# Liquidity Provision in a One-Sided Market: 

# The Role of Dealer-Hedge Fund Relations * 

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February 2024


#### Abstract

We show that dealers' prime brokerage relations with certain hedge funds help improve their liquidity provision in a one-sided market. During the March 2020 liquidity crisis, hedge funds increased their corporate bond positions when the bond market faced excessive selling pressures. Dealers connected with hedge funds that are natural buyers of corporate bonds charged lower transaction costs on heavily sold bonds. Dealers' leverage and funding constraints do not explain our results, nor do connections with hedge funds that are natural buyers of other asset classes. Our findings reveal that dealers' willingness to provide liquidity in a one-sided market depends on their connections with natural buyers of corporate bonds.


JEL classification: G12, G23, G24.
Keywords: broker-dealers, hedge funds, corporate bonds, market liquidity.

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## 1 Introduction

Dealers play a critical role in the U.S. corporate bond market. During times of stress when demand for liquidity surges, dealers' willingness to provide liquidity is essential to the proper functioning of the market. The existing literature has studied bond market liquidity through the lens of dealers' ability to warehouse investor flows on their balance sheets, emphasizing the roles played by funding costs and the regulatory reforms passed in the aftermath of the 2008 financial crisis. ${ }^{1}$ However, what determines dealers' willingness to intermediate trades when the market becomes one-sided is still to be fully understood.

In this paper, we analyze dealers' relationships with hedge funds that are natural buyers of corporate bonds and study the effect that such relationships have on dealers' willingness to provide liquidity in the corporate bond market during times of stress. Dealers facilitate bond trading by serving either as market makers, temporarily absorbing order imbalances and subsequently turning around their inventories, or as matchmakers, searching for counterparties for their customers without committing their own capital for intermediation. In both functions, whether dealers are willing to intermediate depends on their capability to locate entities to take the other side of a trade. Such capability is particularly valuable in a one-sided market when searching for counterparties becomes challenging.

During the COVID liquidity crisis, the corporate bond market faced severe selling pressure amid a dash for liquidity. For example, mutual funds experienced heavy outflows (Falato, Goldstein and Hortaçsu, 2021) and were forced to sell corporate bonds to meet redemptions (Ma, Xiao and Zeng, 2022). With many bond mutual funds and other investors selling bonds, the corporate bond market became one-sided and liquidity deteriorated, as shown in Figure 1. Using redemption-driven sales of corporate bonds by mutual funds at the security level, we show that dealers intermediating these bonds during the crisis charged higher transaction costs.

[^1]Meanwhile, market dislocations caused by the COVID liquidity crisis provide profitable trading opportunities for hedge funds that tend to maintain large long positions in corporate bonds. Similar to (Shleifer and Vishny, 2011), we refer to such hedge funds as natural buyers. As hedge funds are less regulated than dealer banks and generally more willing to absorb risk, they are likely to step in and buy securities while many other investors liquidate bonds to de-risk their portfolios. Indeed, we find that for the investment-grade sector where market dislocations were more severe (Haddad, Moreira and Muir, 2021), overall hedge funds positions in corporate bonds increased significantly in March 2020.

Taking advantage of confidential SEC data on hedge funds' corporate bond positions and the identities of their prime brokers, we construct a measure of a dealer's exposure to the corporate bond holdings of their connected hedge funds. We then link it to dealer's corporate bond trading activities using dealer identities provided by a regulatory version of FINRA's TRACE data. While the liquidity deterioration is more pronounced in bonds more exposed to mutual fund fire sales, such deterioration is attenuated for the corporate bonds traded by dealers that have prime brokerage relations with natural buyers of corporate bonds.

Our results are robust to controlling for alternative channels, including repo funding conditions, the tightness of leverage constraints, or any other time-varying dealer or bond characteristic. These findings suggest that even without regulatory constraints and prohibitive funding costs, dealers might still be reluctant to intermediate trades as they perceive future challenges in locating buyers to turn around their inventories in a one-sided market. We also address concerns that our results could be driven by dealer sophistication or overall dealer-hedge fund connections - instead of relations with natural corporate bond buyers specifically - by performing a set of placebo tests in addition to controlling for dealer-day fixed effects. When we consider dealer relations with hedge funds that are buyers of U.S. Treasuries or equities instead of corporate bonds, we do not find effects on corporate bond liquidity provision.

Our results highlight the importance for dealers to have relations with hedge fund buyers during periods of stress. Dealers act as intermediaries, not ultimate investors. As such, they are not keen to take significant directional bets on the market (Treynor, 1987; Levine, 2015). Indeed, as shown in several recent studies (Boyarchenko, Kovner and Shachar, 2022; Kargar et al., 2021; O’Hara and Zhou, 2021), the corporate bond liquidity crisis of March 2020 ended once a large enough buyer stepped in to absorb a sizable amount of corporate bonds. Specifically, corporate bond liquidity broadly improved after the Federal Reserve acted as the buyer of last resort by establishing the Secondary Market Corporate Credit Facility, which had the goal of supporting liquidity via purchases of corporate bonds in secondary markets.

After documenting that dealer relationships with hedge funds have an effect on corporate bond liquidity provision, we explore factors that influence hedge funds' propensity to be the natural buyers of corporate bonds during times of stress. We consider several hedge fund characteristics, including size, net flows, liquidity transformation, share restrictions, profitability, and risk tolerance. We show that hedge funds' size and risk tolerance are the main factors that predict hedge funds' ability to absorb more corporate bonds during the COVID liquidity crisis, following a heavy sell-off of corporate bonds by mutual funds and other investors. This seems to be an efficient outcome as risky assets move from less to more risk tolerant investors in a downturn, and is in line with the findings of Kruttli et al. (2021) on hedge fund liquidity provision in the U.S. Treasury market. The fact that hedge funds' size and risk tolerance are the primary drivers of their higher corporate bond exposures is in line with our previous findings on dealers. Namely, that dealer leverage and funding conditions did not significantly affect their liquidity provision during the COVID liquidity crisis. In such a one-sided market, dealers refrain from taking inventory risk. As such, internal risk controls may have been more binding than the leverage ratio. Moreover, dealers' funding conditions were generally stable during the COVID liquidity crisis. Ultimately, what seemed to matter the most is the risk-absorbing capacity of different players. While dealers intermediate between
buyers and sellers, some hedge funds took directional bets on the market and increased their exposure to corporate bonds in March 2020.

We contribute to the literature on market making in corporate bonds. The literature mainly focuses on the role of regulatory constraints (Bao, O'Hara and Zhou, 2018; Bessembinder et al., 2018; Breckenfelder and Ivashina, 2021). Recent papers examine dealers' internal risk limits (Anderson, McArthur and Wang, 2023) and how insurers' stable funding structures allowed them to provide liquidity during the COVID crisis (O'Hara, Rapp and Zhou, 2021). We show that liquidity provision is facilitated by having relations with hedge funds, especially during times of stress when most investors are de-risking by selling securities.

We also contribute to the literature on hedge funds as liquidity providers. The liquidity provision of hedge funds during crisis periods has mainly been studied in the context of equity markets (Ben-David, Franzoni and Moussawi, 2012; Jylhä, Rinne and Suominen, 2014; Aragon, Martin and Shi, 2019; Çötelioğlu, Franzoni and Plazzi, 2021; Glossner et al., 2020) due to the available long-equity holdings from the SEC Form 13F filings of investment advisers. An exception is Kruttli et al. (2021), who study liquidity provision of hedge funds in U.S. Treasury markets. In contrast, our paper focuses on how relationships between dealers and hedge funds affect the liquidity provision of dealers, and consequently transaction costs, in corporate bond markets.

Aragon and Strahan (2012) show that stocks traded by hedge funds with Lehman Brothers as their prime broker became more illiquid in the aftermath of the Lehman Brothers' collapse. This finding is attributed to hedge funds being unable to access collateral posted with Lehman Brothers during the bankruptcy proceedings. Our analysis is testing a notably different mechanism. We measure transaction costs at the dealersecurity level and test if relationships with hedge funds allow dealers to provide more liquidity and reduce transaction costs. Han, Kim and Nanda (2020) and Maggio, Egan and Franzoni (2022) show that hedge funds and mutual funds can profit from connections to central dealers because the latter provide lower trading costs. Our paper differs from

Han, Kim and Nanda (2020); Maggio, Egan and Franzoni (2022), as we find that dealers need hedge funds that are natural buyers of bonds to enable them to provide better liquidity in a one-sided market.

The remainder of the paper is organized as follows. Section 2 sets out the data and discusses the sample construction. In Section 3, we develop a measure to capture each dealer's exposure to hedge funds and test how it affects the transaction cost that dealers charge to their customers. In Section 4, we study a number of hedge fund characteristics and link them to their behavior around the crisis. Section 5 concludes the paper.

## 2 Data

Our study relies on data from several sources. To capture dealer liquidity provision, we obtain from the Financial Industry Regulatory Authority (FINRA) the TRACE corporate bond transaction data for the first quarter of 2020. TRACE data provide detailed information on secondary market transactions in corporate bonds, including bond CUSIP, trade execution date and time, trade price and quantity, an indicator for inter-dealer trades, an indicator for agency or principal trades, and an indicator for whether the reporting dealer buys or sells the bond. Unlike the publicly disseminated TRACE data, our data include the identity of the dealer involved in each trade. Such information is essential to our analysis as it allows us to estimate bond liquidity at the dealer-bond level, and link it to each dealer's relationships with hedge funds. We exclude from our sample the following transactions: when issued, canceled, subsequently corrected, and reversed trades.

