increase in fallen angels trading costs is not associated with the extent to which dealers relied on liquidity suppliers before the downgrade (γ_2 is not significantly different from zero).

At first glance, this result seems to reject our hypothesis H3. However, it can stem from the fact the nature of liquidity suppliers for a given bond matters. Indeed, suppose that these liquidity suppliers for a given bond b are mostly insurance companies. As insurance companies face regulatory constraints limiting their ability to hold high-yield bonds, the downgrade is effectively reducing the network of liquidity suppliers for this bond.[34] This effect will amplify the positive effect of the downgrade on transaction costs for the bond according to the model (this is both an increase in B and a decrease in α). If instead, the liquidity suppliers for a given bond b are mostly hedge funds, the downgrade will not reduce their ability to provide liquidity to dealers as their mandate does not prevent them from holding high-yield bonds. In this case, we expect the positive effect of a downgrade on clients' transaction costs to be dampened for bonds with a larger network of liquidity suppliers, as predicted by H2. In sum, for a network of client liquidity support to be useful during a bond downgrade it needs to consist of clients with the corresponding risk appetite and investment mandate to seize the opportunity provided by the temporary price pressure.

To better test our hypothesis H3, we exploit our ability to identify the type of clients in the data. More specifically, we can classify clients into seven sectors: (i) hedge funds (HF),

[33]Note that the sample is restricted to days of the downgrade and the post-downgrade window excluding days that fall within the period of DfC or the LDI-crisis period.

[34]Capital requirements set out under Solvency II for EU and UK insurers prescribe to hold more capital against high-yield bonds than investment grade bonds. Risk-based capital requirements in the US similarly affect US insurers' incentives to hold high-yield bonds.

(ii) asset manager (AM), (iii) non-dealer banks (Bank), (iv) insurers (Insurer), (v) pension and LDI funds (PFLDI), (vi) principal trading firms (PTF) and (vii) trading services firms such as brokers (Broker). Clients who do not belong to any of these categories are classified as "others".

We then measure the share in total liquidity provision in the 100 days prior to the downgrade window accounted for by a given client sector,

$$Lrel_b^s := \frac{\sum_{\tau \in \mathcal{T}_b^s(f_b-200, f_b-100)} fCSL_\tau^{(2)}\, Q_\tau}{\sum_s \sum_{\tau \in \mathcal{T}_b^s(f_b-200, f_b-100)} fCSL_\tau^{(2)}\, Q_\tau}, \tag{6}$$

where $\mathcal{T}_b^s(f_b - 200, f_b - 100)$ are all transactions in bond b by sector s in the 200 to 100 days prior to the day of the downgrade, f_b.

Using the sector-specific share of liquidity provision, we augment our previous regression setup in eq. (5) as follows:

$$\begin{aligned} \Delta^{HY} tc_\tau = {} & \gamma_0\, LPshare_\tau + \gamma_1\, D_\tau + \gamma_2\, LPshare_\tau \times D_\tau \\ & + \gamma_3\, Lrel_\tau^s + \gamma_4\, Lrel_\tau^s \times D_\tau \\ & + x_\tau' \beta + \mathbf{1}' \mu + \varepsilon_\tau . \end{aligned} \tag{7}$$

The results are presented in columns (3) to (9) in Table V and confirm our conjectures. Column (6) shows that a reliance on insurance companies for liquidity supply increases the price impact of fallen angels. For a given level of liquidity provision, if all of the liquidity provided depends on insurance companies, the price impact during the downgrade increases by another 18 bps. Given that insurers are restricted in their ability to hold HY bonds, an outsized reliance on them can be seen as a shock to the potential network of client liquidity support for a given bond during its downgrade window.

In contrast, and consistent with our hypothesis, an increase in HFs' share of fast liquidity providing trades dampens the effect of a downgrade on the transaction costs in a bond. Specifically, we find that if the entire network of liquidity providing clients consist of HFs the overall price impact of fallen angels is reduced by 5 bps, effectively eliminating the fallen angel price pressure.

In sum, the results presented in this section highlight the importance of the composition of the network of liquidity providing clients for a given bond/dealer to be able to source liquidity at all times. A small and under-diversified portfolio of client types in the network of liquidity-providing clients poses liquidity risk for a dealer. Not every client may be able to act as a liquidity provider at all times. This is particularly true for insurers who are constrained in trading HY bonds but also holds more generally when clients are constrained by tight funding or other restrictions.

VI. Who provides liquidity in CSL trades?

Given our previous finding on the importance of the number and mix of liquidity providing clients, the question arises whether certain client types take a special role as liquidity providers. Previous studies have highlighted the role of HFs and insurers as buyers of last resort during the DfC in the US corporate bond market (Kruttli et al., 2023; O'Hara et al., 2023), and the role of contrarian style mutual funds providing relief to dealers' balance sheet (Anand et al., 2021) over the inventory cycle.

In this section we study which client sectors act in the second leg of CSL trades, thereby providing more direct evidence on the engagement of certain sectors in liquidity provision. Moreover, we examine whether dealers reward certain clients more for their past liquidity provision services than others, allowing us to evaluate the importance dealers themselves attach to one client sector over another.

A. *Client sector participation in CSL trades*

Table VI shows the share of trading volume by sector in overall trading and within the various trade types for both normal times and the stress episodes of DfC and fallen angels. The table highlights clearly the unique role of HFs in client liquidity provision. They are the only sector which accounts for a higher share in second leg $fCSL$ trades (17% in normal times) as opposed to first leg trades (13%) and whose participation in second leg trades is also disproportionate to their overall activity (10%). This is not just true during normal times but is particularly pronounced in stress times, such as DfC and during fallen angels where hedge funds account for 19% of second leg $fCSL$ trading volume.

[Insert Table VI about here]

Brokers also tend to be more active in the second leg of $fCSL$ trades. However, they participate in these trades relatively less frequently than they do in overall trading. In fact, brokers typically have a more important role in second leg trades of $sCSL$ trades. However, our previous results show that these trades seem to be less related to liquidity provision.

The table also helps us to obtain a view on the role of insurance companies, which is more nuanced than the evidence from previous studies. They are the second smallest sector after PTFs measured by their overall trading activity (only 3.5% in normal times), and their proportion in second leg $fCSL$ trades is generally smaller (expect during fallen angels). In fact, during DfC their share in second leg trades was lower than their share in first leg trades. Insurers, however, seem to take a special role in matched trades, accounting for over 6% in these trades in both normal times and during DfC. However, given the contemporaneous execution of both legs in matched trades, it is difficult to assess whether insurers take the of role liquidity providers in these trades without any further information.

Insurers participation in matched trades (and overall) during fallen angels is significantly muted, which seems natural given their restrictions on trading HY bonds. Interestingly, the share of HFs in matched trades is unusually high over the same period: 12% compared to only 8% and 6% in normal times and DfC, respectively.

Non-dealer banks show a similar pattern to insurers in terms of their participation in matched trades compared to their overall trading activity. However, their tendency to be relatively more active in the first leg of CSL trades may suggest that they also take the liquidity seeking side in matched trades more often than the liquidity providing side.

Finally, asset managers are by far the largest sector and therefore quite naturally take the largest stake in all of the trading types, including the second leg of $fCSL$ trades. However, they participate relatively less frequently in the second leg of $fCSL$ trades than in first leg trades and their activity in these trades is also relatively low compared to their overall trading activity. Their role as liquidity providers, therefore, seems less clear cut, at least at the sector level.

B. Rewards for liquidity provision

Next we test whether certain sectors are more rewarded than others for their past liquidity provision services. This would provide direct evidence on who dealers themselves value most as liquidity providing clients.

To that aim, we measure a client's share in liquidity provision for a specific dealer at a given point as

$$Lrel_{dct} = \frac{\sum_{\tau \in \mathcal{T}_{dc}(t-90,t-1)} fCSL_{\tau}^{(2)} \, Q_{\tau}}{\sum_{c} \sum_{\tau \in \mathcal{T}_{dc}(t-90,t-1)} fCSL_{\tau}^{(2)} \, Q_{\tau}}, \tag{8}$$

where $\mathcal{T}_{dc}(t-90, t-1)$ are all transactions between dealer d and client c in the 90 days prior to t, $fCSL_{\tau}^{(2)}$ takes the value one if the transaction is the second leg of a fast CSL trade and zero otherwise, and Q_{τ} is the nominal size of the transaction measured in GBP.

To test whether past liquidity provision is rewarded we regress

$$tc_{\tau} = \gamma_{Lrel} \, Lrel_{\tau} + x_{\tau}' \beta + \mathbf{1}' \mu + \varepsilon_{\tau} \tag{9}$$

where tc_{τ} is the transaction cost of trade τ (between dealer d and client c in bond b on day t on a given venue v) and x_{τ} includes the previous variables $iCSL^{(j)}$ for $i = f, s$ and $j = 1, 2$, 'clientsell', 'match', 'algo', and 'logQ', and μ are dealer-day, bond-day, client-month and venue-type fixed effects (refer to Table A.I in the Appendix for the variable definitions).

