LTCM Redux? Hedge Fund Treasury Trading and Funding Fragility*

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March 2023

Abstract

We analyze how external and internal constraints impact arbitrageurs during market turmoil by exploiting the 2020 Treasury market shock. Using hedge fund regulatory filings, we find funds reduced arbitrage activities and increased cash holdings, despite low investor redemptions and stable funding. Creditors' regulatory and liquidity constraints were not passed to funds through uncleared bilateral repo, the predominant financing source for fixed income hedge funds. Fund-creditor borrowing data reveal more regulated dealers provided, and more important clients received, disproportionately higher funding. Value-at-risk reported by funds suggests internal risk limits were binding. Our results show arbitrageur risk constraints can amplify market instability even when external financing remains resilient.

JEL classification: G11, G23, G24, G01.

Keywords: Hedge funds, Treasury markets, arbitrage, VaR, risk constraints, liquidity, creditor constraints, relative value.

*We thank Viral Acharya, Vikas Agarwal, Yu An, George Aragon, Georgia Bush, Darrell Duffie, Andrew Ellul, Francesco Franzoni, Sebastian Infante, Victoria Ivashina, Juha Joenväärä, Petri Jylhä, Andrew Karolyi, Dan Li, Tao Li, Lars Lochstoer, Francis Longstaff, Marco Macchiavelli, Patrick McCabe, Justin Murfin, Giang Nguyen, Andrew Patton, Simon Potter, Tarun Ramadorai, Valeri Sokolovski, Noah Stoffman, Gregory Udell, Annette Vissing-Jorgensen, Min Wei, Joshua Younger, and seminar participants at Indiana University, Cornell University, London Business School, University of Massachusetts-Amherst, National University of Singapore, University of Houston, University of Oklahoma, Baylor University, Federal Reserve Board, Federal Reserve Bank of Chicago, Federal Reserve Bank of Dallas, Financial Stability Oversight Council, Securities Exchange Commission, Fixed Income and Financial Institutions Conference, Paris Hedge Fund and Private Equity Research Conference, Bank of England International Conference on Sovereign Bond Markets, FIN-FIRE-Workshop on Challenges to Financial Stability, RiskLab/BoF/ESRB Conference on Systemic Risk Analytics, CICF, MFA, NFA, Short-Term Funding Markets Conference, UNC Institute for Private Capital Spring Symposium, Inquire Europe Autumn Seminar, Texas Finance Festival, and NBER Summer Institute for helpful comments. The views stated herein are those of the authors and are not necessarily the views of the Federal Reserve Board or the Federal Reserve System.

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1 Introduction

The exposure of hedge fund arbitrage to liquidity and external financing shocks has received much attention since the fall of Long-Term Capital Management (LTCM) in 1998.[1] Creditors may be unwilling or unable to provide stable financing during stress periods due to their own capital or liquidity constraints, subjecting hedge fund arbitrage to external financing constraints (Brunnermeier and Pedersen, 2009; Adrian and Shin, 2010). To reduce shortfalls and withstand stress episodes, hedge funds can impose internal limits to manage risk (Lo, 2001). However, theory suggests such internal constraints may themselves be destabilizing during a crisis by amplifying market illiquidity and volatility (Gârleanu and Pedersen, 2007; Shin, 2010). Given the role of arbitrageurs in supporting market efficiency and liquidity, it is important to empirically examine these theories. However, this has previously not been possible due to a lack of data on hedge fund arbitrage positions, financing, and internal risk metrics at the fund or fund-creditor level.

We fill this gap by collating a novel, granular regulatory dataset and exploiting the shock to the U.S. Treasury (UST) market in March 2020—a systematic episode that generated much debate in industry, policy, and academic circles about the role of hedge funds in UST market functioning (Duffie, 2020; Schrimpf, Shin, and Sushko, 2020).[2] Importantly, in addition to hedge fund financing and risk, we are the first to also obtain a view into the uncleared bilateral repo funding market and its credit relationships. We find that hedge fund repo borrowing in this market was $1.5 trillion prior to the March 2020 turmoil and that it is the main source of funding for fixed income arbitrageurs.[3] Uncleared bilateral repo is the

[1] LTCM suffered massive losses in their arbitrage trades following a series of systematic shocks and were unable to continue to finance the positions, leading to a Fed-arranged takeover of its portfolio by its brokers due to systemic stability concerns (Edward, 1999; Jorion, 2000a; Lowenstein, 2000; Duarte, Longstaff, and Yu, 2007; Shin, 2010).

[2] See also, for example, the report of the Inter-Agency Working Group on Treasury Market Surveillance released on November 8, 2021: https://home.treasury.gov/news/press-releases/jy0470; He, Nagel, and Song (2022); *Revisiting the Ides of March, Parts I-III* (https://www.cfr.org/blog/revisiting-ides-march-part-i-thousand-year-flood); and media coverage such as https://www.nytimes.com/2020/07/23/business/economy/hedge-fund-bailout-dodd-frank.html.

[3] Our novel dataset is primarily constructed using Form PF, which large hedge funds are required to file, following its adoption as part of the Dodd-Frank Act of 2010: https://www.sec.gov/about/forms/formpf.pdf.

largest segment of the repo funding markets. Despite its importance, this funding market has previously remained opaque. Using triparty or cleared repo data in place of uncleared bilateral repo can lead to misleading conclusions.[4]

Just prior to March 2020, hedge fund aggregate long and short UST exposures were around $1.4 trillion and $0.9 trillion, respectively. During the March 2020 UST turmoil, UST yields increased as investors around the world rushed to sell Treasuries amid a sudden economic shutdown, calling into question the safe haven status of US Treasuries.[5] UST arbitrage spreads that hedge funds generally bet will converge widened, presenting seemingly profitable opportunities for arbitrage trading.[6] At the time, market participants and agencies overseeing financial markets were unable to determine whether hedge funds continued to provide liquidity through UST arbitrage activity, or if they contributed to the market turmoil by liquidating their arbitrage positions. Analyzing granular data on hedge fund positions, we find that the average hedge fund with UST holdings significantly reduced its gross exposures and arbitrage activity in UST markets, decreasing arbitrage exposures by around 25%. By the end of the stress episode, these funds also held 20% higher cash holdings and smaller, more liquid portfolios. Overall, we do not find evidence that UST-trading hedge funds provided liquidity by exploiting the market dislocation.

At first pass, these observations might suggest that external financing constraints prevented hedge funds from taking advantage of arbitrage opportunities or even maintaining their existing UST arbitrage activity levels. However, despite the significant fall in UST exposures, we find that the amount borrowed via uncleared bilateral repurchase agreements—the primary source of financing for hedge fund UST holdings—did not significantly change in

[4]For example, Gorton, Metrick, and Ross (2020) find cleared and uncleared repo markets behaved differently from each other during the GFC. They state, on page 1, "Unlike tri-party, bilateral repo is the home of hedge funds, many types of offshore institutions, and other unregulated cash pools. The data gap between tri-party and bilateral repo markets is significant; a 2005 survey by the Bond Market Association finds bilateral repo three times as large as tri-party repo in 2004."

[5]UST markets experienced unprecedented stress, with volatility shooting up above levels seen even during the GFC. UST securities generally see safe haven inflows during crisis periods, but during the March 2020 turmoil sold off sharply (Schrimpf, Shin, and Sushko, 2020).

[6]See Figure A1 and the Online Appendix for an overview of hedge fund fixed income arbitrage strategies.

March 2020 for the average UST-trading hedge fund. In fact, daily aggregate repo lending to hedge funds by the largest dealers show increased lending throughout the month. Further, we find that repo borrowing terms like maturity and collateral haircuts also did not become more adverse.[7] These results are consistent with hedge funds maintaining their borrowing capacity on dealer balance sheets and hoarding liquidity.

We further analyze the external financing channel using granular data to test specific mechanisms proposed in the literature on why hedge fund repo borrowing might be curtailed during a crisis. These analyses address the question of whether hedge funds had unmet borrowing demand due to dealer constraints. There has been much debate about whether post-GFC regulations impose constraints on bank-affiliated broker-dealers and their capacity to support hedge fund arbitrage activity.[8] Given its dependence on funding provided by dealers, hedge fund arbitrage can potentially be limited by dealer balance sheet constraints, particularly in times of stress. Specifically, we test whether the credit supply to some hedge funds was cut due to dealer regulatory and liquidity constraints by studying the differences between funding provided by constrained and unconstrained dealers. We use data on borrowing amounts available at the hedge fund-creditor level and control for time-invariant and time-varying hedge fund characteristics using hedge fund-time fixed effects, as well as relationship-specific factors using hedge fund-creditor fixed effects.[9]

We use three different proxies from the literature to capture creditor constraints. The first two measure creditor regulatory constraints: a creditor's inclusion in the set of global systemically important banks (G-SIBs)—large banks that are subject to enhanced regulations—and its proximity to the Basel III leverage ratio threshold.[10] The third proxy captures creditor

[7]Senior Credit Officer Opinion Surveys (SCOOS) on Dealer Financing Terms also show no evidence of a step back in mid-March in the provision of funding collateralized by Treasuries to relative-value hedge funds.

[8]See, for example, Duffie (2020); Schrimpf, Shin, and Sushko (2020); He, Nagel, and Song (2022).

[9]Kruttli, Monin, and Watugala (2022) use Form PF data and a similar empirical strategy, adapted from Khwaja and Mian (2008), to examine the impact of idiosyncratic prime broker distress.

[10]The Basel III leverage ratio is a non-risk-weighted bank capital requirement. It requires banks to hold capital against exposures, including the total notional value of all Treasury cash and repo transactions, making it likely the most relevant regulatory constraint for Treasury intermediary activity (Duffie, 2018). The U.S. implementation of the Basel III leverage ratio is the Supplementary Leverage Ratio (SLR).

liquidity constraints by exploiting the large and heterogeneous credit line drawdowns by non-financial firms during the crisis. During March 2020, many banks experienced a sudden cash outflow due to revolving credit line drawdowns from non-financial corporations (Acharya, Engle, and Steffen, 2022). First, we find that G-SIBs provided 11-13% higher repo funding to their hedge fund counterparties during this period compared to other dealers. Second, we do not find evidence that a creditor bank's proximity to the minimum required Basel III leverage ratio threshold was a significant factor in the credit supplied to hedge funds during this episode. Third, we do not find evidence that the credit line drawdown channel impacted banks' credit provision to connected hedge funds during March 2020.

These results may seem surprising given discussions on how funding constraints during crisis periods impact market liquidity provision. Even with potentially limited balance sheet capacity, dealers did not significantly step back from repo funding provision to connected hedge funds. Analyzing hedge fund-creditor relationships sheds light on why these connections proved so resilient during the crisis. We find that dealers favor hedge fund clients with whom they have done more business and funds that are likely to bring in greater revenue via higher activity in fixed income markets, highlighting the discretionary aspect of these credit relationships. These results suggest that the value dealers derive from relationships with large hedge fund borrowers may make them reluctant to curtail the flow of credit to these clients during stress periods. Also, during the March 2020 shock, the larger, bank-affiliated broker-dealers—which, in the post-GFC period, are subject to more disclosure requirements, periodic stress tests, and enhanced regulations constraining their liquidity and risk-taking—were not exposed to significant concerns about solvency and run risk, unlike during previous crises like the GFC.[11] Our results show that the more regulated dealers provided more stable funding to hedge fund clients through the stress period.

Overall, our findings are inconsistent with hedge funds' external financing constraints being the driver of their step back from UST liquidity provision during the turmoil. Indeed,

[11]For example, Gorton and Metrick (2012) find that, during the GFC, concerns about bank insolvency and counterparty risk effectively led to a run on repo.

not only was debt financing resilient, we find equity financing also remained stable. Investor outflows remained relatively modest for UST-trading hedge funds in March 2020. Investor outflows during the quarter amounted to less than 2% of net asset value on average, consistent with the the long share restrictions employed by hedge funds stemming outflows.[12] Long share restrictions were likely stabilizing because hedge funds were not forced to engage in fire sales to meet immediate, large investor redemptions.

We next examine how hedge funds' internal risk limits affect their UST trading under stressed market conditions using the internal value-at-risk (VaR) assessments reported by hedge funds. Many hedge funds use VaR methods to measure and manage the risk of their portfolios, dynamically adjusting their portfolio exposures to avoid losses over pre-specified VaR limits (Jorion, 2000b; Lo, 2001). Theory shows that internal risk constraints can effectively induce risk-neutral arbitrageurs to behave as if they were risk-averse by curtailing their risk appetite or risk-bearing capacity (Shin, 2010; Adrian and Shin, 2014). In March 2020, UST-trading hedge funds experienced a loss of around 10%, which substantially exceeded their average VaR.[13] We find that funds with higher ex-ante risk limits—an indicator of greater risk appetite—provided more liquidity during the March 2020 turmoil. Funds that happened to be closer to (or exceeding) their risk limits before the turmoil began and had reduced risk-bearing capacity sold off more of their arbitrage positions in March 2020. This evidence illustrates empirically, for the first time, the importance of internal risk-bearing capacity for hedge funds' ability and willingness to provide liquidity during a crisis period. The economic magnitude of the effect is substantial. Among large arbitrageurs, a one standard deviation decrease in a fund's risk-bearing capacity translates to a 12% decrease in arbitrage positions. These results show that internal risk limits can have a significant impact on arbitrageur liquidity provision during market turmoil.

[12]The median share restrictions of the hedge funds in our sample are such that a fund would have at least 30 days' notice before the first 1% of net asset value of the fund could be redeemed.

[13]We find that hedge funds' 5% monthly VaR, that is, the potential loss (as a percent of NAV) over a one-month horizon with a probability of 5%, is on average of 4.7%, with the 90th percentile around 8%. In comparison, LTCM perceived their 5% monthly VaR equivalent to be around 7% (Jorion, 2000a).

Finally, we conduct a series of robustness and subsample analyses. In particular, we find that UST hedge funds, regardless of the size of their pre-March 2020 UST exposure, stepped back from UST arbitrage. This implies that hedge funds focused on other asset classes did not step in to provide liquidity in UST markets. Compared to other UST hedge funds during the March 2020 turmoil, the funds that predominantly engaged in the Treasury cash-futures basis trade likely faced greater margin pressure stemming from their short futures positions traded on exchange, which are subject to automated daily mark-to-market and require immediate liquidity infusions or position liquidations. We find basis traders' cash positions including posted margin were substantially higher, consistent with margin pressure from exchanges.

Overall, our findings show that even if external financing remains available during times of market stress, internal risk constraints of hedge funds can significantly limit their role as liquidity providers. These findings have important implications for the theoretical literature on limits to arbitrage (Gromb and Vayanos, 2010) and the debates on the role of hedge funds' trading constraints and market resilience. Our findings also highlight the importance of creditor-borrower relationships in repo markets when transactions are not centrally cleared and information about counterparties is valuable. While there is a literature on relationship value in bank-firm lending (see, for example, Petersen and Rajan (1994); Berger and Udell (1995)), many aspects of the relationships between hedge funds and broker-dealers are distinct (Kruttli, Monin, and Watugala, 2022). This paper provides key evidence that the strength of relationships between hedge funds and broker-dealers matters for the resilience of repo funding and the liquidity of corresponding OTC markets.[14]

Due to data limitations, there are few papers analyzing hedge fund borrowing.[15] Kruttli, Monin, and Watugala (2022) show that a prime broker who is liquidity constrained due to

[14]Other papers analyzing the impact of dealer constraints on the provision of repo cover a limited number of dealers and do not observe borrowers (see, for example, Favara, Infante, and Rezende (2022)). Importantly, our granular analysis using fund-creditor level borrowing data controls for borrowing demand effects.

[15]In contrast, several papers focus on constraints due to investor flows (see, for example, Shleifer and Vishny (1997); Aragon (2007); Mitchell, Pedersen, and Pulvino (2007); Agarwal, Daniel, and Naik (2009); Ben-David, Franzoni, and Moussawi (2012); Hombert and Thesmar (2014); Aragon, Spencer, and Shi (2019)).

an idiosyncratic shock can significantly cut credit to its hedge fund clients, and these funds are only able to imperfectly substitute such creditor relationships. In this paper, we focus on hedge fund borrowing during a systematic shock and not an idiosyncratic prime broker event. Based on proprietary data from one fund-of-funds, Ang, Gorovyy, and Van Inwegen (2011) find that hedge fund leverage is predictable by economy-wide factors such as funding costs and stock market valuations.[16] In contrast, our hedge fund-creditor level data allow us to identify a hedge fund's borrowing from a specific creditor, and isolate effects after accounting for observable and unobservable time-varying hedge fund characteristics and relationship-specific factors.

Ours is, to our knowledge, the first paper to empirically examine constraints on hedge fund liquidity provision due to internal risk constraints, and thus, test the theoretical predictions of Gârleanu and Pedersen (2007); Shin (2010); Adrian and Shin (2010, 2014). Gupta and Liang (2005) measure hedge funds' capital adequacy through a value-at-risk measure backed out from realized fund-level returns reported to a commercial hedge fund database. Our measure does not rely on a long historical time series of reported realized returns. We obtain hedge funds' internally assessed monthly VaR measures from regulatory filings, which reflect the current state of a hedge fund's portfolio composition and expectations.

Our paper significantly advances our understanding of hedge funds that engage in fixed income arbitrage.[17] Duarte, Longstaff, and Yu (2007) replicate several common fixed income arbitrage strategies to analyze their potential returns and risks. Barth and Kahn (2021) use a model and aggregate data to analyze the mechanics of the cash-futures basis trade. Our paper contributes to this literature by providing both fund-level and fund-creditor-level analyses of the trading and funding by UST arbitrage hedge funds, and showing the importance of hedge fund internal risk constraints even in the absence of binding external financing constraints.

[16] Mitchell and Pulvino (2012) examine data from one hedge fund and document its step back in arbitrage activity during the GFC.