We supplement TRACE bond transaction data with bond characteristic data, including total amount outstanding, issuance and maturity dates, and credit rating, from the Mergent Fixed Income Securities Database (FISD). We focus on bonds issued in U.S. dollars by U.S. firms in the following three broad FISD industry groups: industrial, financial and utility. Each bond has to be rated by Moody's or S\&P. If a bond is rated differently
by the two rating agencies, we use the lower of the two. To avoid the potential impact of special bond features on the liquidity estimation, we focus on fixed-coupon corporate bonds with semiannual coupon payments, $\$ 1,000$ par amount, and fixed maturity. We also exclude from our sample the following bonds: convertible or putable bonds, private placements, asset-backed issues, and issues that are part of a unit deal. After applying these filters, we end up with a sample of 8,716 corporate bonds.

For each bond in our sample, we obtain data on its par amount held by each mutual fund at the most recent quarter-end from Thomson Reuters' eMAXX database, which provides security-level holdings information of fixed-income mutual funds at a quarterly frequency. We obtain daily data on mutual fund flows from Morningstar.

Our data on hedge funds are from the SEC Form PF and SEC Form ADV filings of hedge fund advisers that file Form PF on a quarterly basis and report granular information about their large hedge funds, called qualifying hedge funds in the form. We focus on qualifying hedge funds because these funds report items that we require in our analysis, such as hedge fund-dealer borrowing amounts and other variables such as corporate bond exposures and returns at a monthly frequency. ${ }^{2}$ Our sample construction follows the methodology described in Kruttli, Monin and Watugala (2022) and our data include filings for Q4 2019 and Q1 2020. Hedge fund borrowing is reported in response to Question 47, which requires the fund to list all its "major" creditors, defined as creditors to whom the hedge fund owes $5 \%$ or more of its NAV in a given quarter. ${ }^{3}$ We manually inspect the "name" entries for Question 47 in the Form PF filings and match these to parent institutions.

To control for funding liquidity at the dealer level, we use triparty repurchase agreements (repos) transaction level data. Triparty repos are collateralized loans used to raise cash against the pledge of collateral, which is held in custody at Bank of New York

[^2]Mellon. Information on triparty repos is provided daily to the Federal Reserve Bank of New York (FRBNY). The triparty repo data include a transaction-level trade file, which provides the loan amount and the interest rate for each repo transaction, as well as the identity of both the borrower and the lender. In this study, we focus on repos backed by corporate debt securities as collateral. For each dealer we compute the average precrisis repo rate weighted by the loan amount, called Repo Rate ${ }_{\text {pre }}$, which controls for the differential pre-crisis funding costs of each dealer. We also compute an exogenous funding shock to the dealer, called Repo Shock, which is the monthly change in corporate bond repos outstanding between the dealer and prime money market funds (MMFs). We first identify each prime MMF among the various repo lenders, and then compute their level of outstanding corporate bond repo lending to each dealer. Finally, we compute its monthly change at the dealer level. Since prime MMFs saw heavy redemptions for reasons unrelated to their exposures to the repo market (Li et al., 2021), they had to cut back on their repo lending. As a result, Repo Shock serves as an exogenous funding shock to dealers.

Data on leverage is obtained in two ways. For dealers affiliated with bank holding companies subject to the Supplementary Leverage Ratio (SLR), we obtain SLR data from the annual Federal Reserve Stress Test results as of 2019Q4. ${ }^{4}$ These bank holding companies are subject to a minimum SLR of $5 \%$. For dealers that are not subject to the SLR, we obtain their leverage ratio from the SEC FOCUS reports as of 2019Q4. These dealers are subject to a minimum leverage ratio (net capital over debits) of $2 \%$.

### 2.1 Summary Statistics

Summary statistics are displayed in Table 1. In the final sample, which corresponds to the intersection of TRACE, Form PF, and eMAXX, there are 19 dealers and 8,716 CUSIPs. The average transaction cost is 41.39 basis points including riskless principal trades (RPTs) and 39.96 excluding them. Following Harris (2015), we denote a trade

[^3]as RPT if a dealer offsets it within one minute by another trade in the same bond and with the same size but opposite trade direction. As such, RPTs do not require capital commitments and, as a result, transaction costs on RPTs tend to be lower than those on trades that require capital commitments. While at first this may seem not to apply to our case, because the average cost including RPT is higher than the cost excluding them, this is actually due to selection. Indeed, once we restrict the sample to observations with non-missing Cost (No RPT), the average cost excluding RPTs, 39.96, is higher than that including RPTs, 38.84. Figure 1 displays the dynamics of transaction costs including RPTs in panel (a) and excluding RPTs in panel (b), separately for investment grade (IG) and high yield (HY) bonds. While transaction costs are usually higher for HY than IG bonds in normal times, they both spike up and reach similar heights during the COVID liquidity crisis of March 2020. The spike is even larger when we exclude riskless principal trades, since these trades do not increase dealers' inventories, thus exposing them to less risk.

The average outflow-weighted bond holdings by mutual funds during the crisis, MF Shock, is $\$ 38.88$ million, which points to significant selling pressure by corporate bond mutual funds during the COVID liquidity crisis. This is in contrast to the average outflow-weighted holdings in the pre-crisis period of - $\$ 5.55$ million (not reported), which suggests that prior to the crisis mutual funds were on average receiving net inflows and, as a result, buying corporate bonds. Figure 2 shows the aggregate dynamics of mutual fund selling shocks for IG and HY bonds, separately. While almost flat before the crisis, selling pressure by mutual funds mounts during the COVID liquidity crisis, slightly more so for HY than IG bonds, as one would expect. Since IG and HY dynamics for transaction costs and selling shocks tend to be comparable, in our main analysis we estimate the average effect across ratings, while controlling for time-varying bond characteristics. Nevertheless, our results are unchanged if we separately estimate the effects for IG and HY bonds, as shown in Appendix Table B.1.

HF Expo is the logarithm of the long exposures in corporate bonds of affiliated hedge
funds. For each dealer and each month, we sum the long exposures in IG and HY corporate bonds (separately) of hedge funds with which the dealer has a prime brokerage relation. Such relation is obtained from Form PF, Question 47, where each hedge fund lists its major prime broker lenders. HF Expo thus varies at the dealer-month-rating class (IG vs HY) level. Repo Shock, the monthly change in corporate bond repos outstanding coming from prime money funds, is 2.29 percent on average over the sample. However, it varies from an average of 3 percent pre-crisis to -1 percent during the crisis. Next, the average corporate repo rate pre-crisis is 1.75 percent, which is consistent with the federal funds rate of about 1.6 percent during that period. Finally, Leverage Intensity, defined as the minimum leverage ratio minus the actual one as of 2019Q4 divided by the minimum, is on average -26.55 , which suggests that the average trade in our sample is carried out by a dealer with a 27 percent buffer above the minimum requirement, which is $5 \%$ for SLR-constrained dealers and $2 \%$ for other dealers.

Table 1 also reports summary statistics for the hedge fund variables used in our analysis. The average fund manages $\$ 4.36$ billion and $\$ 1.86$ billion in gross and net assets, respectively, for a leverage ratio of 2.30 . We use data on hedge funds' corporate bond exposures from Form PF Question 30, which requires hedge funds to report long and short portfolio exposures at a monthly frequency for a range of asset classes. Hedge funds' corporate bond exposures include cash bond holdings at fair value and related bond derivatives at notional value, but do not include exposures from credit default swaps. The average gross notional exposure to corporate bonds is $\$ 383.8$ million, of which $\$ 330.5$ million is long exposure and $\$ 53.3$ million is short exposure. Monthly aggregates for long and short corporate bond exposures of hedge funds, broken out further by investment grade and high yield classifications, are provided in Table 2.

The variable RiskLimit $_{h, t}$ is based on the hedge fund's value at risk (VaR). The VaR shows for each fund and month the potential loss (as a percent of NAV) over a one-month horizon with a probability of $5 \%$. Like Kruttli et al. (2021), we construct the measure
based on the monthly VaR observations. ${ }^{5}$ The measure proxies for a fund's historical risk limit and is the VaR averaged over a rolling 12-month window. The average RiskLimit $_{h, t}$ is $3.84 \%$, which implies that the average fund expects to lose $3.84 \%$ of its NAV in a month $5 \%$ of the time.

The next three variables measure different dimensions of fund liquidity, including portfolio liquidity ( PortIlliq $_{h, t}$ ), investor liquidity as measured by share restrictions (ShareRes ${ }_{h, t}$ ), and the funding liquidity measured as the weighted average maturity of a fund's borrowing ( FinDur $_{h, t}$ ). Form PF asks for the percentage of a hedge fund's assets, excluding cash, that can be liquidated within particular time horizons (within $\leq 1,2-7,8$ 30, 31-90, 91-180, 181-365, and $>365$ days) using a given periods' market conditions. We compute the weighted average liquidation time to obtain the measure PortIlliq ${ }_{h, t}$. The average PortIlliq $_{h, t}$ is 68.8 days in our sample and the median is 23.4 days. ShareRes ${ }_{h, t}$ is a measure of the expected weighted average time it would take for a hedge fund's investors to withdraw the fund's equity. This variable quantifies the restrictions faced by a fund's investors, such as lock-up, redemption frequencies, and redemption notice periods. The average Share $^{\text {Res }}{ }_{h, t}$ is 186.3 days. The weighted average time to maturity of a fund's borrowing is denoted FinDur $_{h, t}$. On average, the financing duration is 67.0 days for our sample of hedge funds with a median of 19 days. The variable LiqMismatch $_{h, t}$, constructed as in Aragon et al. (2021), summarizes these liquidity metrics and measures the average liquidity of the hedge fund's assets relative to its liabilities. Like Aragon et al. (2021), the average fund in our sample has a negative liquidity mismatch. The table further provides summary statistics for monthly returns, quarterly flows, and the manager's stake in the fund.