[Insert Table VII about here]

The first column of Table VII shows that client liquidity provision services are strongly rewarded by dealers. A client that accounts for a 1 percentage point higher share in liquidity provision for a given dealer receives a 0.13 bps additional discount on his trades, including on deal trades.

Previous studies have linked client liquidity provision with dealer-client relationships. In particular, Jurkatis et al. (2023) show that client liquidity provision is a strong motivation for dealers to nurture their relationships with clients by providing transaction cost discounts. Part of our liquidity services discount may therefore be driven by relationship discounts. To account for that possibility we follow previous studies (e.g. Di Maggio et al., 2017; Jurkatis et al., 2023) and measure dealer-client relationships based on past trading volume,

$$Qrel_{dct} = \frac{\sum_{\tau \in \mathcal{T}_{dc}(t-90,t-1)} Q_\tau}{\sum_c \sum_{\tau \in \mathcal{T}_{dc}(t-90,t-1)} Q_\tau}, \tag{10}$$

and include the relationship metric in our regression.

The second column of Table VII presents the results. Our estimate on dealer-client relationships is in line with previous studies and shows that clients receive better prices if they account for a larger share of a dealer's trading volume. Importantly, while the inclusion of the relationship metric dampens somewhat the size of the liquidity services discount, it remains statistically and economically significant, representing two-thirds of the size of the relationship discount. This shows that even in the absence of a general relationship, clients are rewarded the more a dealer relies on that client for liquidity provision.

Finally, to test whether certain sectors are particularly sought after types, we interact our liquidity services metric with sector dummies. Our findings from the previous sections showed that HFs are overproportionately active in liquidity providing trades and that they provide relief from price pressure of fallen angels. We did not find the same for asset managers and insurers which are other sectors linked to liquidity provision in previous studies.

Our regression results shown in column (3) of Table VII confirm the importance of HFs, which receive more than twice the liquidity service discount than the next sector, which are pension funds and LDIs. Given HFs' less regulated nature and their accompanying agility to react quickly to market conditions, they seem to be a sought after client type to have amongst ones liquidity providing clients. Asset managers and insurers, on the other hand, do not receive discounts for their past liquidity provision.

While HFs are clearly the sector most strongly rewarded for past liquidity provision, other sectors receive discounts as well. Banks, PTFs and pendsion funds and LDIs all receive discounts on for their trades the more they account for past liquidity provision for a given dealer. This finding is inline with dealers trying to diversify their network of liquidity providing clients to be able source client liquidity across potential states of the world in which any given client type alone may not be able to provide its services.

In sum, bringing our findings together, it seems that dealers regard client liquidity provision akin to an insurance policy. Our findings on the importance of the size and composition of a dealer's network of liquidity providing clients suggest that clients, if unavailable for liquidity provision, cannot be easily substituted by other, new clients. Dealers, therefore, provide discounts (or pay a premium) to liquidity providing clients, not just in their liquidity providing trades — which is simply the nature of such trades — but also in their liquidity demanding trades in order to maintain their liquidity client network. And while dealers use their liquidity insurance, i.e. CSL trades, only infrequently (about 5% of trading volume), the ability to cash in on the policy when it matters most (such as during stress times) impacts trading outcomes more broadly.

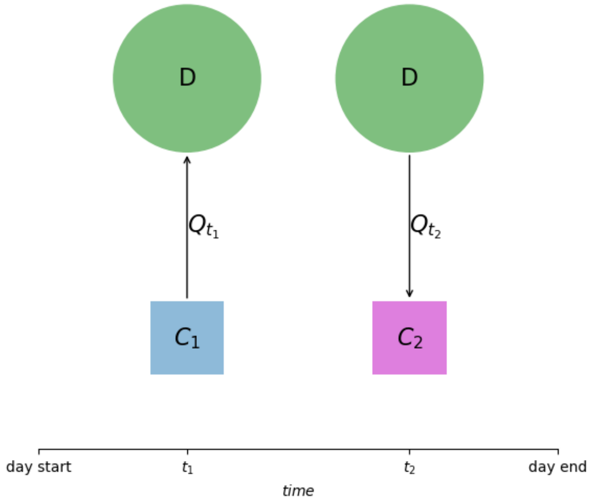
VII. Conclusion

We show that client-sourced liquidity (CSL) is an important tool for dealers to manage balance sheet costs and mitigate liquidity challenges in corporate bond markets. Using transaction-level data we find that dealers' networks of liquidity providing clients play a significant role in determining trading costs, particularly during periods of stress and in more risky bonds. Our findings suggest that CSL trades provide a way for dealers to access liquidity without incurring additional balance sheet costs, as reflected in price discounts offered to clients supplying liquidity.

Our study also demonstrates the contributions of different types of clients to bond market liquidity. Hedge funds tend to provide liquidity reliably during market downturns, while insurance companies and some asset managers are more likely to be constrained, especially after bond downgrades. These differences show that the composition of a dealer's network affects trading outcomes, with bonds supported by less constrained liquidity providers being better able to withstand liquidity shocks. Our research adds to our understanding of trading costs in OTC markets by showing that dealers' ability to secure liquidity through their client networks helps manage costs and market disruptions. The discounts offered to liquidity providers are not just relationship-based but instead function as compensation for being available during periods of higher demand for liquidity. These results highlight the importance of client relationships and network composition for market stability and trading costs, which are key considerations for policy makers and market participants as bond markets evolve.

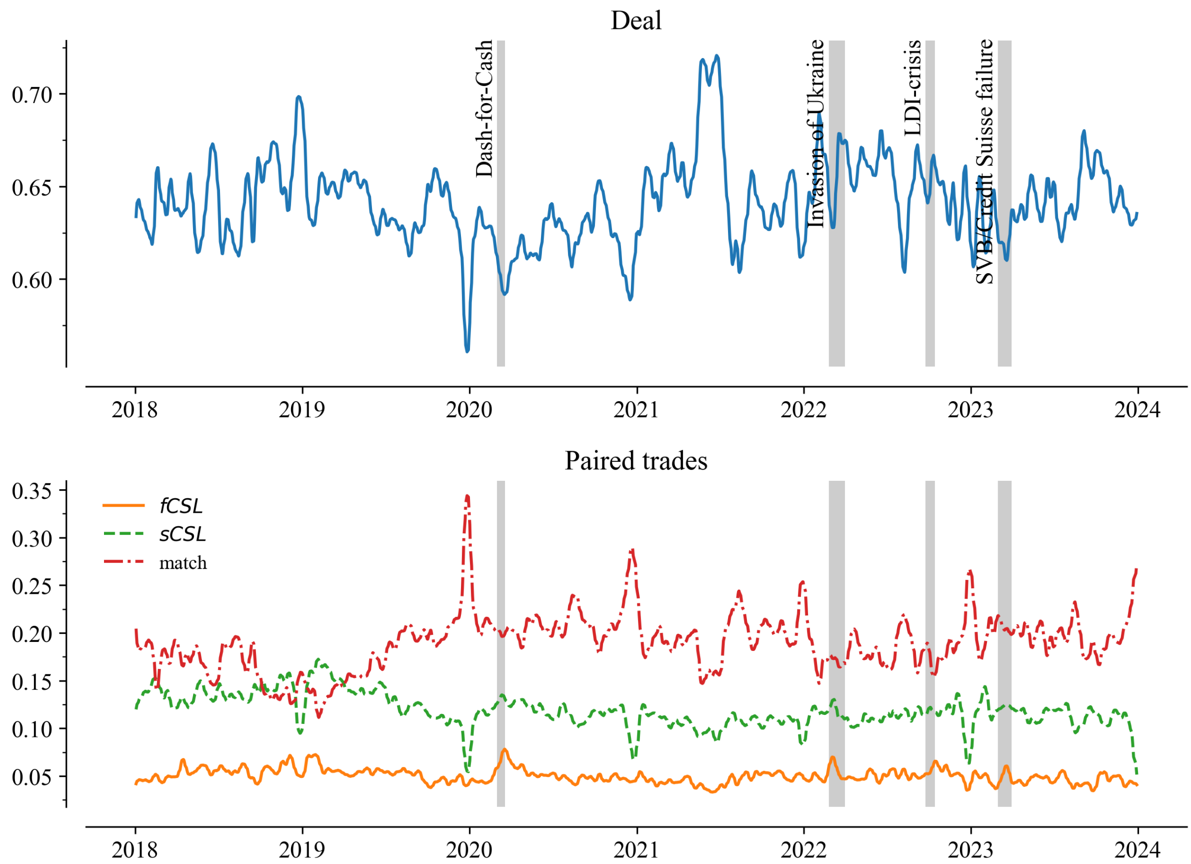
Our findings raise important questions for future research. To what extent do dealers actively manage their liquidity networks over time? How does the ability of investors to provide liquidity vary across different market regimes? Understanding these dynamics could provide deeper insights into the evolving nature of corporate bond market liquidity and inform policies aimed at enhancing market resilience.