[17] Hedge fund liquidity provision in equity markets, which differs significantly in terms of trades and financing from fixed income arbitrage, has been more widely studied (see Khandani and Lo (2011); Aragon and Strahan (2012); Jylhä, Rinne, and Suominen (2014); Çötelioğlu, Franzoni, and Plazzi (2021); Glossner, Matos, Ramelli, and Wagner (2022)).

2 Data and empirical setting

2.1 Hedge fund data

The hedge fund data used in this paper are primarily from Form PF. In our analysis, we use the set of qualifying hedge funds that are required to provide more detailed filings, and follow the data cleaning and validation procedure outlined in Kruttli, Monin, and Watugala (2022).[18] Table 1 presents summary statistics for the key variables of interest. Our sample consists of the set of hedge funds with gross UST exposure of at least $1 million on average over the last three months of 2019. Our findings are robust to varying this threshold. We apply this threshold for two reasons. On the one hand, we want to ensure that the estimates of our regression models are not affected by funds with very small UST exposures. On the other hand, the threshold should be sufficiently low that we capture potential hedge funds that had small UST trading positions before March 2020 but then substantially increased their UST trading during the crisis. A summary reference of variable definitions is included as the last table in this paper in Table A3.

Table 1 Panel A reports the hedge fund characteristics. The variables $RiskLimit_{h,t}$ and $DistAboveRiskLimit_{h,t}$ are based on the hedge fund's value-at-risk (VaR), which quantifies for each fund and month the potential loss (as a percent of NAV) over a one-month horizon with a probability of 5%.[19] A detailed description of the processing of the VaR data is given in the Online Appendix. Trading desks are incentived to fully use their allocated risk limit to generate higher returns. The higher the average VaR carried by a hedge fund over a period, the higher the fund's $RiskLimit_{h,t}$ or general risk appetite. Portfolio and market shocks can temporarily push a hedge fund away from its risk limit in either direction, giving rise to fluctuations in the fund's remaining risk-bearing capacity. The higher the

[18] Form PF data are also used by Aragon, Ergun, Sherman, and Girardi (2021), and aggregate statistics are shown in policy reports, for example, the private fund statistics of the SEC (https://www.sec.gov/divisions/investment/private-funds-statistics) and the Financial Accounts of the Federal Reserve Board https://www.federalreserve.gov/releases/efa/efa-hedge-funds.htm).

[19] Not every fund in our baseline sample reports its VaR in Form PF. Only funds that regularly calculate VaR for their risk management report it. Around 60% of the funds in our sample report the VaR.

$DistAboveRiskLimit_{h,t}$ of a fund, the lower its remaining risk-bearing capacity at that point in time. We construct the two measures based on the monthly VaR series. The first measure is the VaR averaged over a rolling 12-month window,

$$RiskLimit_{h,t} = \frac{1}{12} \sum_{m=t-11}^{t} VaR_{h,m}. \tag{1}$$

The second is the difference between the fund's current VaR and the lagged $RiskLimit_{h,t}$,

$$DistAboveRiskLimit_{h,t} = VaR_{h,t} - RiskLimit_{h,t-1}. \tag{2}$$

The average $RiskLimit_{h,t}$ is 4.7%, which implies that the average fund's risk limits are such that it expects to lose 4.7% of its NAV in a month 5% of the time. $DistAboveRiskLimit_{h,t}$ is on average 0.1%, and the 10^{th} and 90^{th} percentiles are -1.4% and 1.7%, respectively, indicating that sizable deviations from the typical risk limit can occur.

Figure 1 presents the time series of the *RiskLimit* and *DistAboveRiskLimit* for the pre-crisis period up to February 2020, illustrating hedge funds' risk capacity before the onset of the crisis. Both figures show the mean with interquartile range as a shaded region. The average *RiskLimit* stays close to 4% over pre-crisis period but shows a large cross-sectional variation ranging from below 2% to over 5%. Intuitively, the average *DistAboveRiskLimit* stays close to zero throughout the time series.

Form PF data contain granular information on a hedge fund's month-end cash positions. The variable $FreeCashEq_{h,t}$ measures unencumbered cash that is held for liquidity management purposes, including U.S. Treasuries that are not posted as collateral. The variable $Cash_{h,t}$ on the other hand only includes "pure" cash and not U.S. Treasuries. The two measures, normalized by NAV, are on average 26.8% and 30.6%, respectively.

The average hedge fund has $2.8 billion in net asset value (NAV) and a leverage ratio of 2.5. The next three variables measure different dimensions of fund liquidity, including portfolio liquidity ($PortIlliq_{h,t}$), investor liquidity as measured by share restrictions ($ShareRes_{h,t}$),

and funding liquidity measured as the weighted average maturity of a fund's borrowing ($FinDur_{h,t}$). Form PF asks for the percentage of a hedge fund's assets, excluding cash, that can be liquidated within particular time horizons (within $\leq$1, 2-7, 8-30, 31-90, 91-180, 181-365, and >365 days) using a given periods' market conditions. We compute the weighted average liquidation time to obtain the measure $PortIlliq_{h,t}$. The average $PortIlliq_{h,t}$ is 33.1 days in our sample. Similarly, $ShareRes_{h,t}$ is a measure of the expected weighted average time it would take for a hedge fund's investors to withdraw the fund's equity.[20], and the weighted average time to maturity of a fund's borrowing is denoted $FinDur_{h,t}$. Panel A further provides summary statistics for monthly and quarterly returns as well as quarterly flows. Panel A also provides information on the number of a hedge fund's open positions, gross notional exposure (GNE), and portfolio GNE. The difference between the GNE and the portfolio GNE is that portfolio GNE does not include cash.

Form PF requires hedge funds to report the month-end values of long and short portfolio exposures in a range of asset classes. Fixed income holdings are reported both as notional exposures and on a risk-adjusted basis.[21] Panel B of Table 1 provides summary statistics on the hedge funds' UST exposure. The gross notional UST exposure for a hedge fund, $UST_Gross_{h,t}$, is on average \$2.8 billion. Importantly, this measure includes exposure to UST through derivatives like futures, as well as physical exposures. The $UST_Gross_{h,t}$ is the sum of the long and short UST exposure, which we observe separately and are named $UST_Long_{h,t}$ and $UST_Short_{h,t}$, respectively. The net UST exposure is given by the difference of the two and named $UST_Net_{h,t}$. On average, the $UST_Net_{h,t}$ is positive with \$846.0 million, indicating that the average long exposure is larger than the short exposure.

The variable $USTArbitrage_{h,t}$ captures the part of the $UST_Gross_{h,t}$ that is long-short balanced and is used as a proxy for the UST arbitrage activity of a fund. Ex-

[20]This variable quantifies the restrictions faced by a fund's investors, such as lock-up, redemption, and redemption notice periods.

[21]The risk-adjustment is either based on duration, weighted average tenor, or 10-year equivalent. Where we use risk-adjusted exposures, we convert the reported values to the same units, as described further in the Online Appendix.

plicitly, we set $UST Arbitrage = 2 \times min(UST_Long_{h,t}, UST_Short_{h,t})$.[22] This definition captures prominent UST arbitrage trades like the on-the-run/off-the-run and the cash-future basis trade. On the other hand, the variable $UST Directional_{h,t}$ captures the unbalanced directional UST exposure and is set equal to $abs(UST_Net_{h,t})$. The arbitrage and directional exposures add up to a hedge fund's total gross exposures, $UST_Gross_{h,t} = UST Directional_{h,t} + UST Arbitrage_{h,t}$.

Panels C includes summary statistics on month-end hedge fund repo borrowing and lending. Long UST securities positions are primarily financed via repurchase agreements, that is, repo borrowing from the perspective of a hedge fund, while short UST securities positions are primarily sourced through reverse repo, that is, repo lending from the perspective of a hedge fund (see Figure A1). This reliance on repo is one of the major distinctions between hedge fund equity versus fixed income trading. Repo borrowing is on average $3.6 billion, and the average repo lending is $2.7 billion. The maturity or term of the repo borrowing and lending, $RepoBrrwTerm_{h,t}$ and $RepoLendTerm_{h,t}$, are on average 25.7 and 12.2 days, respectively. Repo borrowing is over-collateralized, with the average ratio of total collateral to borrowing of 118%. The type of repo borrowing can vary in two dimensions: (i) centrally cleared vs uncleared and (ii) bilateral repo vs triparty repo (Baklanova, Copeland, and McCaughrin, 2015; Baklanova, Kuznits, and Tatum, 2021). We find that most hedge fund repo is transacted bilaterally, with only 13.7% of the repo centrally cleared.[23] Indeed, most hedge funds in our sample exclusively transact in uncleared bilateral repo market with no reported activity in triparty or cleared repo.

Panel D presents data on hedge fund credit relationships and major creditors. The total amount of borrowing, $TotalMCBorrowing_{h,t}$, is the sum of borrowing across all major counterparties as of the end of a given quarter and includes borrowing from repo as well as other sources such as margin loans. The number of creditors from which a hedge fund

[22] We multiply the minimum by two to ensure comparability to the gross exposure.

[23] This is in line with estimates from the Office Financial Research (https://www.financialresearch.gov/the-ofr-blog/2022/08/24/non-centrally-cleared-bilateral-repo/).

borrowed as of the end of a given quarter, $NumCrdtrsPerHF_{h,t}$, is on average 4.5. The average amount borrowed from a specific creditor is $HF_Ctpty_Credit_{h,p,t}$ is $1.3 billion. In about half of the cases, a hedge fund's creditor is also its custodian.

2.2 Dealer data

We harness data both at the hedge fund-creditor-time level from Form PF and daily dealer-level data from the Complex Institution Liquidity Monitoring Report (FR 2052a) when examining dealers' repo lending to hedge funds.

In our hedge fund-creditor-time level analysis, we use three measures that capture heterogeneity in broker-dealer constraints: $isGSIB_{p,t}$, $DistanceToLRT_{p,t}$, and $DrawnDelta_{p,t}$.[24] The first captures a dealer's status as a global systemically important bank (G-SIB), which is defined as an institution whose failure could threaten the global financial system. G-SIBs face enhanced regulations in the post-GFC period. The Financial Stability Board (FSB), working with the Basel Committee on Banking Supervision (BCBS) and national supervisory authorities, has published the list of G-SIBs on an annual basis since November 2011. As of March 2020, there were 30 G-SIBs, including 8 domiciled in the United States. We define $isGSIB_{p,t}$ as an indicator taking the value 1 if a broker-dealer p is (a subsidiary of) a G-SIB at end of period t, and 0 otherwise. In the Online Appendix, we provide a list of all G-SIB institutions, including the timeline of G-SIB classifications, using information sourced from the Financial Stability Board and the NY Fed.[25]

The Basel Committee on Banking Supervision introduced the (non-risk-based) leverage ratio measure to constrain the build-up of leverage and supplement risk-based capital requirements. The measure compares a bank's capital to total exposures, including repo lending and exposures held off balance sheet. The Basel III accords recommended beginning the

[24] We observe creditors at the parent company level. Therefore, these measures are determined at the parent company level.

[25] Most G-SIB broker-dealers are primary dealers permitted to trade with the Federal Reserve and in the primary market for U.S. Treasuries. Exceptions include the two U.S. custodial banks. We include lists of both G-SIBs and primary dealers in the Online Appendix.

disclosure of bank leverage ratios by Q1 2015 and requiring the maintenance of a minimum leverage ratio threshold (LRT) of 3%, with further add-ons for G-SIBs. The minimum requirement was implemented by legislation and rulemaking across different jurisdictions with a variety of effective dates and calculation methods.[26] We hand-collect the leverage ratios, (time-varying) minimum requirements, and relevant implementation dates for all banks in our sample to measure each dealer's proximity to its leverage ratio threshold as:

$$DistanceToLRT_{p,t} = LRThreshold_{p,t} - LeverageRatio_{p,t}. \tag{3}$$

We obtain daily dealer-level data from the Complex Institution Liquidity Monitoring Report (FR 2052a), which is a confidential regulatory data collection beginning in 2015 that is used to monitor the overall liquidity profile and liquidity risks within different business lines for financial institutions supervised by the Federal Reserve.[27] From these data, we see information such as a dealer's daily total repo lending to hedge funds, which helps us to cross-check the findings from our main analysis at the monthly frequency. Further, these data capture the utilized amount of the credit lines in the dealer-banks' lending portfolios, which we use to construct for each dealer a measure of the liquidity shocks resulting from the credit lines drawdown channel, consistent with Acharya, Engle, and Steffen (2022). For each consolidated entity p and quarter/month t, we define $DrawnCreditLines_{p,t}$ to be the total outstanding draws on revolving credit facilities offered by the entity. We focus on drawdowns from non-financial corporations to minimize endogeneity issues. We then define $DrawnDelta_{p,t}$ to be the quarterly change in credit line drawdowns relative to total assets,

[26] In the US, this regulation is the Supplementary Leverage Ratio (SLR) rule, which was finalized in September 2014 and mandated disclosure starting in January 2015 with the minimum capital requirement effective from January 2018. US banks subject to the SLR have an LRT of 3%, while US G-SIBs are subject to an enhanced SLR of 5%.

[27] U.S. bank holding companies with at least $100 billion in total consolidated assets and foreign banking organizations with combined U.S. assets of at least $100 billion must report for their consolidated entity on at least a monthly basis. Larger institutions, including U.S. G-SIBs, must report on a daily basis and report separately for various subsidiaries. Data elements reported include certain assets and liabilities, and in particular cover funding activities by counterparty type, collateral class, and maturity bucket.

which we source from S&P Market Intelligence.

$$DrawnDelta_{p,t} = \frac{DrawnCreditLines_{p,t} - DrawnCreditLines_{p,t-1}}{TotalAssets_{p,t}}. \tag{4}$$

2.3 Pre-crisis hedge fund UST and repo activity

In the period leading up to the March 2020 COVID-19 shock, we find that hedge fund UST exposures doubled from early 2018 to February 2020, reaching $1.4 trillion and $0.9 trillion in long and short notional exposure, respectively, primarily driven by relative value arbitrage funds, which held close to $600 billion in long UST exposure in February 2020 (see Figure 2).

From early 2018 to February 2020, we find that there was also a significant increase in hedge fund repo borrowing, consistent with the marked increase in long UST securities holdings. Until that point, aggregate hedge fund repo borrowing and lending exposures were generally matched, as one would observe with UST arbitrage strategies such as trading on-the-run/off-the-run spreads or yield spreads.[28] The divergence between hedge fund repo borrowing and lending is likely driven by a significant increase over the period in UST cash-futures basis trading.[29] As with many other spread trades hedge funds engage in, these trades are primarily "short liquidity" and perform worst in states of the world in which liquidity is scarce. As shown in Figure 6, hedge funds that predominantly engage in the basis trade represented about 50% of the aggregate hedge fund UST notional exposure.

[28] We summarize the cash flows and exposures for hedge funds involved with such fixed income arbitrage strategies in Figure A1 and provide further description in the Online Appendix.

[29] In this trading strategy, as described in the Online Appendix, a hedge fund goes long the (cheapest-to-deliver) Treasury security and goes short the corresponding Treasury futures contract. The futures leg does not require reverse repo, so the divergence between hedge fund repo borrowing and lending is consistent with reports of a significant increase in recent years in UST cash-futures basis trading. Typically, this is a low volatility, low yield convergence strategy that is operationally intensive and requires leverage to be worthwhile. The trade is profitable as long as the actual cost of carrying the cash position (the "repo rate" or the cost of repo borrowing for the hedge fund) is below the implied cost of carry on the futures (the "implied repo rate").

2.4 Hedge fund UST activity and the COVID-19 market turmoil

The unprecedented March 2020 Treasury market turmoil represents an ideal setting to analyze hedge fund arbitrage activity during a crisis in general and in UST markets in particular. At the time, even regulators were unable to determine whether hedge funds were liquidity providers or consumers, and if hedge funds did change their activity why they did so.

We first document the changes to hedge fund UST trading activity during the turmoil. The grey shaded line in Figure 2 shows that aggregate UST exposures fell significantly in March 2020. Figure 3 illustrates that UST trading hedge funds experienced a significant loss during the turmoil and also increased unencumbered cash holdings significantly.

To provide an initial fund-level view of the changes that occurred to UST exposures, while separating out differences due to different hedge fund characteristics and fund-specific effects, we estimate panel regressions of the form,

$$\Delta y_{h,t} = \beta_1 D_t + \gamma Z_{h,t-1} + \mu_h + \epsilon_{h,t}, \tag{5}$$

where $\Delta y_{h,t}$ is the change in the outcome of interest. D_t is 1 for March 2020 and 0 otherwise. $Z_{h,t-1}$ is the set of lagged controls ($LogNAV$, $NetRet$, $NetFlows$, $PortIlliq$, $ShareRes$, $FinDur$, $MgrStake$, and $LeverageRatio$). μ_h denote fund fixed effects. Standard errors are double clustered by fund and time. The data for this regression are monthly from January 2013 to March 2020 and include all hedge funds with gross UST exposure of at least $1 million on average over the last three months of 2019.

Table 2 presents regression results with dependent variables capturing different aspects of a hedge fund's UST exposure. Panel A analyzes changes to the notional exposure—both gross notional exposures and long and short exposures separately—measured either in dollar terms or as a fraction of NAV. The coefficient on $March2020$ is significant and negative for all outcome variables. The first three columns show that, in March 2020, hedge funds reduced UST exposure by around 20%, on both the long and the short sides. The last three

columns show that this change is significant even when UST exposures are normalized by a fund's NAV. UST exposure as a fraction of NAV went down by about 8% on the long and short side. Total (gross) UST exposure as a fraction of NAV went down by about 15% in March. These results provide robust evidence of a significant, abnormal decline in hedge funds' Treasury exposures in March 2020. Despite the widening of spreads during the Treasury market turmoil, hedge funds refrained from providing liquidity. In fact, they consumed liquidity by reducing their gross, long, and short exposures.