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## 3 Dealer-Hedge Fund Relationships and Corporate Bond Liquidity

Most corporate bonds trade in over-the-counter (OTC) markets and heavily rely on dealers for intermediation. Dealers use their networks with customers and other dealers to facilitate the matching between buyers and sellers, and the remaining order imbalances remain on their balance sheets as inventories. Following the 2008 financial crisis, various banking regulations increased dealer balance sheet costs and discouraged them from committing their own capital to market making. Under such regulation-induced constraints, dealers' ability to locate counterparties for their customers became particularly valuable. In addition to balance sheet constraints, dealers do not want to take significant inventory risk in turbulent times and especially in a one-sided market. Indeed, committing capital to purchase bonds may lead to large losses if market prices move against the dealer before it can offload these bonds to other customers. Indeed, facing heavy selling pressure, dealer usually charge higher transaction costs, as the dynamics of transaction costs and mutual fund selling shocks displayed in Figures 1 and 2 suggest. For all these reasons, dealers' connections with natural buyers are especially important in a one-sided market.

We hypothesize that dealers' relations with hedge funds play an important role in their liquidity provision during the COVID liquidity crisis. First, the crisis introduced opportunities for hedge funds to step in to profit from market dislocations. Second, hedge funds tend to trade with their prime brokers that also provide them with financing. Such relationship-based trading can help dealers address the unusually high selling pressures in the bond markets. To test this hypothesis, we analyze how a dealer's relation with hedge funds affects its bond trading costs when facing large sell-offs.

We start by measuring liquidity provision at the dealer-bond level. For that purpose, we first estimate the transaction cost for each bond trade as in Hendershott and Madhavan
(2015):

$$
\begin{equation*}
\operatorname{Cost}_{i, j, r}=\ln \left(\frac{P_{i, j, r}}{P_{i, j, r}^{B}}\right) \cdot \operatorname{Sign}_{i, j, r} . \tag{1}
\end{equation*}
$$

$P_{i, j, r}$ refers to the price for trade $r$ by dealer $i$ in bond $j . P_{i, j, r}^{B}$ is the benchmark price for trade $r$, which refers to the last trade price in the inter-dealer markets. ${ }^{6}$ Sign $_{i, j, r}$ represents the sign of the trade $r$, which takes the value of +1 for customer buy and -1 for customer sell. We then calculate a daily average transaction cost for dealer $i$ in bond $j$ during day $t\left(\operatorname{Cost}_{i, j, t}\right)$. Finally, we divide the cost measure by 100 to facilitate our interpretation of the magnitude.

To test whether dealers relations with natural bond buyers can attenuate the effect of mutual funds selling pressures on the liquidity of a bond, we estimate the following empirical model:

$$
\begin{align*}
\text { Cost }_{i, j, t} & =\beta_{1} \text { HFExpo }_{i, j, t-1}+\beta_{2} \text { MFShock }_{j}+\beta_{3} \text { HFExpo }_{i, j, t-1} \times \text { MFShock }_{j} \\
& +\beta_{4} \text { HFExpo }_{i, j, t-1} \times \text { Crisis }+\beta_{5} \text { MFShock }_{j} \times \text { Crisis } \\
& +\beta_{6} \text { HFExpo }_{i, j, t-1} \times \text { MFShock }_{j} \times \text { Crisis }+\gamma \text { Controls }+\mu_{i, j, t}+\varepsilon_{i, j, t}, \tag{2}
\end{align*}
$$

where Cost $_{i, j, t}$ is the transaction cost charged by dealer $i$ on bond $j$ at day $t$, as defined in Equation (1). HFExpo $i_{i, j, t-1}$ is the logarithm of the long exposures to IG and HY corporate bonds of hedge funds affiliated to dealer $i$ as of the previous month. When dealer $i$ trades an IG (HY) bond $j$, HFExpo $\operatorname{Eij,t-1}$ captures the exposure of dealer $i$ to affiliated hedge funds' long positions in IG (HY) bonds. MFShock $j_{j}$ is a proxy for bond sales by mutual funds during the crisis. It equals the outflow-weighted holdings of bond $j$ by corporate bond mutual funds during the crisis period (March 5 to March 20). Crisis is an indicator variable equal to one between March 5 and March 20, 2020, at the height of the dislocation in capital markets. Control variables include Log(TTM), Repo Shock,

[^5]and Repo Rate pre . Log(TTM) is the logarithm of the time to maturity of each bond. Repo Shock is the monthly change in dealer-level corporate bond repo outstanding with prime money market funds. It controls for exogenous variation in access to repo markets. Repo $^{\text {Rate }}$ pre is the average pre-crisis dealer-level corporate bond repo rate, which is zero pre-crisis and is switched on during the crisis. It controls for predetermined differences in repo funding costs. Finally, we include a set of fixed effects. Standard errors are two-way clustered at the bond and dealer level.

The results in Table 3 support our hypothesis. Consistent with the literature on firesales and liquidity (Ambrose, Cai and Helwege, 2008; Ellul, Jotikasthira and Lundblad, 2011; Bao, O'Hara and Zhou, 2018), the coefficient of Crisis $\times$ MFShock is positive and highly significant, suggesting that dealer liquidity provision deteriorates significantly for the bonds heavily sold during the crisis (column 1). More importantly, the coefficient of the triple interaction term, Crisis $\times$ HFExpo $\times$ MFShock, is negative and highly significant. This finding suggests that a dealer with more hedge fund connections is able to charge a relatively lower transaction cost in bonds facing heavy mutual fund sell-offs. To control for the potential time-varying impact of bond characteristics, we replace bond fixed effects and day fixed effects with bond-day fixed effects. Column (2) shows that, even after controlling for bond-day fixed effects, the coefficient of Crisis $\times$ HFExpo $\times$ MFShock remains negative and highly significant. This finding suggests that among dealers that trade the same bond on the same day, those with stronger relations with hedge funds charge lower transaction costs for bonds facing higher selling pressure during the crisis.

A key assumption underlying our triple-difference empirical design is the parallel trend assumption, which requires that the difference in liquidity costs charged by dealers with different relations with hedge funds (first difference) across bonds with different exposure to mutual fund sell-offs (second difference) do not already exhibit different patterns prior to the crisis period. To validate the parallel trend assumption, we construct three indicator variables for three pre-crisis sub-periods, each 2 weeks long. Specifically,

Crisis_2 equals one between February 6 and 19; Crisis_3 equals one between January 23 and February 5; and Crisis_4 equals one between January 9 and 22. Following Borusyak and Jaravel (2017), the first and last two-week intervals of the pre-crisis period are left in the omitted group. We then interact HFExpo $\times$ MFShock with each of the three precrisis sub-period indicators and include them as regressors. Column (3) shows that the parallel trends assumption seems to hold in the data. All the pre-crisis interaction terms exhibit little economic and statistical significance. The coefficient of Crisis $\times$ HFExpo $\times$ MFShock is only slightly less than that in column (1) in terms of magnitude and remains negative and highly significant. Controlling for bond-day fixed effects in column (4) does not materially affect the results. We also repeat our analysis by focusing on dealers' liquidity costs excluding RPT trades, which do not require capital commitments and are thus executed at a lower cost. Displayed in columns (5) to (8), the results are qualitatively the same.

There are several confounding factors that may drive our results. First, dealers finance a significant portion of their inventories in the repo markets (Macchiavelli and Zhou, 2022). As a result, both access and cost of repo funding for corporate bond collateral may affect our results. To control for differential access to repo funding, we measure the monthly change in the quantity repo funding backed by corporate bonds coming from prime MMFs, called Repo Shock. This represents an exogenous shock to the dealers, because in March 2020 prime MMFs faced a run that was unrelated to dealers' exposures to corporate bonds (Li et al., 2021). Columns (1) and (2) of Table 4 shows that controlling for dealers' access to repo funding does not materially affect our results. To further account for the differential cost of repo funding, we also control for the pre-crisis repo rate paid by each dealer to finance corporate bond collateral. Columns (5) and (6) again show that our results hold.

Second, dealers face balance sheet constraints that may hinder their ability to make markets. In particular, the leverage ratio may constrain dealers' willingness to hold inventories on the balance sheet. Alternatively, dealers facing a more binding leverage ratio
may charge higher transaction costs to intermediate a trade. To control for the dealerlevel leverage constraint, we construct a measure of how tight the leverage constraint is relative to the minimum requirement. Leverage Intensity pre equals 5 minus the the 2019Q4 SLR divided by 5 for dealers subject to the SLR, and 2 minus the 2019Q4 leverage ratio divided by 2 for dealers that are not subject to the SLR. Leverage Intensity pre $^{\text {a }}$ is negative for dealers with a leverage ratio above the minimum and converges to zero as dealers get closer to the minimum leverage ratio requirement. Columns (3), (4), (7), and (8) of Table 4 show that leverage constraints do not appear to affect liquidity provision around the COVID liquidity crisis. The coefficient of Leverage Intensity pre is not significant. Importantly, the main coefficient of interest, Crisis $\times H F E x p o \times M F S h o c k$, is still negative and statistically significant. The effect is also economically significant. While a one standard deviation selling shock (23.16) increases transaction costs by 10 bps if the dealer has connections with natural buyers in the lowest decile ( $H F E x p o=19.05$ ), the same shock has a 6 bps lower effect if the dealer has connections with natural buyers in the top decile $(H F E x p o=22.12)$. As a result, moving a dealer from the bottom to the top decile of natural buyer connections reduces the liquidity decline due to a one standard deviation selling shock by $60 \% .^{7}$ In sum, having relations with natural corporate bond buyers reduces the liquidity costs associated with making markets in heavily sold bonds during the crisis.