Figure 1: Identifying CSL trades



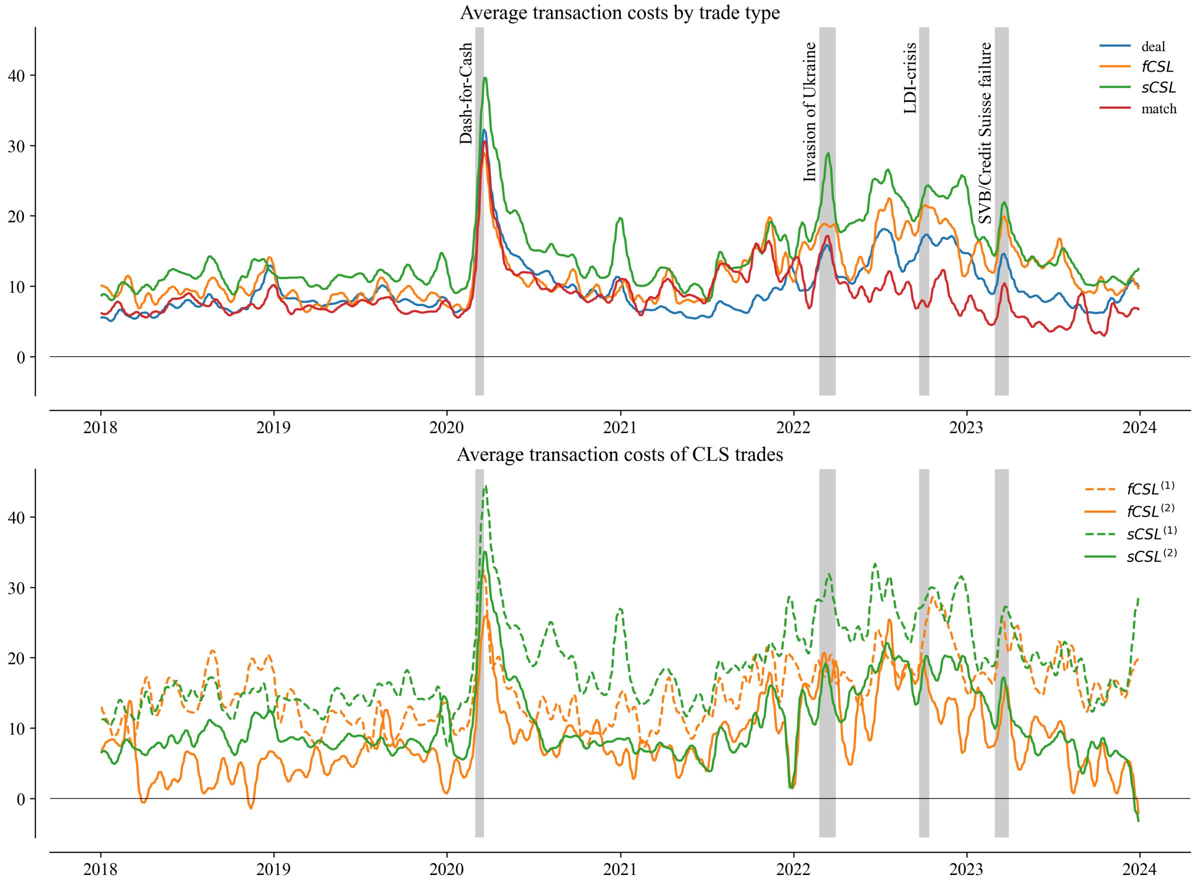
Notes: Example of a client-sourced liquidity trade. Dealer D trades (buying or selling) with client C_1 at time t_1 and subsequently trades with client $C_2 \neq C_1$ the same bond in the opposite direction at $t_2 > t_1$. The pair of trades is labelled a CSL trade and the trade at t_1 is referred to as the 1st leg, the trade at t_2 as the second leg. There are no other trades by dealer D in the same bond between (t_1, t_2), and there maybe more than on client in either leg. A transaction cannot be the 1st and second leg of two CSL trades.

Figure 2: Time-series of the share of volume by trade type



Notes: This figure shows the moving average (weighted using a Gaussian kernel) of the daily share of different trade types. The top panel shows the share of 'deal' trades, i.e. all trades that are not paired, instantly or consecutively within the same day, between counterparties trading in opposite directions. The bottom panel shows paired trades, i.e. trades that are matched instantly between opposing counterparties ('match'), trades that are matched within 15 minutes (fCSL), and trades that are matched within the same day but within more than 15 minutes (sCSL). The grey-shaded areas mark various stress episodes: Dash-for-Cash (1 to 18 March), the invasion of Ukraine and the following commodity crisis (24 Feb to 31 March 2022), the LDI-crisis (23 Sept to 14 Oct) and the failures of Silicon Valley Bank and Credit Suisse (1 to 31 March 2023).

Figure 3: Time-series of average transaction costs



Notes: This figure shows the moving average (weighted using a Gaussian kernel) of the daily average transaction costs of different trade types: 'deal' trades (all trades that are not paired with counterparties trading in opposite directions), 'match' trades (riskless principal trades that are matched instantly by a dealer between counterparties trading in opposite directions), fCSL trades (trades that are paired successively within 15 minutes between opposing coutnerparties), and sCSL trades (trades that are paired within the same day but within more than 15 minutes). The grey-shaded areas mark various stress episodes: Dash-for-Cash (1 to 18 March), the invasion of Ukraine and the following commodity crisis (24 Feb to 31 March 2022), the LDI-crisis (23 Sept to 14 Oct) and the failures of Silicon Valley Bank and Credit Suisse (1 to 31 March 2023). The bottom Panel plot average transaction costs for CSL trades split by the first and second leg in these paired trades.

Figure 4: Model: Actions and Payoffs

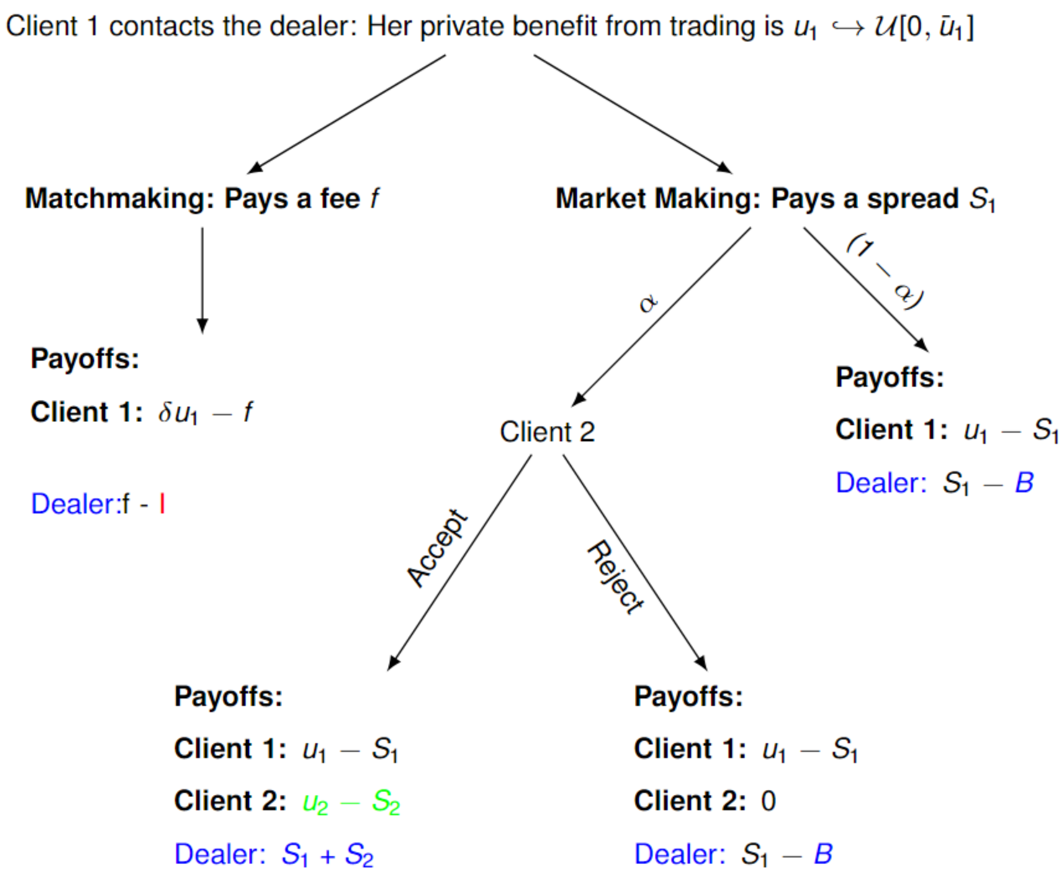
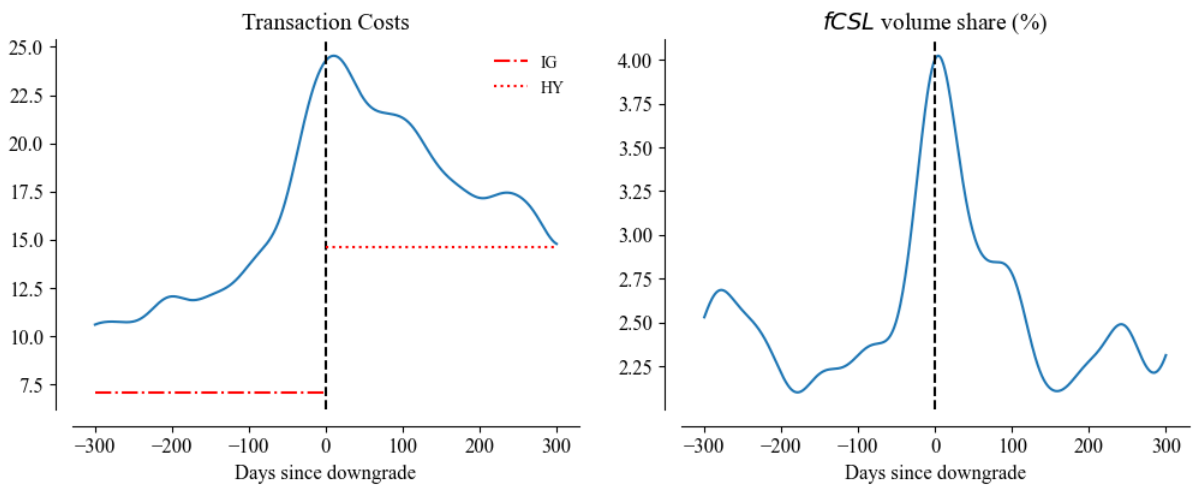