Among the control variables, flows are positively related to UST exposure: the first three columns show a positive and significant coefficient on $NetFlows$, indicating that funds adjust their portfolios in response to investor inflows and outflows. As expected, flows do not change UST allocations as a fraction of a fund's NAV. Most other control variables are not significantly related to Treasury exposures after controlling for fund fixed effects.

Table 2 Panel B examines the directional exposure and arbitrage activity in UST portfolios. The regression in column 1 indicates that purely directional exposures, $USTDirectional$, dropped by close to 15%. Column 2 shows that following the March 2020 shock, hedge funds reduced their UST arbitrage portfolios by around 25%. The next column confirms that long-short balanced exposures declined disproportionately more than directional exposures in UST hedge fund portfolios. Columns 4 to 7 show changes to arbitrage exposures for the set of UST hedge funds that had "moderate" or "large" arbitrage exposures on average over the last three months of 2019.[30]

These estimates of decreases in notional UST exposures are based on end-of-month Treasury securities valuations. In the Online Appendix, we also estimate valuation-adjusted and risk-adjusted UST exposures and show results of regressions using them as dependent variables. These adjustments yield qualitatively similar results. Further, we also show robustness to including time series controls, namely the Bank of America / Merrill Lynch

[30]The moderate (large) set is defined as the UST-trading hedge funds with $\frac{USTArbitrage_{h,t}}{UST_Gross_{h,t}}$ of 15.75% (43.75%), which correspond to the 25^{th} (50^{th}) percentile from all hedge funds that have non-zero $USTArbitrage$ over the last three months of 2019. This captures the set of hedge funds with significant long-short UST exposures, excluding those with only directional positions, prior to the UST turmoil.

Option Volatility Estimate (MOVE1), the yield slope (computed as the Treasury 10-year constant maturity rate minus 2-year constant maturity rate), and the Hu, Pan, and Wang (2013) noise measure (HPW). In Table A1, we also show the change in UST exposures separately for hedge funds with different levels of pre-crisis exposure to US Treasuries. Hedge funds with the smallest pre-crisis exposures (of less than US$100 million in gross exposures) likely increased long UST holdings as part of their boost in precautionary liquidity, but that did little to counteract the overall selling by other UST hedge funds. Across the spectrum of pre-crisis UST exposures, we robustly find that hedge funds significantly reduced UST arbitrage positions. In the Online Appendix, analyzing data six months post-crisis, we find that hedge funds continued to reduce exposures in UST markets even after the turmoil subsided.

The UST market turmoil mostly subsided following the unprecedented Fed intervention on March 23, 2020, close to the end of the month and quarter. If hedge funds sold off significantly more UST positions intra-month and bought back positions following Fed intervention, our March 2020 coefficient estimates would underestimate the extent of hedge funds' UST sell-off. Our analyses of hedge fund returns, cash, and post-crisis UST arbitrage positions together bolster the interpretation that hedge funds sold off UST positions and went into cash during the turmoil, and did not step up UST arbitrage trading during or immediately after the turmoil subsided.[31]

In the aggregate, we estimate that in March 2020, hedge funds sold $173 billion in UST securities after accounting for valuation changes (see also Banegas, Monin, and Petrasek (2021) for further discussion of this evaluation). Our estimate is in line with Vissing-Jorgensen (2021) who estimates that hedge funds had at least $183 billion in Treasury sales during Q1 2020 using publicly available private fund statistics from the SEC and Treasury futures data from the CFTC. He, Nagel, and Song (2022) use publicly available quarterly Flow of Funds data published by the Federal Reserve—which covers only the subset of the hedge funds in

[31] If hedge funds retained or increased their UST arbitrage positions through the peak of the turmoil, and sold off their exposure significantly just after the Fed intervention, average UST hedge fund returns would have been flat or significantly positive in March 2020. Instead, we find average UST hedge fund returns of -10% for March 2020.

Form PF domiciled in the US and excludes offshore funds—and find that this subset sold $30 billion in Q1 2020. The data that we use provide, to our knowledge, the most comprehensive view of hedge fund UST activity during March 2020.

3 External financing and hedge fund UST liquidity provision

A high volatility, low liquidity environment, in which convergence spreads that hedge funds generally bet will converge widen, represents a profit-making opportunity for an unconstrained arbitrageur. However, our findings indicate that not only did hedge funds fail to provide liquidity or market support through increased arbitrage activity, they in fact sold positions and reduced UST exposures significantly. What constrained UST hedge fund activity during the market turmoil?

A common conjecture is that external financing makes hedge fund arbitrage fragile during crises. Hedge fund UST arbitrage is funded via repo borrowing. As we document, hedge funds primarily engage in uncleared bilateral repo borrowing, which is considered the most opaque segment of the repo market (Gorton, Metrick, and Ross, 2020). While a crucial market to understand due to financial stability implications, this is a previously unstudied credit market due to data limitations.

This section focuses on hedge fund's debt financing, but we document in Table A2 that equity financing remained largely stable for hedge funds in March 2020. The average outflow during this crisis was -1.7 percent, which is a rather modest outflow based on the distribution of historical flows shown in Panel A of Table 1. Long share restrictions likely helped to keep hedge fund equity financing resilient. The median hedge fund in our sample would receive at least 30 days of notice before the first 1% of fund's NAV (equity) could be redeemed.[32]

[32]In contrast, other asset managers like mutual funds and money market funds do not have such share restrictions, and faced destabilizing investor runs during March 2020 (see, for example, Ma, Xiao, and Zeng (2020); Li, Li, Macchiavelli, and Zhou (2021))

3.1 Repo funding during the COVID-19 shock

Table 3 presents results from analyzing hedge funds' repo activity using a panel regression specification similar to (5). Hedge funds' repo borrowing was surprisingly resilient on average during the March 2020 sell-off in Treasury markets. The estimates in the first column show no significant change in repo borrowing levels in March 2020. Given the declines in UST arbitrage positions during the period, the relatively unchanged repo borrowing levels suggest that hedge funds wished to maintain the allocated borrowing capacity on the balance sheets of their dealers and were able to do so, potentially using previously non-financed securities.

In contrast to repo borrowing, column 5 shows that hedge fund repo lending or "reverse repo" decreased in March 2020 by around 25% for the average fund. When trading Treasury securities, UST short bond positions are typically sourced through reverse repo, with the hedge fund obtaining the security as collateral from the borrower in exchange for lending cash. A reduction in repo lending is therefore consistent with the decline in short UST exposures shown in Table 2 Panel A, as well as with hedge funds conserving their cash holdings during the crisis.

The unchanged repo borrowing volumes do not support the hypothesis that a tightening of hedge funds' repo funding caused hedge funds to sell their UST positions. However, this result still leaves open the possibility that while the amounts of repo borrowing were unchanged, the terms of the bilateral repo transactions changed. Form PF allows us to observe two important terms of repo transactions at the fund level: the maturity and the collateral haircut.

Columns 2 and 6 in Panel A show the changes to repo and reverse repo maturities in March 2020. The maturity of hedge funds' repo borrowing increased in March by about 3 days, which is considerable. It is noteworthy that the average and median repo borrowing maturity, $RepoBrrwTerm_{h,t}$, are 26 and 9 days, respectively. This means that hedge funds' repo borrowing is predominantly term repo, not overnight repo, and rolled over relatively less frequently. In contrast, the maturity of repo *lending* by hedge funds decreased by around 1

day. The average and median repo lending maturity, $RepoLendTerm_{h,t}$, are 12 and 4 days, respectively. Borrowing for longer periods and lending for shorter periods boosts hedge funds' access to cash. Table 3 columns 3 and 4 examine the collateral and collateral haircuts on repo financing. Surprisingly, we do not find evidence that repo haircuts became significantly more onerous for hedge funds during this stress period. In fact, the total collateral as a fraction of repo borrowing, $\frac{RepoTotalCollateral}{RepoBorrowing}$, shows a statistically significant decrease of around 0.7 percentage points.

These findings suggest that hedge funds sought to mitigate liquidity risks and obtained increasingly favorable repo financing terms during the March sell-off. These results are inconsistent with hedge funds facing greater constraints on repo borrowing in March 2020.

A natural question is whether the frequency of the repo data used in the regression analysis misses any crucial intramonth fluctuations that would lead to starkly different conclusions. The March turmoil subsided following the Fed intervention on March 23, 2020. Form PF yields a comprehensive view on the state of funds soon after, at the end of the month. Several key observations give confidence that our baseline analysis does not miss any significant intra-month fluctuations. First, a sharp decrease in repo lending to hedge funds by dealers in the middle of March and followed by an increase of equal magnitude in the days after the Fed intervention is unlikely because uncleared bilateral repo is relatively operationally intensive and borrowing allocations generally change slowly. Second, the Senior Credit Officer Opinion Surveys (SCOOS) on Dealer Financing Terms show no evidence of a step back in the provision of funding collateralized by Treasuries to relative-value hedge fund clients in mid-March.[33] Finally, we investigate whether the dynamics in the last week of March were substantially different using the *daily* time series of uncleared bilateral repo lending to asset managers collateralized by Treasuries by the top G-SIB dealers from the regulatory dataset FR2052a.[34] The data are plotted in Figure 4. There is clearly an increase

[33]See the SCOOS reports at https://www.federalreserve.gov/data/scoos/scoos-202006.htm and https://www.federalreserve.gov/data/scoos/scoos-202012.htm.

[34]This captures uncleared bilateral repo lending to hedge funds by the major dealers. Money market funds do not borrow in repo markets—they are on the cash lending side (Baklanova, Kuznits, and Tatum, 2021).

in repo lending at the beginning of March. Then the lending stays elevated throughout the month until it slightly drops at the end of March but remains elevated compared to the start of the month. These dynamics suggest that our month-end analysis in Table 3 does not miss any crucial intramonth developments that would lead to different conclusions.

Overall, these baseline results on repo amounts, maturity, and collateral haircuts do not support the view that repo funding volumes and terms became significantly tighter for hedge funds that invest in Treasuries following the March 2020 shock. However, although the average hedge fund did not experience a funding shock, it is possible that certain lending counterparties tightened their provision of credit to hedge funds more than other creditors. We next conduct a granular analysis on hedge fund repo borrowing in section 3.2 using hedge fund-creditor (fund-dealer) level data, focusing on whether dealers subject to enhanced regulations limited the supply of funding to connected hedge funds.

3.2 Dealer constraints and bilateral repo lending

There is much debate on whether post-GFC regulations constrain bank-affiliated broker-dealers' provision of repo and intermediation in fixed income markets,[35] and this debate intensified after the market turmoil in March 2020. As we discuss in section 2.2, under the Basel III accords, banks are required to measure their leverage ratio—defined as Tier 1 capital divided by leverage exposure—and maintain it above a specified threshold. When dealers hold Treasuries or when they lend via repo to hedge funds and receive Treasuries as collateral, the leverage exposure increases, and thus, the leverage ratio decreases.

In the aftermath of the Treasury market turmoil in March 2020, several commentators raised the possibility that regulatory constraints on dealer balance sheets—particularly the Basel III leverage ratio—caused the lack of demand for US Treasuries (see, for example,

Other asset managers like mutual funds and pension funds are restricted in their borrowing activity.

[35] See discussions on the potential impact of post-GFC regulatory constraints of bank dealers on intermediation, for example, in UST markets (Duffie, 2020; Infante and Saravay, 2021; Yadav and Yadav, 2021) and other fixed income (Bao, O'Hara, and Zhou, 2018; Boyarchenko, Eisenbach, Gupta, Shachar, and Van Tassel, 2020; Allahrakha, Cetina, Munyan, and Watugala, 2021).

Schrimpf, Shin, and Sushko (2020); He, Nagel, and Song (2022)). However, while a dealer might refrain from buying Treasuries due to concerns about their leverage ratio becoming too low, it is a separate decision to cut off lending to a hedge fund in the middle of an unprecedented crisis, with likely more adverse implications for the broker-dealer's franchise. The hedge fund is a dealer's client, and thus, the relationship with the hedge fund is an important revenue stream. In this section, we analyze whether the credit supply to hedge funds was limited due to constraints on dealers stemming from regulations or liquidity shocks, or if dealers were able to insulate their hedge fund clients and make financing available.

Using data on borrowing amounts available at the hedge fund-creditor level, we conduct a granular analysis to identify the impact of dealer regulatory and liquidity constraints on hedge fund repo borrowing. We employ a within hedge fund-time methodology to test for differences between funding provided by creditors that are constrained and those that are not, allowing us to compare hedge funds' borrowing from different creditors while controlling for unobserved time-varying hedge fund characteristics.[36] The methodology is illustrated with an example hedge fund-dealer network in Figure 5. The panel regressions take the form,

$$\begin{aligned}\Delta \log HF_Crdtr_Credit_{h,p,t} =& \gamma_1 DealerConstraint_{p,t} + \gamma_2 DealerConstraint_{p,t} \times D_t \\ &+ \phi Z_{h,p,t-1} + \mu_h + \theta_t + \psi_p + \epsilon_{h,p,t}, \qquad (6)\\ \Delta \log HF_Crdtr_Credit_{h,p,t} =& \gamma_1 DealerConstraint_{p,t} + \gamma_2 DealerConstraint_{p,t} \times D_t \\ &+ \nu_{h,t} + \psi_p + \epsilon_{h,p,t}, \qquad (7)\\ \Delta \log HF_Crdtr_Credit_{h,p,t} =& \gamma_1 DealerConstraint_{p,t} + \gamma_2 DealerConstraint_{p,t} \times D_t \\ &+ \nu_{h,t} + \xi_{h,p} + \epsilon_{h,p,t}, \qquad (8)\end{aligned}$$

where D_t is 1 for March 2020, 0 otherwise. $DealerConstraint_{p,t}$ is a measure that captures heterogeneity across dealers in terms of potential constraints to their intermediary role in

[36] This identification strategy is similar to Khwaja and Mian (2008), Kruttli, Monin, and Watugala (2022), and many others that use borrower-creditor data to isolate credit supply effects.

repo markets. Equation (6) includes hedge fund (μ_h), creditor (ψ_p), and time (θ_t) fixed effects. Equation (7) includes creditor fixed effects and hedge fund-time fixed effects ($\nu_{h,t}$). Fund-time fixed effects control for all time invariant and time-varying fund characteristics, absorbing fund-level borrower demand shocks, which allows for the identification of dealer-specific supply effects. Equation 8 includes both fund-time and fund-creditor ($\xi_{h,p}$) fixed effects, with the latter allowing us to control for relationship-specific factors. Standard errors are clustered at the dealer and quarter level. Since Treasury positions are typically financed by repo, we limit the sample for this analysis to hedge funds that primarily borrow via repo (50% or more of their borrowing is via repo) on average over the last three months of 2019. Given the within fund-time analysis, the sample includes only hedge funds that borrow simultaneously from at least two creditors. The vast majority of the hedge funds in our sample borrow from multiple creditors simultaneously (see $NumCrdtrsPerHF_{h,t}$ in Table 1 Panel D).

First, we use a dealer's status as a global systemically important financial institution, $isGSIB_{p,t}$, as the $DealerConstraint_{p,t}$ measure. G-SIBs are the largest, most interconnected institutions and face enhanced regulations in the post-GFC period—including the U.S. enhanced SLR based on the total size of their balance sheet and off-balance sheet exposures—and are therefore subject to the most stringent regulatory constraints. However, the findings reported in Table 4 are inconsistent with these constraints limiting dealers' funding provision during the March 2020 UST sell-off. Interestingly, G-SIBs provided disproportionately *higher* funding during the crisis to hedge funds engaged in repo borrowing. Relative to other dealers, G-SIBs increased repo lending to hedge funds by 11-13% in March 2020. These results suggest that the larger, more regulated G-SIB dealers were better able to provide more resilient funding during the March 2020 sell-off than smaller dealers. The findings also imply that hedge funds connected to G-SIB dealers had access to disproportionately greater funding during the March sell-off.

There are several possible reasons for this result. Larger dealers may have greater

economies of scale and risk-bearing capacity. Their regulated status can give greater access to cheaper funding, which is further augmented during crisis periods via Fed facilities like the Primary Dealer Credit Facility (PCDF).[37] During the COVID-19 shock, these institutions—subject to enhanced regulations constraining their liquidity and risk-taking, greater disclosures, and periodic stress tests conducted by the Federal Reserve post-GFC—were not exposed to significant concerns about solvency and run risk, unlike during the GFC. This may have mitigated precautionary liquidity hoarding behavior by G-SIB-affiliated dealers.

Next, we use a continuous measure of how close a dealer is to its regulatory constraints. Specifically, we use the distance between a bank's leverage ratio and its Basel III minimum required leverage ratio threshold (LRT), $DistanceToLRT_{p,t}$ defined in section 2.2, as the $DealerConstraint_{p,t}$ measure. A bank closer to its minimum LRT would have a smaller $DistanceToLRT_{p,t}$, and hence, potentially be more constrained by the leverage ratio requirement. Table 5 presents the results. In Panel A, the sample consists of US G-SIBs only and the indicator variable $PostJanuary2018_t$ controls for the effective date of the leverage ratio requirement in the US. In Panel B, the sample consists of all US and foreign banks. The indicator variable $PostEffectiveDate_{p,t}$ is included to control for the effective date of the leverage ratio requirement specific to each bank, which varies across countries and institutions. If the leverage ratio requirement was a binding constraint on the funding provided to hedge funds by bank-affiliated broker-dealers in March 2020, we expect the coefficient on $March2020_t \times DistancetoLRT_{p,t-1}$ to be positive and significant. However, the coefficients are insignificant. We do not find evidence that the distance to the leverage ratio threshold was a significant factor in the credit supplied to hedge funds during this episode.[38]

Finally, we analyze whether the credit lines drawdown channel had a differential impact

[37] As we show in the Online Appendix, the set of primary dealers' parent companies overlaps significantly with the set of G-SIB institutions.

