Liquidity Provision in a One-Sided Market: The Role of Dealer-Hedge Fund Relationships *

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Abstract

During the bond market liquidity crisis of March 2020, dealers connected with corporate bond trading hedge funds charged lower transaction costs on bonds subject to more mutual fund fire sales. This effect was particularly strong in bonds with limited alternative buyers, such as insurance companies. Further, dealers with stronger hedge fund connections committed less capital to inventories. Despite selling equities and U.S. Treasuries, hedge funds purchased corporate bonds in March 2020, partly due to the widening CDS-bond basis. We show that hedge fund connections help dealers overcome search frictions and increase their willingness to provide liquidity in a one-sided market.

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1 Introduction

Dealers play a vital role in the U.S. corporate bond market. Given that trades are typically large and infrequent, dealers often need to absorb order imbalances into their inventories and then search for counterparties to offload these positions. Carrying inventory consumes dealer balance sheet capacity and requires funding. As a result, a large body of literature has examined how funding liquidity and post-2008 regulatory reforms, particularly regarding capital requirements, influence dealers' liquidity provision.[1] However, since dealers operate as intermediaries, their willingness to provide liquidity ultimately hinges on their ability to find counterparties. More efficient search processes reduce funding needs and demand less balance sheet capacity, thereby mitigating the constraints these factors impose on liquidity provision. Indeed, theoretical models of over-the-counter (OTC) trading (Duffie, Gârleanu and Pedersen, 2005, 2007; Üslü, 2019) underscore the crucial role of search frictions in market functioning.

To reduce search costs and improve inventory management, dealers strategically build trading relationships. Previous research has primarily focused on inter-dealer trading relationships as a means to enhance liquidity provision (e.g., Di Maggio, Kermani and Song, 2017; Li and Schürhoff, 2019; Colliard, Foucault and Hoffmann, 2021). While these relationships are important, connections with end-customers ultimately drive dealers' ability to absorb order imbalances—especially during periods of market stress when dealers' behavior tends to converge, limiting each dealer's ability to offset trades in the inter-dealer market.

This paper examines the role of dealer relationships with a specific group of end-customers, namely hedge funds, and evaluates how these relationships help mitigate search frictions and support corporate bond liquidity in times of stress. We focus on the COVID crisis of March 2020, when the market experienced extreme selling pressure. For example, mutual funds faced heavy outflows and were forced to sell corporate bonds to meet redemptions (Falato,

[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).

Goldstein and Hortaçsu, 2021; Ma, Xiao and Zeng, 2022). With many investors selling simultaneously, the market became one-sided, intensifying dealers' inventory risks and search challenges. By analyzing redemption-driven sales of corporate bonds by mutual funds at the security level, we first demonstrate that dealers intermediating these bonds during the crisis charge higher transaction costs.

Meanwhile, the collapse of bond prices caused by the COVID-induced economic uncertainty created opportunities for hedge funds. Unlike other players in the corporate bond market, such as dealer banks and insurance firms, hedge funds face less regulation and are generally more inclined to take risks. Additionally, many hedge funds use sophisticated trading strategies to capitalize on mispricing. During the COVID crisis, the emergence of arbitrage spreads, such as the CDS-bond basis (Haddad, Moreira and Muir, 2021), presented profitable investment opportunities for these funds in the corporate bond market. Moreover, compared to mutual funds, hedge funds are less susceptible to large outflows due to their share restrictions, making them more likely to step in and purchase bonds during turbulent times. We estimate that net corporate bond purchases of hedge funds were around $20 billion in March 2020. As in Shleifer and Vishny (2011), we refer to hedge funds as natural buyers.

Taking advantage of confidential data from the Securities and Exchange Commission (SEC) on credit relationships between dealers and hedge funds and hedge funds' corporate bond exposures, we measure a dealer's connection to hedge funds that hold large quantities of long corporate bond positions pre-crisis (February 2020). We construct this measure for different issuer types (financial versus non-financial) and credit ratings (investment grade versus high yield) and link it to the dealer's corporate bond transactions using dealer identities provided in a regulatory version of Financial Industry Regulatory Authority's (FINRA) TRACE corporate bond transaction data. Our hypothesis is that a dealer that has established connections with corporate bond trading hedge funds going into the March 2020 crisis is more likely to find a willing buyer for the bonds that mutual funds sell during the crisis.

Consistent with our hypothesis, 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 stronger hedge fund relations. This result holds after controlling for time-varying bond and dealer characteristics (such as issuer type or dealer size and centrality) through bond-day and dealer-day fixed effects, respectively.[2] The importance of having relations with corporate bond trading hedge funds in a one-sided market is corroborated by the additional finding that dealers with stronger connections to such hedge funds commit less capital to holding corporate bonds in their inventory. In other words, dealers with stronger natural buyer connections are better able to offset order imbalances in a one-sided market. As such, our findings provide supportive evidence to theoretical models of OTC trading with search frictions (Duffie, Gârleanu and Pedersen, 2005, 2007; Üslü, 2019).

Our results are robust to controlling for alternative channels, including repo funding conditions and the tightness of leverage constraints. These findings suggest that even without regulatory constraints and prohibitive funding costs, dealers might still be reluctant to intermediate trades as they perceive challenges in locating buyers to turn around their inventories in a one-sided market. Indeed, abstracting from funding and balance sheet costs, the longer dealers hold on to a bond amid deteriorating market conditions, the higher is the likelihood that they will incur a loss. We also address concerns that our results could be driven by dealers' overall hedge fund connections—instead of connections with corporate bond trading hedge funds—by performing a set of placebo tests in addition to controlling for dealer-day fixed effects. When we construct our measure with dealers' connections to hedge funds that trade U.S. Treasuries or equities instead of corporate bonds, we do not find effects on the dealers' corporate bond liquidity provision. Moreover, our coefficient estimates are qualitatively similar for sub-samples of investment grade (IG) and high yield (HY) bonds, respectively.

[2]For example, Di Maggio, Kermani and Song (2017) show how a dealer's network centrality affects its liquidity provision during the Global Financial Crisis.

Further, we find that the value of dealer relationships with hedge funds varies across bonds, depending on the participation of other potential buyers of corporate bonds. Insurance firms, the largest domestic investor type in the U.S. corporate bond market, were net buyers of corporate bonds at the height of the COVID liquidity crisis of March 2020 (O'Hara, Rapp and Zhou, 2021). However, in the cross-section of corporate bonds there are differences in how much insurers purchased during the crisis. We find that in bonds where insurers have also contributed to the excessive selling pressure, dealer relationships with hedge funds have a particularly strong impact on their liquidity provision.

Our findings 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, the corporate bond liquidity crisis of March 2020 ended once the Federal Reserve stepped in and promised to absorb a sizable amount of corporate bonds.[3]

After documenting the impact of dealer relationships with hedge funds on dealers' corporate bond liquidity provision, we explore factors that influence hedge funds' propensity to buy corporate bonds during times of stress. Our analysis suggests that hedge funds' ability to deploy complex arbitrage trading strategies provides support for dealers' liquidity provision. In the IG sector, hedge funds' aggregate long positions in corporate bonds remained relatively stable up to February, and increased substantially in March. We find evidence that hedge funds took advantage of the discrepancy between bond and credit default swap (CDS) spreads in the IG sector (Haddad, Moreira and Muir, 2021) by taking long positions in bonds and short positions in CDS. In the HY sector, where the CDS-bond basis was much smaller than in the IG sector, hedge funds refrained from trading the CDS-bond basis in March 2020.

This finding that hedge funds increased their CDS-bond basis trading in the corporate

[3]See for example, Boyarchenko, Kovner and Shachar (2022); Kargar et al. (2021); O'Hara and Zhou (2021). 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.

bond market stands in sharp contrast to their behavior in the U.S. Treasury market. Banegas, Monin and Petrasek (2021) and Kruttli et al. (2024) find that hedge funds exited U.S. Treasury arbitrage trades, for example, the cash-futures basis trade, in March 2020. Widening arbitrage spreads during a crisis period can provoke different trading behavior. On the one hand, widening spreads represent profitable opportunities to enter new arbitrage positions. On the other hand, widening spreads lead to losses on existing arbitrage positions. We find that corporate bond arbitrage positions were modest relative to the hedge funds' gross asset value (GAV) in February 2020, while their U.S. Treasury arbitrage positions were substantial. Therefore, hedge funds may have had the capacity to increase corporate bond exposures to trade the CDS-bond basis in March 2020, but losses on existing Treasury cash-futures basis trades prevented them from taking advantage of a widening U.S. Treasury basis.

We also analyze how cross-sectional differences in hedge funds' risk appetite, funding structure, size, and performance as of February predict their liquidity provision in March 2020. Hedge funds that are larger, better performing, and have more risk appetite disproportionally increased their long corporate bond exposure in March 2020. However, hedge funds that entered the crisis with more leverage and a larger liquidity mismatch tended to disproportionally reduce their long corporate bond exposure during the crisis.

We contribute to the literature on market making in corporate bonds. As discussed above, a large literature has studied the role of funding liquidity and regulatory constraints in shaping liquidity conditions in the corporate bond market. 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). In contrast, we show that dealer relations with hedge funds are particularly important for dealers' liquidity provision in bonds that are sold by both mutual funds and insurance companies during the COVID liquidity crisis. Dealers' liquidity provision is facilitated by having relations with hedge funds, especially when a market becomes one-sided,

because dealers connected to hedge funds are more likely to find an ultimate buyer for the bonds sold by other investors.

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 (e.g., Ben-David, Franzoni and Moussawi, 2012; Jylhä, Rinne and Suominen, 2014; Aragon, Martin and Shi, 2019; Çötelioğlu, Franzoni and Plazzi, 2021; Glossner et al., 2025).[4] An exception is Kruttli et al. (2024), 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. Further, we show that while hedge funds sold equities and U.S. Treasuries in March 2020, they bought corporate bonds. This shift in hedge funds' asset allocation to an asset class that presents a more attractive investment opportunity has been hypothesized by Ben-David, Franzoni and Moussawi (2012) in the context of the Global Financial Crisis. However, by using our data on hedge funds' complete portfolio exposures, we are to our knowledge the first paper to present empirical analysis that explicitly tests this hypothesis.

In the literature that focuses on how hedge funds and dealers interact, 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 and rehypothecated by Lehman Brothers during the bankruptcy proceedings. Our analysis is testing a notably different mechanism. We measure transaction costs at the dealer-bond level and test if relationships with hedge funds allow dealers to provide more liquidity and reduce transaction costs. Han, Kim and Nanda (2020) and Di Maggio, Egan and Franzoni (2022) show that hedge funds and mutual funds can profit from connections to central dealers because the latter provide them with lower trading costs. Our paper differs from both studies, as we

[4]This focus on equity markets is partially due to the available long-equity holdings from the SEC's Form 13F filings of investment advisers.

find that dealers are more likely to provide liquidity in a one-sided market when they have connections to hedge funds that are natural buyers of bonds.

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 potential drivers behind hedge fund behavior in the corporate bond market around the crisis, focusing on fund level characteristics and their positions in credit derivatives. Section 5 concludes the paper.

2 Data

Our study relies on data from several sources, which are described in this section.

2.1 Corporate Bond Data

To capture dealer liquidity provision, we obtain from FINRA the TRACE corporate bond transaction data. TRACE data provide detailed information on secondary market transactions in corporate bonds, including the bond's 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.