Even though our results are robust to controlling for dealer-level repo funding conditions as well as leverage constraints, the reader may be concerned that our findings could still be explained by some unobservable time-varying dealer characteristics. Given the rich dimensionality of the panel, we can add dealer-day fixed effects and still identify the triple interaction of interest. In Table 5 we show that adding dealer-day fixed effects to our model does not affect our results.

[^6]Finally, one may argue that overall dealer sophistication in prime brokerage activities, rather than specifically its connections to corporate bond hedge funds, may drive our results. If that were the case, we would observe the same results once we substitute the corporate bond exposures of affiliated hedge funds with the equity or Treasury exposures of affiliated hedge funds. To address this concern, we run some placebo tests where we use dealer-level equity or Treasury exposures of affiliated hedge funds instead of corporate bond exposures. Table 6 shows that overall dealer sophistication in prime brokerage activities is an unlikely explanation for our findings. When a dealer's hedge fund connections are captured using either equity or Treasury positions, the coefficient of the triple interaction term no long exhibits any significance. On the other hand, what seems to specifically matter is dealer connections with natural corporate bond buyers.

Overall, our results suggest that in times of market stress and heavy selling by mutual funds, dealers step back from providing liquidity because it becomes challenging to find willing buyers. Afraid of finding themselves on the wrong side of the trade as asset prices are falling, dealers reduce their market making activities instead of buying larger and larger quantities of depreciating bonds from mutual funds. Corroborating this narrative is the evidence that dealers that are connected with natural bond buyers provide more liquidity. With access to both sellers and buyers, a dealer is more willing to make markets and intermediate trades.

In the tumultuous times of March 2020, funding conditions remained quite stable, especially if compared to the 2008 financial crisis in which repo markets for corporate collateral were severely stressed and some dealers lost more repo finding than others (Gorton and Metrick, 2012; Copeland, Martin and Walker, 2014). The relative stability of the repo markets in March 2020 is possibly the reason why repo market conditions seems not to significantly affect liquidity provision during the COVID liquidity crisis. This result is not necessarily in contrast with the fact that repo funding conditions tend to affect liquidity provision over longer time periods (Macchiavelli and Zhou, 2022). Finally, we also find that the proximity to the leverage constraint did not play a significant
role in March 2020. We argue that in a one-sided market, dealers step back from making markets because they are less likely to find buyers and do not want to buy large quantities of bonds and be on the wrong side of a trade while asset prices are falling. In this scenario, the leverage ratio may not play a primary role. This, however, does not mean that the leverage ratio has no impact on market making. On the contrary, it is likely that in normal times the leverage ratio may be a primary factor affecting the cost of carrying inventories. Indeed, Breckenfelder and Ivashina (2021) find evidence that liquidity provision is negatively affected by leverage constraints.

## 4 Hedge Fund Characteristics and Corporate Bond Liquidity Provision

We have shown that dealer relations with hedge funds that invest in corporate bonds matter for corporate bond liquidity during the COVID liquidity crisis. In the midst of selling pressures from mutual funds, dealers are more willing to step in and provide liquidity if they can turn around and sell those bonds to connected buyers. We now study what factors matter for the ability of hedge funds to behave as bond buyers in times of stress. Specifically, we explore in a monthly panel the hedge fund characteristics that predict increases in corporate bond exposures during the COVID liquidity crisis.

We restrict our sample to hedge funds that have exposures to corporate bonds. The average hedge fund in our sample has $\$ 4.36$ billion in gross assets and a VaR of $4.35 \%$, which means that there is a $5 \%$ chance that the fund may lose $4.35 \%$ of its value over the next month. The average fund has a fairly illiquid portfolio, being able to liquidate its assets at little to no cost in 69 days. On the other hand, its average equity investors can withdraw their stakes in 186 days and the average maturity of its debts is 67 days. As a result, the assets of the representative fund are more liquid than its liabilities, allowing it to potentially hold on to illiquid assets for quite some time before it may be forced to sell them to meet redemptions. Consistent with Kruttli et al. (2021), funds with a higher risk
tolerance tend to have managers with more skin in the game (higher manager stake) and display greater return volatility. On the other hand, funds with longer share restrictions and financing duration tend to have lower risk tolerance.

The literature on hedge fund liquidity provision has mainly focused on equity markets and the role of share restrictions and finds mixed results (e.g., Ben-David, Franzoni and Moussawi, 2012; Hombert and Thesmar, 2014; Aragon, Martin and Shi, 2019). Recent work highlights the importance of hedge funds' internal risk limits in the U.S. Treasury market (Kruttli et al., 2021). Corporate bond markets differ notably from equity markets as they trade OTC instead of on an exchange. Further, the corporate bond market is much less liquid than the U.S. Treasury market. Therefore, which hedge fund characteristics drive the liquidity provision might differ for corporate bond trading hedge funds. On the one hand, the lower liquidity of corporate bonds might make share restrictions and liquidity mismatches more important for corporate bond trading than equity trading hedge funds due to the document inverse relationship between a fund's share restrictions and the liquidity of the assets that it trades (Aragon, 2007; Agarwal, Daniel and Naik, 2009; Teo, 2011; Sadka, 2010). On the other hand, the importance of fund internal risk limits as a predictor of hedge fund liquidity provision in the U.S. Treasury market (Kruttli et al., 2021) might also hold for other fixed income markets.

To test these hypotheses, we run the following panel regression model:

$$
\begin{equation*}
\Delta \log \operatorname{CorpBondLNE} E_{h, t}=\gamma_{1} Z_{h, t-1}+\gamma_{2} Z_{h, t-1} \times \text { Crisis }+\mu_{h}+\theta_{t}+\varepsilon_{h, t} \tag{3}
\end{equation*}
$$

where $\Delta \log C \operatorname{orpBondLN} E_{h, t}$ is the log change of the long corporate bond exposure of hedge fund $h$ at month $t$, and Crisis is 1 in March 2020 and 0 otherwise. The vector $Z$ includes RiskLimit, liquidity mismatch (LiqMismatch), the log of net asset values (LogNAV), net returns (NetRetM), net flows (NetFlows), and manager stake (MgrStake). To estimate how each of these characteristics contributes to corporate bond exposures during the COVID liquidity crisis, we add their interactions with Crisis.

Finally, $\mu_{h}$ and $\theta_{t}$ denote fund and time fixed effects, respectively. Standard errors are clustered at the fund level. The data are monthly from October 2019 to March 2020 and the independent variables, except for the indicator variable Crisis, are standardized.

The results are shown in Table 7. Panel A contains the main results and shows that, relative to other funds, hedge funds with more risk tolerance significantly increased their corporate bond exposures in March 2020. The economic magnitude of these estimates is substantial, with a one standard deviation move in the RiskLimit predicting a roughly $10 \%$ increase in the corporate bond exposure of a hedge fund. Similarly, larger hedge funds bought corporate bonds during the market turmoil. A higher degree of liquidity transformation indicates that the liabilities of a hedge fund can be redeemed sooner than the time it takes for the fund to liquidate its assets at fair value. Interestingly, the degree of liquidity transformation of a fund seems not to be associated with bond exposures.

Panel B of Table 7 contains some robustness tests. In the first two columns, we incorporate funds that do not calculate or report VaR, and thus do not have a defined RiskLimit according to our methodology. In the last two columns, we decompose LiqMismatch into its components PortIlliq, ShareRes, and FinDur. Indeed, it is possible that while liquidity transformation is not associated with bond exposures, some of its components may be. The only component that is marginally significant is PortIlliq, suggesting that funds that tend to hold less liquid assets are more willing to increase bond exposures during periods of market stress. On the other hand, funds with longerterm liabilities, in the form of greater share restrictions or longer debt maturity, did not significantly increase bond exposures during the COVID liquidity crisis. In other words, within the set of hedge funds investing in corporate bonds, the stability of their funding structure does not predict bond exposures in times of stress. This result, however, does not negate that hedge funds with less liquid investment strategies (distressed debt instead of Treasury cash-futures basis trades) employ longer-term funding structures, such as longer share restrictions or longer-term repo.

Importantly, across the different specifications, the RiskLimit coefficient estimate
remains positive and statistically significant. Hedge funds with greater risk capacity are willing to absorb more corporate bonds during a market sell-off and hold on to them until market confidence is restored. In late March 2020, the Federal Reserve intervened to avoid further market dislocations (O'Hara and Zhou, 2021) and provided ample funding to dealers. As a result, dealers could support the funding needs of their hedge fund clients. Had there been significant runs on dealers (as during the 2008 financial crisis), we may have seen a deterioration in hedge funds' financing conditions, which in turn may have led to a further bond selloff.