[38] Note that the temporary exemption of UST securities from the U.S. leverage ratio calculation was only announced on April 1, 2020, and thus, does not affect these results, which are analyzing data for March 2020.

on repo funding provided to bank-dealer's hedge fund clients.[39] Here, we use $DrawnDelta_{p,t}$ as the $DealerConstraint_{p,t}$, which captures the change in how much corporations drew down the credit lines in a bank p's C&I loan portfolio during quarter t. Table 6 presents the results. The sample in Panel A consists of US G-SIBs only, while Panel B includes all banks. If the liquidity shocks from unexpected credit line drawdowns were passed on to hedge funds by bank-affiliated broker-dealers in March 2020, we expect the coefficient on $March2020_t \times DrawnDelta_{p,t-1}$ to be negative and significant. However, the coefficients are insignificant. We do not find evidence that credit line drawdown shocks were passed on to hedge fund clients during the March 2020 turmoil.

There has been much debate about the impact of post-GFC regulations on bank affiliated broker-dealers on Treasury and other fixed income market liquidity. Overall, our findings show that dealers' regulatory and liquidity constraints were not passed on to hedge fund clients via reduced access to repo funding.

3.3 Hedge fund-creditor relationships and bilateral repo lending

The finding that dealers insulated their repo lending to hedge funds from regulatory constraints and liquidity shocks is potentially driven by the importance of relationships between dealers and hedge funds. Hedge funds are often important clients of the dealer banks, and generate revenue for multiple lines of business such as prime brokerage and OTC market making. To test if relationship strength is indeed related to repo funding to hedge funds during a crisis, we use the empirical strategy discussed in section 3.2 but interact the March 2020 indicator variable with hedge fund characteristics that measure a hedge fund's importance as a dealer's client.

The results are presented in Table 7. In Panel A, we consider interaction variables that measure a hedge funds importance to a creditor and vice versa. The first interaction variable,

[39] Acharya, Engle, and Steffen (2022) find that bank liquidity was impacted by corporations drawing down their credit lines during the early stage of the COVID-19 shock period and relates this channel to the underperformance of bank share prices compared to non-financial firms.

$HFRankInCrdtr_{h,p,t-1}$, measures whether the hedge fund client ranked among the most important clients of a dealer in terms of financing volume before the crisis. The coefficient estimate on the interaction term is positive and strongly significant, indicating that more important hedge fund clients obtained relatively higher repo funding during March 2020. Also, the positive significant coefficient on the second interaction variable $CrdtrRankInHF_{h,p,t-1}$ shows that the most important creditors of a hedge fund provided relatively higher funding than less important creditors, again indicating that the strength of credit relationship matters. Because the interaction variable of interest varies at the fund-creditor-time level, the regressions in this panel can include both fund-time and creditor-time fixed effects to control for both fund demand and creditor supply shocks. The lagged level of credit between a hedge fund and a creditor is also included as a control by itself and interacted with the March 2020 indicator variable.[40]

Table 7 Panel B, we use three different trading turnover measures to capture the revenue-generating potential of a hedge fund. Consistent with relative preference given to clients that generate greater revenue for the dealer, we find that hedge funds with higher fixed income or UST turnover obtained relatively higher repo funding in March 2020. In contrast, hedge funds with higher equity turnover did not see a significant difference in their repo funding, in line with dealers giving preferential access to repo to clients that generate greater revenue for fixed income desks, which often support both trade execution and financing.

4 Internal risk constraints and liquidity management

4.1 Portfolio risk limits

If shocks to external financing did not drive the hedge funds' sell-off in the Treasury market in March 2020, what did? A theoretical literature posits that internal risk constraints

[40] As expected, coefficients on the uninteracted lagged rank variables and $LogHF_Ctpty_Credit_{h,p,t-1}$ are negative in these regressions, likely capturing mean reversion and the fact that both creditors and hedge funds manage the relative size of counterparty exposures.

can prevent liquidity provision of financial institutions during crisis periods, and thus, amplify market illiquidity and volatility (see, for example, Gârleanu and Pedersen (2007); Shin (2010). Shin (2010) demonstrates that internal risk constraints can effectively induce risk-neutral arbitrageurs to behave as if they were risk-averse by limiting risk-bearing capacity and preventing them from providing liquidity during a crisis period. Adrian and Shin (2014) provide the microfoundations for VaR limits in a contracting framework with risk-shifting moral hazard. In their framework, financial intermediaries subject to a VaR limit are forced to shed risk during times of market stress. Tighter limits therefore imply more substantial de-risking when the financial system is under most stress. This implies that funds entering a crisis close to or above their internal risk limit would have less room to provide liquidity during the crisis. Increased volatility is likely to push risk in these funds closer to or further above their limit, constraining their capacity to take on additional risk and possibly forcing them into deleveraging and fire sales. In contrast, a hedge fund with a ex-ante high risk bearing capacity could be better placed to hold onto its trades or even double down and put "risk on" during a crisis.

Our data allow, for the first time, to analyze how hedge funds self-regulate risk-taking and investigate how their risk management metrics affect trading during a crisis period. Most large hedge funds employ VaR to manage the risk of their portfolio. While these VaRs are primarily used for internal risk management, the VaRs are frequently shared with current and potential investors, prime brokers and creditors, who rely on these metrics to assess a fund's risk and manage their counterparty exposures. Fund managers therefore have a strong incentive not to significantly exceed these internal risk limits. In effect, these risk limits measure heterogeneity in the cross-section and across time in hedge fund risk appetite and risk-bearing capacity.

As described in section 2.1, funds that use VaR for their risk management are required to report their portfolio VaR at a monthly frequency on Form PF. The VaR shows for each fund and month the potential loss (as a % of NAV) over a one-month horizon with a probability

of 5%. We use this information to create the variable $RiskLimit_{h,t}$, which is the rolling 12-month average VaR (as a % of NAV). The greater the risk appetite of a hedge fund, the higher its $RiskLimit_{h,t}$. In the Online Appendix, we show how $RiskLimit_{h,t}$ varies with other fund characteristics that are included as controls in our regressions. Also, we define a measure capturing the extent to which a hedge fund has exceeded its risk-bearing capacity, $DistAboveRiskLimit_{h,t}$, as the difference between the current VaR and the prior risk limit. For a fund with a current VaR that is higher than the risk limit, $DistAboveRiskLimit_{h,t}$ is positive, indicating that the fund has likely exceeded its target risk limit or the typical level of risk that its managers are willing to bear. The higher the $DistAboveRiskLimit_{h,t}$, the lower the risk-bearing capacity or constraint slack of a hedge fund.

We estimate the following panel regression models where we condition the trading in March 2020 on a hedge fund's risk-bearing capacity:

$$\begin{aligned}\Delta y_{h,t} &= \beta_1 DistAboveRiskLimit_{h,t-1} + \beta_2 D_t \times DistAboveRiskLimit_{h,t-1} \\ &\quad + \gamma_1 Z_{h,t-1} + \gamma_2 D_t \times Z_{h,t-1} + \mu_h + \theta_t + \epsilon_{h,t}, \qquad (9) \\ \Delta y_{h,t} &= \beta_1 DistAboveRiskLimit_{h,t-1} + \beta_2 D_t \times DistAboveRiskLimit_{h,t-1} \\ &\quad + \beta_3 RiskLimit_{h,t-1} + \beta_4 D_t \times RiskLimit_{h,t-1} \\ &\quad + \gamma_1 Z_{h,t-1} + \gamma_2 D_t \times Z_{h,t-1} + \mu_h + \theta_t + \epsilon_{h,t}, \qquad (10)\end{aligned}$$

where $\Delta y_{h,t}$ is the portfolio change of interest. Again, D_t is 1 for March 2020 and 0 otherwise. $Z_{h,t-1}$ is the same set of controls as in equation (5) and are also included in the regression interacted with D_t. The regression is run with just fund fixed effects (not shown) or both fund and time fixed effects, with qualitatively similar results. β_2 is again the coefficient of interest and captures the differential effect between funds with a high and low risk-bearing capacity.

The results are reported in Table 8. In Panels A and B, the coefficient estimate on the interaction between the March 2020 indicator variable and the distance to the risk

limit, $March2020_t \times DistAboveRiskLimit_{h,t-1}$, is negative and strongly significant for all specifications. These estimates show that funds with a high VaR in February 2020 relative to their typical risk capacity over the previous year sold disproportionately more of their UST positions during March 2020. This effect is also economically significant as can be seen directly from the coefficient estimates because the independent variables are standardized. A one standard deviation higher exceedance of risk limit, $DistAboveRiskLimit_{h,t}$, translates into a 9% reduction in arbitrage positions, with a stronger effect of a 12% reduction for the largest arbitrage funds. Including additional controls individually and interacted with $March2020_t$ in Panel B yields qualitatively similar results, indicating that the effects we find are not driven by correlation with observables.

The results in Table 8 Panel C show that even when including both $DistAboveRiskLimit_{h,t-1}$ and $RiskLimit_{h,t-1}$ variables in the same regression, the coefficients on $March2020_t \times DistAboveRiskLimit_{h,t-1}$ remain qualitatively the same. Intuitively, across the different dependent variables, the coefficient estimates show that funds with a high risk limit were less likely to reduce their UST positions than funds with a low risk limit. The effect of the risk limit is also economically large. A one standard deviation increase in $RiskLimit_{h,t}$ allowed UST funds to hold on to 47.2% more of their arbitrage positions, with even the largest UST arbitrage funds holding 16% more. These findings illustrate the importance of internal risk limits and the proximity to those limits for hedge funds' ability and willingness to maintain their sizeable Treasury market exposures in March 2020.

Table 9 presents the combined regression results including all the factors discussed so far–funding, redemption risk, and internal risk limits. The two internal risk limit variables remain strongly significant in explaining the pullback from UST arbitrage, regardless of the specification and controls included. To examine the role of funding in this setting, we aggregate the creditor regulatory constraints to the fund level by taking the creditor share of each fund's pre-crisis borrowing volume that is constrained by enhanced regulations, as proxied by the creditors' GSIB status. With this aggregation, the role of creditor regulatory

constraints remains significant in explaining changes in hedge fund arbitrage in March 2020, with a positive sign indicating that funds connected to GSIB dealers reduced their UST arbitrage by less.

Redemption risk has been widely studied in the hedge fund literature (Hombert and Thesmar (2014); Ben-David, Franzoni, and Moussawi (2012); Aragon, Spencer, and Shi (2019); Agarwal, Aragon, and Shi (2019)). While these prior studies mostly conclude that share restrictions are helpful to prevent redemptions during crisis periods, they have been restricted to equity markets that are covered by 13-F filings. Since these filings do not cover short equity positions, it has previously been challenging to derive an empirical measure of arbitrage positions as present in the model of Hombert and Thesmar (2014).

In contrast, regulatory data from Form PF allow us to observe both the long and short UST positions of a hedge fund. Therefore, we can explicitly test the effect of share restrictions on arbitrage positions during a crisis period. Table 9 shows that funds with higher redemption risk sold off more of their UST arbitrage portfolios. We find that share restrictions were, in general, stabilizing for hedge funds, with more prominent effects for funds with larger UST arbitrage exposures. The magnitude of the coefficients on these standardized variables allows directly comparison of the economic significance of the effects of internal risk limits and share restrictions. Interestingly, the results in columns 5 through 7 show that the economic effect of risk limits on hedge arbitrage positions are comparable and in some cases larger than the effects of share restrictions.

4.2 Cash and liquidity management

Our results show that while external financing remained stable, hedge funds refrained from providing liquidity in the Treasury market because of their internal risk constraints. We can test if "risk-off" behavior is observable in other investment decisions besides a reduction in UST arbitrage positions.

A hedge fund that wishes to reduce portfolio risk will likely go into cash and reduce

portfolio illiquidity. On the other hand, a hedge fund that wishes to borrow more to fund portfolio positions but cannot obtain financing will deplete its cash positions and increase portfolio illiquidity. The results in Table 10 Panel A show that, by the end of March 2020, funds held significantly higher cash and more liquid portfolios than at the beginning of the month. We show changes to two different measures of cash holdings. $FreeCashEq$ refers to unencumbered "cash and cash equivalents" (e.g., bank deposits, certificates of deposits, money market fund investments, U.S. Treasury and agency securities) held for the purposes of liquidity management. $FreeCashEq$ increased by 26% in March 2020. $Cash$ refers to cash positions (not including U.S. Treasury and agency securities) both unencumbered or posted as collateral, which also increased in March 2020, by around 23%. Also in line with the risk-off hypothesis, the illiquidity of hedge fund portfolios (separate from cash) dropped by 11% during this period.

We analyze changes to fund size and leverage in Panel B. Columns 1 shows that hedge fund $PortfolioGNE$—the notional exposure of securities and derivatives excluding $Cash$—fell by around 22%, while the number of open positions fell by close to 5%. $PortfolioGNE$ excluding UST exposures—$PortGNEnoUST$—also fell by comparable amounts, showing that hedge funds did not reduce UST exposures to divert capital to other asset classes. Columns 3 and 4 show that hedge fund NAV (equity) and GAV (total gross assets) generally dropped proportionally, by 13-14%. As such, the ratio of hedge fund GAV to NAV—$Leverage$—was unchanged at the end of the market stress episode. The reduction of derivative positions and portfolio size are also in line with hedge funds taking risk off due to binding risk constraints.

These findings also speak to the literature on how a hedge fund manages its liquidity during a systematic stress period. In such scenarios, hedge fund managers face a trade-off: selling the more liquid assets first likely has smaller price impact and mitigates current realized losses, but increases overall portfolio illiquidity and thus the probability of future fire sales should the crisis persist or deepen. On the other hand, selling illiquid assets first,

while potentially incurring greater current realized losses, improves the liquidity condition of the fund and its ability to withstand a protracted crisis. Our findings show that hedge funds took the latter, more prudent approach when managing liquidity during the March 2020 shock.

Our findings contrast with the behavior of LTCM in 1998, which sold off its most liquid holdings first as the crisis began to unfold.[41] Analyzing the LTCM meltdown in 1998, Jorion (2000a) concludes that:

> The firm [LTCM] reportedly tried to reduce its risk profile, but made a major mistake: instead of selling off less-liquid positions, or raising fresh capital, it eliminated its most liquid investments because they were less profitable. ... This made LTCM more vulnerable to subsequent margin calls. [pg. 288, Jorion (2000a)]

Given the contrast between LTCM's behavior and our findings for UST hedge funds during March 2020, it is possible that the hedge funds in our sample learned from the risk management choices of LTCM and other subsequent hedge fund meltdowns, which influenced their decisions how to manage liquidity during this stress episode. Indeed, as we show in the Online Appendix, the hedge fund advisers that experienced the LTCM period, that is, were incepted in or before 1998, reduced their portfolio illiquidity by more than younger advisers.[42]

4.3 Basis trading and futures margin pressure

The previous results show that uncleared bilateral repo funding remained stable for hedge funds. However, as illustrated in Figure A1 and described in the overview of hedge fund fixed income arbitrage strategies in the Online Appendix, not all fixed income strategies are exclusively funded via repo. The cash-futures basis trade—an arbitrage strategy popular

[41] Interestingly, our findings on portfolio illiquidity also stand in contrast to the behavior of mutual funds as described by Choi, Hoseinzade, Shin, and Tehranian (2020) and Ma, Xiao, and Zeng (2020), who show for the GFC and the March 2020 shock, respectively, corporate bond mutual funds sold the relatively *more* liquid positions to meet investor redemptions.

[42] Because Form PF does not have information on adviser or fund age, we hand-collected data on the founding years of hedge fund advisers.

with certain large fixed income relative value hedge funds in the run up to the March 2020 turmoil—comprises a long Treasury position that is generally financed through repo and a corresponding short futures position funded via implicit leverage obtained through margin. This contrasts with other UST arbitrage strategies such as on-the-run/off-the-run bond spread trading that involve simultaneously going long and short bonds, where the two sides are generally funded via repo borrowing and repo lending, respectively.

The dynamics of repo and margin borrowing are likely quite different. As discussed in section 3.1, relationships and counterparty considerations matter in uncleared bilateral repo markets. In contrast, exchange-traded futures contracts subject all traders to the same automated rules and are marked-to-market daily. As such, during the March 2020 turmoil, hedge funds predominantly engaged in the Treasury cash-futures basis trade likely faced greater margin calls, compared to other UST arbitrage funds, requiring immediate liquidity infusions or position liquidations stemming from their short futures positions. Indeed, initial and maintenance margin requirements on UST futures contracts traded on Chicago Mercantile Exchange for different maturities rose by 30–210% during March 2020.

At the inception of the March turmoil, while UST securities declined in value, UST futures *appreciated* in value, exposing the basis risk of this trade as it went against hedge fund positions. We take the set of hedge funds that predominantly engage in the cash-futures basis trade as the hedge funds that faced greater margin pressure and examine the differential impact of such immediate liquidity needs on hedge fund UST market activities.[43]

Figure 6 presents the times series of UST exposures, repo borrowing and lending, equity and assets, separately for hedge funds that predominantly engage in the basis trade and for hedge funds that predominantly engage in other UST trading strategies. The basis trader fund set represents roughly a half of the aggregate UST notional exposure of the hedge funds in our sample, with a similar share of the aggregate repo exposures. The bottom two panels of the figure show that in aggregate, the total assets under management are substantially

[43]The Online Appendix includes a detailed description of the methodology used to classify a UST hedge fund as a "basis trader."

larger for non-basis traders, but basis traders on average use much more leverage.

We analyze differences in how basis traders fared during the March 2020 shock compared to other UST traders adapting the panel regression specification in equation (9). Table 11 Panel A examines changes to UST exposures. The coefficients on $March2020 \times BasisTrader$ show that, after controlling for fund characteristics such as size and leverage, basis trading hedge funds did not change their UST notional exposures significantly more than other hedge funds. However, basis traders predominantly reduced their directional exposures in favor of retaining their arbitrage positions. As a result, they held more balanced portfolios in terms of long-short UST notional exposure at the end of March 2020.