Our study focuses on the period from January 2 to March 20, 2020, right before the Federal Reserve announced a number of interventions in response to acute stress in the corporate bond market caused by the COVID pandemic on March 23, 2020. We start with the list of dealers included in the TRACE data, and require a dealer to have leverage information available either in the Federal Reserve Stress Testing data or the SEC FOCUS report data. We then merge it with the list of prime brokers in the Form PF data. This leads to a total of 17 dealers that include almost all the largest dealers in the corporate bond market, accounting for 76% of the trade volume in corporate bonds. For these dealers, we keep their trading in the list of bonds that exist both in TRACE and FISD data, after applying the filters described above. Our final bond transaction sample covers a total of 7,333 CUSIPs. Summary statistics for these bonds are reported in Table 1, Panel A.

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.

2.2 Hedge Fund Data

Our data on hedge funds are from the SEC's Form PF. Hedge fund advisers file Form PF and report granular information about each of 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 the monthly frequency.[5]

Our sample construction follows the methodology described in Kruttli, Monin and Watugala (2022) and our data include filings from January 2013 to March 2020. We restrict our sample of hedge funds to those that have corporate bond exposures. 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.[6] We manually inspect the creditor name entries in Question 47 and match these to parent institutions.

As of Q4 2019, on average each dealer in our sample lends a total of $98 billion to 69 corporate bond-trading hedge funds. Each fund borrows an average of $4.6 billion spread across 3.2 of the 17 dealers. These funds borrow an average of $0.6 billion from 0.7 additional creditors that are not in our sample of 17 dealers. Therefore, most corporate bond-trading hedge funds' borrowings are from the 17 dealers in the sample.

2.3 Dealer Data

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 Mellon. Information on triparty repos is provided daily to the Federal Reserve Bank of New York (FRBNY). Since this paper studies dealer liquidity provision in the corporate bond market, we focus on repos backed by corporate debt securities as collateral. 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.

[5] 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.

[6] 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).

Information in this file is used to calculate both cost and amount of repo borrrowing at the dealer level.

Data on dealer's 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 the fourth quarter of 2019.[7] 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 the fourth quarter of 2019. These dealers are subject to a minimum leverage ratio (net capital over debits) of 2%.

3 Dealer-Hedge Fund Relationships and Corporate Bond Liquidity

Most corporate bonds trade in 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 taking bonds into their inventories. These regulatory constraints raise the value of dealers' ability to locate counterparties for their customers without committing their own capital to market making.

In addition to balance sheet constraints, dealers also face significant inventory risks when intermediating corporate bond trading, especially in turbulent times. Since committing capital to purchase bonds may lead to large losses if market prices move against the dealer before they can offload these bonds to other customers, dealers might be reluctant to increase their inventories if they perceive future challenges in turning them over. Therefore, dealers' connections with natural buyers might reduce search frictions and could be particularly

[7] See https://www.federalreserve.gov/publications/files/2020-dfast-results-20200625.pdf.

valuable in a one-sided market. Dealers might be more inclined to provide liquidity if they know that they can offset some of the trades with other counterparties.

That hedge funds acted as natural buyers in the corporate bond market is shown in Figure 3. Hedge funds substantially increased their investment-grade and, to a lesser extent, high-yield corporate bond exposures in March 2020. Of the $20.7 billion in net purchases in March 2020, $18.6 billion came from hedge funds with corporate bonds in their portfolio in February 2020.[8] In other asset markets, the picture looks drastically different. Figure B.1 shows that the hedge funds in our sample sold around $125 billion U.S. Treasuries in aggregate and around $30 billion equities in March 2020.

Buying corporate bonds in March 2020 at depressed prices was a profitable investment for hedge funds. In Table B.8, we show that hedge funds that had bought more U.S. corporate bonds during the crisis generated higher returns in the months after the crisis.

If hedge funds decide to step in to profit from market dislocations, it is natural for them to turn to dealers who also serve as their prime brokers to execute these trades. Prime brokers provide several services to their hedge fund clients. They not only execute trades, but also provide leverage and custody of securities (Kruttli, Monin and Watugala, 2022; Kumar et al., 2020). As hedge funds use leverage to increase returns, prime brokers execute levered trades on behalf of their hedge fund clients. To provide leverage, prime brokers finance some of the positions taken by the hedge fund through margin loans or repo lending. In a standard prime brokerage agreement, clients allow the prime broker to rehypothecate a fraction of the securities bought with leverage. Indeed, to raise the necessary cash used to finance clients' securities, prime brokers pledge a fraction of them in repo markets.

3.1 Empirical Strategy

We hypothesize that dealers' relations with hedge funds play an important role in their liquidity provision during the COVID liquidity crisis. To test this hypothesis, we analyze

[8] In our sample, 700 hedge funds held corporate bonds in February 2020. Only 41 hedge funds bought corporate bonds in March 2020 but held no corporate bonds in the preceding month.

how dealers' relations with hedge funds affect bond trading costs that dealers charge when facing large sell-offs.

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

$$Cost_{i,j,r} = ln\left(\frac{P_{i,j,r}}{P^{B}_{j,r}}\right) \cdot Sign_{i,j,r}. \tag{1}$$

$P_{i,j,r}$ refers to the price for trade r by dealer i in bond j. $P^{B}_{j,r}$ refers to the last trade price of bond j between any two dealers in the inter-dealer market.[9] This price is used as a proxy for the true value of the bond, and hence serves as the benchmark price for customer trade r. $Sign_{i,j,r}$ 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 ($Cost_{i,j,t}$). Finally, we divide the cost measure by 100 to facilitate our interpretation of the magnitude. During our sample period, the average transaction cost is 41 basis points (Table 1, Panel B). The distribution is skewed, with a substantially lower median at only 18 basis points. The top 10 percentile of the cost measure is at 118 basis points, reflecting the drastic deterioration of liquidity at the height of the COVID crisis.

Figure 1 displays the dynamics of transaction costs separately for IG and HY bonds. They both spike up and reach similar heights during the COVID liquidity crisis of March 2020.

We then construct a measure, $HFExpo_{i,j,m}$, to capture a dealer's relationship with hedge funds that are potential buyers of corporate bonds. The measure is estimated as the logarithm of the long exposures of a dealer's related hedge funds in certain groups of bonds, but our results are qualitatively the same when using gross corporate bond exposure instead

[9] 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.

of long corporate bond exposure.[10] Specifically, for each dealer and each month, we create four groups of bonds split by bond issuer type (financial and non-financial issuer) and rating category (IG and HY), and sum the long exposures of hedge funds in each of the four groups with which the dealer has a lending relation. $HFExpo_{i,j,m}$ thus varies at the dealer-month-rating class-bond issuer type level. For example, when dealer i trades an IG bond of a non-financial issuer j, $HFExpo_{i,j,m}$ captures the exposure of dealer i to affiliated hedge funds' long positions in IG bonds of non-financial issuers. The average $HFExpo_{i,j,m}$ is 20.85 (Table, 1, Panel B).

We construct a bond-dealer-day level sample that covers the period from January 2 to March 20, 2020, and estimate the following empirical model:

$$\begin{aligned} Cost_{i,j,t} = {} & \beta_1 HFExpo_{i,j,m-1} + \beta_2 MFShock_j + \beta_3 HFExpo_{i,j,m-1} \times MFShock_j \\ & + \beta_4 HFExpo_{i,j,m-1} \times Crisis_t + \beta_5 MFShock_j \times Crisis_t \\ & + \beta_6 HFExpo_{i,j,m-1} \times MFShock_j \times Crisis_t + \gamma Controls + \mu_i + \mu_j + \mu_t + \varepsilon_{i,j,t}, \end{aligned} \tag{2}$$

where $Cost_{i,j,t}$ is the transaction cost charged by dealer i on bond j at day t, as defined in equation (1). $Crisis_t$ is an indicator variable equal to one between March 5 and March 20, 2020, at the height of the dislocation in capital markets. $MFShock_j$ captures mutual fund selling pressure at the bond level and is constructed as in Ma, Xiao and Zeng (2022). We combine data on mutual funds' daily net flows from Morningstar and the eMaxx mutual fund bond-level holding data, and estimate the measure by calculating for bond j and day t, a weighted average of outflows at funds k that held bond j at the end of 2019, where weights are defined by funds' holdings of bond j:

$$MFHoldingWeightedOutflows_{j,t} = \sum_k Fund\ outflow_{k,t} \times \frac{Holding_{j,k,2019Q4}}{\sum_l Holding_{j,l,2019Q4}}. \tag{3}$$

[10] See Appendix Tables B.4 and B.5.

A larger $MFHoldingWeightedOutflows_{j,t}$ implies that the funds holding the bond suffer more outflows, and hence subject the bond to more fire sale pressure. Figure 2 shows the aggregate dynamics of mutual fund selling pressure. While almost flat before the crisis, selling pressure by mutual funds mounts during the COVID liquidity crisis. To construct the $MFShock_j$ variable, we average the $MFHoldingWeightedOutflows_{j,t}$ for a given bond j during the crisis period.[11] We control for time varying bond characteristic, such as the logarithm of a bond's remaining time to maturity, $Log(TTM)$. We also include bond fixed effects, μ_i, and dealer fixed effects, μ_j, to control for potential impact of unobservable bond and dealer characteristics on bond transaction costs, and use day fixed effects, μ_t, to control for general time trends and the impact of macroeconomic conditions. Standard errors are two-way clustered at the bond and dealer level.

3.2 Baseline Results

If mutual-fund-induced fire sales contributed to the deterioration in liquidity during the crisis (Ma, Xiao and Zeng, 2022; Haddad, Moreira and Muir, 2021), we should expect a positive coefficient for the interaction of $Crisis$ and $MFShock$. In other words, dealers charge higher trading costs for bonds that are heavily sold by mutual funds. More importantly, our hypothesis predicts that a dealer's relationship with hedge fund can offset some of the impact of mutual fund fire sales on liquidity, leading to a negative coefficient of the triple interaction term, $Crisis \times HFExpo \times MFShock$. Results in Table 2 support our hypothesis. As shown in column (1), the coefficient of $Crisis \times MFShock$ is positive and highly significant, suggesting that transaction costs were larger for bonds subject to mutual fund fire sales. Meanwhile, the coefficient of $Crisis \times HFExpo \times MFShock$ 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. The effect is also

[11] Averaging the holding-weighted outflows allows us to measure which bonds experienced strong selling pressure from mutual funds without making assumptions about the exact day on which the bond was sold by the mutual funds.

economically significant. For a one standard deviation $MFShock$ (23.16), the transaction costs are 7 basis points lower if the dealer has connections with hedge funds in the top decile ($HFExpo = 22.12$) than if the dealer has connections with hedge funds in the bottom decile ($HFExpo = 19.05$). This magnitude is considerable as the average (median) transaction costs are around 40 (18) basis points.

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 including 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.[12]

A key assumption underlying our triple-difference empirical design is the parallel trends 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 trends 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. The first and last two-week intervals of the pre-crisis period are left in the omitted group.[13] We then interact $HFExpo \times MFShock$ with each of the three pre-crisis sub-period indicators and include them as independent variables. Column (3) shows that the parallel trends assumption seems to hold in the data. Each of the pre-crisis interaction terms are not statistically significant. 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. Including bond-day fixed effects in column (4) does not materially affect the results.