## 5 Conclusion

The secondary market for corporate bonds relies on dealer intermediation. With infrequent trading, dealers step in between sellers and buyers to provide a timely trade execution and charge a bid-ask spread for the incurred risk. During periods of market turmoil, many investors rush to sell corporate bonds. Dealers face an increasing risk that by the time they find a buyer, the bond they just purchased has already decreased in value. In such a one-side market, dealers' relations with hedge funds become very valuable. Indeed, hedge funds were net buyers of corporate bonds during the 2020 liquidity crisis. Dealers with stronger prime broker relations with hedge funds were better able to offload their positions and reduce their inventory risk. As a result, these dealers could provide more secondary market liquidity.

Consistent with this explanation we find that, for the bonds more heavily sold by mutual funds, dealers with stronger hedge fund connections charged smaller bid-ask spreads. Our results are not driven by other factors that could affect dealers' liquidity provision, such as leverage constraints and repo funding availability and costs. Hedge funds that were better positioned to absorb risk proved to be valuable to dealers, particularly when dealers were facing a one-side market with mutual funds and other institutional investors trying to sell bonds at the same time.

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Figure 1: Transaction costs over time. This figure shows the evolution of average transaction costs over time for investment grade bonds in solid blue and high yield bonds in dashed red. Panel (a) shows transactions costs including riskless principal trades (RPT), while panel (b) shows transaction costs excluding riskless principal trades. Sources: TRACE, authors' calculations.
(a) Transaction Cost (including RPT)

(b) Transaction Cost (excluding RPT)


Figure 2: Mutual fund selling shocks over time. This figure shows the evolution of average holdings-weighted outflows from mutual funds. Sources: eMAXX, Morningstar, authors' calculations.


## Table 1: Summary Statistics

Cost is the average transaction cost (relative cost of customer trades to inter-dealer trades) at the dealer-bond-day level. Cost (NoRPT) is the average transaction cost (relative cost of customer trades to inter-dealer trades) excluding riskless principal trades at the dealer-bond-day level. MF Shock is a CUSIP-level proxy for bond sales by mutual funds during the crisis. It equals the outflow-weighted holdings of a certain CUSIP by corporate bond mutual funds. HF Expo is the logarithm of the long exposures in corporate bonds of affiliated hedge funds at the dealer-month level, as of the previous month. $\log (T T M)$ is the logarithm of the time to maturity of each bond. Repo Shock is the monthly change in dealer-level corporate repo outstanding coming from prime MMFs. Repo Rate ${ }_{\text {pre }}$ is the average precrisis dealer-level corporate repo rate. Leverage Intensity pre is equal to 100 times the minimum leverage ratio minus the 2019:Q4 leverage ratio divided by the minimum. NAV is net asset values in $\$$ million. CorpBondGNE is gross (long plus short) exposures to corporate bonds in $\$$ million. CorpBondLNE and CorpBondSNE are long and short exposures to corporate bonds in\$ million, respectively. VaR is value at risk with a $5 \%$ probability and a horizon of 1 month. 12-month rolling average Var. RiskLimit is the 12 -month rolling average of VaR while DistAboveRiskLimit is the difference between VaR and lagged RiskLimit. PortIlliq measures the days it would take for the assets to be liquidated at no fire sale discount. ShareRes is the number of days it would take for investors to withdraw all their funds. FinDur is the weighted average maturity of the fund's borrowings. NetRet is the monthly return and NetFlows measures investor flows. Finally, MgrStake is the percent of NAV owned by the managers. See Appendix A for more details on the variables.

Panel A: Bond-Dealer-Day Level

| Variables | count | mean | st.dev. | $\mathrm{p}(10)$ | $\mathrm{p}(50)$ | $\mathrm{p}(90)$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| Cost | 230,555 | 41.39 | 54.97 | 1.10 | 18.38 | 117.75 |
| Cost (No RPT) | 152,441 | 39.96 | 57.03 | 1.89 | 17.42 | 108.57 |
| MF Shock | 230,555 | 38.88 | 23.16 | 3.65 | 39.54 | 67.86 |
| HF Expo | 230,555 | 20.85 | 1.11 | 19.05 | 20.93 | 22.12 |
| Log(TTM) | 230,555 | 7.57 | 1.07 | 6.18 | 7.61 | 9.12 |
| Repo Shock | 194,531 | 2.29 | 33.36 | -26.88 | 0 | 15.80 |
| Repo Rate $_{\text {pre }}$ | 201,959 | 1.75 | 0.21 | 1.61 | 1.77 | 1.95 |
| Leverage Intensity $_{\text {pre }}$ | 230,555 | -26.55 | 9.98 | -41.40 | -27.20 | -12.50 |

Summary Statistics (continued)

Panel B: Fund-Month Level

| Variables | count | mean | st.dev. | $\mathrm{p}(10)$ | $\mathrm{p}(50)$ | $\mathrm{p}(90)$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| NAV $_{h, t}$ (m US\$) | 1,419 | $1,863.68$ | $2,902.84$ | 220.21 | 952.91 | $3,964.29$ |
| GAV $_{h, t}$ (m US\$) | 1,419 | $4,335.31$ | $9,690.56$ | 323.69 | $1,391.36$ | $8,140.68$ |
| CorpBondGNE $_{h, t}$ (m US\$) | 4,189 | 383.82 | 752.96 | 1.51 | 111.74 | $1,013.33$ |
| CorpBondLNE $_{h, t}$ (m US\$) | 4,189 | 330.47 | 655.35 | 0.42 | 95.51 | 853.76 |
| CorpBondSNE $_{h, t}$ (m US\$) | 4,189 | 53.33 | 178.85 | 0.00 | 0.00 | 103.33 |
| VaR $_{h, t}(\%)$ | 1,745 | 4.35 | 4.75 | 0.83 | 3.07 | 8.43 |
| RiskLimit $_{h, t}(\%)$ | 1,568 | 3.84 | 4.33 | 0.94 | 2.71 | 6.73 |
| PortIlliq $_{h, t}$ (days) | 1,419 | 68.77 | 96.10 | 1.78 | 23.41 | 213.27 |
| ShareRes $_{h, t}($ days $)$ | 1,419 | 186.31 | 136.55 | 0.50 | 185.50 | 366.00 |
| FinDur $_{h, t}$ (days) | 1,147 | 66.99 | 106.48 | 0.50 | 19.00 | 273.00 |
| LiqMismatch $_{h, t}$ (days) | 1,140 | -92.21 | 94.58 | -241.64 | -72.02 | 1.99 |
| NetRet $_{h, t}$ (\%) | 3,829 | -1.33 | 5.66 | -8.74 | 0.20 | 2.55 |
| NetFlows $_{h, t}(\%)$ | 1,353 | -0.76 | 17.91 | -14.67 | -0.86 | 10.75 |
| MgrStake $_{h, t}(\%)$ | 1,352 | 12.88 | 23.79 | 0.00 | 3.00 | 37.00 |

Table 2: Hedge fund corporate bond exposures by month
This table reports the corporate bond exposure of hedge funds in our sample. Reported are the long and short notional exposure for investment grade and high yield bonds from October 2019 to March 2020.

|  | Oct-19 | Nov-19 | Dec-19 | Jan-20 | Feb-20 | Mar-20 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| CorpBondIG_LNE $h_{h, t}$ (m US\$) | 86,730 | 85,300 | 86,268 | 85,983 | 87,309 | 97,029 |
| CorpBondIG_SNE ${ }_{h, t}$ (m US\$) | 20,703 | 19,744 | 20,077 | 21,164 | 21,555 | 15,222 |
| CorpBondHY_LNE | (m US $\$$ ) | 157,499 | 155,718 | 159,399 | 162,708 | 160,300 |
| 137,940 |  |  |  |  |  |  |
| CorpBondHY_SNE |  |  |  |  |  |  |

Table 3: Bond Liquidity, Mutual Fund Sales, and Hedge Fund Relations.
The sample goes from January 02, 2020 to March 20, 2020. Cost is the average transaction cost (relative cost of customer trades to inter-dealer trades) at the dealer-bond-day level. Cost (NoRPT) is the average transaction cost (relative cost of customer trades to inter-dealer trades) excluding riskless principal trades at the dealer-bond-day level. Crisis equals one between March 5 and March 20. Crisis_2 equals one between February 6 and 19; Crisis_3 equals one between January 23 and February 5; and Crisis ${ }_{-4}$ equals one between January 9 and 22. Following Borusyak and Jaravel (2017), the first and last two-week intervals of the pre-crisis period are left in the omitted group. HF Expo is the logarithm of the long exposures in corporate bonds of affiliated hedge funds as of the previous month. MF Shock is a CUSIP-level proxy for bond sales by mutual funds during the crisis. It equals the outflow-weighted holdings of a certain CUSIP by corporate bond mutual funds during the crisis period. $\log (T T M)$ is the logarithm of the time to maturity of each bond. Standard errors in parentheses are two-way clustered at the bond and dealer level; ${ }^{* * *},{ }^{* *}$, ${ }^{*}$ indicate statistical significance at $1 \%, 5 \%$, and $10 \%$, respectively.