Panel B shows the differences for basis traders in repo borrowing. Relative to other UST trading funds, basis traders increased their repo borrowing in March 2020, which suggests greater liquidity needs due to margin pressure on the futures positions. Consistent with the increase in borrowing levels, borrowing terms appear to have tightened for basis traders. The maturity of repo borrowing declined, and the ratio of total collateral to borrowing increased.

The regression results in columns 1 and 2 of Panel C show that compared to other hedge funds, basis traders have significantly less unencumbered cash (including UST bonds) held for liquidity management at the end of March 2020. However, columns 3 and 4 show that their "pure" cash position—including both unencumbered cash *and* cash already posted as margin/collateral, but excluding UST securities held for liquidity purposes—was significantly higher than that of other UST hedge funds, which is consistent with greater margin pressure. We further find that basis traders have comparatively more *illiquid* portfolio positions at the end of March 2020.

Overall, these findings show that hedge funds engaged in the UST cash-futures basis trade faced greater margin pressure. However, the results also suggest that the major reasons for the decline in hedge funds' UST exposures were not specific to the basis trade as other hedge funds saw comparable or larger declines in UST exposures.

5 Conclusion

During the U.S. Treasury markets turmoils in response to the March 2020 COVID-19 shock, the average hedge fund with UST holdings reduced its notional UST exposures on both the long and short sides by around 20%. Measures of hedge fund arbitrage and directional exposures declined by similar magnitudes.

Why did hedge funds refrain from providing liquidity when spreads of typical UST arbitrage trades widened? A common perception is that during crisis periods, hedge funds are limited in their ability to provide liquidity due to external financing constraints. However, we show that uncleared bilateral repo—the primary source of financing for hedge funds' UST holdings—remained resilient, with stable financing volumes and haircuts. We conduct a granular analysis of specific channels proposed in the prior literature through which hedge funds might face repo borrowing constraints, including dealer regulatory and liquidity constraints. Using hedge fund-creditor level data, we find that large creditors subject to enhanced regulations provided disproportionately higher repo financing to hedge funds during the crisis. Also, the proximity of a creditor to its minimum required Basel III leverage ratio or drawdowns on C&I credit lines extended by a creditor were not significant factors in the credit supply to hedge fund arbitrageurs during the turmoil. Our findings support the importance of hedge fund-creditor relationships in explaining why creditors insulated the uncleared bilateral repo funding allocated to their hedge fund clients during this crisis. In particular, we show hedge fund clients that generate greater revenue streams for a creditor, received disproportionately higher funding from that creditor.

The stable repo funding together with low contemporaneous investor outflows indicate that external financing constraints were not binding for hedge fund arbitrage. Instead, we find that the reduction in hedge fund UST exposures was robustly related to internal risk management considerations. Hedge funds with higher ex-ante VaR risk limits were able to hold onto more of their arbitrage positions during the crisis, and funds close to or exceeding their VaR risk limits saw significantly larger selloffs. These empirical results are consistent

with theories on internal risk limits of arbitrageurs and liquidity provision (see, for example, Shin (2010) and Adrian and Shin (2014)). Further, hedge funds increased their cash holdings by over 20% and scaled down the size and illiquidity of their portfolios in March 2020, in line with a risk-off strategy in the face of binding risk constraints.

Compared to previous crisis episodes, the March 2020 shock was unique, particularly in the speed and scale at which extreme moves occurred and in its impact on otherwise safe and liquid markets such as the UST market. By analyzing the activity of hedge funds during this episode in U.S. Treasury markets and uncleared bilateral repo funding markets, this paper sheds light on how the risk management and funding structures of hedge funds affect the role they play in vital financial markets. Our analysis shows that hedge fund arbitrage can be fragile in times of stress due to limited risk-bearing capacity, even if external financing remains stable.

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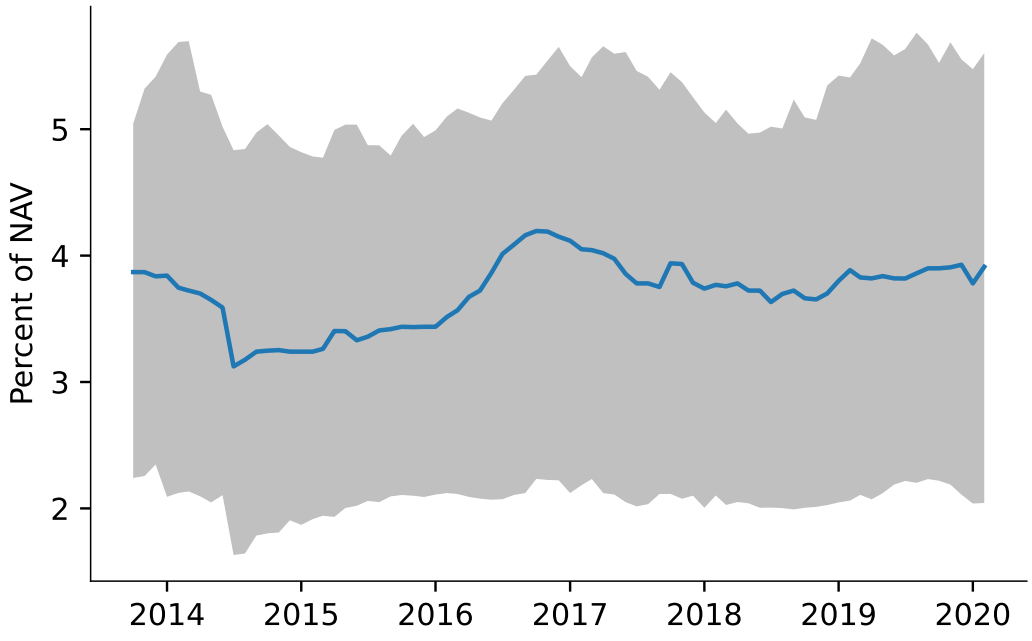
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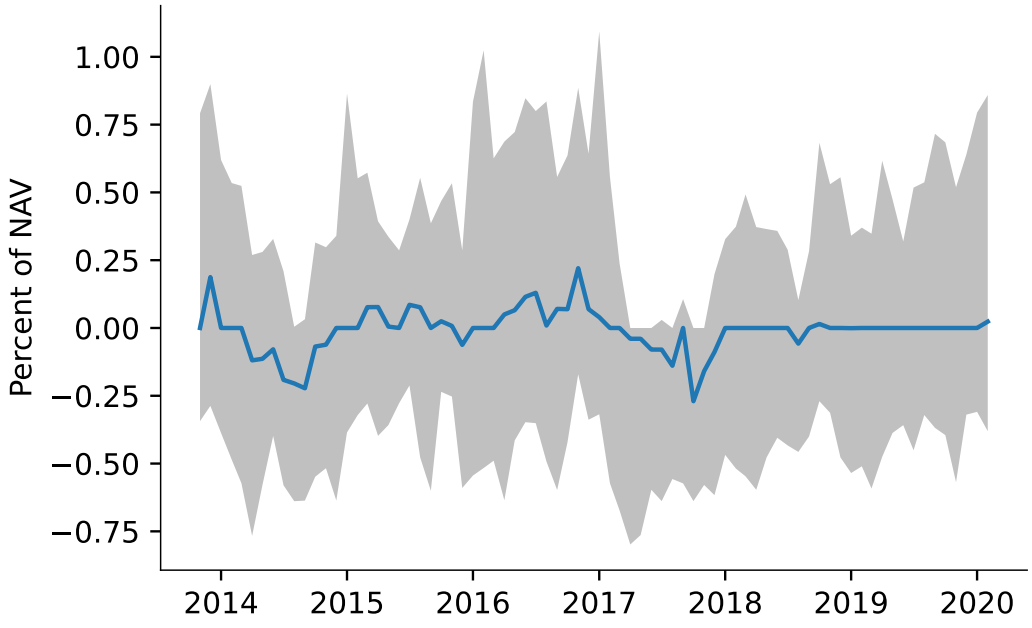
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(a) $RiskLimit_{h,t}$



(b) $DistAboveRiskLimit_{h,t}$

Figure 1: Distribution of $RiskLimit_{h,t}$ and $DistAboveRiskLimit_{h,t}$

This figure illustrates in subfigures (a) and (b) the time series of the median (solid line) and 25^{th}-75^{th} percentile interquartile range (shaded area) of $RiskLimit_{h,t}$ and $DistAboveRiskLimit_{h,t}$, respectively, for the pre-crisis period up to February 2020.

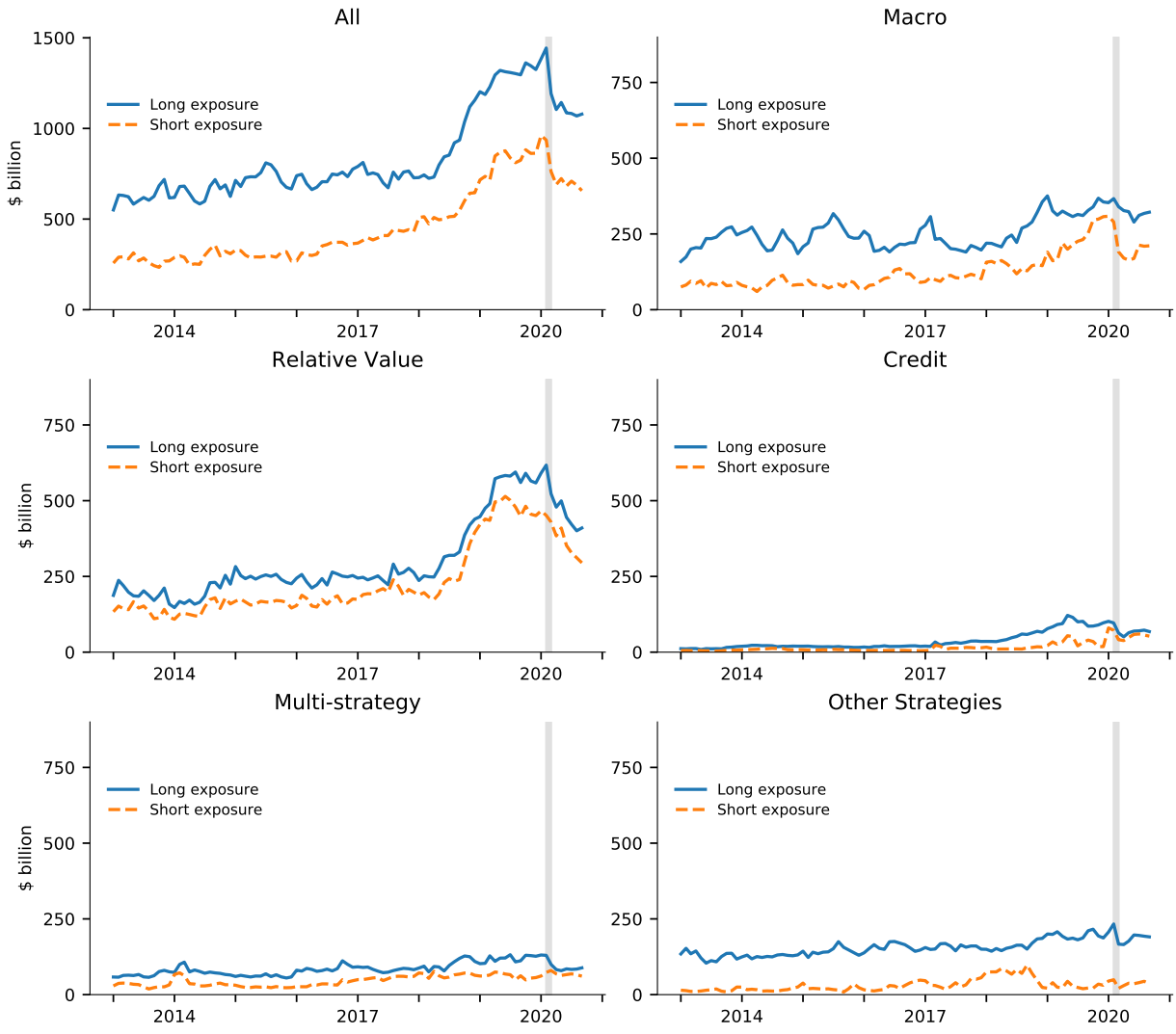


Figure 2: Hedge fund U.S. Treasury exposures

This figure presents the times series of aggregate long and short UST exposures from January 2013 to September 2020 for all hedge funds and hedge funds separated into broad strategies: macro, relative value, credit, multi-strategy, and all other strategies. March 2020 is shaded gray.

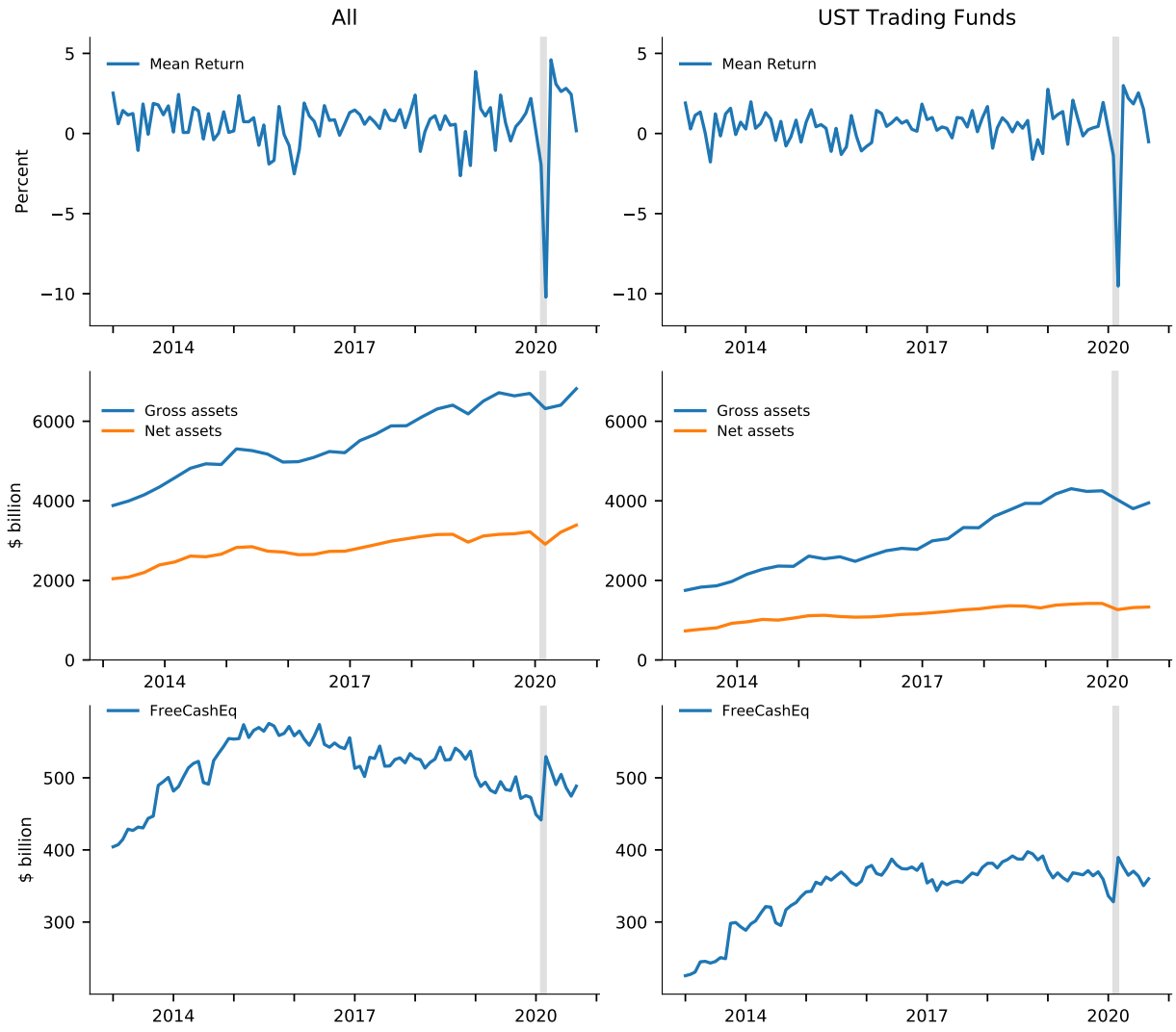


Figure 3: Hedge fund returns, assets, and cash held for liquidity management

This figure presents the times series of returns, assets under management, and unencumbered cash and cash equivalents from January 2013 to September 2020 for all hedge funds (left) and all hedge funds with gross UST exposure of at least $1 million on average over the last three months of 2019 (right). The subfigures on the first row show the monthly mean returns, net-of-fees. The second row shows the aggregate value of gross and net assets under management. The third row shows aggregate holdings of unencumbered cash and cash equivalents ($FreeCashEq$). March 2020 is shaded gray.