[12] Our results hold for both IG and HY bonds, as shown in Appendix Table B.1.

[13] The results are qualitatively similar when omitting only the last two-week interval of the pre-crisis period.

One might argue that our transaction cost estimate does not reflect the true liquidity conditions faced by investors. Since the measure is estimated based on price information, it does not reflect the time taken to complete the trade, which can be of first order importance for investors during times of stress. Kargar et al. (2021) show that during the COVID liquidity crisis, some dealers avoid taking bonds into inventories by serving as agents and prearranging trades, i.e., riskless principal trades (RPTs). Given that agency trades tend to incur lower transaction costs, our results might simply reflect dealers with hedge fund relations prearranging more trades. However, during a time when investors dash for cash, the longer time that it takes to prearrange trades reflect a decline, rather than an improvement, in liquidity provision.

To address this concern, we follow Harris (2015) and classify a trade as RPT if it is offset by another trade that occurred within one minute with the same trade size but with opposite trade direction. As our regulatory TRACE data include information on dealer identity, we further require that a trade has to be reversed by the same dealer in order to be classified as RPT. We then re-estimate the transaction cost measure $Cost_{i,j,t}$ by excluding RPTs, and repeat the analysis using all alternative specifications of equation (2). As shown in columns (5) to (8), our results are qualitatively the same. These results suggest that during the crisis period, dealers with stronger hedge funds relations tend to charge lower transaction costs in bonds under price pressure, knowing that they are able to offset these trades with their relationship hedge funds.

3.3 Additional Analysis

A large literature has shown that funding liquidity and balance sheet constraints can affect dealer behavior and liquidity of the corporate bond market. We conduct additional tests to ensure that our results are not explained by dealers' characteristics other than their relationship with hedge funds. First, dealers finance a significant portion of their inventories in the repo markets. Both access to repo funding for corporate bond collateral and its cost

may affect dealers' liquidity provision (Macchiavelli and Zhou, 2022).

To control for dealers' differential access to repo funding, we use the triparty repo data from FRBNY and measure the monthly change in the quantity of repo funding backed by corporate bonds coming from prime money market funds (MMFs). We first identify each prime MMF among the various repo lenders, and compute their level of outstanding corporate bond repo lending to each dealer. 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, the measure captures a funding shock to dealers and hence is named *RepoShock*. Indeed, during our sample period, *RepoShock* has a mean of 2.29%, and it dropped from 3% during the pre-crisis period to -1% during the crisis period. We then include *RepoShock* as an control and re-estimate equation (2). Column (1) Table 3 show that controlling for dealers' access to repo funding does not materially affect our results. Our results continue to hold when we include bond-day fixed effects (column (2)). We also account for predetermined differences in dealers' repo funding cost by using $RepoRate_{pre}$, the average pre-crisis dealer-level corporate bond repo rate weighted by loan amount, which is set to zero outside of the crisis and switched on during the crisis. The average $RepoRate_{pre}$ is 1.75%, which is consistent with the federal funds rate of about 1.6% during that period. Columns (5) and (6) show that our results change little when we control for $RepoRate_{pre}$.[14]

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 dealer-level leverage constraint, we use dealer leverage data from the Federal Reserve Stress Test results and the

[14]It is worth noting that in the tumultuous times of March 2020, overall funding conditions remained generally stable, especially if compared to the 2008 Global 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 seem not to significantly affect dealers' liquidity provision during the COVID liquidity crisis in corporate bond markets. 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).

SEC FOCUS reports, and construct a measure of how tight the leverage constraint is relative to the minimum regulatory requirement. During the crisis period, $LeverageIntensity_{pre}$ 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. Outside of the crisis period, $LeverageIntensity_{pre}$ is set to zero. $LeverageIntensity_{pre}$ 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. For our sample dealers, the average $LeverageIntensity_{pre}$ is -26.55, suggesting that the average trade in our sample is carried out by a dealer with a 27 percent buffer above the regulatory minimum requirement.

We then repeat our analysis by including $LeverageIntensity_{pre}$ as an additional control. Columns (3), (4), (7), and (8) of Table 3 show that the coefficient of interest, $Crisis \times HFExpo \times MFShock$, is still negative and statistically significant. Meanwhile, the coefficient of $LeverageIntensity_{pre}$ is not significant, suggesting that leverage constraints do not appear to affect liquidity provision around the COVID liquidity crisis in the corporate bond market. This finding complements Breckenfelder and Ivashina (2021) who find evidence that liquidity provision is negatively affected by leverage constraints during normal times and implies that, in a one-sided market, inventory risk concerns might play a more important role than leverage constraints in dealers' liquidity provision decisions.

Lastly, to further ensure the robustness of our finding, we re-estimate equation (2) with several additional fixed effects. First, we control for unobservable time-varying dealer characteristics by including dealer-day fixed effects. Specifically, we estimate the following model:

$$\begin{aligned} Cost_{i,j,t} = {} & \beta_1 HFExpo_{i,j,m-1} + \beta_2 HFExpo_{i,j,m-1} \times MFShock_j + \beta_3 HFExpo_{i,j,m-1} \times Crisis_t \\ & + \beta_4 HFExpo_{i,j,m-1} \times MFShock_j \times Crisis_t + \mu_{i,t} + \mu_{j,t} + \varepsilon_{i,j,t}, \end{aligned} \tag{4}$$

where $\mu_{i,t}$ and $\mu_{j,t}$ refer to dealer-day and bond-day fixed effect respectively. The other variables are defined as in equation (2). Column (1) of Table 4 show that our results hold

with dealer-day fixed effects. Second, we add dealer-bond fixed effects to the model to control for dealers' potential special treatment of some bonds stemming from their commitment to these bonds. For example, lead underwriters who organize a new bond offering tend to be the major liquidity provider for the new bond in secondary market trading (e.g., Flanagan, Kedia and Zhou, 2021). Column (2) shows that adding dealer-bond fixed effects does not materially affect our results. Third, since a given dealer's hedge fund relationship measure varies across rating category and bond type, we replace dealer-day fixed effects with dealer-day-rating-type fixed effects, where the rating is HY and the type is financial, and find qualitatively similar results (column (3)). Fourth, the results continue to hold when we add dealer-bond fixed effects (dolumn (4)).

Another concern regarding our findings is that overall dealer sophistication in prime brokerage activities, rather than its connections to corporate bond hedge funds, may drive our results. If this was the case, we would observe similar results once we compute $HFExpo$ not with hedge funds' corporate bond exposures but with their equity or U.S. Treasury exposures. Table 5 shows that overall dealer sophistication in prime brokerage activities is not an explanation for our findings. When a dealer's hedge fund connections are captured using either long equity or long U.S. Treasury positions, the coefficients of the triple interaction terms are no longer significant.

3.4 Dealer-Hedge Fund Relationships and Dealer Capital Commitment

To further study the role played by hedge fund relationship in facilitating dealers' inventory risk management and influencing their willingness to provide liquidity, we directly link the amount of capital that a dealer commits to hold inventories to its hedge fund relationships. If hedge funds indeed support their relationship dealers by offsetting some of their trades, these dealers should end up committing less capital in market making.

As in Bessembinder et al. (2018), we calculate an overnight dealer capital commitment

measure at the dealer-day level by taking the absolute value of the difference between dealer's buy volume and sell volume based on bond market value. We then estimate the following empirical model:

$$CapCommit_{i,t} = \beta_1 HFExpo_{i,m-1} + \beta_2 HFExpo_{m,t-1} \times Crisis_t + DealerControls + \mu_t + \varepsilon_{i,t}, \quad (5)$$

where $CapCommit_{i,t}$ refers to dealer i's overnight capital commitment on day t, and $HFExpo_{m,t-1}$ refers to the previous month-end aggregate long exposures of the dealer's affiliated hedge funds. Other variables are defined as in equation (2).

Results in Table 6 support the hypothesis that hedge fund relationships benefit dealers by supporting their inventory management. Column (1) shows that the coefficient of the interaction term, $HFExpo_{i,m-1} \times Crisis_t$, is negative and highly significant, suggesting that dealers with stronger relations with hedge funds were able to commit less capital to market making during the COVID crisis. Including dealer fixed effects to control for unobservable dealer characteristics does not materially change our results (column (2)). Our results also hold when we re-estimate dealer capital commitment using bond par value (columns (3) and (4)). Finally, we control for potential impact of dealers' repo funding costs and continue to find similar results (columns (5) to (8)). Together, these results lend further support to our hypothesis that connections to hedge funds are beneficial to dealers' market making activities, especially in times of stress.

3.5 Dealer-Hedge Fund Relationships and Insurers' Trading

O'Hara, Rapp and Zhou (2021) study the role played by insurance companies during the COVID liquidity crisis in the corporate bond market and show that those with stable funding structures were net buyers of corporate bonds prior to the Federal Reserve's interventions on March 23, 2020. However, the collective buying by insurance companies was not sufficient to

stabilize the market, and the impact of their trading was more pronounced in certain bonds, for example, bonds by issuers to which the insurers had prior exposure. One interesting question is how the value of dealer-hedge fund relationships varies across bonds with different insurer presence.

To study this question, we start by collecting data on insurance companies' corporate bond transactions from the National Association of Insurance Commissioners (NAIC). The NAIC data provide detailed information on each bond transaction made by insurance companies, including issue and issuer identifiers, execution date, dollar amount, par value of the transaction, and trade direction (i.e., a buy or a sell by an insurance company).[15] For each bond in our sample, we calculate the net buying by insurance companies during the crisis period, and use it to split our sample. In the bottom tercile we have bonds that were on net sold by insurance companies while the top tercile include bonds on net purchased by insurance companies. We then estimate equation (2) on these subsamples. As shown in Table 7, the coefficient of interest, the triple interaction term is negative and highly significant in the bottom tercile subsample (column (1)) but insignificant in the top tercile subsample (column (2)). This finding suggests that the value of dealers' relationships with hedge funds is mostly pronounced in bonds for which insurance firms might have also contributed to the selling pressure. We also form subsamples based on the quintiles and deciles of insurers' net purchases in crisis and present the results in columns (3) to (6). The coefficients of the triple interaction terms remain negative and highly significant only in subsamples of bonds which also experienced selling by insurance companies (columns (3) and (5)). When insurance companies are net purchasers, dealer connections to hedge funds do not seem to be much of a benefit, with the coefficient of the triple interaction remaining negative but not statistically significant (columns (4) and (6)). Notably, the coefficient of the triple interaction term is monotonically larger in magnitude as we move from the bottom tercile to the bottom decile, again pointing to the value of hedge fund relationships in the absence of other buyers of

[15] A more detailed discussion on the NAIC data can be found in O'Hara, Rapp and Zhou (2021).

corporate bonds.

4 Drivers of Hedge Fund Corporate Bond Exposures

In this section, we study potential drivers behind hedge funds' decisions to change their corporate bond exposure during the crisis and act as natural buyers in an otherwise one-sided market.

4.1 CDS-Bond Basis Trading

Hedge funds engage in a variety of arbitrage strategies to take advantage of price discrepancies between related securities. One such opportunity arose when the COVID crisis in March 2020 led to significant dislocations in the corporate bond market. Haddad, Moreira and Muir (2021) shows that corporate bonds traded at a large discount to their corresponding CDS contracts, and thus, the CDS-bond basis widened substantially. This increase in the CDS-bond basis presents an arbitrage opportunity for hedge funds that can be exploited by buying corporate bonds and simultaneously selling CDS.