Figure 5: Transaction costs and client liquidity supply in fallen angels



Notes: This figure shows the moving average (weighted using a Gaussian kernel) of daily average transaction costs (left Panel) and the daily share of fCSL trades for bonds being downgraded from investment-grade to high-yield (i.e. fallen angels). Days shown on the x-axis are displayed relative to the downgrade date. The dotted red lines in the left Panel show overall sample average transaction costs for investment-grade and high-yield bonds respectively. Days falling into the crisis periods of Dash-for-Cash (1 to 18 March) or the LDI-crisis (23 Sept to 14 Oct) are excluded.

Table I: Descriptive statistics

Panel A: Overall		Per day statistics				
	Sample total	mean	std	25%	50%	75%
#Dealers	52	44.08	4.67	41	43	48
#Clients	18,158	799.88	221.57	657	798	941
#Bonds	40,257	1,786.74	552.41	1404	1837	2191
#Trades (in k)	6,627.45	4.38	1.64	3.31	4.30	5.43
Volume (in £ bn)	5,495.32	3.63	1.48	2.59	3.61	4.63
Panel B: Dealer averages		Per dealer-day statistics				
	Sample total	mean	std	25%	50%	75%
#Clients	1,337.96	46.07	54.82	4	20	73
#Bonds	8,869.87	70.07	90.32	6	29	106
#Trades	127,450.88	99.38	131.28	7	38	150
Volume (in £ bn)	105.68	0.08	0.12	0.01	0.02	0.12
Panel C: Client averages		Per client-day statistics				
	Sample total	mean	std	25%	50%	75%
#Dealers	3.83	2.54	3.00	1	1	3
#Bonds	94.45	4.44	11.41	1	2	4
#Trades	364.99	5.48	14.85	1	2	4
Volume (in £ m)	302.64	4.54	12.78	0.31	1.18	3.99
Panel D: Bond averages		Per bond-day statistics				
	Sample total	mean	std	25%	50%	75%
#Dealers	11.46	1.73	1.25	1	1	2
#Clients	42.60	1.99	2.03	1	1	2
#Trades	164.63	2.45	3.15	1	2	3
Volume (in £ m)	136.51	2.03	4.62	0.16	0.52	1.95

Notes: This table presents descriptive statistics for our sample of transaction reports in corporate bonds spanning 3 Jan 2018 (the start of MiFID II reporting regime) to 31 Dec 2023. Panel A presents overall statistics, while Panels B to D present the statistics per dealer, client, and bond, respectively. The first column shows totals over the entire sample, while column 2 to 6 show the mean, standard deviation and selected percentiles of the corresponding per-day statistics. These statistics are conditional on their being a trade in the given category (e.g. the number of trades per dealer, conditional on that dealer trading). The sample excludes trades involving a natural person (i.e. no Legal Entity Identifier).

Table II: Trade type summary statistics

Panel A: Trade volume across trade types (in %)

	Volume share		Maturity distribution				
	Normal	DfC	< 1	$[1, 3)$	$(3, 7]$	$[7, 15)$	≥ 15
deal	63.72	60.01	4.83	15.29	38.21	21.49	20.19
match	18.82	20.12	6.66	17.26	34.27	21.82	19.98
fCSL	5.08	6.63	5.46	15.12	37.84	19.86	21.72
sCSL	12.38	13.24	4.58	13.66	37.05	22.18	22.54

	Rating distribution			Tradesize distribution			
	AAA-A	BBB	HY	micro	odd	round	block
deal	29.61	37.56	32.83	13.53	50.18	28.27	8.01
match	35.10	34.63	30.27	24.57	46.45	22.65	6.33
fCSL	20.43	31.64	47.93	11.46	40.16	32.63	15.75
sCSL	22.67	36.17	41.16	9.35	38.80	36.54	15.31

Panel B: Average transaction costs across trade types (in bps)

	Normal times			DfC		
	All	Buy	Sell	All	Buy	Sell
all	9.67	9.83	9.49	21.79	13.68	28.70
deal	9.49	9.57	9.39	22.02	13.14	29.24
match	8.53	8.84	8.14	19.73	13.54	25.17
fCSL	10.89	11.72	10.09	20.58	11.88	29.23
sCSL	13.99	14.55	13.44	26.53	18.13	34.83

Notes: This table shows descriptive statistics for different trades types across our dealer-to-client sample spanning the period 3 Jan 2018 to 31 Dec 2023. Trades types include 'deal' (all trades where the dealer does not match counterparties trading in opposite directions), 'matched' (trades where a dealer matches instantly counterparties trading in opposite directions), 'fCSL' (trades where the dealer matches opposing couterparties successively within 15 minutes), and 'sCSL' (trades where the dealer matches counterparties within the same day but within more than 15 minutes). Panel A shows various distributions of trade volume across or within trade types. The tow top-left columns show the trade volume across trade types for normal and crisis times, with the latter being defined as the Dash-for-Cash episode from 1 to 18 March 2020. The top-right columns show the share of trade volume across maturity buckets (measured in years) conditional on the trade type (rows sum to 100). The tables in the middle show the share of trading volume conditional on the trade type by bond rating and trade sizes (again, rows sum to 100). Trade sizes are split into four categories: micro (trades below and including £50,000), odd (trades between £50,000 and £500,000), round (trades between £500,000 and £2,500,000) and block (trades above £2,500,000). Panel B shows average transaction costs across trade types during normal and crisis times, split by the trade direction of the client (buy or sell) and in aggregate ('All').

Table III: Transaction costs and paired trades

Dependent Variable:	transaction costs			
Model:	(1)	(2)	(3)	(4)
$CSL^{(2)}$	-2.869^{**}	-1.491		
	(1.159)	(0.983)		
$CSL^{(1)}$		4.027^{***}		
		(0.465)		
$fCSL^{(2)}$			-3.785^{***}	-3.788^{***}
			(1.303)	(1.306)
$CSL^{(2)}_{(15,30]}$			-0.547	
			(0.387)	
$CSL^{(2)}_{(30,60]}$			0.041	
			(0.522)	
$CSL^{(2)}_{(60,\infty)}$			-0.859	
			(1.057)	
$sCSL^{(2)}$				-0.664
				(0.839)
$fCSL^{(1)}$			2.414^{***}	2.412^{***}
			(0.805)	(0.803)
$CSL^{(1)}_{(15,30]}$			4.193^{***}	
			(0.386)	
$CSL^{(1)}_{(30,60]}$			4.604^{***}	
			(0.360)	
$CSL^{(1)}_{(60,\infty)}$			4.683^{***}	
			(0.805)	
$sCSL^{(1)}$				4.604^{***}
				(0.556)
clientsell	0.149	0.093	0.093	0.092
	(0.418)	(0.421)	(0.421)	(0.421)
match	-2.987^{***}	-2.626^{***}	-2.667^{***}	-2.667^{***}
	(1.005)	(0.960)	(0.975)	(0.976)
algo	2.529^{***}	2.479^{***}	2.551^{***}	2.552^{***}
	(0.419)	(0.439)	(0.420)	(0.418)
logQ	0.850^{***}	0.793^{***}	0.797^{***}	0.797^{***}
	(0.092)	(0.088)	(0.088)	(0.088)
Fixed-effects				
	Yes	Yes	Yes	Yes
Fit statistics				
Observations	5,112,462	5,112,462	5,112,462	5,112,462
R^2	0.36178	0.36202	0.36206	0.36206
Within R^2	0.00087	0.00125	0.00132	0.00132