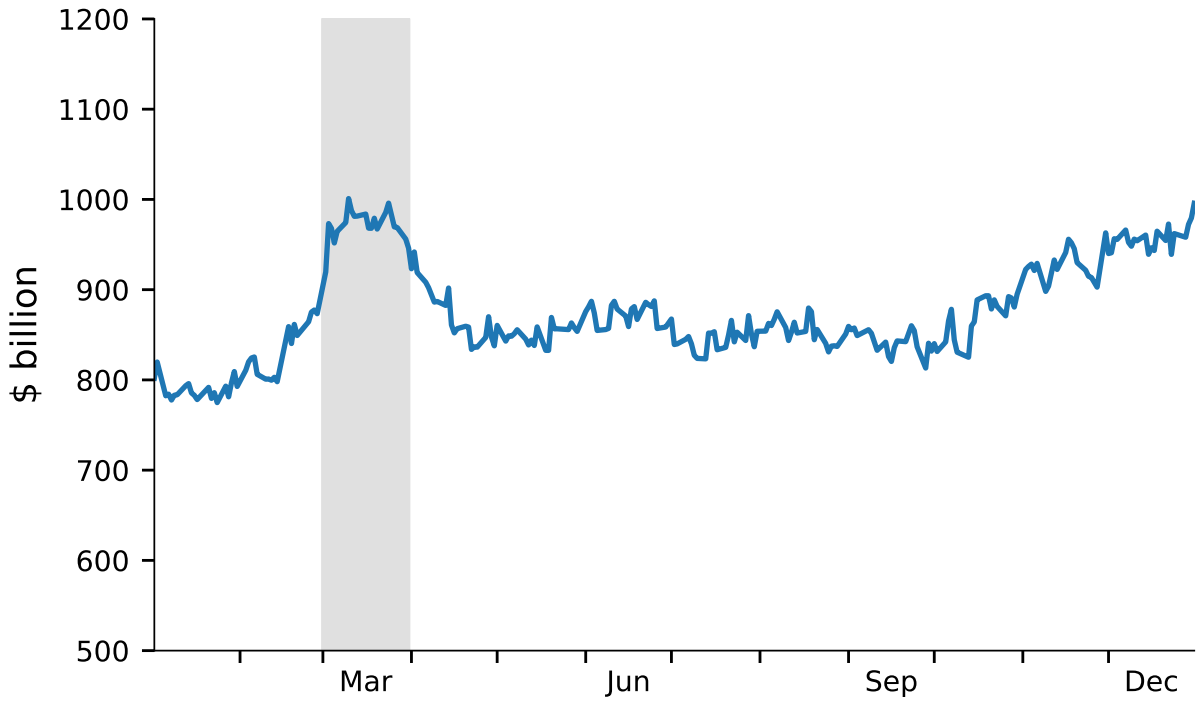


Figure 4: Daily UST bilateral repo lending by the top 10 G-SIB dealers in 2020

The figure presents the aggregate bilateral UST reverse repo (repo lending) to asset managers during 2020 by 10 G-SIB dealers, including Bank of America, Barclays, Citi, Credit Suisse, Deutsche Bank, Goldman Sachs, JP Morgan, Morgan Stanley, UBS, and Wells Fargo. March 2020 is shaded gray.

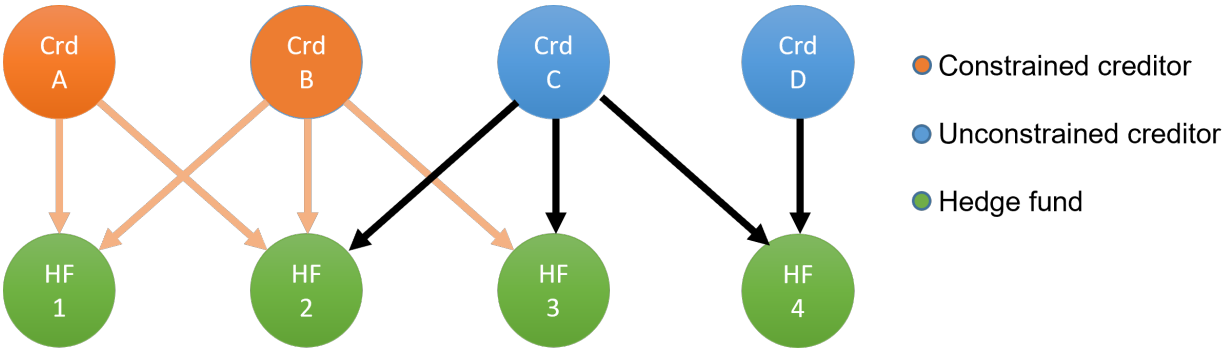


Figure 5: Empirical strategy for analyzing hedge fund-creditor bilateral data

This figure illustrates the identification strategy used when analyzing hedge fund-creditor bilateral repo data to test whether dealers constrained by enhanced regulation cut repo lending to their hedge fund clients. The figure depicts an example bilateral repo lending network with eight nodes: four dealers (A, B, C, and D) and four hedge funds (1, 2, 3, and 4). The amount of repo lending from dealer p to hedge fund h at time t, $HF_Crdtr_Credit_{h,p,t}$, determines the strength of the link (edge) between that hedge fund-dealer pair. All hedge funds in this analysis borrow simultaneously from at least two dealers allowing for the use of hedge fund-time fixed effects. In this sample network, two dealers A and B (nodes in orange) are subject to enhanced regulation, while two dealers C and D (nodes in blue) are not. Hedge funds 2 and 3 both borrow from at least one dealer subject to enhanced regulation and at least one that is not.

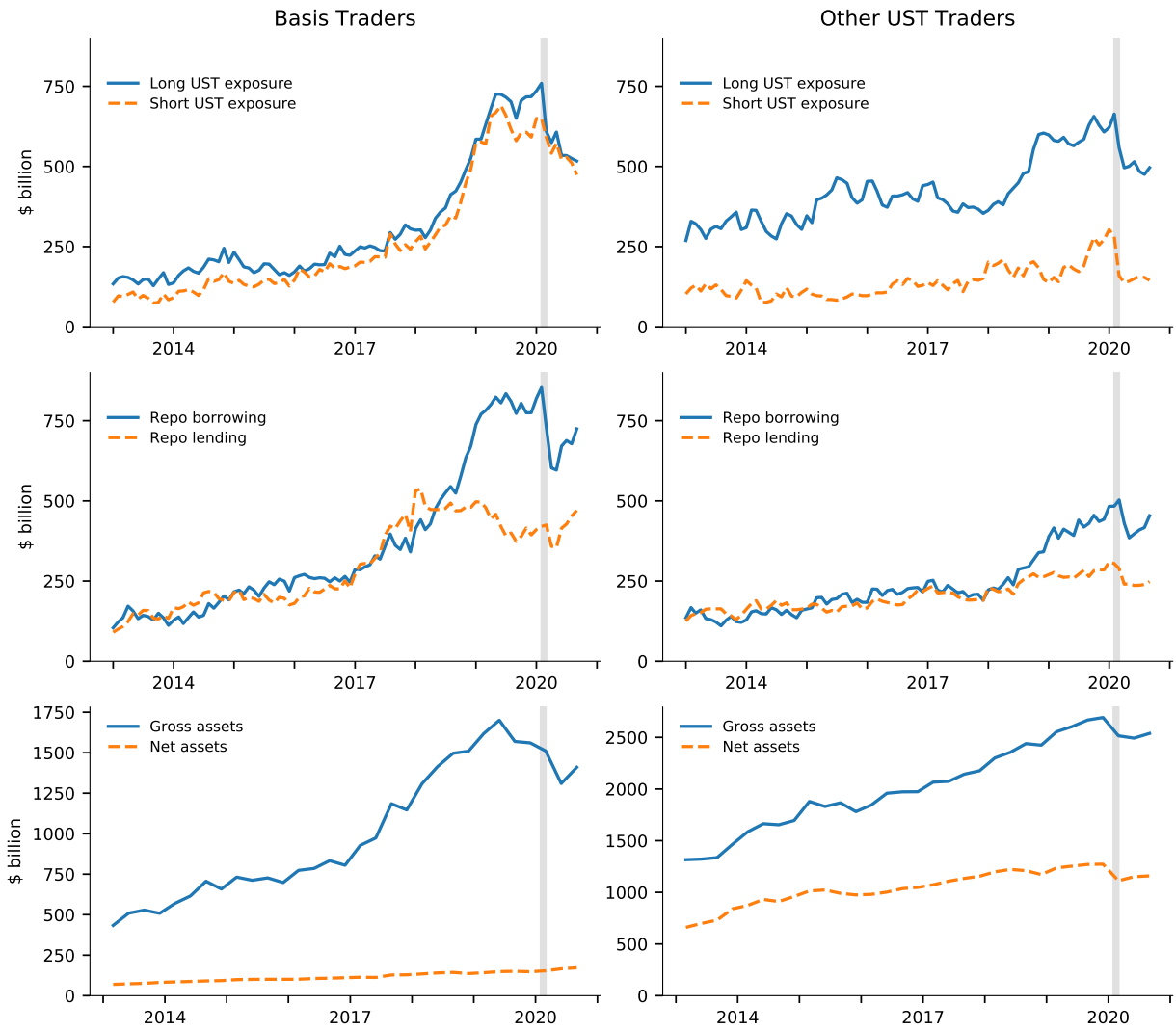


Figure 6: UST cash-futures basis trader versus other UST trader hedge funds

This figure presents the times series of UST exposure, repo exposures, and leverage from January 2013 to September 2020 for hedge funds predominantly engaged in the UST cash-futures basis trade (left) and other UST trading hedge funds (right). Both sets of funds are hedge funds with gross UST exposure of at least $1 million on average over the last three months of 2019. The subfigures on the first row show aggregate long and short UST exposures. The second row shows the aggregate repo and reverse repo exposures. The third row shows aggregate gross and net assets under management. March 2020 is shaded gray.

Table 1: Summary statistics

This table shows the summary statistics for the main variables used in the paper. The data are from January 2013 to September 2020. All variables are described in Table A3. The N column shows the number of observations used to calculate the statistics in a particular row. The last four columns show percentiles.

Panel A: Hedge fund characteristics

	N	Mean	Median	Stdev	25th	75th	10th	90th
$RiskLimit_{h,t}$ (%)	17,898	4.676	3.783	4.496	2.100	5.411	1.146	7.925
$DistAboveRiskLimit_{h,t}$ (%)	17,314	0.135	0.000	1.676	-0.479	0.573	-1.432	1.732
$FreeCashEq_{h,t}$ (m US$)	37,133	824.945	219.609	1,650.080	39.652	784.817	0.056	2,180.929
$Cash_{h,t}$ (m US$)	32,140	759.771	253.933	1,372.204	65.022	805.677	11.794	1,933.981
$\frac{FreeCashEq_{h,t}}{NAV_{h,t}}$ (%)	36,596	26.779	16.276	27.846	3.888	43.313	0.013	72.622
$\frac{Cash_{h,t}}{NAV_{h,t}}$ (%)	31,716	30.623	16.572	41.535	5.216	39.079	1.128	74.434
$NAV_{h,t}$ (m US$)	12,503	2,828.349	1,397.077	4,127.828	714.734	3,068.911	379.007	6,894.295
$LeverageRatio_{h,t}$	12,503	2.476	1.335	3.713	1.042	2.120	1.002	3.923
$PortIlliq_{h,t}$ (days)	12,284	33.096	7.181	61.221	1.725	35.325	0.500	90.399
$ShareRes_{h,t}$ (days)	12,492	125.835	60.500	123.596	19.000	227.625	0.500	316.278
$FinDur_{h,t}$ (days)	9,836	37.107	10.710	54.451	0.500	59.256	0.500	118.853
$MgrStake_{h,t}$ (%)	11,472	13.761	3.000	25.690	0.000	13.000	0.000	44.000
$NetRetQ_{h,t}$ (%)	12,713	2.316	1.690	8.129	-0.470	4.080	-4.160	8.286
$NetRetM_{h,t}$ (%)	36,351	0.437	0.510	2.668	-0.490	1.560	-2.220	3.100
$NetFlows_{h,t}$ (%)	12,023	-0.605	-0.179	13.905	-4.462	2.770	-12.404	10.974
$OpenPositions_{h,t}$	37,548	2,561.640	599.000	6,366.386	219.000	1,804.000	86.000	5,768.300
$GNE_{h,t}$ (m US$)	37,292	25,642.859	5,957.733	61,005.277	1,932.317	18,433.384	784.600	59,207.269
$PortfolioGNE_{h,t}$ (m US$)	37,292	24,592.608	5,445.073	59,761.393	1,752.156	17,174.351	710.106	56,505.466
$EqTurnover_{h,t}$	33,292	9,792.620	1,302.997	22,957.386	141.588	7,999.925	0.191	19,414.891
$FITurnover_{h,t}$	33,292	21,610.450	2,824.357	42,959.217	411.433	15,878.278	56.848	85,010.462
$USTTurnover_{h,t}$	33,292	14,266.717	1,161.214	33,230.990	101.455	7,261.607	0.001	45,533.569

Panel B: U.S. Treasury exposures

	N	Mean	Median	Stdev	25th	75th	10th	90th
$UST_Gross_{h,t}$ (m US$)	33,027	2,790.343	348.228	8,451.260	76.688	1,553.683	18.180	5,736.337
$UST_Long_{h,t}$ (m US$)	33,027	1,858.255	240.291	5,192.603	34.999	1,131.989	0.484	4,337.850
$UST_Short_{h,t}$ (m US$)	33,027	896.717	17.140	3,351.960	0.000	214.722	0.000	1,554.543
$UST_Net_{h,t}$ (m US$)	33,027	846.016	124.704	2,262.571	-2.692	737.179	-134.569	2,616.289
$USTDirectional_{h,t}$ (m US$)	33,027	1,096.909	220.822	2,386.734	48.658	906.084	12.505	2,939.572
$USTArbitrage_{h,t}$ (m US$)	33,027	1,559.734	3.967	6,330.412	0.000	253.073	0.000	2,201.270
$\frac{UST_Gross_{h,t}}{NAV_{h,t}}$	32,612	99.720	26.663	248.848	7.294	78.759	1.802	189.425
$\frac{USTDirectional_{h,t}}{UST_Gross_{h,t}}$	33,027	75.219	97.864	32.881	50.827	100.000	17.330	100.000
$\frac{USTArbitrage_{h,t}}{UST_Gross_{h,t}}$	33,027	24.781	2.136	32.881	0.000	49.173	0.000	82.670

Panel C: Repo, other borrowing, and collateral

	N	Mean	Median	Stdev	25th	75th	10th	90th
$RepoBorrowing_{h,t}$ (m US$)	14,261	3,616.378	280.089	11,129.562	37.898	1,440.943	0.000	7,039.536
$RepoLending_{h,t}$ (m US$)	15,340	2,710.582	126.539	8,668.318	12.569	850.733	0.000	5,916.215
$RepoBrrwTerm_{h,t}$ (days)	12,439	25.683	8.661	43.691	1.463	29.220	0.000	69.398
$RepoLendTerm_{h,t}$ (days)	13,037	12.198	3.653	22.079	0.000	10.958	0.000	40.178
$\frac{RepoTotalCollateral_{h,t}}{RepoBorrowing_{h,t}}$ (%)	13,250	118.174	103.290	27.569	100.388	128.431	100.000	152.999
$RepoClearedCCP_{h,t}$ (%)	5,059	13.721	0.000	33.782	0.000	0.000	0.000	100.000

Panel D: Creditor exposures

	N	Mean	Median	Stdev	25th	75th	10th	90th
$TotalMCBorrowing_{h,t}$ (m US$)	6,129	6,008.282	975.979	17,719.835	329.311	3,729.416	112.594	11,833.454
$NumCrdtrsPerHF_{h,t}$	6,129	4.512	3.000	4.404	2.000	5.000	1.000	9.000
$HF_Crdtr_Credit_{h,p,t}$ (m US$)	27,930	1,327.842	434.083	2,701.381	154.146	1,230.545	69.509	3,012.068
$\Delta logHF_Crdtr_Credit_{h,p,t}$ (%)	23,294	1.304	0.798	48.744	-20.583	22.976	-54.101	56.342
$HFRankInCrdtr_{h,p,t}$	27,930	0.602	0.640	0.287	0.366	0.858	0.177	0.965
$CrdtrRankInHF_{h,p,t}$	27,930	0.610	0.600	0.295	0.333	0.889	0.200	1.000
$IsCrdtrCustodian_{h,p,t}$	27,930	0.504	1.000	0.500	0.000	1.000	0.000	1.000

Table 2: Hedge fund U.S. Treasury exposures

This table presents results of the panel regression model given in equation (5). The dependent variables are shown in the first row. The data are monthly from January 2013 to March 2020. Panel B show changes to arbitrage exposures for the set of UST hedge funds that had "moderate" or "large" arbitrage exposures over the last three months of 2019. The specifications include fund fixed effects. The standard errors are clustered at the fund and time level. The independent variables, with the exception of the indicator variable $March2020_t$, are standardized. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: U.S. Treasury exposure

	$\Delta LogUST_Gross$	$\Delta LogUST_Long$	$\Delta LogUST_Short$	$\Delta\frac{UST_Gross}{NAV}$	$\Delta\frac{UST_Long}{NAV}$	$\Delta\frac{UST_Short}{NAV}$
	(1)	(2)	(3)	(4)	(5)	(6)
$March2020_t$	-19.374***	-18.888***	-23.642***	-15.013***	-8.386***	-7.522***
	-15.499	-11.425	-7.661	-11.459	-8.851	-10.242
$ShareRes_{h,t-1}$	3.037*	3.653*	-1.899	1.799	1.239*	0.564
	1.744	1.962	-0.524	1.299	1.810	0.775
$PortIlliq_{h,t-1}$	1.181	-0.886	1.533	0.125	0.084	0.137
	0.795	-0.418	0.656	0.095	0.126	0.168
$FinDur_{h,t-1}$	-0.543	-0.669	0.729	-0.360	-0.130	-0.175
	-0.808	-0.788	0.360	-1.034	-0.424	-0.602
$LogNAV_{h,t-1}$	-2.117*	-0.460	-2.897	0.579	0.533	-0.050
	-1.886	-0.345	-1.308	0.329	0.429	-0.063
$NetRet_{h,t-1}$	0.888	1.859**	-0.212	-0.417	0.070	-0.488
	1.142	2.425	-0.107	-0.773	0.189	-1.243
$NetFlows_{h,t-1}$	0.901**	0.821**	1.714*	0.046	-0.256	0.246
	2.409	2.286	1.927	0.142	-1.115	1.489
$MgrStake_{h,t-1}$	0.432	0.218	0.280	1.251	0.412	0.948*
	0.803	0.200	0.342	0.919	0.397	1.684
$Leverage_{h,t-1}$	-2.151*	-1.318	-2.735*	-3.533	-1.312	-2.294**
	-1.818	-1.037	-1.777	-1.572	-0.860	-2.189
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,849	16,874	12,978	18,801	18,801	18,801
R^2	0.016	0.015	0.017	0.017	0.016	0.014