To shed light on whether hedge fund CDS-bond basis trading explains some of the increase in hedge fund corporate bond positions in March 2020, we test whether increases in hedge funds' long positions in corporate bonds are accompanied by simultaneous increase in their short positions in CDS. Since the widening of CDS-bond basis occurred mostly in investment-grade bonds in March 2020 (Haddad, Moreira and Muir, 2021), we expect the link between hedge funds' positions in corporate bonds and CDS to be mostly observed in the investment-grade sector.

We construct a fund-month level sample that spans a period from January 2013 to March

2020. We then estimate the following panel regression:

$$\begin{aligned}\Delta \log CorpBondLong_{h,m} = \alpha + \beta_1 \Delta \log CDSShort_{h,m} + \beta_2 Crisis + \beta_3 Controls_{h,m-1} + \\ + \beta_4 \Delta \log CDSShort_{h,m} \times Crisis_m + \beta_5 Controls_{h,m-1} \times Crisis_m + \\ + \mu_h + \mu_m + \varepsilon_{h,t} \qquad (6)\end{aligned}$$

where $\Delta \log CorpBondLong_{h,t}$ is the log change of the long corporate bond exposure of hedge fund h at month t, estimated separately for IG bonds ($\Delta \log CorpBondIGLong_{h,t}$) and HY bonds($\Delta \log CorpBondHYLong_{h,t}$). $Crisis$ is a dummy for March 2020, and $\Delta \log CDSShort_{h,t}$ is the log change of the fund's short CDS exposure in the same month t. On average, the hedge funds in our sample have \$71.7 (\$209.0) million in long IG (HY) corporate bond exposure and \$430 million in short CDS exposure (Table 1, Panel C).[16]

We start by estimating equation (6) using $\Delta \log CorpBondLong$ estimated for the IG sector. Table 8 shows that the coefficient of $\Delta \log CDSShort_{h,t}$ is positive and highly significant, suggesting the existence of hedge fund arbitrage activity between the two markets even prior to the COVID crisis. More importantly, the coefficient of the interaction of $\Delta \log CDSShort_{h,t}$ with the Crisis indicator is also positive and highly significant, with the magnitude substantially larger than the coefficient of $\Delta \log CDSShort_{h,t}$.

We then use $\Delta \log CorpBondLong$ for the HY sector and estimate the model in equation (6). The coefficient of $\Delta \log CDSShort_{h,t}$ is also positive and highly significant, with a magnitude that is comparable to that estimated for the investment-grade sector. This result suggests that outside of the crisis, similar arbitrage between bonds and CDS by hedge funds also exists in the riskier end of the credit spectrum. Interestingly, the coefficient of the interaction of $\Delta \log CDSShort$ and $Crisis$ is negative and significant. This result is consistent with the fact that the CDS-bond basis was much smaller in the HY sector in March 2020 Haddad, Moreira and Muir (2021). Hedge funds likely abandoned the CDS-bond basis trade

[16]Form PF's CDS exposure data are only shown in aggregate and not split into IG and HY.

in the HY sector in favor of the same trade in the IG sector.

To further analyze how hedge funds' corporate bond positions relate to their CDS positions during the crisis, we estimate the following cross-sectional regression for March 2020:

$$\Delta \log CorpBondLong_h = \alpha + \beta_1 \Delta \log CDSShort_h + \beta_2 Controls_{h,Feb2020} + \varepsilon_h \qquad (7)$$

All variables are defined as in equation (6) and the results are presented in Table B.2. Consistent with Table 8, in the IG sector, hedge funds' long corporate bond exposures are positively related to their short CDS exposures (column (3)). The result holds when we control for fund characteristics (column (4)). Meanwhile, the bond CDS position link disappears in the HY sector (columns (5) and (6)). Together, these findings support the hypothesis that hedge funds' increased exposure to IG bonds during the COVID crisis is partially explained by their CDS-bond basis trading.

Our findings suggesting that hedge funds increased their corporate bond positions in March 2020 partly to support increased CDS-bond basis trading contrasts with results on the U.S. Treasury basis trade during that time. Like the CDS-bond basis, the Treasury cash-futures basis widened in March 2020, but rather than increase basis trade positions, Banegas, Monin and Petrasek (2021) find that hedge funds sold $173 billion in Treasury securities and that the selling was largely driven by unwinds in the Treasury cash-futures basis trade (see Figure B.1). Widening relative value spreads like the basis can provoke different behavior from arbitrageurs because a larger spread leads to losses on *existing* positions and, at the same time, presents potentially profitable opportunities for *new* positions. We speculate that the different behavior of hedge funds in corporate bond and U.S. Treasury markets in March 2020 may have been because hedge funds appeared to have large and rapidly growing Treasury basis trade exposures going into the crisis, while their CDS-bond basis exposures were relatively small and flat.

Table B.6 present estimates of hedge funds' activity in the CDS-bond basis and U.S.

Treasury basis trades on the eve of the crisis at the end of February 2020 as well as in the two years prior. Hedge funds' U.S. Treasury basis trade exposures increased rapidly from $272 billion in February 2018 (23.8% of gross assets) to $1.11 trillion in February 2020 (71.4% of gross assets), while CDS-bond basis trade activity remained relatively steady, increasing slightly from $174 billion (6.8% of gross assets) to $190 billion (6.6% of gross assets). In addition to basis trading activity, Table B.7 shows that overall exposures of IG and HY corporate bonds remained relatively constant between February 2018 and February 2020, while Treasury exposures increased markedly. These statistics suggest that hedge funds may have had the capacity to increase corporate bond exposures to trade the CDS-bond basis in March 2020, but losses on the large amount of existing Treasury cash-futures basis trades and subsequent unwinds prevented them from taking advantage of a widening Treasury basis.

4.2 Hedge Fund Characteristics and Corporate Bond Liquidity Provision

Hedge fund characteristics besides the hedge funds' involvement in the CDS-bond basis trade can affect their propensity to provide liquidity in the corporate bond market in March 2020.

The literature on hedge fund liquidity provision has mainly focused on equity markets and the role of fund liquidity (e.g., share restrictions) and finds mixed results (e.g., Ben-David, Franzoni and Moussawi, 2012; Hombert and Thesmar, 2014; Aragon, Martin and Shi, 2019). Corporate bond markets differ notably from equity markets in terms of trading and liquidity. 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 documented 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). We construct a variable $LiqMismatch_{h,t}$ as in Aragon et al. (2021) to summarize a hedge fund's liquidity metrics and measure the average liquidity of a hedge fund's assets relative to its liabilities. The three liquidity metrics that measure different

dimensions of fund liquidity are portfolio liquidity, investor liquidity as measured by share restrictions, and the funding liquidity measured as the weighted average maturity of a fund's borrowing. As in Aragon et al. (2021), the average fund in our sample displays a negative liquidity mismatch, meaning that its assets are more liquid than its liabilities (see Table 1, Panel C).[17]

Recent work highlights the importance of funds' internal risk limits as a predictor of hedge fund liquidity provision in the Treasury market (Kruttli et al., 2024). During the COVID crisis, the stressed corporate bond market condition may lead some risk tolerant hedge funds to increase their exposure to corporate bonds. We estimate the measure $VaRConstraint_{h,t}$ to capture a fund's risk limit. Following Kruttli et al. (2024), we construct the measure based on the monthly VaR observations.[18] The measure proxies for a fund's historical risk appetite and is the VaR averaged over a rolling 12-month window. The average $VaRConstraint_{h,t}$ is 3.66%, which implies that the average fund expects to lose 3.66% of its NAV in a month 5% of the time (Table 1, Panel C).

In addition to fund liquidity mismatch and internal VaR constraint, we also analyze other time-varying fund level characteristics, such as the log of net asset values ($LogNAV_{h,t}$), net returns ($NetRet12M_{h,t}$), and leverage ($Leverage_{h,t}$). Summary statistics on these variables are also presented in Table 1, Panel C.

The coefficient estimates in Table 8 show that outside the COVID crisis, hedge funds with greater liquidity mismatch between assets and liabilities were less likely to increase their corporate bond exposure. This effect becomes substantially larger in magnitude during the

[17]For the asset side, 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 as portfolio illiquidity measure, which on average is 60 days. For the liability side, share restrictions 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 restrictions are 183 days. The financing duration is the weighted average time to maturity of a fund's borrowing and has a mean of 52 days.

[18]Qualifying hedge funds are required to report the VaR of the fund at a monthly frequency if they regularly calculate it. Kruttli et al. (2024) show that most funds report their VaR. The authors also provide a method, which we adopt, to convert reported VaRs to a 5% significance level and monthly horizon.

crisis for IG bonds. Hedge funds for which the liquidity mismatch is large sold substantially more IG bonds in March 2020. This finding is in line with Aragon, Martin and Shi (2019) in that hedge funds with more resilient capital are able to provide liquidity during crisis periods. Interestingly, the coefficient estimate for liquidity mismatch during the crisis in the HY sample has the opposite sign albeit with a much smaller magnitude. This finding suggests that a few hedge funds that carry a high liquidity mismatch had a different liquidity pecking order and sold IG but bought HY bonds March 2020.[19]

In line with the finding in Kruttli et al. (2024) for hedge funds' Treasury market trading, hedge funds with higher internal VaR constraints as of February 2020 increased their exposure to corporate bonds in March 2020. The coefficient estimates on the interaction of the VaR constraint and the crisis variable are substantial, with a one standard deviation move in the $VaRConstraint_{h,t-1}$ predicting a up to 12.5% increase in the bond exposure of a hedge fund.

Other hedge fund characteristics show similar effects on corporate bond liquidity provision across the IG and HY segments. Hedge funds that were larger and better performing before the crisis increased their corporate bond long exposures in March 2020. However, hedge funds that entered the crisis with more leverage reduced their long corporate bond exposure disproportionally more.

Not all hedge funds in our sample trade CDS in addition to corporate bonds. Therefore, we investigate the effects of hedge fund characteristics on corporate bond liquidity provision by estimating equation (6) without the short CDS variable. The results are shown in Table 9. The estimates are qualitatively the same as for the sample of hedge funds that take on short CDS positions.

Because the VaR information is not available for the whole sample, we show in Appendix Table B.3 that the estimates on the other hedge fund characteristics are qualitatively similar when not restricting the sample to hedge funds that report their VaR.

Together, our results indicate that CDS-bond basis trading by hedge funds contributed

[19]However, for the full sample of hedge funds the coefficient on the interaction of liquidity mismatch and the crisis period for HY bonds is not significant (Table B.3, Panel B).

to their increased exposure to IG corporate bonds. The hedge funds' risk tolerance, size, performance, and leverage played an important role in their decisions to increase their bond positions during the COVID liquidity crisis.

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 the COVID liquidity crisis, as many investors rushed to sell corporate bonds, dealers were exposed to substantial inventory risks—bond prices could continue to decline following their purchases. In such a one-side market, dealers' relations with potential buyers become particularly valuable.

Importantly, dealers with stronger prime broker relations with hedge funds that are natural buyers of corporate bonds were better able overcome search frictions when looking to offload their corporate bond positions and reduce their inventory risk. As a result, these dealers could provide better liquidity, especially in bonds that were subject to mutual fund fire sales. Dealer-hedge fund relationships are particularly valuable when other potential buyers of corporate bonds are either absent or may also contribute to the selling pressure.