Notes: This table shows the results of panel fixed-effects regressions of the type

$$tc_\tau = \sum_{j=1}^{2} \gamma_j CSL^{(j)} + x'_\tau \beta + \mathbf{1}'\mu + \varepsilon_\tau$$

where tc_τ are transaction costs (in bps) of transaction τ in a trade between dealer d and client c in bond b at time t on given platform or over-the-counter, $CSL^{(j)}$ are dummy variables for the first and second leg of client-sourced liquidity trades, x_τ include additional controls, and μ are dealer-day, client-month, bond-day and venue-type fixed effects (refer to Table Table A.I for the variable definitions). In columns (3) and (4) CSL trades split by the time between the first and second leg trades. Standard errors (shown in parenthesis) are clustered by dealer and bond. (Signif. Codes: ***: 0.01, **: 0.05, *: 0.1).

Table IV: Transaction costs during Dash-for-Cash and unavailable liquidity clients

Dependent Variable: tc					
Model:	(1)	(2)	(3)	(4)	(5)
$LPshare$	0.08	2.96			
	(4.91)	(4.96)			
$BlockedLP$	-10.81^{***}	-14.84^{***}	-10.44^{**}	-15.39^{***}	
	(3.84)	(3.91)	(4.34)	(4.45)	
clientsell	10.90^{***}	9.26^{***}	12.13^{***}	10.85^{***}	9.44^{***}
	(1.88)	(1.69)	(1.77)	(1.64)	(1.77)
$BlockedLP$ × clientsell	22.47^{***}	23.01^{***}	24.66^{***}	24.65^{***}	19.78^{**}
	(6.15)	(6.06)	(6.46)	(6.53)	(7.43)
$fCSL^2$	-8.19^{*}	-8.53^{**}	-7.88^{**}	-8.45^{**}	-7.53^{**}
	(4.31)	(4.21)	(3.29)	(3.32)	(3.63)
$fCSL^1$	−3.17	−3.46	−2.55	−2.94	−1.93
	(2.51)	(2.44)	(2.28)	(2.19)	(2.12)
$sCSL^2$	−1.15	−1.86	−0.75	−1.13	−1.16
	(2.45)	(2.43)	(2.18)	(2.18)	(2.22)
$sCSL^1$	3.65	3.18	3.24	2.91	2.19
	(2.23)	(2.20)	(2.01)	(1.88)	(1.97)
match	-5.55^{***}	-5.47^{***}	-4.71^{**}	-4.67^{**}	-4.36^{**}
	(1.70)	(1.69)	(2.10)	(1.94)	(1.92)
algo	1.54	1.34	1.08	0.97	2.94
	(3.84)	(4.12)	(3.32)	(3.59)	(2.74)
logQ	0.76	0.30	0.92^{***}	0.68^{***}	0.96^{**}
	(0.47)	(0.32)	(0.29)	(0.25)	(0.36)
t2m	0.15^{***}	0.18^{***}			
	(0.04)	(0.04)			
Fixed-effects					
dealer	Yes		Yes		
client	Yes	Yes	Yes	Yes	Yes
rating	Yes				
venue-type	Yes	Yes	Yes	Yes	Yes
dealer-day		Yes		Yes	Yes
rating-day		Yes			
bond			Yes	Yes	
bond-day					Yes
Fit statistics					
Observations	79,314	79,281	89,136	89,117	78,625
R^2	0.07680	0.10421	0.14979	0.17115	0.33451
Within R^2	0.00595	0.00493	0.00652	0.00550	0.00437

Notes: This table shows the results of panel fixed-effects regressions of the type

$$tc_\tau = \gamma_0\, LPshare_\tau + \gamma_1\, BlockedLP_\tau + \gamma_2\, BlockedLP_\tau \times clientsell_\tau \\ + x_\tau'\beta + \mathbf{1}'\mu + \varepsilon_\tau$$

where tc_τ is the transaction cost of trade τ (executed between a given dealer d and client c, at a certain time t on a given platform or over-the-counter), $LPshare_\tau$ is a bonds' share of fCSL trades over a window of 180 days prior to 1 March 2020, $BlockedLP_\tau$ is the share in $fCSL^{(j)}$ trade volume in a given bond over the same window accounted for by clients that are sellers only on day t, x_τ include the controls $iCSL^{(j)}$ for $i = f, s$ and $j = 1, 2$, 'clientsell', 'match', 'algo', 'logQ', and 't2m', and μ are fixed effects (refer to Table A.I for the variable definitions). Standard errors (shown in parenthesis) are clustered by dealer and bond. (Signif. Codes: ***: 0.01, **: 0.05, *: 0.1). The sample only considers transactions during the Dash-for-Cash (1 to 18 March 2020), excluding bonds sold by clients who were sellers only on that day and who supplied liquidity in the 180 day prior to Dash-for-Cash in that same bond.

Table V: Transaction costs of fallen angels and client liquidity supply

Dependent Variable: $\Delta^{HY} tc$			Liquidity supply share by sector s						
			HF	AM	Bank	Insurer	PFLDI	PTF	Broker
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
D	3.87***	3.57***	3.78***	3.55***	3.35***	3.67***	3.64***	3.57***	3.54***
	(0.75)	(0.72)	(0.74)	(0.75)	(0.73)	(0.71)	(0.72)	(0.73)	(0.75)
$LPshare$		−9.27	−10.72	0.42	−9.32	−5.58	−12.55	−9.54	−8.05
		(10.90)	(10.49)	(12.83)	(10.89)	(14.29)	(10.42)	(10.93)	(11.40)
$D \times LPshare$		17.21	22.21	18.51	17.13	9.03	21.32	17.01	16.96
		(17.46)	(16.98)	(17.49)	(17.56)	(20.66)	(17.56)	(17.51)	(17.55)
$Lrel^s$			1.23	−4.15***	−0.64	−4.07	6.84***	−2.36**	−1.86
			(1.68)	(1.06)	(0.82)	(4.33)	(1.40)	(1.12)	(1.95)
$D \times Lrel^s$			−4.52**	0.47	1.33	17.79**	−8.26	0.59	0.73
			(2.23)	(1.75)	(1.17)	(8.84)	(5.26)	(1.88)	(2.85)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	235,094	235,094	235,094	235,094	235,094	235,094	235,094	235,094	235,094
R^2	0.06940	0.06942	0.06947	0.06958	0.06943	0.06945	0.06947	0.06943	0.06943
Within R^2	0.00336	0.00337	0.00343	0.00355	0.00338	0.00340	0.00342	0.00339	0.00338

Notes: This table shows the results of panel fixed-effects regressions of the type

$$\Delta^{HY} tc_\tau = \gamma_0\, LPshare_\tau + \gamma_1\, D_\tau + \gamma_2\, LPshare_\tau \times D_\tau + \gamma_3\, Lrel^s_\tau + \gamma_4\, Lrel^s_\tau \times D_\tau + x'_\tau \beta + \mathbf{1}'\mu + \varepsilon_\tau,$$

where $\Delta^{HY} tc_\tau$ is the transaction cost of a trade between dealer d and client c in bond b (a fallen angel) at time t and a given venue v minus the average transaction costs of high-yield bonds on the same date (excluding fallen angels), D_τ is a dummy indicating that the trade took place in a window from 100 days prior to 300 days after the downgrade, $LPshare^\tau$ is the share of $fCSL$ trades in total trading volume in a given bond over a window of 200 to 100 days prior to the downgrade and $Lshare^s_\tau$ is the share in $fCSL^{(2)}$ trading volume in a given bond over the same period accounted for by sector s, x_τ include the controls $iCSL^{(j)}$ for $i = f, s$ and $j = 1, 2$, 'clientsell', 'match', 'algo' and 'logQ', and μ are dealer, client, rating and venue-type fixed effects (refer to Table A.I for the variable definitions). Standard errors (shown in parenthesis) are clustered by dealer and bond. (Signif. Codes: ***: 0.01, **: 0.05, *: 0.1). The sample only considers transactions in bonds that were downgraded from investment-grade to high-yield not earlier than 200 days prior to the start of the sample and no later than 300 prior to the end of the sample. Moreover the sample is restricted to days from 100 days prior to the downgrade excluding days that fall within the period of Dash-for-Cash (1 to 18 March 2020) or the LDI-crisis (23 Sept to 14 Oct 2022).