Panel B: U.S. Treasury directional and arbitrage exposure

	All UST funds			Moderate UST arbitrage		Large UST arbitrage	
	$\Delta LogUSTDir$	$\Delta LogUSTArb$	$\Delta\frac{USTArb}{Gross}$	$\Delta LogUSTArb$	$\Delta\frac{USTArb}{Gross}$	$\Delta LogUSTArb$	$\Delta\frac{USTArb}{Gross}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$March2020_t$	-15.502***	-24.949***	-2.065***	-46.938***	-5.965***	-44.433***	-7.863***
	-8.370	-8.300	-6.139	-14.233	-8.284	-10.893	-8.428
$ShareRes_{h,t-1}$	2.966	-2.109	-0.252	-0.162	0.231	-0.056	0.003
	1.374	-0.533	-0.542	-0.040	0.327	-0.011	0.005
$PortIlliq_{h,t-1}$	0.638	1.356	0.685	0.121	0.287	0.197	0.456
	0.344	0.675	1.558	0.080	0.677	0.080	0.840
$FinDur_{h,t-1}$	-0.677*	1.969	-0.063	1.598	-0.022	-0.296	-0.572
	-1.743	0.940	-0.184	0.630	-0.046	-0.121	-0.945
$LogNAV_{h,t-1}$	-1.447	-2.393	-0.157	-2.367	-0.218	-4.471	-0.679
	-1.053	-1.171	-0.490	-0.847	-0.586	-1.076	-1.325
$NetRet_{h,t-1}$	0.566	0.595	-0.001	0.720	0.155	1.119	0.134
	0.582	0.331	-0.003	0.294	0.335	0.419	0.243
$NetFlows_{h,t-1}$	0.585	1.640	0.056	1.726	-0.010	1.760	-0.350
	0.843	1.590	0.309	1.622	-0.029	1.123	-0.823
$MgrStake_{h,t-1}$	-0.999	1.008	0.312	1.849	0.416	1.287	0.493
	-1.095	0.666	1.204	1.364	1.266	0.874	0.965
$Leverage_{h,t-1}$	-0.427	-3.191*	-0.386	-3.299**	-0.388	-2.915	-0.377
	-0.205	-1.901	-0.910	-2.036	-0.862	-1.490	-0.763
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,834	11,053	18,849	7,642	9,155	5,322	6,186
R^2	0.007	0.013	0.005	0.016	0.005	0.017	0.008

Table 3: Hedge fund bilateral repo activity

This table presents results of the panel regression model given in equation (5). The dependent variables are shown in the first row. The data are monthly from January 2013 to March 2020. The specifications include fund fixed effects. The standard errors are clustered at the fund and time level. The independent variables, with the exception of the indicator variable $March2020_t$, are standardized. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

	Repo Borrowing				Repo Lending	
	Amount	*Maturity*	*Collateral*	*Haircut*	*Amount*	*Maturity*
	$\Delta LogRepoBrrw$	$\Delta RepoBrrwTerm$	$\Delta LogRepoCollat$	$\Delta \frac{RepoCollat}{RepoBrrw}$	$\Delta LogRepoLend$	$\Delta RepoLendTerm$
	(1)	(2)	(3)	(4)	(5)	(6)
$March2020_t$	-1.467	3.002***	0.711	-0.671**	-24.760***	-0.994**
	-0.722	6.182	0.352	-2.332	-9.233	-2.289
$ShareRes_{h,t-1}$	-0.418	0.471	0.986	0.698	1.418	0.807**
	-0.250	1.298	0.559	1.487	0.435	2.560
$PortIlliq_{h,t-1}$	0.778	-0.182	0.707	0.104	-2.221	0.218
	0.366	-0.219	0.464	0.404	-0.665	0.422
$FinDur_{h,t-1}$	-0.164	-0.094	-0.171	0.132	2.695*	-0.033
	-0.126	-0.191	-0.121	0.741	1.726	-0.210
$LogNAV_{h,t-1}$	-0.527	0.415	-0.573	-0.230	0.800	0.170
	-0.214	1.483	-0.287	-0.873	0.353	0.660
$NetRet_{h,t-1}$	1.564	-0.155	1.135	0.016	0.718	-0.292
	1.146	-1.103	0.958	0.151	0.546	-0.959
$NetFlows_{h,t-1}$	2.297***	0.120	1.773***	0.038	0.092	0.080
	3.260	0.654	2.814	0.440	0.107	0.510
$MgrStake_{h,t-1}$	0.001	-0.323	-0.158	0.219***	0.627	-0.095
	0.001	-1.109	-0.202	3.439	0.407	-0.622
$Leverage_{h,t-1}$	-2.556***	-0.040	-2.142**	0.036	-1.976**	0.004
	-2.831	-0.362	-2.394	0.585	-2.098	0.034
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,387	9,387	9,810	9,810	9,083	9,083
R^2	0.014	0.022	0.015	0.012	0.014	0.021

Table 4: Enhanced regulation of creditors and hedge fund borrowing

This table presents results of the panel regression model given in equations (6), (7), and (8). The dependent variable is $\Delta \log HF_Crdtr_Credit_{h,p,t}$ (in %). The data are quarterly from March 2013 to March 2020 and include UST hedge funds that borrow predominantly through repo on average over the last three months of 2019. The specifications include combinations of fund, quarter, and creditor fixed effects where indicated. The standard errors are clustered at the creditor and time level. The independent variables, with the exception of the indicator variables $March2020_t$ and $IsGSIB_{p,t}$, are standardized. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
$March2020_t \times IsGSIB_{p,t}$	12.032***	11.285***	13.374***	12.637**	13.335***	13.375***
	9.589	4.141	3.701	2.496	3.318	3.316
$IsGSIB_{p,t}$	-0.602	-5.143***	-6.230**	-2.516	14.215***	13.540***
	-0.464	-2.972	-2.315	-0.840	4.630	4.742
$LogHF_Crdtr_Credit_{h,p,t-1}$					-80.762***	-74.351***
					-27.208	-16.801
$CrdtrRankInHF_{h,p,t-1}$						-0.325
						-0.222
$HFRankInCrdtr_{h,p,t-1}$						-6.428**
						-2.451
Other Controls	No	No	No	No	No	Yes
Fund FE	Yes	Yes	No	No	No	No
Time FE	Yes	Yes	No	No	No	No
Creditor FE	No	Yes	Yes	No	No	No
Fund × Time FE	No	No	Yes	Yes	Yes	Yes
Fund × Creditor FE	No	No	No	Yes	Yes	Yes
Observations	9,816	9,816	9,816	9,816	9,816	9,816
R^2	0.031	0.038	0.236	0.318	0.516	0.517

Table 5: Creditor proximity to leverage constraints and hedge fund borrowing

This table presents results of the panel regression model in equations (6), (7), and (8). The dependent variable is $\Delta \log HF_Crdtr_Credit_{h,p,t}$ (in %). The independent variable $DistanceToLRT_{p,t-1}$ measures the distance between a bank's leverage ratio and its minimum required leverage ratio threshold (LRT). The data are quarterly from March 2015 (when banks were required to start disclosing leverage ratios) to March 2020 and include UST hedge funds that borrow predominantly through repo on average over the last three months of 2019. The specifications include combinations of fund, quarter, and creditor fixed effects where indicated. The standard errors are clustered at the creditor and time level. In Panel A, the sample consists of US G-SIBs and the indicator variable $PostJanuary2018_t$ captures the effective date of the LRT requirement in the US. In Panel B, the sample consists of both US and foreign banks. The indicator variable $PostEffectiveDate_{p,t}$ captures the effective date of the LRT requirement for each bank, which can differ across countries and institutions. The independent variables, with the exception of the indicator variables, are standardized. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: US G-SIBs

	(1)	(2)	(3)	(4)	(5)
$March2020_t \times DistanceToLRT_{p,t-1}$	22.452*	10.179	5.625	4.472	4.665
	2.122	0.750	0.364	0.325	0.334
$PostJanuary2018_t \times DistanceToLRT_{p,t-1}$	-2.227*	-0.488	-0.998	1.376	1.704
	-1.963	-0.319	-0.329	0.248	0.318
$DistanceToLRT_{p,t-1}$	-0.441	1.025	4.168	-1.359	-1.242
	-0.112	0.224	0.938	-0.212	-0.202
$LogHF_Crdtr_Credit_{h,p,t-1}$				-81.877***	-73.071***
				-19.573	-12.035
Observations	3,281	3,281	3,281	3,281	3,281
R^2	0.074	0.435	0.507	0.641	0.642

Panel B: All banks

$March2020_t \times DistanceToLRT_{p,t-1}$	-2.246	-1.580	0.922	-2.383	-2.173
	-1.283	-0.795	0.397	-0.942	-0.786
$PostEffectiveDate_{p,t} \times DistanceToLRT_{p,t-1}$	0.569	0.709	-0.731	2.604	2.643
	0.234	0.267	-0.284	0.819	0.841
$DistanceToLRT_{p,t-1}$	1.801	1.907	3.086	-0.463	-0.229
	0.692	0.747	1.060	-0.124	-0.061
$PostEffectiveDate_{p,t}$	-0.481	-0.638	1.754	-6.614	-6.495
	-0.118	-0.141	0.410	-1.191	-1.147
$LogHF_Crdtr_Credit_{h,p,t-1}$				-85.796***	-80.519***
				-21.366	-14.995
Observations	7,385	7,385	7,385	7,385	7,385
R^2	0.042	0.232	0.329	0.531	0.532

For both panels

Other Controls	No	No	No	No	Yes
Fund FE	Yes	No	No	No	No
Time FE	Yes	No	No	No	No
Creditor FE	Yes	Yes	No	No	No
Fund × Time FE	No	Yes	Yes	Yes	Yes
Fund × Creditor FE	No	No	Yes	Yes	Yes

Table 6: Creditor revolver drawdown channel and hedge fund borrowing

This table presents results of the panel regression model given in equations (6), (7), and (8). The dependent variable is $\Delta \log HF_Crdtr_Credit_{h,p,t}$ (in %). The independent variable $DrawnDelta_{p,t}$ measures the change in the drawn amount of credit lines of commercial and industrial borrowers of a bank. The data are quarterly from March 2015 (when banks were required to start disclosing leverage ratios) to March 2020 and include UST hedge funds that borrow predominantly through repo on average over the last three months of 2019. The specifications include combinations of fund, quarter, and creditor fixed effects where indicated. The standard errors are clustered at the creditor and time level. In Panel A, the sample consists of US G-SIBs only. In Panel B, the sample consists of both US and foreign banks. The independent variables, with the exception of the indicator variables, are standardized. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: US G-SIBs

	(1)	(2)	(3)	(4)	(5)	(6)
$March2020_t \times DrawnDelta_{p,t}$	-1.289	1.121	3.381	6.917*	2.630	2.714
	-0.966	0.413	1.448	2.270	1.275	1.065
$DrawnDelta_{p,t}$	2.134**	2.368***	1.917	1.026	1.027	1.001
	3.409	3.818	1.743	1.029	1.073	0.917
$LogHF_Crdtr_Credit_{h,p,t-1}$					-80.169***	-72.669***
					-18.681	-9.754
Other Controls	No	No	No	No	No	Yes
Fund FE	Yes	Yes	No	No	No	No
Time FE	Yes	Yes	No	No	No	No
Creditor FE	No	Yes	Yes	No	No	No
Fund × Time FE	No	No	Yes	Yes	Yes	Yes
Fund × Creditor FE	No	No	No	Yes	Yes	Yes
Observations	3,031	3,031	3,031	3,031	3,031	3,031
R^2	0.074	0.079	0.427	0.505	0.641	0.642

Panel B: All banks

	(1)	(2)	(3)	(4)	(5)	(6)
$March2020_t \times DrawnDelta_{p,t}$	-1.418	-0.599	0.970	3.313	-0.176	-0.093
	-0.913	-0.255	0.399	1.368	-0.110	-0.054
$DrawnDelta_{p,t}$	0.917	1.136	1.136	0.351	0.529	0.500
	0.873	1.151	1.069	0.302	0.479	0.433
$LogHF_Crdtr_Credit_{h,p,t-1}$					-88.005***	-82.955***
					-15.847	-14.427
Other Controls	No	No	No	No	No	Yes
Fund FE	Yes	Yes	No	No	No	No
Time FE	Yes	Yes	No	No	No	No
Creditor FE	No	Yes	Yes	No	No	No
Fund × Time FE	No	No	Yes	Yes	Yes	Yes
Fund × Creditor FE	No	No	No	Yes	Yes	Yes
Observations	4,527	4,527	4,527	4,527	4,527	4,527
R^2	0.053	0.057	0.308	0.405	0.585	0.585

Table 7: Hedge fund-creditor relationships and bilateral repo

This table presents results of a panel regression model similar to equation (7). The dependent variable is $\Delta \log HF_Crdtr_Credit_{h,p,t}$ (in %). The data are quarterly from March 2013 to March 2020 and include UST hedge funds that borrow predominantly through repo on average over the last three months of 2019. The specifications include combinations of fund, quarter, and creditor fixed effects where indicated. The standard errors are clustered at the creditor and time level. The independent variables, with the exception of the indicator variable are standardized. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Relative importance of credit relationship

	(1)	(2)	(3)	(4)	(5)	(6)
$March2020_t$	8.423***	7.324***			8.138**	6.674**
$\times HFRankInCrdtr_{h,p,t-1}$	5.956	5.058			2.757	2.365
$HFRankInCrdtr_{h,p,t-1}$	-31.227***	-14.877***			-23.195***	-14.408***
	-20.341	-7.762			-11.823	-6.531
$March2020_t$			2.841***	2.226***	-0.032	2.022*
$\times CrdtrRankInHF_{h,p,t-1}$			17.908	7.129	-0.032	1.830
$CrdtrRankInHF_{h,p,t-1}$			-15.432***	-2.730*	-5.698***	-1.456
			-16.956	-1.897	-4.945	-0.966
$March2020_t$		2.264***		5.896***		-0.416
$\times LogHF_Ctpty_Credit_{h,p,t-1}$		5.230		16.279		-0.433
$LogHF_Ctpty_Credit_{h,p,t-1}$		-20.478***		-29.627***		-18.497***
		-7.544		-9.521		-6.091
Fund × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Creditor × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,816	9,816	9,816	9,816	9,816	9,816
R^2	0.447	0.454	0.435	0.451	0.450	0.454

Panel B: Hedge fund activity levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$March2020_t$	-0.798	0.659					0.467	0.172
$\times LogEqTurnover_{h,t-1}$	-0.407	0.379					0.258	0.095
$LogEqTurnover_{h,t-1}$	2.022	0.060					-0.276	0.070
	1.184	0.028					-0.119	0.031
$March2020_t$			4.178*	7.470***			7.275***	
$\times LogFITurnover_{h,t-1}$			1.940	3.359			2.858	
$LogFITurnover_{h,t-1}$			2.314	12.735**			12.779**	
			1.024	2.267			2.282	
$March2020_t$					4.409	10.527***		10.413***
$\times LogUSTTurnover_{h,t-1}$					1.148	3.438		3.138
$LogUSTTurnover_{h,t-1}$					-0.360	-0.342		-0.347
					-0.333	-0.172		-0.167
$March2020_t$		1.826		0.372		0.062	0.392	0.076
$\times LogHF_Ctpty_Credit_{h,p,t-1}$		0.407		0.082		0.013	0.085	0.016
$LogHF_Ctpty_Credit_{h,p,t-1}$		-75.798***		-76.699***		-75.732***	-76.719***	-75.729***
		-16.933		-18.597		-16.829	-18.671	-16.861
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund × Creditor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Creditor × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,534	8,534	8,534	8,534	8,534	8,534	8,534	8,534
R^2	0.051	0.480	0.051	0.483	0.051	0.480	0.483	0.480

Table 8: Portfolio risk limits and hedge fund UST activity

This table presents results of the panel regression model given in equations (9) and (10). The dependent variables are shown in the first row. The data are monthly from January 2013 to March 2020. Columns 5 to 7 show changes to arbitrage exposures for the set of UST hedge funds that had "moderate" or "large" arbitrage exposures over the last three months of 2019. The specifications include fund and time fixed effects. The standard errors are clustered at the fund and time level. The independent variables, with the exception of the indicator variable $March2020_t$, are standardized. Controls are included separately and interacted with the $March2020_t$ variable. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Proximity to risk limit

					$\Delta LogUSTArb$		
	$\Delta LogUST_Gross$	$\Delta LogUST_Long$	$\Delta LogUST_Short$	$\Delta LogUSTDir$	All	Moderate	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$DistAboveRiskLimit_{h,t-1}$	-0.394	0.348	-0.714	-0.817	0.961	1.766	1.593
	-0.679	0.511	-0.545	-0.801	0.749	1.175	0.933
$March2020_t$	-7.518***	-6.269***	-5.521**	-7.106***	-7.947***	-9.333***	-12.344***
$\times DistAboveRiskLimit_{h,t-1}$	-5.058	-4.100	-2.589	-3.619	-3.138	-3.230	-3.471
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,103	13,329	9,170	14,103	8,436	6,082	4,132
R^2	0.032	0.032	0.049	0.019	0.045	0.057	0.066

Panel B: Proximity to risk limit, with controls

					$\Delta LogUSTArb$		
	$\Delta LogUST_Gross$	$\Delta LogUST_Long$	$\Delta LogUST_Short$	$\Delta LogUSTDir$	All	Moderate	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$DistAboveRiskLimit_{h,t-1}$	-0.532	0.488	-0.993	-1.413	0.933	2.003	1.938
	-0.774	0.677	-0.705	-1.177	0.618	1.104	0.964
$March2020_t$	-8.162***	-10.605***	-4.875**	-8.357***	-9.204***	-8.098**	-11.901***
$\times DistAboveRiskLimit_{h,t-1}$	-4.088	-5.291	-2.495	-3.259	-3.230	-2.424	-3.207
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls $\times March2020_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,254	9,599	7,598	10,254	6,975	5,004	3,461
R^2	0.047	0.046	0.065	0.022	0.055	0.077	0.088