We find that hedge funds were net buyers of corporate bonds at the peak of the COVID crisis. The drivers behind their corporate bond exposure decisions seem to differ across the risk spectrum. In the IG sector, increases in long positions in corporate bonds are accompanied by simultaneous increases in short positions in CDS, consistent with hedge funds engaging in CDS-bond basis trades to profit from market dislocations. In the IG and HY sectors, hedge funds' characteristics like risk tolerance, size, performance and leverage determined whether a hedge fund provided liquidity in corporate bonds in March 2020.

Our study illustrates the important role played by natural buyers in the corporate bond market during times of stress. In the aftermath of the COVID liquidity crisis, policymakers

have raised concerns about the instability of bond markets and discussed new regulations to bolster the provision of liquidity, including widening the central clearing of Treasury transactions. In this search for a more resilient bond market, our study highlights the value of dealers' relationships with hedge funds for dealers' liquidity provision.

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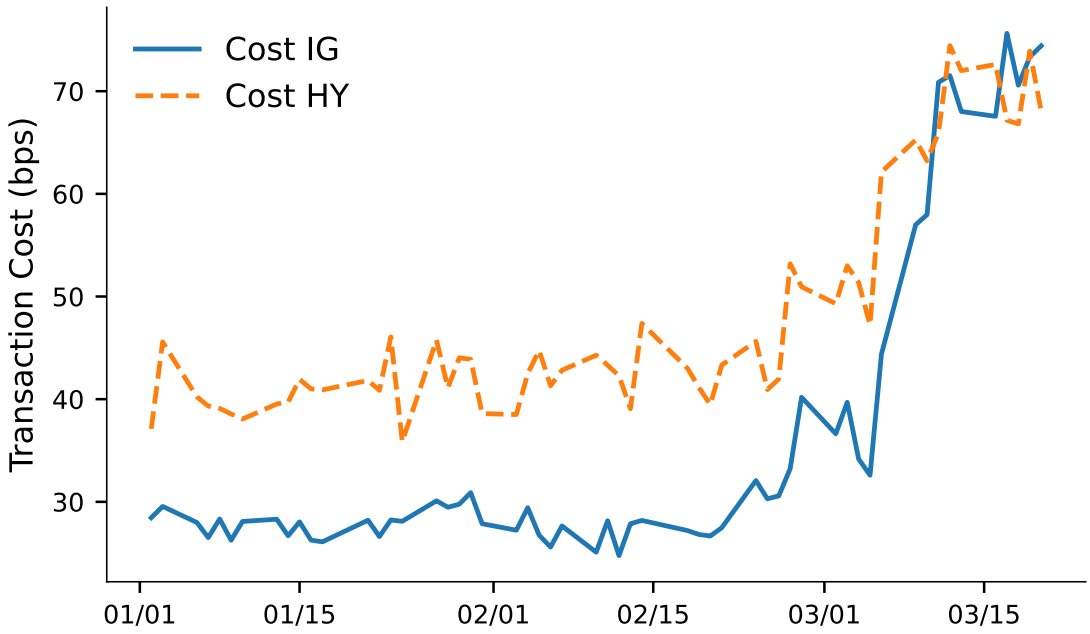
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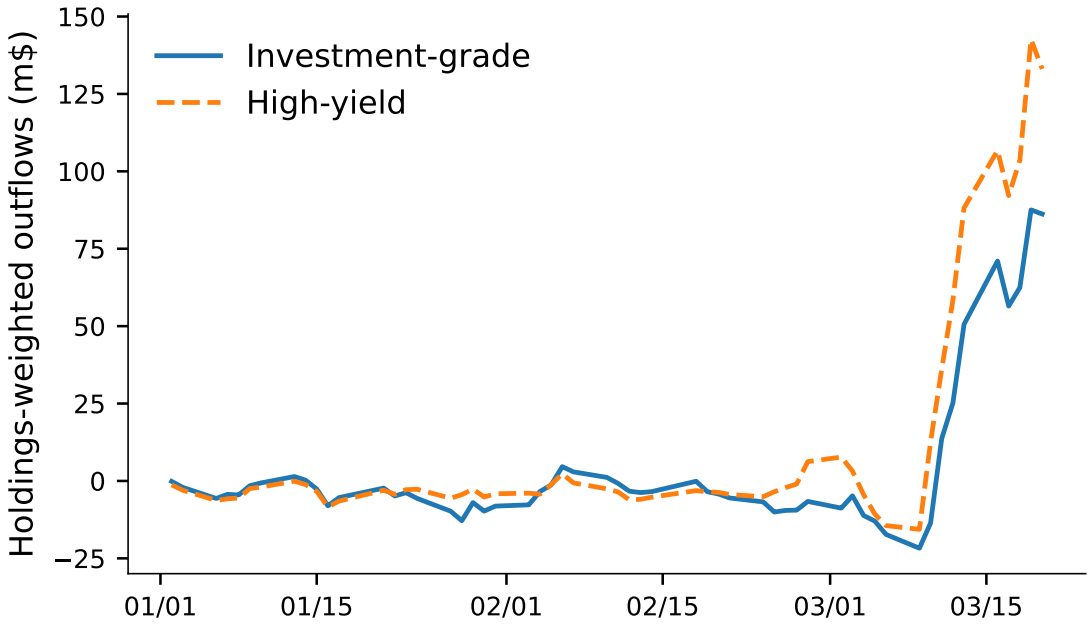
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Figure 1: Transaction costs over time



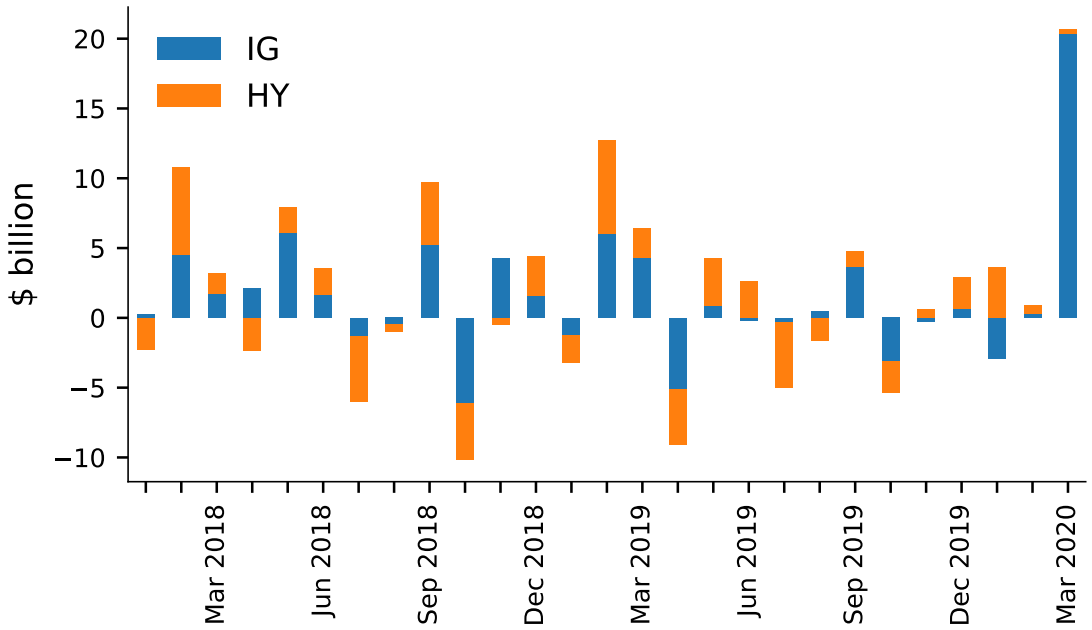
This figure shows average daily transaction costs given in equation (1) from January 2 to March 20, 2020, for investment grade and high yield corporate bonds, respectively.

Figure 2: Mutual funds' corporate bond holdings-weighted outflows



This figure shows the corporate bond holdings-weighted outflows from mutual funds given in equation (3) from January 2 to March 20, 2020, averaged for each day across all IG and HY bonds, respectively.

Figure 3: Hedge funds' net purchases/sales of corporate bonds



This figure plots hedge funds' estimated net purchases/sales of investment grade and high yield corporate bonds, respectively, from January 2018 to March 2020.

Table 1: Summary statistics

This table provides summary statistics for the main variables used in the paper. Panel A contains information at the bond level for the daily sample from January 2 to March 20, 2020. Panel B contains data at the bond-dealer-day level for the daily sample from January 2 to March 20, 2020. Panel C contains information at the hedge fund-time level for the from January 2013 to March 2020. In Panel C, the variables are at the fund-month level except those indicated by (q), which are at a fund-quarter level..

Panel A: Bond level

	Obs.	Avg.	St. dev.	10^{th}	50^{th}	90^{th}
Investment grade						
Amount outstanding	6,319	737,439	746,362	23,195	500,000	1,500,000
TTM as of 1/1/20 (days)	6,319	3,708	3,714	463	2,270	9,635
High yield						
Amount outstanding	1,014	573,766	480,560	36,325	500,000	1,073,168
TTM as of 1/1/20 (days)	1,014	2,335	2,454	536	1,810	4,049

Panel B: Bond-dealer-day level

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

Table 1: Summary statistics (continued)

Panel C: Hedge fund-time level

	Obs.	Avg.	St. dev.	10^{th}	50^{th}	90^{th}
$CorpBondGross_{h,t}$ (m$)	59,553	340.76	630.11	2.22	102.32	933.91
$CorpBondLong_{h,t}$ (m$)	59,553	286.00	506.92	1.00	87.47	775.13
$CorpBondShort_{h,t}$ (m$)	59,553	48.94	156.77	0.00	0.00	113.93
$CorpBondIGLong_{h,t}$ (m$)	59,553	71.67	212.55	0.00	0.00	179.56
$\Delta logCorpBondIGLong_{h,t}$ (%)	26,241	-0.20	40.28	-29.66	0.00	27.69
$CorpBondHYLong_{h,t}$ (m$)	59,553	209.04	372.54	0.034	57.27	604.33
$\Delta logCorpBondHYLong_{h,t}$ (%)	52,496	-1.29	26.05	-19.16	0.00	16.14
$CDSShort_{h,t}$ (m$)	59,553	431.36	1343.38	0.00	3.42	1,004.88
$\Delta logCDSShort_{h,t}$ (%)	31,075	-1.18	40.36	-30.66	0.00	25.92
$NAV_{h,t}$ (m$) (q)	20,046	1,942.57	2,650.81	205.26	1,039.50	4,566.72
$GAV_{h,t}$ (m$) (q)	20,046	3,939.05	7,701.32	261.20	1,512.90	8,733.42
$Leverage_{h,t}$ (ratio) (q)	20,046	2.00	3.72	1.00	1.26	2.93
$VaR_{h,t}$ (%)	23,793	3.63	3.69	0.83	2.80	6.74
$VaRConstraint_{h,t}$ (%)	18,945	3.66	3.69	0.98	2.83	6.45
$LiqMismatch_{h,t}$ (days) (q)	19,569	-90.17	93.24	-230.03	-71.03	3.45
$NetRetM_{h,t}$ (%)	54,337	0.46	2.69	-1.99	0.45	2.77