Table VI: Volume share by trade type and client sector

		Trade type					
sector	all	deal	$fCSL^{(1)}$	$fCSL^{(2)}$	match	$sCSL^{(1)}$	$sCSL^{(2)}$
Panel A: Normal times							
AM	40.51	41.10	43.39	38.74	35.22	46.74	42.46
Bank	16.98	15.76	18.70	15.10	24.04	14.38	12.43
Broker	15.05	16.82	9.02	12.73	11.19	9.65	16.16
HF	10.05	9.80	12.60	16.95	8.35	11.74	12.25
Insurer	3.46	2.86	2.32	2.66	6.25	3.59	2.50
PFLDI	6.76	6.89	6.84	6.14	5.83	7.83	7.23
PTF	1.23	1.36	1.56	1.36	0.90	0.92	0.76
Other	5.96	5.41	5.55	6.30	8.23	5.14	6.22
Panel B: Dash for Cash (1-18 March 2020)							
AM	39.60	40.78	42.91	36.71	35.35	39.17	41.14
Bank	22.18	20.33	21.43	17.49	31.66	20.52	15.94
Broker	9.35	10.52	5.18	7.74	5.86	8.20	12.67
HF	9.64	9.72	12.21	18.65	6.10	11.39	11.86
Insurer	4.43	3.90	3.06	2.73	6.49	5.10	4.09
PFLDI	6.82	6.92	8.18	9.43	5.24	8.46	6.85
PTF	1.77	2.08	2.34	1.53	0.87	1.48	1.62
Other	6.22	5.74	4.69	5.72	8.44	5.67	5.84
Panel C: Fallen Angels window							
AM	45.76	43.96	55.36	49.42	44.31	51.48	49.77
Bank	14.86	14.57	11.20	7.83	23.85	10.38	8.26
Broker	10.64	12.91	6.93	7.25	5.96	7.30	10.42
HF	14.95	15.21	12.08	18.80	11.84	16.15	17.60
Insurer	2.39	1.81	2.17	2.63	4.17	2.74	2.56
Other	4.52	4.54	4.50	5.84	4.51	3.95	4.29
PFLDI	5.94	5.92	6.48	7.59	4.65	7.04	6.55
PTF	0.95	1.07	1.29	0.65	0.71	0.96	0.55
Other	4.52	4.54	4.50	5.84	4.51	3.95	4.29

Notes: This table shows the share of trading volume by client sector across different trade types. Column 'all' shows the share of trading volume across all trade types, columns $fCSL^{(j)}$ ($sCSL^{(j)}$) for $j = 1, 2$ across all first ($j = 1$) and second ($j = 2$) legs of fast (slow) CSL trades, 'match' across all trades that are riskless principal trades where the dealer matches clients instantaneously, and 'deal' across all trades that are not paired trades (i.e. neither CSL nor matched trades). The shares are shown for different periods. Panel A presents the results for normal times spanning 3 Jan 2018 to 31 Dec 2023, excluding Dash-for-Cash (1 to 18 March 2020) shown Panel B, and fallen angel windows running from 100 days prior to 300 days after a bonds downgrade from IG to HY, shown in Panel C. The sectors are: AM - asset managers; Bank - non-dealer banks; Broker - brokers and other trading services firms; HF - hedge funds; Insurer - insurance companies; PFLDI - pension funds and liability driven investment funds; PTF - principal trading firms; Other - unclassified, non-financial or other-financial companies.

Table VII: Transaction costs and clients' share in liquidity provision

Dependent Variable:	transaction costs		
Model:	(1)	(2)	(3)
Lrel	-12.642^{***}	-9.592^{***}	-0.521
	(3.652)	(3.581)	(3.461)
Qrel		-16.742^{***}	-16.082^{***}
		(3.411)	(3.492)
$Lrel \times HF$			-61.814^{***}
			(17.648)
$Lrel \times PFLDI$			-26.594^{*}
			(13.318)
$Lrel \times Bank$			-12.619^{**}
			(5.428)
$Lrel \times PTF$			-4.668
			(3.999)
$Lrel \times Broker$			-0.543
			(4.230)
$Lrel \times AM$			0.596
			(3.968)
$Lrel \times Ins$			55.620^{**}
			(25.416)
Controls	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes
Fit statistics			
Observations	4,917,535	4,917,535	4,917,535
R^2	0.36284	0.36288	0.36300
Within R^2	0.00143	0.00149	0.00169

Notes: This table shows the results of panel fixed-effects regressions of the type

$$tc_\tau = \gamma_{Lrel}\, Lrel_\tau + \gamma_{Qrel}\, Qrel_\tau + \sum_s \gamma_s\, Lrel_\tau \times \mathbf{1}_{\{sector_\tau = s\}} + x'_\tau \beta + \mathbf{1}'\mu + \varepsilon_\tau$$

where tc_τ are transaction costs (in bps) in a trade between dealer d and client c in bond b at time t on venue v, $Qrel_\tau$ ($Lrel_\tau$) is the client's share in a dealers total ($fCSL^{(j)}$) trading volume over the 90 days prior to the transaction day, $\mathbf{1}_{\{sector_\tau = s\}}$ is a dummy taking the value 1 if the transacting client belongs to sector s, x_τ include the controls $iCSL^{(j)}$ for $i = f, s$ and $j = 1, 2$, 'clientsell', 'match', 'algo' and 'logQ', and μ are dealer, client, rating and venue-type fixed effects (refer to Table A.I for the variable definitions). Standard errors (shown in parenthesis) are clustered by dealer and bond. (Signif. Codes: ***: 0.01, **: 0.05, *: 0.1).

VIII. Appendix

A. Hypotheses Development

In this section, we use the model sketched in Section IV to derive our testable hypotheses. We first derive the equilibrium prices (f^*, S_1^*, S_2^*). We proceed backward and first consider the choice of S_2 by the dealer.

C_2 rejects the dealer's offer if and only if $u_2 \leq S_2$. Thus, she rejects the offer with probability $G_2(S_2) = \frac{S_2+\bar{u}_2}{2\bar{u}_2}$ and accepts it with probability $(1 - G(S_2))$. The dealer chooses her take-or-leave it offer to minimize her expected cost following the first trade, that is, S_2 solves:

$$Min_{S_2 \in [-\bar{u}_2, \bar{u}_2]} \quad C_{mm}(S_2, B) = G_2(S_2)B - (1 - G_2(S_2))S_2. \tag{11}$$

Straightforward calculations show that the optimal offer for the dealer is

$$\begin{aligned} S_2^* &= \frac{\bar{u}_2 - B}{2} \quad if \quad B < 3\bar{u}_2, \\ S_2^* &= -\bar{u}_2 \quad if \quad B \geq 3\bar{u}_2. \end{aligned} \tag{12}$$

Now consider the dealer's problem at date 1. The client prefers a market-making trade (immediate execution) to a riskless principal trade (delayed execution) if the former is less costly. That is, if

$$\delta u_1 - f \leq u_1 - S_1, \tag{13}$$

or

$$u_1 \geq u_1^*(S_1, f) = \frac{S_1 - f}{1 - \delta}. \tag{14}$$

If $u_1 \leq u_1^*$, the client chooses a riskless principal trade if $u_1 \geq \frac{f}{\delta}$ and does not trade otherwise. In sum, (i) the client does not trade if $u_1 < \frac{f}{\delta}$, (ii) chooses a matchmaking trade if $\frac{f}{\delta} \leq u_1 \leq u_1^*(S_1, f)$ and (iii) a market making trade otherwise.

For given f and S_1, clients with a sufficiently large private benefit (larger than u_1^*) choose to get immediate execution from the dealer while those with small private benefits choose either not to trade or matchmaking. The reason is that clients' waiting costs ($(1-\delta)u_1$), the difference between their private benefit if they get immediate execution and their realized benefit if they need to wait) increases with their private benefit.

This feature leads to a natural sorting of clients between the two trading options offered by the dealer. In turn, this enables the dealer to optimally charge different fees (S_1^*, f^*) for each option as this choice reflects different private benefit from trading (see below). This is similar to price discrimination in models of vertical differentiation (see Mussa and Rosen (1979)).

A necessary condition for matchmaking trades to occur is that $u_1^* > \frac{f}{\delta}$, that is, $f < S_1$. This is intuitive. If $S_1 < f$, market making is a cheaper option than matchmaking for all clients since (i) the trading cost charged by the dealer is smaller and (ii) it does not entail a waiting cost. In the rest of the analysis, we choose parameter values (see below) such that the condition $0 < \frac{f^*}{\delta} < u_1^*(S_1^*, f^*) < \bar{u}_1$ is satisfied, so that, in equilibrium, there are both market making and matchmaking trades (as we observe in the data).