| Dependent variable: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Cost |  | Cost |  | Cost (No RPT) |  | Cost (No RPT) |  |
| HF Expo $\times$ Crisis | $\begin{aligned} & -0.556 \\ & (2.276) \end{aligned}$ | $\begin{gathered} 0.045 \\ (2.357) \end{gathered}$ | $\begin{aligned} & -1.486 \\ & (2.036) \end{aligned}$ | $\begin{aligned} & -0.329 \\ & (2.345) \end{aligned}$ | $\begin{gathered} \hline 0.893 \\ (2.498) \end{gathered}$ | $\begin{aligned} & 4.874^{* *} \\ & (1.899) \end{aligned}$ | $\begin{aligned} & -0.040 \\ & (2.304) \end{aligned}$ | $\begin{aligned} & 4.632^{* *} \\ & (1.898) \end{aligned}$ |
| MF Shock $\times$ Crisis | $\begin{aligned} & 1.779^{* *} \\ & (0.662) \end{aligned}$ |  | $\begin{aligned} & 1.656^{* *} \\ & (0.611) \end{aligned}$ |  | $\begin{aligned} & 1.221^{* *} \\ & (0.568) \end{aligned}$ |  | $\begin{aligned} & 1.344^{* *} \\ & (0.562) \end{aligned}$ |  |
| HF Expo×MF Shock $\times$ Crisis $_{-4}$ |  |  | $\begin{gathered} -0.019 \\ (0.011) \end{gathered}$ | $\begin{gathered} -0.007 \\ (0.017) \end{gathered}$ |  |  | $\begin{gathered} -0.008 \\ (0.014) \end{gathered}$ | $\begin{gathered} 0.019 \\ (0.022) \end{gathered}$ |
| HF Expo×MF Shock $\times$ Crisis -3 |  |  | $\begin{gathered} -0.002 \\ (0.009) \end{gathered}$ | $\begin{gathered} -0.007 \\ (0.018) \end{gathered}$ |  |  | $\begin{gathered} -0.010 \\ (0.013) \end{gathered}$ | $\begin{gathered} -0.023 \\ (0.023) \end{gathered}$ |
| HF Expo $\times$ MF Shock $\times$ Crisis_2 $^{2}$ |  |  | $\begin{gathered} 0.014 \\ (0.012) \end{gathered}$ | $\begin{gathered} 0.014 \\ (0.018) \end{gathered}$ |  |  | $\begin{gathered} 0.004 \\ (0.012) \end{gathered}$ | $\begin{aligned} & -0.002 \\ & (0.018) \end{aligned}$ |
| HF Expo×MF Shock $\times$ Crisis | $\begin{gathered} -0.073^{* *} \\ (0.032) \end{gathered}$ | $\begin{gathered} -0.065^{* * *} \\ (0.022) \end{gathered}$ | $\begin{gathered} -0.069^{* *} \\ (0.029) \end{gathered}$ | $\begin{gathered} -0.061^{* *} \\ (0.026) \end{gathered}$ | $\begin{aligned} & -0.059^{*} \\ & (0.028) \end{aligned}$ | $\begin{gathered} -0.081^{* *} \\ (0.033) \end{gathered}$ | $\begin{gathered} -0.064^{* *} \\ (0.028) \end{gathered}$ | $\begin{gathered} -0.089^{* *} \\ (0.037) \end{gathered}$ |
| Log(TTM) | $\begin{gathered} 33.369^{* * *} \\ (7.526) \end{gathered}$ |  | $\begin{gathered} 31.986^{* * *} \\ (7.763) \end{gathered}$ |  | $\begin{gathered} 59.140 * * * \\ (7.585) \end{gathered}$ |  | $\begin{gathered} 60.724^{* * *} \\ (7.878) \end{gathered}$ |  |
| $N$ | 229,856 | 161,633 | 229,856 | 161,633 | 151,629 | 93,197 | 151,629 | 93,197 |
| $R^{2}$ | 0.335 | 0.582 | 0.335 | 0.582 | 0.426 | 0.671 | 0.427 | 0.671 |
| Dealer FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Bond FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Bond-Day FE | No | Yes | No | Yes | No | Yes | No | Yes |

## Table 4: Controlling for Alternative Channels.

The sample goes from January 02, 2020 to March 20, 2020. Cost is the average transaction cost (relative cost of customer trades to inter-dealer trades) at the dealer-bond-day level. Crisis equals one between March 5 and March 20. HF Expo is the logarithm of the long exposures in corporate bonds of affiliated hedge funds as of the previous month. MF Shock is a CUSIP-level proxy for bond sales by mutual funds during the crisis. It equals the outflow-weighted holdings of a certain CUSIP by corporate bond mutual funds during the crisis period. $\log (T T M)$ is the logarithm of the time to maturity of each bond. Repo Shock is the monthly change in dealer-level corporate repo outstanding coming from prime money market funds. It controls for differential access to repo markets. Repo Rate ${ }_{\text {pre }}$ is the average pre-crisis dealer-level corporate repo rate, which is switched on during the crisis. It controls for predetermined differences in repo funding costs. Leverage Intensity pre is equal to 100 times the minimum leverage ratio minus the 2019:Q4 leverage ratio divided by the minimum, which is switched on during the crisis. Standard errors in parentheses are two-way clustered at the bond and dealer level; ${ }^{* * *,{ }^{* *}, * \text { indicate }}$ statistical significance at $1 \%, 5 \%$, and $10 \%$, respectively.

| Dependent variable: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Cost |  | Cost |  | Cost |  | Cost |  |
| HF Expo $\times$ Crisis | $\begin{aligned} & -1.170 \\ & (2.475) \end{aligned}$ | $\begin{aligned} & -0.625 \\ & (2.324) \end{aligned}$ | $\begin{gathered} 2.122 \\ (3.478) \end{gathered}$ | $\begin{gathered} 3.867 \\ (3.659) \end{gathered}$ | $\begin{aligned} & -2.216 \\ & (1.965) \end{aligned}$ | $\begin{aligned} & -0.445 \\ & (2.118) \end{aligned}$ | $\begin{gathered} 0.806 \\ (3.602) \end{gathered}$ | $\begin{gathered} 3.806 \\ (3.674) \end{gathered}$ |
| MF Shock $\times$ Crisis | $\begin{aligned} & 2.031^{* *} \\ & (0.761) \end{aligned}$ |  | $\begin{gathered} 2.291^{* * *} \\ (0.589) \end{gathered}$ |  | $\begin{aligned} & 1.815^{* *} \\ & (0.651) \end{aligned}$ |  | $\begin{gathered} 2.014^{* * *} \\ (0.570) \end{gathered}$ |  |
| HF Expo×MF Shock $\times$ Crisis | $\begin{gathered} -0.084^{* *} \\ (0.037) \end{gathered}$ | $\begin{gathered} -0.066^{* *} \\ (0.027) \end{gathered}$ | $\begin{gathered} -0.097^{* * *} \\ (0.029) \end{gathered}$ | $\begin{gathered} -0.062^{* *} \\ (0.026) \end{gathered}$ | $\begin{gathered} -0.073^{* *} \\ (0.031) \end{gathered}$ | $\begin{gathered} -0.065^{* *} \\ (0.025) \end{gathered}$ | $\begin{gathered} -0.083^{* * *} \\ (0.028) \end{gathered}$ | $\begin{gathered} -0.062^{* *} \\ (0.023) \end{gathered}$ |
| Log(TTM) | $\begin{gathered} 29.454^{* * *} \\ (6.489) \end{gathered}$ |  | $\begin{gathered} 29.194^{* * *} \\ (7.064) \end{gathered}$ |  | $\underset{(6.573)}{29.240^{* * *}}$ |  | $\underset{(6.920)}{29.187^{* * *}}$ |  |
| Repo Shock | $\begin{aligned} & -0.005 \\ & (0.013) \end{aligned}$ | $\begin{gathered} 0.002 \\ (0.011) \end{gathered}$ | $\begin{gathered} -0.005 \\ (0.014) \end{gathered}$ | $\begin{gathered} 0.003 \\ (0.011) \end{gathered}$ |  |  |  |  |
| Repo Rate $_{\text {pre }}$ |  |  |  |  | $\begin{gathered} 1.435 \\ (19.548) \end{gathered}$ | $\begin{gathered} -3.335 \\ (10.783) \end{gathered}$ | $\begin{gathered} 8.444 \\ (14.640) \end{gathered}$ | $\begin{gathered} 2.820 \\ (7.608) \end{gathered}$ |
| Leverage Intensity pre |  |  | $\begin{gathered} -0.447 \\ (0.639) \end{gathered}$ | $\begin{gathered} -0.544 \\ (0.445) \end{gathered}$ |  |  | $\begin{array}{r} -0.443 \\ (0.554) \\ \hline \end{array}$ | $\begin{aligned} & -0.538 \\ & (0.405) \end{aligned}$ |
| $N$ | 193,803 | 126,532 | 193,803 | 126,532 | 202,560 | 134,757 | 202,560 | 134,757 |
| $R^{2}$ | 0.336 | 0.582 | 0.336 | 0.583 | 0.332 | 0.578 | 0.333 | 0.579 |
| Dealer FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Bond FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Bond-Day FE | No | Yes | No | Yes | No | Yes | No | Yes |

Table 5: Bond Liquidity and Hedge Fund Relations: Within Bond-Day and Dealer-Day.
The sample goes from January 02 , 2020 to March 20, 2020. Cost is the average transaction cost (relative cost of customer trades to inter-dealer trades) at the dealer-bond-day level. Crisis equals one between March 5 and March 20. HF Expo is the logarithm of the long exposures in corporate bonds of affiliated hedge funds as of the previous month. MF Shock is a CUSIP-level proxy for bond sales by mutual funds during the crisis. It equals the outflow-weighted holdings of a certain CUSIP by corporate bond mutual funds during the crisis period. HY refers to high yield bonds and FIN to bonds issued by financial companies. Standard errors in parentheses are two-way clustered at the bond and dealer level; ;**,**,* indicate statistical significance at $1 \%, 5 \%$, and $10 \%$, respectively.