Table 2: Bond liquidity, mutual fund sales, and hedge fund relations

This table shows the estimates of the regression given in equation (4). The sample starts on January 2 and ends on March 20, 2020. The dependent variable is the average transaction cost (relative cost of customer trades to inter-dealer trades) at the dealer-bond-day level with and without riskless principal trades (RPT). Crisis equals one between March 5 and March 20 and zero otherwise. 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. HF Expo is the logarithm of the long exposures in corporate bonds for an issuer type (financial and non-financial) and rating (IG and HY) of a dealers' affiliated hedge funds as of the previous month. MF Shock is a CUSIP-level measure for bond sales by mutual funds during the crisis. Log(TTM) is the logarithm of the time to maturity of each bond. Lower order terms (e.g., HF Expo by itself) are included in the regression but not shown or absorbed by the fixed effects. 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)	(5)	(6)	(7)	(8)
Dependent variable:	Transaction cost				Transaction cost (No RPT)			
HF Expo×Crisis	-0.556	0.045	-1.486	-0.329	0.893	4.874**	-0.040	4.632**
	(2.276)	(2.357)	(2.036)	(2.345)	(2.498)	(1.899)	(2.304)	(1.898)
MF Shock×Crisis	1.779**		1.656**		1.221**		1.344**	
	(0.662)		(0.611)		(0.568)		(0.562)	
HF Expo×MF Shock ×Crisis_{-4}			-0.019	-0.007			-0.008	0.019
			(0.011)	(0.017)			(0.014)	(0.022)
HF Expo×MF Shock ×Crisis_{-3}			-0.002	-0.007			-0.010	-0.023
			(0.009)	(0.018)			(0.013)	(0.023)
HF Expo×MF Shock ×Crisis_{-2}			0.014	0.014			0.004	-0.002
			(0.012)	(0.018)			(0.012)	(0.018)
HF Expo×MF Shock ×Crisis	-0.073**	-0.065***	-0.069**	-0.061**	-0.059*	-0.081**	-0.064**	-0.089**
	(0.032)	(0.022)	(0.029)	(0.026)	(0.028)	(0.033)	(0.028)	(0.037)
Log(TTM)	33.369***		31.986***		59.140***		60.724***	
	(7.526)		(7.763)		(7.585)		(7.878)	
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 3: Controlling for alternative channels

This table shows the estimates of the regression given in equation (4) when controlling for dealers' funding and balance sheet constraints. The sample starts on January 2 and ends on March 20, 2020. The dependent variable 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 and zero otherwise. HF Expo is the logarithm of the long exposures in corporate bonds for an issuer type (financial and non-financial) and rating (IG and HY) of a dealers' affiliated hedge funds as of the previous month. MF Shock is a CUSIP-level measure for bond sales by mutual funds during the crisis. Log(TTM) 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. Repo Rate$_{pre}$ is the average pre-crisis dealer-level corporate repo rate, which is set to zero outside of the crisis. It controls for predetermined differences in repo funding costs. Leverage Intensity$_{pre}$ is equal to 100 times the minimum leverage ratio threshold minus the fourth quarter 2019 leverage ratio divided by the minimum leverage ratio threshold. Leverage Intensity$_{pre}$ is also set to zero outside of the crisis. Lower order terms (e.g., HF Expo by itself) are included in the regression but not shown or absorbed by the fixed effects. 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)	(5)	(6)	(7)	(8)
Dependent variable: Transaction cost								
HF Expo×Crisis	-1.170	-0.625	2.122	3.867	-2.216	-0.445	0.806	3.806
	(2.475)	(2.324)	(3.478)	(3.659)	(1.965)	(2.118)	(3.602)	(3.674)
MF Shock×Crisis	2.031**		2.291***		1.815**		2.014***	
	(0.761)		(0.589)		(0.651)		(0.570)	
HF Expo×MF Shock	-0.084**	-0.066**	-0.097***	-0.062**	-0.073**	-0.065**	-0.083***	-0.062**
×Crisis	(0.037)	(0.027)	(0.029)	(0.026)	(0.031)	(0.025)	(0.028)	(0.023)
Log(TTM)	29.454***		29.194***		29.240***		29.187***	
	(6.489)		(7.064)		(6.573)		(6.920)	
Repo Shock	-0.005	0.002	-0.005	0.003				
	(0.013)	(0.011)	(0.014)	(0.011)				
Repo Rate$_{pre}$					1.435	-3.335	8.444	2.820
					(19.548)	(10.783)	(14.640)	(7.608)
Leverage Intensity$_{pre}$			-0.447	-0.544			-0.443	-0.538
			(0.639)	(0.445)			(0.554)	(0.405)
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 4: Bond liquidity and hedge fund relations within bond- and dealer-day

This table shows the estimates of the regression given in equation (4) when including bond-day and dealer-day fixed effects. The sample starts on January 2 and ends on March 20, 2020. The dependent variable 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 and zero otherwise. HF Expo is the logarithm of the long exposures in corporate bonds for an issuer type (financial and non-financial) and rating (IG and HY) of a dealers' affiliated hedge funds as of the previous month. MF Shock is a CUSIP-level measure for bond sales by mutual funds during the crisis. Lower order terms (e.g., HF Expo by itself) are included in the regression but not shown or absorbed by the fixed effects. 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: Transaction cost				
HF Expo×Crisis	-0.097	1.264		
	(2.351)	(2.506)		
HF Expo×MF Shock	-0.063**	-0.055*	-0.086***	-0.081***
×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 5: Placebo test with hedge funds' equity and Treasury positions

This table shows the estimates of the regression given in equation (4) when computing HF Expo with hedge funds' equity and Treasury long exposures, respectively, instead of hedge funds' long corporate bond exposures. The sample starts on January 2 and ends on March 20, 2020. The dependent variable 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 and zero otherwise. HF Eqty (Tsy) is the logarithm of the long exposures in equities (Treasuries) of a dealers' affiliated hedge funds as of the previous month. MF Shock is a CUSIP-level measure for bond sales by mutual funds during the crisis. Log(TTM) 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. Repo Rate$_{pre}$ is the average pre-crisis dealer-level corporate repo rate, which is set to zero outside of the crisis. It controls for predetermined differences in repo funding costs. Leverage Intensity$_{pre}$ is equal to 100 times the minimum leverage ratio threshold minus the fourth quarter 2019 leverage ratio divided by the minimum leverage ratio threshold. Leverage Intensity$_{pre}$ is also set to zero outside of the crisis. Lower order terms (e.g., HF Eqty by itself) are included in the regression but not shown or absorbed by the fixed effects. 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)	(5)	(6)
Dependent variable: Transaction cost						
HF Eqty×Crisis	2.261	3.868	2.368			
	(3.207)	(3.238)	(3.758)			
HF Tsy×Crisis				-1.577	6.256	5.457
				(5.932)	(8.065)	(7.962)
MF Shock×Crisis	0.783	0.796	0.394	1.223	1.882*	1.510
	(0.624)	(1.159)	(0.715)	(0.925)	(1.039)	(0.975)
HF Eqty×MF Shock	-0.022	-0.021	-0.005			
×Crisis	(0.025)	(0.047)	(0.029)			
HF Tsy×MF Shock				-0.041	-0.066	-0.051
×Crisis				(0.038)	(0.043)	(0.040)
Log(TTM)	33.968***	30.619***	30.511***	33.646***	29.481***	29.800***
	(8.009)	(7.505)	(7.251)	(7.297)	(7.183)	(7.139)
Repo Shock		-0.012			-0.031*	
		(0.018)			(0.016)	
Repo Rate$_{pre}$			9.487			8.223
			(15.821)			(16.804)
Leverage Intensity$_{pre}$		-0.697	-0.736		-0.747	-0.778
		(0.536)	(0.459)		(0.602)	(0.532)
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 6: Capital commitments and hedge fund relations

This table shows the estimates of the regression given in equation (5). The sample starts on January 2 and ends on March 20, 2020. The dependent variable is dealer i's overnight capital commitment on day t, which is computed as the absolute value of the difference between dealer's buy volume and sell volume based on bond market values. Inventories are marked to market in columns (1), (2), (5), and (6), and expressed at par value in columns (3), (4), (7), and (8). Crisis equals one between March 5 and March 20 and zero otherwise. HF Expo is the logarithm of the long exposures in corporate bonds of a dealers' affiliated hedge funds as of the previous month. Repo Shock is the monthly change in dealer-level corporate repo outstanding coming from prime money market funds. Repo Rate$_{pre}$ is the average pre-crisis dealer-level corporate repo rate, which is set to zero outside of the crisis. It controls for predetermined differences in repo funding costs. Leverage Intensity$_{pre}$ is equal to 100 times the minimum leverage ratio threshold minus the fourth quarter 2019 leverage ratio divided by the minimum leverage ratio threshold. Leverage Intensity$_{pre}$ is also set to zero outside of the crisis. Lower order terms (e.g., HF Expo by itself) are included in the regression but not shown or absorbed by the fixed effects. 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)	(5)	(6)	(7)	(8)
Dependent variable:	AbsInventory_Mkt		AbsInventory		AbsInventory_Mkt		AbsInventory	
HF Expo	46.883***	-101.946**	43.625***	-88.852**	47.324***	-97.377**	44.067***	-84.900**
	(11.253)	(42.426)	(10.320)	(38.311)	(11.740)	(39.508)	(10.817)	(36.122)
HF Expo × Crisis	-42.578*	-24.430***	-39.747*	-21.025***	-40.566*	-24.831***	-37.806*	-20.932**
	(20.759)	(7.807)	(20.629)	(6.657)	(20.142)	(7.972)	(20.343)	(7.283)
Leverage Intensity_pre	2.599*	1.491***	2.657*	1.543***	2.532*	1.488***	2.570*	1.471***
	(1.314)	(0.384)	(1.300)	(0.412)	(1.383)	(0.403)	(1.399)	(0.433)
Repo Shock	-0.415*	-0.127	-0.416**	-0.147				
	(0.198)	(0.111)	(0.193)	(0.112)				
Repo Rate_pre					-50.102	-17.772	-46.271	-9.948
					(50.999)	(24.036)	(51.304)	(27.587)
N	833	833	833	833	833	833	833	833
R^2	0.31	0.56	0.31	0.57	0.30	0.56	0.30	0.56
Dealer FE	No	Yes	No	Yes	No	Yes	No	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Split by insurance companies' corporate bond net buys

This table shows the estimates of the regression given in equation (4) when splitting the sample into bonds bought and sold by insurance companies during the crisis. In columns (1) and (2) the samples include the bottom and top terciles of bonds ranked by insurance companies net buys during the crisis period. In columns (3) and (4) the samples include the bottom and top quintiles of bonds ranked by insurance companies net buys during the crisis period. Finally, in columns (5) and (6) the samples include the bottom and top deciles of bonds ranked by insurance companies net buys during the crisis period. The sample starts on January 2 and ends on March 20, 2020. The dependent variable 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 and zero otherwise. HF Expo is the logarithm of the long exposures in corporate bonds for an issuer type (financial and non-financial) and rating (IG and HY) of a dealers' affiliated hedge funds as of the previous month. MF Shock is a CUSIP-level measure for bond sales by mutual funds during the crisis. Log(TTM) is the logarithm of the time to maturity of each bond. Lower order terms (e.g., HF Expo by itself) are included in the regression but not shown or absorbed by the fixed effects. 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)	(5)	(6)
Dependent variable: Transaction cost						
Insurance net buy split:	Bottom tercile	Top tercile	Bottom quintile	Top quintile	Bottom decile	Top decile
HF Expo × Crisis	-0.450	-2.747	0.863	-2.580	4.560	-1.778
	(2.986)	(2.554)	(3.212)	(2.400)	(3.462)	(3.059)
MF Shock × Crisis	1.739**	0.290	2.165**	0.345	3.336**	0.716
	(0.657)	(0.677)	(0.967)	(0.706)	(1.490)	(0.751)
HF Expo × MF Shock × Crisis	-0.081**	-0.011	-0.102**	-0.015	-0.163**	-0.032
	(0.033)	(0.033)	(0.048)	(0.034)	(0.072)	(0.036)
Log(TTM)	26.640***	126.284***	22.045***	153.394***	16.412***	133.199***
	(5.672)	(30.854)	(4.685)	(26.858)	(3.767)	(26.102)
N	62,331	64,021	46,293	46,164	23,322	23,538
R^2	0.32	0.31	0.32	0.31	0.32	0.32
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 8: Hedge Funds' long bond and short CDS positions