In this case, at date 1, the dealer's optimal offers f and S_1 solve:

$$Max_{\{f,S_1\}} \quad (G_1(u_1^*) - G_1(\frac{f}{\delta}))(f - I) + (1 - G_1(u_1^*))\Pi_{mm}(S_1, S_2^*), \tag{15}$$

where $G_1(x) = \frac{x}{\bar{u}_1}$ is the cumulative probability distribution of the first client's private valuation and $\Pi_{mm}(S_1, S_2^*) = S_1 - (1-\alpha)B - \alpha C_{mm}(S_2^*, B)$ is the dealer's expected profit if C_1 chooses market-making. Solving for this problem, we obtain that the dealer charges the following prices at date 1:

$$f^* = \frac{\delta \bar{u}_1 + I}{2}, \tag{16}$$

and

$$S_1^* = \frac{\bar{u}_1 + (1-\alpha)B + \alpha C_{mm}(S_2^*, B)}{2}. \tag{17}$$

The condition $0 < \frac{f^*}{\delta} < u_1^*(S_1^*, f^*) < \bar{u}_1$ is therefore satisfied iff $\frac{I}{\delta} \leq (1-\alpha)B + \alpha C_{mm}(S_2^*, B) \leq (1-\delta)\bar{u_1}$. The first inequality is satisfied by choosing $\bar{u_1}$ large enough while the second is satisfied by choosing I low enough. Moreover, $\bar{u}_2 < f^*$ if and only if $\bar{u}_2 \leq \frac{\delta \bar{u}_1 + I}{2}$. As explained, it is natural to assume that this condition is satisfied as otherwise C_2 would have traded with the dealer either via matchmaking or market making in the first place.

Eq.(17) shows that S_1^* increases with the expected cost of the trade, $(1-\alpha)B + \alpha C_{mm}(S_2^*, B)$, for the dealer. Thus, S_1^* reflects the dealer's cost of obtaining liquidity from clients in her liquidity network ($C_{mm}(S_2^*, B)$). Calculations show that $C_{mm}(S_2^*, B)$ increases with B. Hence, S_1^* increases with B while S_2^* decreases with B (eq.(12)). Moreover, for $B = 0$, $S_1^* = \frac{\bar{u}_1}{2}$ and $S_2^* = \frac{\bar{u}_2}{2}$. Thus, as $\bar{u}_2 < \bar{u}_1$, we deduce that $S_1^* > S_2^*$ for all values of B, which is our first testable htypothesis (H1).

Let $\bar{TC}(\alpha, B)$ be the average dealer's spread across clients (C_1 and C_2), then:

$$\begin{aligned} \bar{TC}(\alpha, B) &= (\alpha G(S_2^*) + (1-\alpha))S_1^* + \alpha(1 - G(S_2^*))(S_1^* + S_2^*) \\ &= S_1^* + \alpha(1 - G(S_2^*))S_2^*. \end{aligned} \tag{18}$$

Straightforward calculations show that $\frac{\partial \bar{TC}(\alpha,B)}{\partial \alpha} < 0$, $\frac{\partial \bar{TC}(\alpha,B)}{\partial B} > 0$ and $\frac{\partial^2 \bar{TC}(\alpha,B)}{\partial \alpha \partial B} < 0$. These observations yield our second and third testable hypotheses.

B. Variable Definitions

Table A.I: Variable Definitions

Variable name	Description
Dependent variable	
tc	Transaction cost of a trade measured in basis points. Defined as the log-difference between the transaction price (in percentage of par) and the closest inter-dealer price prior to the trade, but not older than 24 hours, times the trade direction of the client (1 for client-buy, -1 for client-sell): $tc = \log(p/p^*) \times D \times 10,000$. Prices have been cleaned for outliers and transaction costs outside the 1st or 99th percentile are dropped.
$\Delta^{HY} tc$	Transaction costs of a trade (tc) minus the average transaction costs of high-yield bonds traded on the same day, excluding fallen angels, i.e. bonds that were downgraded from investment-grade to high-yield within the sample period. (See equation (4))
Controls	
clientsell	Dummy for client sales: 1 if client is selling, 0 otherwise.

match	Dummy for riskless principal trades where a dealer matches orders of different counterparties that want to trade in opposite directions instantly: 1 if dealer matched client with another counterparty, 0 otherwise. Except for the results shown in Table Table A.II, the dummy also includes trades flagged with the MiFID trade capacity category 'MTCH' which identifies trades in which the executing firm acts in a riskless matched capacity (see Article 4(1)(38) of MiFID II).
algo	Dummy for trades executed by an algorithm. 1 if traded using an algorithm, 0 otherwise.
logQ	Natural logarithm of nominal quantity traded (in GBP). Sample only includes bonds issued in GBP, EUR or USD and only trades executed in those currencies. Trades in EUR or USD are converted to GBP using the exchange rate at close on that day. Quantities are cleaned for outliers and subsequently winsorized at the 1st and 99th percentile.
t2m	Time-to-maturity of a given bond in a given trade measured in years.

Main variables

CSL A client-sourced liquidity trade. These are transactions where a dealer trades the same bond in opposite directions in subsequent trades (e.g. buys first from one non-dealer counterparty and then sells to another non-dealer counterparty). The dealer does not execute another trade in the same bond (including with other dealers) between the first and second leg. The first leg is the trade that comes first in time. The time difference between both legs is strictly positive, but both legs must have been executed on the same day. Both the first and second leg can include multiple transactions if the dealer traded simultaneously with several counterparties at that point in time. The same counterparty cannot be active in both the first and second leg. (See section III.A for a detailed description.)

$CSL^{(j)}$ for $j = 1, 2$ Dummy taking the value 1 if the transaction is the first ($j = 1$) or second ($j = 2$) leg in a CSL trade.

$CSL_l^{(j)}$ for $j = 1, 2$ Same as $CSL^{(j)}$ with the additional condition that the first and second leg occurred within a given time window:

- $l = (15, 30]$: within 15 and 30 minutes
- $l = (30, 60]$: within 30 minutes and 1 hour
- $l = (60, \infty)$: after one hour but within the same day.

$iCSL$ for $i = f, s$ Dummy taking the value 1 if the trade is either fast ($i = f$) or slow ($i = s$) CSL trade. Fast CSL trades are CSL trades where the first and second leg are executed within 15 minutes of each other, slow CSL trades are CSL trades where the legs are executed within more than 15 minutes (but still within the same day).

$iCSL^{(j)}$ — The first ($j = 1$) and second leg ($j = 2$) of a fast ($i = f$) or slow ($i = s$) CSL trade.

$LPshare_b$ — A bond's share of trading volume in $fCSL$ trades over a given time window. More specifically:

$$LPshare_b = \frac{\sum_{\tau \in \mathcal{T}_b(l,r)} fCSL_\tau \, Q_\tau}{\sum_{\tau \in \mathcal{T}_b(l,r)} Q_\tau}$$

where $\mathcal{T}_b(l, r)$ are all transactions in bond b between the dates l and r, and Q_τ is the size of transaction τ measured in GBP nominal amount. For $LPshare$ measured related to downgrades, $l = f_b - 200$ and $r = f_b - 100$ where f_b is the day of the downgrade from investment-grade to high-yield (fallen angel). For $LPshare$ related to Dash-for-Cash, $l = t - 180$ and $r = t - 1$ where t is 1 March 2020.

$BlockedLP_{bt}$ — The share in $fCSL^{(2)}$ trade volume in a bond prior to dash-for-cash accounted for by clients that are sellers only on day t. More specifically,

$$BlockedLP_{bt} = \frac{\sum_{\tau \in \mathcal{T}_b(t-180,t-1)} \mathbf{1}_{\{c_\tau \in \mathcal{S}_t\}} fCSL_\tau^{(2)} \, Q_\tau}{\sum_{\tau \in \mathcal{T}_b(t-180,t-1)} fCSL_\tau^{(2)} \, Q_\tau},$$

where $\mathcal{T}_b(l, r)$ is the set of all trades in bond b between dates l and r, t is 1 March 2020, c_τ is the client in transaction τ, $\mathcal{S}_t$ is the set of all clients that exclusively sold bonds on day t (i.e. clients with positive sell volume and zero buy volume across all dealer-client transactions in the sample), and $\mathbf{1}_{\{\cdot\}}$ is an indicator function taking the value 1 if the condition in $\{\cdot\}$ is met.

D_τ A "fallen angel" dummy indicating if a trade took place within a period where the corresponding bond is downgraded from investment-grade to high-yield. The window starts 100 days prior to the date of the downgrade to 300 days after the downgrade date.