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ |
| :--- | :---: | :---: | :---: | :---: |
| Dependent variable: | Cost |  |  | Cost |
| HF Expo $\times$ Crisis | -0.097 | 1.264 |  |  |
|  | $(2.351)$ | $(2.506)$ |  |  |
|  |  |  |  |  |
| HF Expo $\times$ MF Shock | $-0.063^{* *}$ | $-0.055^{*}$ | $-0.086^{* * *}$ | $-0.081^{* * *}$ |
| $\times$ Crisis | $(0.024)$ | $(0.030)$ | $(0.022)$ | $(0.026)$ |
|  |  |  |  |  |
| $N$ | 161,606 | 146,066 | 161,314 | 145,666 |
| $R^{2}$ | 0.597 | 0.692 | 0.611 | 0.700 |
| Dealer-Day FE | Yes | Yes | No | No |
| Bond-Day FE | Yes | Yes | Yes | Yes |
| Dealer-Day-HY-FIN FE | No | No | Yes | Yes |
| Dealer-Bond FE | No | Yes | No | Yes |

Table 6: Placebo Test: Equity and Treasury Long Positions.
The sample goes from January 02, 2020 to March 20, 2020. Cost is the average transaction cost (relative cost of customer trades to inter-dealer trades) at the dealer-bond-day level. Crisis equals one between March 5 and March 20. HF Eqty (Tsy) L is the logarithm of the long exposures to equities (Treasuries) of affiliated hedge funds as of the previous month. MF Shock is a CUSIP-level proxy for bond sales by mutual funds during the crisis. It equals the outflow-weighted holdings of a certain CUSIP by corporate bond mutual funds during the crisis period. Log(TTM), Repo Shock, and Repo Rate ${ }_{\text {pre }}$ are defined in Table 4. Standard errors in parentheses are two-way clustered at the bond and dealer level; ${ }^{* * *}, * *$, , indicate statistical significance at $1 \%, 5 \%$, and $10 \%$, respectively.

| Dependent variable: | (1) | (2) | (3) | (4) | (5) | (6) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | Cost |  |  | Cost |  |
| HF Eqty L×Crisis | $\begin{gathered} 2.261 \\ (3.207) \end{gathered}$ | $\begin{gathered} \hline 3.868 \\ (3.238) \end{gathered}$ | $\begin{gathered} \hline 2.368 \\ (3.758) \end{gathered}$ |  |  |  |
| HF Tsy $\mathrm{L} \times$ Crisis |  |  |  | $\begin{aligned} & -1.577 \\ & (5.932) \end{aligned}$ | $\begin{gathered} 6.256 \\ (8.065) \end{gathered}$ | $\begin{gathered} 5.457 \\ (7.962) \end{gathered}$ |
| MF Shock $\times$ Crisis | $\begin{gathered} 0.783 \\ (0.624) \end{gathered}$ | $\begin{gathered} 0.796 \\ (1.159) \end{gathered}$ | $\begin{gathered} 0.394 \\ (0.715) \end{gathered}$ | $\begin{gathered} 1.223 \\ (0.925) \end{gathered}$ | $\begin{aligned} & 1.882^{*} \\ & (1.039) \end{aligned}$ | $\begin{gathered} 1.510 \\ (0.975) \end{gathered}$ |
| HF Eqty L×MF Shock $\times$ Crisis | $\begin{aligned} & -0.022 \\ & (0.025) \end{aligned}$ | $\begin{gathered} -0.021 \\ (0.047) \end{gathered}$ | $\begin{aligned} & -0.005 \\ & (0.029) \end{aligned}$ |  |  |  |
| HF Tsy L×MF Shock $\times$ Crisis |  |  |  | $\begin{gathered} -0.041 \\ (0.038) \end{gathered}$ | $\begin{gathered} -0.066 \\ (0.043) \end{gathered}$ | $\begin{gathered} -0.051 \\ (0.040) \end{gathered}$ |
| Log(TTM) | $\begin{gathered} 33.968^{* * *} \\ (8.009) \end{gathered}$ | $\begin{gathered} 30.619 * * * \\ (7.505) \end{gathered}$ | $\begin{gathered} 30.511^{* * *} \\ (7.251) \end{gathered}$ | $\begin{gathered} 33.646 * * * \\ (7.297) \end{gathered}$ | $\begin{gathered} 29.481^{* * *} \\ (7.183) \end{gathered}$ | $\begin{gathered} 29.800^{* * *} \\ (7.139) \end{gathered}$ |
| Repo Shock |  | $\begin{gathered} -0.012 \\ (0.018) \end{gathered}$ |  |  | $\begin{aligned} & -0.031^{*} \\ & (0.016) \end{aligned}$ |  |
| Repo Rate pre |  |  | $\begin{gathered} 9.487 \\ (15.821) \end{gathered}$ |  |  | $\begin{gathered} 8.223 \\ (16.804) \end{gathered}$ |
| Leverage Intensity pre |  | $\begin{array}{r} -0.697 \\ (0.536) \\ \hline \end{array}$ | $\begin{array}{r} -0.736 \\ (0.459) \\ \hline \end{array}$ |  | $\begin{gathered} -0.747 \\ (0.602) \end{gathered}$ | $\begin{aligned} & -0.778 \\ & (0.532) \\ & \hline \end{aligned}$ |
| $N$ | 229,856 | 193,803 | 202,560 | 229,856 | 193,803 | 202,560 |
| $R^{2}$ | 0.334 | 0.336 | 0.333 | 0.334 | 0.337 | 0.333 |
| Dealer FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bond FE | Yes | Yes | Yes | Yes | Yes | Yes |

Table 7: Hedge fund characteristics and corporate bond trading
This table presents results of the panel regression model given in Equation (3). The dependent variable is $\Delta \log \operatorname{CorpBondLN} E_{h, t}$ (in \%). The data are monthly from October 2019 to March 2020. All explanatory variables (excluding Crisis) are lagged. The specifications include fund and/or time fixed effects where indicated. The standard errors are clustered at the fund level. The independent variables, with the exception of the indicator variable Crisis, are standardized. ${ }^{* * *},{ }^{* *}$, ${ }^{*}$ indicate statistical significance at $1 \%, 5 \%$, and $10 \%$, respectively.

Panel A: Main

|  | (1) | (2) | (3) | (4) |
| :---: | :---: | :---: | :---: | :---: |
| Dependent variable: | $\Delta \log$ CorpBondLNE |  |  |  |
| RiskLimit $\times$ Crisis | $\begin{gathered} 10.080^{* * *} \\ (3.853) \end{gathered}$ | $\begin{gathered} 10.082^{* * *} \\ (3.848) \end{gathered}$ | $\begin{gathered} 14.425^{* * *} \\ (4.296) \end{gathered}$ | $\begin{gathered} 14.431^{* * *} \\ (4.299) \end{gathered}$ |
| LiqMismatch $\times$ Crisis | $\begin{gathered} 0.709 \\ (4.981) \end{gathered}$ | $\begin{gathered} 0.716 \\ (4.984) \end{gathered}$ | $\begin{aligned} & -0.693 \\ & (4.962) \end{aligned}$ | $\begin{gathered} -0.679 \\ (4.963) \end{gathered}$ |
| LogNAV $\times$ Crisis |  |  | $\begin{gathered} 11.155^{* *} \\ (4.713) \end{gathered}$ | $\begin{gathered} 11.181^{* *} \\ (4.721) \end{gathered}$ |
| NetRetM $\times$ Crisis |  |  | $\begin{aligned} & -1.538 \\ & (5.305) \end{aligned}$ | $\begin{aligned} & -1.452 \\ & (5.360) \end{aligned}$ |
| NetFlows $\times$ Crisis |  |  | $\begin{aligned} & -9.413 \\ & (5.964) \end{aligned}$ | $\begin{gathered} -9.281 \\ (6.010) \end{gathered}$ |
| MgrStake $\times$ Crisis |  |  | $\begin{aligned} & -6.490 \\ & (4.526) \end{aligned}$ | $\begin{aligned} & -6.486 \\ & (4.519) \end{aligned}$ |
| $N$ | 1,054 | 1,054 | 1,054 | 1,054 |
| $R^{2}$ | 0.164 | 0.165 | 0.195 | 0.196 |
| Fund FE | Yes | Yes | Yes | Yes |
| Month FE | No | Yes | No | Yes |

Hedge fund characteristics and corporate bond trading (continued)