This table shows the estimates of the regression given in equation (6). The data are monthly from January 2013 to March 2020. The dependent variable is the log change in a hedge funds IG or HY long exposure (in %). The independent variable Crisis takes the value one for March 2020 and zero otherwise. Other independent variables are the log change in a hedge fund's short CDS exposure, liquidity mismatch, size, performance, leverage, and VaR constraint. The independent variables, with the exception of the indicator variable Crisis, are standardized. Standard errors in parentheses are two-way clustered at the fund and month level; ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	ΔlogCorpBondIGLong$_{h,t}$			ΔlogCorpBondHYLong$_{h,t}$		
ΔlogCDSShort$_{h,t}$	0.049***	0.058***	0.046***	0.047***	0.044***	0.049***
	(0.012)	(0.014)	(0.016)	(0.007)	(0.008)	(0.012)
ΔlogCDSShort$_{h,t}$ $\times$ Crisis	0.261***	0.197***	0.136***	-0.038***	-0.046***	-0.111***
	(0.027)	(0.032)	(0.051)	(0.012)	(0.013)	(0.019)
LiqMismatch$_{h,t-1}$		-3.331**	-5.229**		-0.732	-1.579
		(1.522)	(2.028)		(0.698)	(1.127)
LiqMismatch$_{h,t-1}$ $\times$ Crisis		-12.091***	-17.528***		0.527	3.336***
		(2.253)	(3.467)		(0.609)	(0.925)
LogNAV$_{h,t-1}$		1.151	4.892**		0.205	0.461
		(1.611)	(2.428)		(1.104)	(1.327)
LogNAV$_{h,t-1}$ $\times$ Crisis		14.046***	12.976***		2.713***	6.055***
		(1.511)	(1.523)		(0.904)	(1.242)
NetRet12M$_{h,t-1}$		0.332	1.062		0.856	2.425
		(2.714)	(3.650)		(1.355)	(2.055)
NetRet12M$_{h,t-1}$ $\times$ Crisis		62.286***	43.992***		13.081***	16.460***
		(11.328)	(15.160)		(1.908)	(2.301)
Leverage$_{h,t-1}$		-0.038	1.050		-0.772	0.171
		(0.981)	(1.081)		(0.521)	(0.636)
Leverage$_{h,t-1}$ $\times$ Crisis		-8.660***	-11.242***		-3.557***	-4.973***
		(0.709)	(1.195)		(0.608)	(0.628)
VaRConstraint$_{h,t-1}$			0.497			0.914
			(1.671)			(0.757)
VaRConstraint$_{h,t-1}$ $\times$ Crisis			12.472***			8.563***
			(2.060)			(1.141)
N	16,637	13,643	6,779	29,714	24,810	10,790
R^2	0.056	0.067	0.069	0.056	0.056	0.070
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Hedge fund characteristics and corporate bond trading

This table shows the estimates of the regression given in equation (6) without restricting the sample to hedge funds that trade short CDS. The data are monthly from January 2013 to March 2020. The dependent variable is the log change in a hedge funds IG (Panel A) or HY (Panel B) long exposure (in %). The independent variable Crisis takes the value one for March 2020 and zero otherwise. Other independent variables are the log change in a hedge fund's liquidity mismatch, size, performance, leverage, and VaR constraint. The independent variables, with the exception of the indicator variable Crisis, are standardized. Standard errors in parentheses are two-way clustered at the fund and month level; ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Investment-grade

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: ΔlogCorpBondIGLong$_{h,t}$						
VaRConstraint$_{h,t-1}$	0.149					0.170
	(1.003)					(1.018)
VaRConstraint$_{h,t-1}$ × Crisis	-0.597					2.193**
	(1.007)					(1.034)
LiqMismatch$_{h,t-1}$		-2.883*				-2.968*
		(1.499)				(1.620)
LiqMismatch$_{h,t-1}$ × Crisis		-11.408***				-8.862***
		(2.368)				(2.194)
LogNAV$_{h,t-1}$			3.690*			3.662*
			(2.179)			(2.119)
LogNAV$_{h,t-1}$ × Crisis			10.841***			12.038***
			(1.017)			(0.939)
NetRet12M$_{h,t-1}$				1.227		1.284
				(2.578)		(2.570)
NetRet12M$_{h,t-1}$ × Crisis				40.576***		44.579***
				(9.683)		(9.249)
Leverage$_{h,t-1}$					-0.360	0.338
					(0.851)	(0.872)
Leverage$_{h,t-1}$ × Crisis					-6.661***	-9.922***
					(1.260)	(1.199)
Observations	9,873	9,873	9,873	9,873	9,873	9,873
R^2	0.059	0.060	0.061	0.061	0.060	0.065
Fund	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: High-yield

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: ΔlogCorpBondHYLong$_{h,t}$						
VaRConstraint$_{h,t-1}$	0.775					0.759
	(0.509)					(0.485)
VaRConstraint$_{h,t-1}$ × Crisis	6.990***					7.592***
	(0.632)					(0.638)
LiqMismatch$_{h,t-1}$		-0.255				-0.268
		(0.783)				(0.796)
LiqMismatch$_{h,t-1}$ × Crisis		1.786**				2.363***
		(0.765)				(0.726)
LogNAV$_{h,t-1}$			1.097			1.192
			(1.235)			(1.168)
LogNAV$_{h,t-1}$ × Crisis			5.248***			7.316***
			(0.748)			(0.749)
NetRet12M$_{h,t-1}$				2.317		2.385
				(1.677)		(1.683)
NetRet12M$_{h,t-1}$ × Crisis				9.897***		9.580***
				(1.236)		(1.497)
Leverage$_{h,t-1}$					-0.204	-0.133
					(0.560)	(0.557)
Leverage$_{h,t-1}$ × Crisis					-1.347**	-3.925***
					(0.567)	(0.570)
Observations	15,923	15,923	15,923	15,923	15,923	15,923
R^2	0.061	0.060	0.060	0.061	0.060	0.063
Fund	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes

Appendix

This appendix 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 at the rating (IG and HY) and issuer (financial and non-financial issuer) level. *Source:* Form PF.
MF Shock	Outflow-weighted holdings at the CUSIP level from corporate bond mutual funds during the crisis. *Source:* eMAXX and Morningstar.
Log(TTM)	Logarithm of the time to maturity of a 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. This dealer-level variable takes the value zero outside of the crisis. *Source:* FRBNY.
Leverage Intensity$_{pre}$	The minimum leverage ratio minus the 2019:Q4 leverage ratio times 100, divided by the minimum. This dealer-level variable takes the value zero outside of the crisis. 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**
CorpBondGross	The gross corporate bond exposure of a hedge fund. *Source:* Form PF.
CorpBondLong	The long corporate bond exposure of a hedge fund. *Source:* Form PF.
CorpBondShort	The short corporate bond exposure of a hedge fund. *Source:* Form PF.
CDSShort	The short CDS exposure of a hedge fund. *Source:* Form PF.
Leverage	The balance sheet leverage of the hedge fund, computed as the ratio of its gross asset value to its net asset value (NAV). *Source:* Form PF.
VaR	Value-at-Risk, required to be reported if the fund "regularly calculates" VaR. Reported values are converted, if necessary, to a monthly time horizon at a 5% confidence level using methods in Kruttli et al. (2024). *Source:* Form PF.
VaRConstraint	The 12-month rolling average VaR with a time horizon of one month and a probability of 5%. *Source:* Form PF.
Log(NAV)	The logarithm of net asset value, or the amount of investor equity, of the hedge fund. *Source:* Form PF.
LiqMismatch	The average liquidity of the hedge fund's assets relative to its liabilities, computed as in Aragon et al. (2021) by subtracting $(1/Leverage) \times ShareRes + (1 - 1/Leverage) \times FinDur$ from $PortIlliq$ (adjusted for cash holdings). *Source:* Form PF.
NetRet12M	Rolling 12-month average net-of-fee returns of the hedge fund. *Source:* Form PF.

B Additional Figures and Tables

Figure B.1: Hedge funds' net purchases/sales of U.S. Treasury and equity securities. This figure plots estimated net purchases/sales of U.S. Treasury securities and equity securities by corporate bond-trading hedge funds.

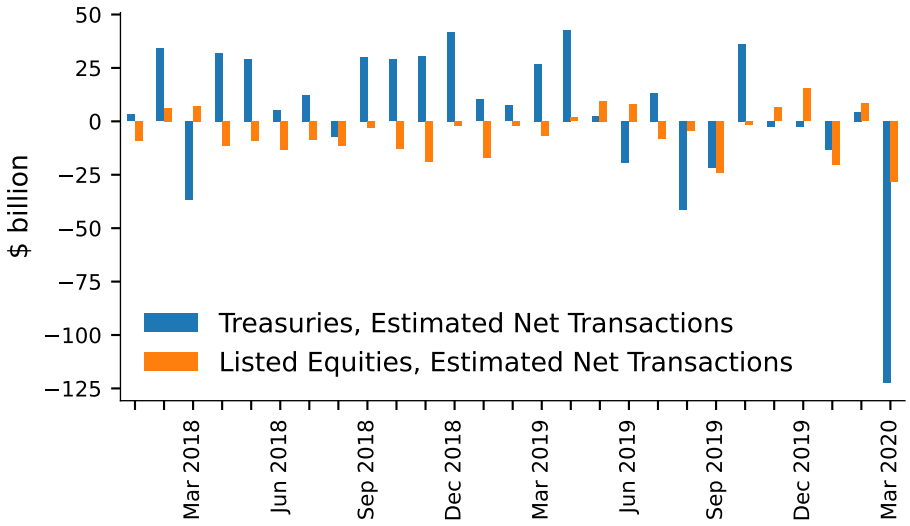


Table B.1: Bond liquidity for investment-grade and high-yield sub-samples

This table shows the estimates of the regression given in equation (4) for sub-samples of IG and HY bonds. The sample starts on January 2 and ends on March 20, 2020. The dependent variable is the average transaction cost (relative cost of customer trades to inter-dealer trades) at the dealer-bond-day level with and without riskless principal trades (RPT). Crisis equals one between March 5 and March 20 and zero otherwise. HF Expo is the logarithm of the long exposures in corporate bonds for an issuer type (financial and non-financial) and rating (IG and HY) of a dealers' affiliated hedge funds as of the previous month. MF Shock is a CUSIP-level measure for bond sales by mutual funds during the crisis. Log(TTM) is the logarithm of the time to maturity of each bond. Lower order terms (e.g., HF Expo by itself) are included in the regression but not shown or absorbed by the fixed effects. 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)
	Investment-grade		High-yield	
Dependent variable: Transaction cost				
HF Expo×Crisis	0.662	-0.506	10.298**	10.277*
	(2.451)	(2.749)	(3.948)	(5.226)
MF Shock×Crisis	2.120**		2.923***	
	(0.779)		(0.947)	
HF Expo×MF Shock ×Crisis	-0.090**	-0.076***	-0.119**	-0.147*
	(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