$Lrel_b^s$ The share of sector s (see sector dummies below) in a bond's total $fCSL^{(2)}$ trades prior to being downgraded from investment-grade to high-yield. More specifically:

$$Lrel_b^s = \frac{\sum_{\tau \in \mathcal{T}_b(t-200,t-100)} \mathbf{1}_{\{s_\tau = s\}} \, fCSL_\tau^{(2)} \, Q_\tau}{\sum_{\tau \in \mathcal{T}_b(t-200,t-100)} fCSL_\tau^{(2)} \, Q_\tau},$$

where t is the date of the downgrade, $\mathcal{T}_b(l, r)$ are all trades in bond b between dates l and r, $\mathbf{1}_{\{s_\tau = s\}}$ is an indicator function taking the value one if the client in trade τ belongs to sector s and zero otherwise, and Q_τ is the size of transaction τ measured in GBP nominal amount.

$Lrel_{dct}$ Share of client c's trade volume in dealer d's total $fCSL^{(2)}$ trading volume over the window t minus 90 days to $t-1$:

$$Lrel_{dct} = \frac{\sum_{\tau \in \mathcal{T}_{dc}(t-90,t-1)} fCSL_\tau^{(2)} \, Q_\tau}{\sum_c \sum_{\tau \in \mathcal{T}_{dc}(t-90,t-1)} fCSL_\tau^{(2)} \, Q_\tau},$$

where $\mathcal{T}_{dc}(t-90, t-1)$ are all transactions between dealer d and client c in the 90 days prior to t, $fCSL_\tau^{(2)}$ takes the value one if the transaction is the second leg of a fast CSL trade and zero otherwise, and Q_τ is the nominal size of the transaction measured in GBP.

$Qrel_{dct}$	Share of clients c's trade volume in dealer d's total trade volume over the window t minus 90 days to t: $$Qrel_{dct} = \frac{\sum_{\tau \in \mathcal{T}_{dc}(t-90,t-1)} Q_\tau}{\sum_c \sum_{\tau \in \mathcal{T}_{dc}(t-90,t-1)} Q_\tau},$$ where $\mathcal{T}_{dc}(t-90, t-1)$ is the set of all transactions between client c and dealer d over the 90 days prior to day t, and Q_τ is the GBP nominal amount in transaction τ.
sector dummies	AM: asset manager, Bank: bank, HF: hedge fund, PFLDI: pension fund or liability driven investor, Ins: insurer, Broker: trading services firm such as platforms and brokers, PTF: proprietary trading firm.
Other variables	
deal	All trades that are not match or CSL trades.
DfC	Dash-for-Cash episode spanning 1 to 18 March 2020.

C. *Additional Empirical Findings*

Table A.II: Share by MiFID trade-capacity flag

	MiFID II capacity flag		
	AOTC	DEAL	MTCH
fCSL	2.72	96.46	0.82
sCSL	3.66	95.61	0.73
match	8.24	86.58	5.18
deal	8.51	89.41	2.09
all	7.56	90.04	2.40

Notes: This table shows the percentage of trading volume across different MiFID II trade capacity flags for each trade type. Trades types include 'deal' (all trades where the dealer does not match counterparties trading in opposite directions), 'matched' (trades where a dealer matches instantly counterparties trading in opposite directions), fCSL (trades where the dealer matches opposing couterparties successively within 15 minutes), and sCSL (trades where the dealer matches counterparties within the same day but within more than 15 minutes). MiFID II trade capacity flags are 'DEAL', trades where the executing firm deals on own account; 'MTCH', trades where the executing firm trades in a matched principal capacity; and 'AOTC' where the executing firm act in any other capacity not covered by 'MTCH' or 'DEAL' (see pp. 15 in the ESMA reporting guidelines).

References

Adrian, T., N. Boyarchenko, and O. Shachar (2017). Dealer balance sheets and bond liquidity provision. *Journal of Monetary Economics 89*, 92–109.

Anand, A., C. Jotikasthira, and K. Venkataraman (2021). Mutual fund trading style and bond market fragility. *The Review of Financial Studies 34*(6), 2993–3044.

Bao, J., M. O'Hara, and X. (Alex) Zhou (2018). The volcker rule and corporate bond market making in times of stress. *Journal of Financial Economics 130*(1), 95–113.

Bessembinder, H., S. Jacobsen, W. Maxwell, and K. Venkataraman (2018). Capital commitment and illiquidity in corporate bonds. *The Journal of Finance 73*(4), 1615–1661.

Bessembinder, H., C. Spatt, and K. Venkataraman (2020). A survey of the microstructure of fixed-income markets. *Journal of Financial and Quantitative Analysis 55*(1), 1–45.

CGFS (2014). Market-making and proprietary trading: industry trends, drivers and policy implications. *CGFS Papers 52*, 1–57.

Choi, J., Y. Huh, and S. Seunghun Shin (2024). Customer liquidity provision: Implications for corporate bond transaction costs. *Management Science 70*(1), 187–206.

Colliard, J.-E., T. Foucault, and P. Hoffmann (2021). Inventory management, dealers' connections, and prices in over-the-counter markets. *The Journal of Finance 76*(5), 2199–2247.

Czech, R., B. Gual-Ricart, J. Lillis, and J. Worlidge (2021). The role of non-bank financial intermediaries in the 'dash for cash' in sterling markets. Financial Stability Paper 45, Bank of England.

Czech, R., S. Huang, D. Lou, and T. Wang (2022). An unintended consequence of holding dollar assets. Working Paper 953, Bank of England.

Czech, R. and W. Monroe (2025). Dealers, information and liquidity provision in safe assets. *Bank of England Financial Stability Paper* (1,113).

Di Maggio, M., A. Kermani, and Z. Song (2017). The value of trading relations in turbulent times. *Journal of Financial Economics 124*(2), 266–284.

Dick-Nielsen, J. and M. Rossi (2018, 07). The Cost of Immediacy for Corporate Bonds. *The Review of Financial Studies 32*(1), 1–41.

Duffie, D., M. Fleming, F. Keane, C. Nealson, O. Shachar, and P. van Tassel (2023). Dealer capacity and us treasury market functionality. *Federal Reserve Bank of New York Staff Reports 70*, 1–68.

Ellul, A., C. Jotikasthira, and C. T. Lundblad (2011). Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics 101*(3), 596–620.

Giannetti, M., C. Jotikasthira, A. C. Rapp, and M. Waibel (2023). Intermediary balance sheet constraints, bond mutual funds' strategies, and bond returns. *Swedish House of Finance Research Paper* (23-10).

Goldstein, M. A. and E. S. Hotchkiss (2020). Providing liquidity in an illiquid market: Dealer behavior in us corporate bonds. *Journal of Financial Economics 135*(1), 16–40.

Hendershott, T., D. Li, D. Livdan, and N. Schurhoff (2020). Relationship trading in over-the-counter markets. *The Journal of Finance 75*(2), 683–734.

Hendershott, T. and A. Madhavan (2015). Click or call? auction versus search in the over-the-counter market. *The Journal of Finance 70*(1), 419–447.

Hendershott, T. J., D. Li, D. Livdan, N. Schuerhoff, and K. Venkataraman (2024). Quote competition in corporate bonds.

Henning, L., S. Jurkatis, M. Powar, and G. Valentini (2023, July). Lifting the lid on a liquidity crisis. Blog post on Bank Underground, accessed: 2024-10-08.

Hollifield, B., A. Neklyudov, and C. Spatt (2017, 05). Bid-Ask Spreads, Trading Networks, and the Pricing of Securitizations. *The Review of Financial Studies 30*(9), 3048–3085.

Jacobsen, S. and K. Venkataraman (2023). Receiving investors in the block market for corporate bonds.

Jurkatis, S. (2024). An approach to cleaning MiFID II corporate bond transaction reports. *Bank of England Staff Working Paper*.

Jurkatis, S., A. Schrimpf, K. Todorov, and N. Vause (2023). Relationship discounts in corporate bond trading. *Bank of England Staff Working Paper*.

Kargar, M., B. Lester, D. Lindsay, S. Liu, P.-O. Weill, and D. Zuniga (2021, 05). Corporate bond liquidity during the covid-19 crisis. *The Review of Financial Studies 34*(11), 5352–5401.

Kruttli, M. S., M. Macchiavelli, P. Monin, and X. A. Zhou (2023). Liquidity provision in a one-sided market: The role of dealer-hedge fund relations. *Available at SSRN 4662272*.

Li, D. and N. Schurhoff (2019). Dealer networks. *The Journal of Finance 74*(1), 91–144.

Ma, Y., K. Xiao, and Y. Zeng (2022). Mutual fund liquidity transformation and reverse flight to liquidity. *The Review of Financial Studies 35*(10), 4674–4711.

O'Hara, M., A. C. Rapp, and X. A. Zhou (2023). The value of value investors. *Available at SSRN*.

Pintér, G., C. Wang, and J. Zou (2022). Staff working paper no. 971 information chasing versus adverse selection.

Saar, G., J. Sun, R. Yang, and H. Zhu (2022, 09). From Market Making to Matchmaking: Does Bank Regulation Harm Market Liquidity? *The Review of Financial Studies 36*(2), 678–732.