Panel B: Robustness
(1)
(2)
(3)
(4)

| Dependent variable: |  | $\Delta \log$ Cor |
| :--- | :---: | :---: |
| RiskLimit $\times$ Crisis | $12.913^{* * *}$ | $12.881^{* * *}$ |
|  | $(4.157)$ | $(4.155)$ |
| NoRiskLimit $\times$ Crisis | -4.986 | -5.025 |
|  | $(5.080)$ | $(5.081)$ |
| LiqMismatch $\times$ Crisis | 0.308 | 0.312 |
|  | $(2.762)$ | $(2.762)$ |


| PortIlliq $\times$ Crisis |  |  | 10.423 <br> $(6.919)$ | 10.415 <br> $(6.923)$ |
| :--- | :---: | :---: | :---: | :---: |
|  |  |  | -3.825 | -3.818 |
| ShareRes $\times$ Crisis |  |  | $(5.226)$ | $(5.226)$ |
|  |  |  | 4.390 | 4.416 |
| FinDur $\times$ Crisis |  |  | $(6.093)$ | $(6.092)$ |
|  |  |  |  |  |
| LogNAV $\times$ Crisis | $6.466^{* *}$ | $6.477^{* *}$ | $12.251^{* * *}$ | $12.276^{* * *}$ |
|  | $(2.943)$ | $(2.943)$ | $(4.668)$ | $(4.676)$ |
| NetRetM $\times$ Crisis | 0.914 | 1.061 | -2.193 | -2.103 |
|  | $(2.770)$ | $(2.790)$ | $(5.399)$ | $(5.475)$ |
| NetFlows $\times$ Crisis | 4.081 | 4.135 | $-10.810^{*}$ | $-10.692^{*}$ |
|  | $(3.091)$ | $(3.088)$ | $(5.628)$ | $(5.663)$ |
| MgrStake $\times$ Crisis | -4.091 | -4.078 | -5.399 | -5.386 |
|  | $(3.560)$ | $(3.562)$ | $(4.349)$ | $(4.339)$ |
| $N$ | 2,599 | 2,599 | 1,054 | 1,054 |
| $R^{2}$ | 0.223 | 0.224 | 0.216 | 0.217 |
| Fund FE | Yes | Yes | Yes | Yes |
| Month FE | No | Yes | No | Yes |

## Online Appendix

This section includes additional material, including variable definitions, figures and tables.

## A Variable Definitions

| Variable Name | Description |
| :---: | :---: |
| Cost | Relative cost of customer trades to inter-dealer trades at the dealer-bond-day level. See Eq. (1) for more details. Source: TRACE. |
| Cost (No RPT) | Relative cost of customer trades to inter-dealer trades at the dealer-bond-day level, excluding riskless principal trades (RPTs). Following Harris (2015), we denote a trade as RPT if a dealer offsets it within one minute by another trade in the same bond and with the same size but opposite trade direction. Source: TRACE. |
| HF Expo | Logarithm of the long exposures in corporate bonds of affiliated hedge funds as of the previous month. Source: Form PF. |
| MF Shock | Outflow-weighted holdings of a certain CUSIP by corporate bond mutual funds during the crisis period. Source: eMAXX and Morningstar. |
| Log(TTM) | Logarithm of the time to maturity of each bond. Source: Mergent FISD. |
| Repo Shock | Monthly change in dealer-level corporate repo outstanding coming from prime money market funds. Source: FRBNY. |
| Repo Rate pre | Average pre-crisis dealer-level corporate repo rate multiplied by the Crisis dummy. Source: FRBNY. |
| Leverage Intensity pre | The minimum leverage ratio minus the 2019:Q4 leverage ratio times 100, divided by the minimum. It is also multiplied by the Crisis dummy. The minimum is $5 \%$ for banks subject to the SLR and $2 \%$ otherwise. Source: SEC FOCUS, Annual Reports. |

Continued on next page

Table A. 1 - Continued from previous page

| Variable | Description |
| :--- | :--- |
| RiskLimit | The 12 -month rolling average VaR with a time horizon of one <br> month and a probability of $5 \%$. Source: Form PF. |
| Log(NAV) | The logarithm of net asset value, or the amount of investor equity, <br> of the hedge fund. Source: Form PF. |
| PortIlliq | The weighted average time (in days) it would take to liquidate the <br> hedge fund's portfolio, assuming no fire sale discounting. Source: <br> Form PF. |
| ShareRes | The weighted average time (in days) it would take for the investors <br> of the hedge fund to withdraw all the fund's NAV. Source: Form <br> PF. |
| FinDur | The weighted average maturity (in days) of the hedge fund's bor- <br> rowing. Source: Form PF. |
| NetRet | Net-of-fee monthly returns of the hedge fund. Source: Form PF. |
| NetFlows | Net investor flows to the hedge fund, estimated as NetFlows $h, t$ <br> $\left(N A V_{h, t}-N A V_{h, t-1} \times\left(1+r_{h, t}\right)\right) / N A V_{h, t-1} . S o u r c e:$ Form PF. |
| MgrStake | The percent of the net asset value of the hedge fund owned by the <br> managers or their related persons. Source: Form PF. |

## B Additional Tables

Table B.1: Bond Liquidity, Mutual Fund Sales, and Hedge Fund Relations: Investment Grade and High Yield Split

The sample goes from January 02, 2020 to March 20, 2020. Cost is the average transaction cost (relative cost of customer trades to inter-dealer trades) at the dealer-bond-day level. Cost (NoRPT) is the average transaction cost (relative cost of customer trades to inter-dealer trades) excluding riskless principal trades at the dealer-bond-day level. Crisis equals one between March 5 and March 20. Following Borusyak and Jaravel (2017), the first and last two-week intervals of the pre-crisis period are left in the omitted group. HF Expo is the logarithm of the long exposures in corporate bonds (investment grade in columns (1) and (2), high yield in columns (3) and (4)) of affiliated hedge funds as of the previous month. MF Shock is a CUSIP-level proxy for bond sales by mutual funds during the crisis. It equals the outflow-weighted holdings of a certain CUSIP by corporate bond mutual funds during the crisis period. $\log (T T M)$ is the logarithm of the time to maturity of each bond. Standard errors in parentheses are two-way clustered at the bond and dealer level; ${ }^{* * *},{ }^{* *}$,* indicate statistical significance at $1 \%, 5 \%$, and $10 \%$, respectively.

|  | $(1)$ <br> Cost | $(2)$ <br> Cost | $(3)$ <br> Cost | $(4)$ <br> Cost |
| :--- | :---: | :---: | :---: | :---: |
| HF Expo $\times$ Crisis | 0.662 | -0.506 | $10.298^{* *}$ | $10.277^{*}$ |
|  | $(2.451)$ | $(2.749)$ | $(3.948)$ | $(5.226)$ |
| MF Shock $\times$ Crisis | $2.120^{* *}$ |  | $2.923^{* * *}$ |  |
|  | $(0.779)$ |  | $(0.947)$ |  |
|  |  |  |  |  |
| HF Expo $\times$ MF Shock | $-0.090^{* *}$ | $-0.076^{* * *}$ | $-0.119^{* *}$ | $-0.147^{*}$ |
| $\times$ Crisis | $(0.039)$ | $(0.026)$ | $(0.044)$ | $(0.071)$ |
|  |  |  |  |  |
| Log(TTM) | $37.241^{* * *}$ |  | 11.383 |  |
|  | $(7.766)$ |  | $(7.602)$ |  |
| $N$ | 187,689 | 130,838 | 42,157 | 30,795 |
| $R^{2}$ | 0.360 | 0.595 | 0.237 | 0.530 |
| Dealer FE | Yes | Yes | Yes | Yes |
| Day FE | Yes | No | Yes | No |
| Bond FE | Yes | No | Yes | No |
| Bond-Day FE | No | Yes | No | Yes |


[^0]:    ${ }^{*}$ We thank the Financial Industry Regulatory Authority (FINRA) for providing the regulatory version of the TRACE data used in this study. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Board of Governors, the Federal Reserve System, the Office of Financial Research, or the Department of the Treasury.
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[^1]:    ${ }^{1}$ See for example,Adrian et al. (2017); Anderson and Stulz (2017); Bao, O'Hara and Zhou (2018); Bessembinder et al. (2018); Choi, Huh and Seunghun Shin (2023); Dick-Nielsen and Rossi (2019); Duffie (2022); Macchiavelli and Zhou (2022); Saar et al. (2023); Schultz (2017); Trebbi and Xiao (2019).

[^2]:    ${ }^{2}$ Advisers with at least $\$ 1.5$ billion in regulatory assets under management across all of their hedge funds file Form PF on a quarterly basis. Qualifying hedge funds are hedge funds with at least $\$ 500$ million in net asset value.
    ${ }^{3}$ On average, $87.3 \%$ of all the borrowing by a hedge fund is from its major creditors, as shown in the Online Appendix of Kruttli, Monin and Watugala (2022).

[^3]:    ${ }^{4}$ See https://www.federalreserve.gov/publications/files/2020-dfast-results-20200625.pdf.

[^4]:    ${ }^{5}$ Qualifying hedge funds are required to report the VaR of the fund at a monthly frequency if they regularly calculate it. Kruttli et al. (2021) show that most funds report their VaR and provide a method, which we adopt, to convert reported VaRs to a $5 \%$ significance level and monthly horizon.

[^5]:    ${ }^{6}$ Schultz (2001), Bessembinder, Maxwell and Venkataraman (2006), Goldstein, Hotchkiss and Sirri (2006), and Edwards, Harris and Piwowar (2007) use alternative benchmark prices but broadly similar approaches to estimate transaction costs.

[^6]:    ${ }^{7}$ Using the estimated coefficients of Table 4, column (7), a one standard deviation selling shock (23.16) increases transaction costs by $2.014 \times 23.16-0.083 \times 23.16 \times 19.05=10$ for a dealer with a natural buyer connection in the bottom decile (19.05). The same mutual fund selling shock has a $-0.083 \times 23.16 \times(22.12-19.05)=-5.90$ differential effect for a dealer with natural buyer connections in the top decile (22.12). These magnitudes are sizable if compared to the average and median transaction costs of 41 and 18 bps in our sample, respectively.