Table B.2: Hedge funds' long bond and short CDS positions in March 2020

This table shows the estimates of the cross-sectional regression given in equation (7). The data are from March 2020. The dependent variable is the log change in a hedge funds IG or HY long exposure (in %). The independent variables are the log change in a hedge fund's short CDS exposure, liquidity mismatch, size, performance, and leverage. The independent variables are standardized. Heteroskedasticity-robust standard errors are used; ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables:	ΔlogCorpBondLong$_{h,t}$		ΔlogCorpBondIGLong$_{h,t}$		ΔlogCorpBondHYLong$_{h,t}$	
Constant	-7.144***	3.735	15.591**	45.202***	-17.339***	-10.039***
	(2.441)	(4.962)	(6.670)	(12.098)	(2.102)	(3.850)
ΔlogCDSShort$_{h,t}$	0.096***	0.087**	0.292***	0.234***	0.010	-0.003
	(0.033)	(0.037)	(0.073)	(0.073)	(0.028)	(0.029)
LiqMismatch$_{h,t-1}$		1.749		-13.787*		-0.192
		(2.828)		(8.274)		(2.518)
LogNAV$_{h,t-1}$		4.372*		12.724**		2.633
		(2.430)		(4.997)		(2.815)
NetRet12M$_{h,t-1}$		21.542***		58.945***		12.914**
		(7.266)		(19.391)		(5.701)
Leverage$_{h,t-1}$		-3.984**		-8.103***		-4.003**
		(1.611)		(2.863)		(1.747)
N	297	297	168	168	286	286
R^2	0.031	0.094	0.065	0.182	0.0005	0.051

Table B.3: Hedge fund characteristics and corporate bond trading (no VaR)

This table shows the estimates of the regression given in equation (6) without restricting the sample to hedge funds that trade short CDS or report their VaR. The data are monthly from January 2013 to March 2020. The dependent variable is the log change in a hedge funds IG (Panel A) or HY (Panel B) long exposure (in %). The independent variable Crisis takes the value one for March 2020 and zero otherwise. Other independent variables are the log change in a hedge fund's liquidity mismatch, size, performance, and leverage. The independent variables, with the exception of the indicator variable Crisis, are standardized. Standard errors in parentheses are two-way clustered at the fund and month level; ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Investment-grade

	(1)	(2)	(3)	(4)	(5)
Dependent variable: $\Delta logCorpBondIGLong_{h,t}$					
$\text{LiqMismatch}_{h,t-1}$	-2.504**				-2.452**
	(1.089)				(1.096)
$\text{LiqMismatch}_{h,t-1} \times \text{Crisis}$	-13.368***				-9.938***
	(1.644)				(1.712)
$\text{LogNAV}_{h,t-1}$		0.658			0.447
		(1.341)			(1.289)
$\text{LogNAV}_{h,t-1} \times \text{Crisis}$		12.794***			12.180***
		(0.952)			(0.950)
$\text{NetRet12M}_{h,t-1}$			-0.395		-0.390
			(0.747)		(0.758)
$\text{NetRet12M}_{h,t-1} \times \text{Crisis}$			4.124***		2.780***
			(0.105)		(0.540)
$\text{Leverage}_{h,t-1}$				-0.842	-0.347
				(0.913)	(0.856)
$\text{Leverage}_{h,t-1} \times \text{Crisis}$				-3.561***	-3.914***
				(0.794)	(0.765)
N	20,928	20,928	20,928	20,928	20,928
R^2	0.053	0.053	0.052	0.052	0.054
Fund	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes

Panel B: High-yield

	(1)	(2)	(3)	(4)	(5)
Dependent variable: ΔlogCorpBondHYLong$_{h,t}$					
LiqMismatch$_{h,t-1}$	-0.747				-0.624
	(0.455)				(0.465)
LiqMismatch$_{h,t-1}$ $\times$ Crisis	-0.999				-0.748
	(0.621)				(0.770)
LogNAV$_{h,t-1}$		-0.359			-0.430
		(0.819)			(0.804)
LogNAV$_{h,t-1}$ $\times$ Crisis		1.953**			1.873**
		(0.799)			(0.870)
NetRet12M$_{h,t-1}$			0.099		0.114
			(0.762)		(0.764)
NetRet12M$_{h,t-1}$ $\times$ Crisis			-1.134		-1.084
			(0.807)		(0.826)
Leverage$_{h,t-1}$				-0.960*	-0.877
				(0.525)	(0.529)
Leverage$_{h,t-1}$ $\times$ Crisis				-0.814	-0.752
				(0.734)	(0.778)
N	40,285	40,285	40,285	40,285	40,285
R^2	0.057	0.057	0.057	0.057	0.057
Fund	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes

Table B.4: Bond liquidity and hedge fund relations based on gross bond exposure

This table shows the estimates of the regression given in equation (4). The sample starts on January 2 and ends on March 20, 2020. The dependent variable is the average transaction cost (relative cost of customer trades to inter-dealer trades) at the dealer-bond-day level with and without riskless principal trades (RPT). Crisis equals one between March 5 and March 20 and zero otherwise. 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. HF Expo is the logarithm of the gross exposures in corporate bonds for an issuer type (financial and non-financial) and rating (IG and HY) of a dealers' affiliated hedge funds as of the previous month. MF Shock is a CUSIP-level measure for bond sales by mutual funds during the crisis. Log(TTM) is the logarithm of the time to maturity of each bond. Lower order terms (e.g., HF Expo by itself) are included in the regression but not shown or absorbed by the fixed effects. 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)	(5)	(6)	(7)	(8)
Dependent variable: Transaction cost								
HF Expo Gross × Crisis	0.444	0.743	-0.645	0.166	1.266	4.974**	0.363	4.763**
	(2.199)	(2.275)	(1.950)	(2.272)	(2.211)	(1.911)	(2.029)	(1.950)
MF Shock × Crisis	1.885**		1.745***		1.191**		1.352**	
	(0.646)		(0.595)		(0.507)		(0.530)	
HF Expo Gross×MF Shock ×Crisis_{-4}			-0.020	-0.007			-0.009	0.022
			(0.013)	(0.017)			(0.014)	(0.021)
HF Expo Gross×MF Shock ×Crisis_{-3}			-0.003	-0.010			-0.013	-0.026
			(0.009)	(0.018)			(0.014)	(0.024)
HF Expo Gross×MF Shock ×Crisis_{-2}			0.016	0.016			0.004	-0.007
			(0.013)	(0.018)			(0.012)	(0.019)
HF Expo Gross×MF Shock ×Crisis	-0.077**	-0.066***	-0.072**	-0.062**	-0.057**	-0.073*	-0.064**	-0.086**
	(0.031)	(0.022)	(0.028)	(0.027)	(0.025)	(0.035)	(0.025)	(0.039)
Log(TTM)	33.503***		32.015***		59.336***		60.792***	
	(7.454)		(7.673)		(7.590)		(7.865)	
N	229,856	161,633	229,856	161,633	151,629	93,197	151,629	93,197
R^2	0.33	0.58	0.33	0.58	0.43	0.67	0.43	0.67
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 B.5: Bond liquidity and hedge fund relations based on gross bond exposure within bond- and dealer-day

This table shows the estimates of the regression given in equation (4) when including bond-day and dealer-day fixed effects. The sample starts on January 2 and ends on March 20, 2020. The dependent variable 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 and zero otherwise. HF Expo is the logarithm of the gross exposures in corporate bonds for an issuer type (financial and non-financial) and rating (IG and HY) of a dealers' affiliated hedge funds as of the previous month. MF Shock is a CUSIP-level measure for bond sales by mutual funds during the crisis. Lower order terms (e.g., HF Expo by itself) are included in the regression but not shown or absorbed by the fixed effects. 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: Transaction cost				
HF Expo Gross × Crisis	-0.546	0.945		
	(2.503)	(2.723)		
HF Expo Gross × MF Shock × Crisis	-0.060**	-0.056*	-0.083***	-0.081***
	(0.023)	(0.028)	(0.022)	(0.025)
N	161,606	146,066	161,314	145,666
R^2	0.60	0.69	0.61	0.70
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 B.6: Basis trading in corporate bonds and Treasuries

The maximal size of the CDS-bond basis trade is computed as twice the minimum of the long corporate bond exposure and short CDS positions. The estimated size of the Treasury basis trade is computed as twice the minimum of the estimated long Treasury securities holdings and the estimated notional value of short Treasury futures positions of hedge funds classified as likely basis traders (see Banegas, Monin and Petrasek, 2021). Each estimation method is performed at the fund level and then aggregated. We also provide the ratio of each trade's estimated volume to the gross assets of the funds with nonzero estimated basis trade activity.

	Feb 2018	Feb 2019	Feb 2020
CDS-bond basis trade			
Estimated (maximal) gross size($bn)	$174	$178	$190
Ratio to gross asset value (%)	6.8	6.4	6.6
Treasury basis trade			
Estimated gross size ($bn)	$272	$909	$1,114
Ratio to gross asset value (%)	23.8	69.5	71.4

Table B.7: Hedge funds' exposures to corporate bonds and Treasuries

The ratios of IG and HY exposures to gross asset value (GAV) are computed based on the set of hedge funds that have positive corporate bond exposures. The ratios of Treasury exposures to gross asset value are based on the set of hedge funds that have positive Treasury exposures (see Kruttli et al., 2024).

	Feb 2018	Feb 2019	Feb 2020
Ratio of IG corporate bond exposures to GAV (%)	2.4	2.7	2.8
Ratio of HY corporate bond exposures to GAV (%)	5.5	5.3	4.8
Ratio of U.S. Treasury exposures to GAV (%)	37.8	48.9	56.0

Table B.8: Hedge funds' post-March 2020 performance

This table presents results of a cross-sectional regression model. The dependent variable is the hedge fund return from April to June 2020 (columns (1) and (2)) or April to September 2020 (columns (3) and (4)), respectively. The independent variables are as of March 2020. The independent variables are standardized. Heteroskedasticity-robust standard errors are in parentheses. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Dependent variables:	NetRetQ		NetRet2Q	
Constant	8.871***	8.949***	13.477***	13.632***
	(0.301)	(0.302)	(0.461)	(0.470)
ΔlogCorpBondLong$_h$	0.672*	0.640*	1.379**	1.313**
	(0.360)	(0.367)	(0.588)	(0.603)
LiqMismatch$_h$		0.014		-0.587
		(0.325)		(0.490)
LogNAV$_h$		-1.132***		-1.628***
		(0.326)		(0.511)
NetRet12M$_h$		0.919**		0.939
		(0.438)		(0.594)
Leverage$_h$		-0.045		0.323
		(0.249)		(0.385)
N	592	592	537	537
R^2	0.008	0.043	0.015	0.046