Panel C: Level and proximity to risk limit, with controls

					$\Delta LogUSTArb$		
	$\Delta LogUST_Gross$	$\Delta LogUST_Long$	$\Delta LogUST_Short$	$\Delta LogUSTDir$	All	Moderate	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$DistAboveRiskLimit_{h,t-1}$	-0.574	0.510	-1.170	-1.375	1.024	2.246	2.195
	-0.861	0.671	-0.748	-1.185	0.628	1.174	1.014
$RiskLimit_{h,t-1}$	-1.333	0.042	-3.738	0.567	-0.003	5.122	5.292
	-0.895	0.017	-0.798	0.211	-0.000	0.781	0.708
$March2020_t$	-9.155***	-11.854***	-4.148*	-8.928***	-7.878**	-10.010***	-14.049***
$\times DistAboveRiskLimit_{h,t-1}$	-4.940	-5.964	-1.959	-3.517	-2.383	-2.725	-3.541
$March2020_t$	16.373***	15.806***	19.530***	7.995***	47.165***	29.395***	15.844***
$\times RiskLimit_{h,t-1}$	8.557	6.659	4.119	2.671	10.341	5.924	3.034
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls $\times March2020_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,254	9,599	7,598	10,254	6,975	5,004	3,461
R^2	0.049	0.047	0.066	0.023	0.057	0.077	0.088

Table 9: Internal risk limits, funding, redemption risk, and UST activity

This table presents results of the panel regression model of the form given in equation (10). The dependent variables are shown in the first row. The data are monthly from January 2013 to March 2020. Columns 5 to 7 show changes to arbitrage exposures for the set of UST hedge funds that had "moderate" or "large" arbitrage exposures over the last three months of 2019. The specifications include fund and time fixed effects. The standard errors are clustered at the fund and time level. The independent variables, with the exception of the indicator variable $March2020_t$, are standardized. Controls are included separately and interacted with the $March2020_t$ variable. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Redemption risk

					$\Delta LogUSTArb$		
	$\Delta LogUST_Gross$	$\Delta LogUST_Long$	$\Delta LogUST_Short$	$\Delta LogUSTDir$	All	Moderate	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ShareRes_{h,t-1}$	2.768	3.595*	-3.009	3.069	-3.308	-2.314	-2.937
	1.594	1.987	-0.819	1.421	-0.847	-0.564	-0.661
$March2020_t$	-0.863	-8.172***	15.523***	-9.155***	-1.558	13.446***	21.407***
$\times ShareRes_{h,t-1}$	-0.659	-4.250	5.966	-4.666	-0.421	2.978	4.385
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls $\times March2020_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,849	16,874	12,978	18,834	11,053	7,642	5,322
R^2	0.031	0.032	0.040	0.017	0.035	0.050	0.060

Panel B: Funding, redemption risk, and internal risk limits

					$\Delta LogUSTArb$		
	$\Delta LogUST_Gross$	$\Delta LogUST_Long$	$\Delta LogUST_Short$	$\Delta LogUSTDir$	All	Moderate	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$DistAboveRiskLimit_{h,t-1}$	-0.572	0.505	-1.134	-1.381	1.069	2.305	2.313
	-0.806	0.643	-0.730	-1.177	0.654	1.160	1.018
$RiskLimit_{h,t-1}$	-1.337	0.054	-3.837	0.578	-0.122	4.771	5.060
	-0.892	0.022	-0.811	0.212	-0.022	0.700	0.658
$GSIB_BrrwShare_{h,t-1}$	-0.392	0.833	-5.216	1.279	-5.800	-7.420	-8.913
	-0.176	0.268	-1.123	0.315	-1.087	-1.155	-1.063
$ShareRes_{h,t-1}$	1.998	2.404	-5.873	1.249	-6.386	-5.317	-3.379
	1.250	1.102	-1.532	0.464	-1.501	-1.188	-0.674
$March2020_t$	-9.123***	-11.989***	-4.872**	-9.052***	-9.242***	-12.317***	-17.180***
$\times DistAboveRiskLimit_{h,t-1}$	-4.889	-5.965	-2.299	-3.514	-2.799	-3.431	-5.156
$March2020_t$	16.196***	16.140***	20.241***	8.692***	48.155***	33.055***	21.757***
$\times RiskLimit_{h,t-1}$	8.440	6.819	4.403	2.892	10.521	6.943	4.917
$March2020_t$	-4.629	7.201	45.767***	18.237***	41.305***	57.513***	72.247***
$\times GSIB_BrrwShare_{h,t-1}$	-1.097	1.270	6.025	2.702	5.016	5.976	7.144
$March2020_t$	15.186***	7.042**	23.037***	-1.981	3.347	24.977***	34.907***
$\times ShareRes_{h,t-1}$	6.821	2.456	4.581	-0.537	0.653	4.057	4.413
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls $\times March2020_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,254	9,599	7,598	10,254	6,975	5,004	3,461
R^2	0.049	0.048	0.066	0.023	0.058	0.079	0.091

Table 10: Hedge fund cash, liquidity, and leverage

This table presents results of the panel regression model given in equation (5). The dependent variables are shown in the first row. The data are from January 2013 to March 2020. The specifications include fund fixed effects. The standard errors are clustered at the fund and time level. The independent variables, with the exception of the indicator variable $March2020_t$, are standardized. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Cash and liquidity

	$\Delta LogFreeCashEq$	$\Delta \frac{FreeCashEq}{NAV}$	$\Delta LogCash$	$\Delta \frac{Cash}{NAV}$	$\Delta PortIlliq$
	(1)	(2)	(3)	(4)	(5)
$March2020_t$	25.708***	6.284***	23.001***	8.817***	-10.682***
	18.866	36.677	20.196	27.559	-8.389
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Observations	20,236	21,377	18,765	18,973	7,625
R^2	0.012	0.025	0.015	0.021	0.084

Panel B: Fund size and leverage

	$\Delta LogPortfolioGNE$	$\Delta LogPortGNEnoUST$	$\Delta LogOpenPositions$	$\Delta LogNAV$	$\Delta LogGAV$	$\Delta LeverageRatio$
	(1)	(2)	(3)	(4)	(5)	(6)
$March2020_t$	-21.735***	-23.942***	-4.634***	-14.102***	-13.046***	-0.005
	-44.125	-43.468	-8.262	-25.187	-18.178	-0.194
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,694	21,611	21,676	7,625	7,625	7,625
R^2	0.071	0.073	0.026	0.246	0.188	0.121

Table 11: Basis traders versus other UST traders

This table presents results of the panel regression model adapted from the specification in equation (9). The dependent variables are shown in the first row. The data are from January 2013 to March 2020. Panel A columns 5 to 7 show changes to arbitrage exposures for the set of UST hedge funds that had "moderate" or "large" arbitrage exposures over the last three months of 2019. All regressions are with monthly data with the exception of the last two columns in Panel C. The specifications include fund and time fixed effects. The standard errors are clustered at the fund and time level. The independent variables, with the exception of the indicator variables $March2020_t$ and $BasisTrader_h$, are standardized. Controls are included separately and interacted with the $March2020_t$ variable. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: U.S. Treasury exposure

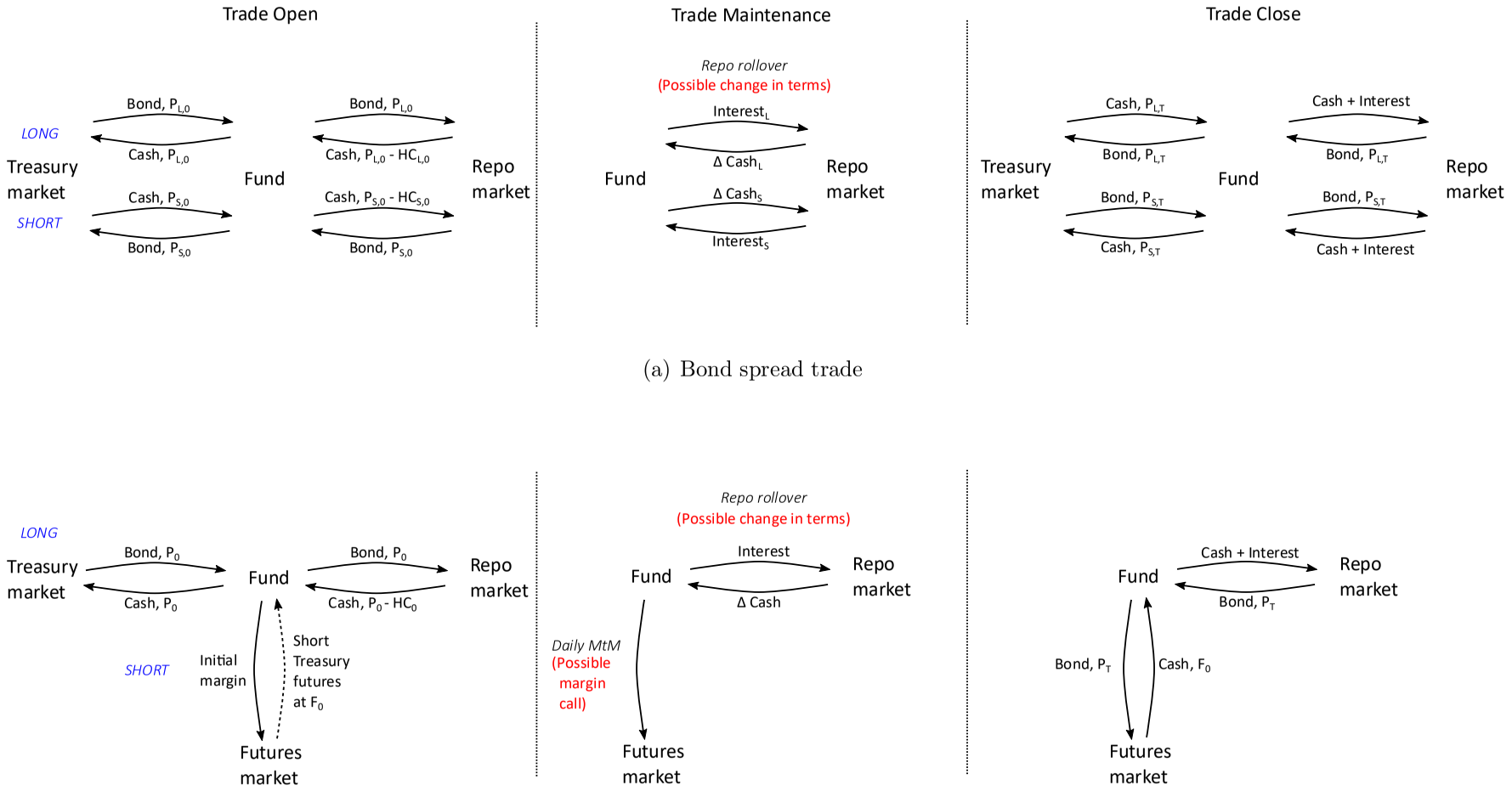
					$\Delta LogUSTArb$		
	$\Delta LogUST_Gross$	$\Delta LogUST_Long$	$\Delta LogUST_Short$	$\Delta LogUSTDir$	All	Moderate	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$March2020_t$	4.938	0.120	4.325	-9.176	9.161	22.586***	22.612***
$\times BasisTrader_h$	1.243	0.028	0.630	-1.328	1.233	3.308	3.193
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls $\times March2020_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,849	16,874	12,978	18,834	11,053	7,642	5,322
R^2	0.031	0.032	0.040	0.017	0.035	0.050	0.060

Panel B: Repo exposure, maturity, and collateral haircuts

	Exposure		Maturity		Haircut
	$\Delta LogRepoBorrowing$	$\Delta LogRepoLending$	$\Delta RepoBrrwTerm$	$\Delta RepoLendTerm$	$\Delta \frac{RepoTotalCollateral}{RepoBorrowing}$
	(1)	(2)	(3)	(4)	(5)
$March2020_t$	23.206***	-6.666	-3.355***	-0.414	1.361**
$\times BasisTrader_h$	4.174	-1.054	-5.801	-0.355	2.307
Controls	Yes	Yes	Yes	Yes	Yes
Controls $\times$ $March2020_t$	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	9,387	9,083	9,387	9,083	9,810
R^2	0.039	0.041	0.045	0.072	0.029

Panel C: Cash and liquidity position

	$\Delta LogFreeCashEq$	$\Delta \frac{FreeCashEq}{NAV}$	$\Delta LogCash$	$\Delta \frac{Cash}{NAV}$	$\Delta LogPortIlliq$
	(1)	(2)	(3)	(4)	(5)
$March2020_t$	-15.382***	-2.178***	18.269***	8.902***	15.363***
$\times BasisTrader_h$	-4.976	-2.856	2.869	4.338	3.464
Controls	Yes	Yes	Yes	Yes	Yes
Controls $\times$ $March2020_t$	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	20,236	21,377	18,765	18,973	7,625
R^2	0.022	0.044	0.022	0.032	0.099



(a) Bond spread trade

(b) Cash-futures basis trade

Figure A1: Exposures and cash flows at trade open, trade maintenance, and trade close

This figure illustrates the securities flows, cash flows, and the exposures created at trade open, trade maintenance and trade close when trading a typical (a) long-short bond spread trade and (b) Treasury cash-futures basis trade. HC represents the amount of the haircut, i.e., the difference between the repo loan amount provided to the hedge fund by the dealer and the value (P) of the collateral posted with the dealer by the fund.

Table A1: Pre-crisis UST exposure and hedge fund UST activity

This table presents results of the panel regression model given in equation (5). The dependent variables are shown in the first row. The data are monthly from January 2013 to March 2020. Results are shown for three sets of hedge funds that, on average over the last three months of 2019, had: (i) \$1 million $\leq UST_Gross <$ \$100 million; (ii) \$100 million $\leq UST_Gross <$ \$1 billion; and (iii) $UST_Gross \geq$ \$1 billion. Columns 5 to 7 show changes to arbitrage exposures for the set of UST hedge funds that had "moderate" or "large" arbitrage exposures over the last three months of 2019. The specifications include fund fixed effects. The standard errors are clustered at the fund and time level. The independent variables, with the exception of the indicator variable $March2020_t$, are standardized. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

						$\Delta LogUSTArb$		
Pre-crisis		$\Delta LogUST_Gross$	$\Delta LogUST_Long$	$\Delta LogUST_Short$	$\Delta LogUSTDir$	All	Moderate	Large
UST_Gross		(1)	(2)	(3)	(4)	(5)	(6)	(7)
1m to 100m	$Mar2020_t$	8.634***	8.778***	-4.514	23.918***	-34.651***	-40.714***	12.019
		4.066	2.684	-1.094	8.110	-3.292	-2.947	0.859
	Obs	5,326	3,821	3,360	5,326	1,887	1,069	571
	R^2	0.015	0.021	0.022	0.012	0.018	0.017	0.020
100m to 1b	$Mar2020_t$	-16.659***	-19.717***	0.005	-20.109***	-3.978	-33.261***	-35.930***
		-7.112	-6.979	0.001	-6.143	-0.616	-4.742	-3.825
	Obs	6,904	6,511	4,344	6,889	3,966	2,402	1,672
	R^2	0.016	0.011	0.021	0.009	0.014	0.017	0.019
≥1b	$Mar2020_t$	-47.600***	-33.687***	-53.132***	-46.861***	-35.607***	-55.458***	-55.666***
		-25.913	-12.703	-10.846	-13.785	-9.209	-13.818	-9.854
	Obs	6,619	6,542	5,274	6,619	5,200	4,171	3,079
	R^2	0.036	0.024	0.016	0.010	0.014	0.019	0.020

Table A2: Hedge fund returns and investor flows

This table presents results of the panel regression model given in equation (5). The dependent variables are shown in the first row. The data are from January 2013 to March 2020. Regression (1) is on monthly net returns ($NetRetM$), while regressions (2) and (3) are on quarterly returns ($NetRetQ$) and flows ($NetFlows$), respectively. The specifications include fund fixed effects. The standard errors are clustered at the fund and time level. The independent variables, with the exception of the indicator variable $March2020_t$, are standardized. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

	$NetRetM$	$NetRetQ$	$NetFlows$
	(1)	(2)	(3)
$March2020_t$	-6.629***	-9.903***	-1.792***
	-37.528	-23.493	-5.967
$ShareRes_{h,t-1}$	0.055	0.022	1.196
	0.761	0.148	1.387
$PortIlliq_{h,t-1}$	-0.142	-0.111	-2.011***
	-1.319	-0.208	-3.364
$FinDur_{h,t-1}$	0.042	0.398	0.517*
	0.874	1.315	1.812
$LogNAV_{h,t-1}$	-0.402***	-1.162**	-7.696***
	-2.714	-2.275	-7.402
$NetRet_{h,t-1}$	0.025	1.331*	-0.989**
	0.193	1.790	-2.346
$NetFlows_{h,t-1}$	-0.021	-0.583***	3.054***
	-0.570	-3.301	6.573
$MgrStake_{h,t-1}$	-0.076*	-0.171	0.709
	-1.731	-1.319	1.450
$Leverage_{h,t-1}$	0.081	0.128	-0.634
	1.347	0.624	-1.405
Fund FE	Yes	Yes	Yes
Observations	21,659	7,630	7,618
R^2	0.194	0.549	0.344

Table A3: Variable definitions

This table presents definitions of the main variables used in this paper. The first column gives the variable name. The second column includes a short description. The last column gives the reference to the raw data source in Form PF (https://www.sec.gov/about/forms/formpf.pdf) or Form ADV (https://www.sec.gov/about/forms/formadv.pdf). Variables are monthly where the description indicates "(m)" and quarterly otherwise . Detailed descriptions and summary statistics of these variables are in section 2.

Variable Name	Description	Source
$RiskLimit_{h,t}$	The 12 month rolling average VaR with a time horizon of one month and a probability of 5% (m)	PF Q40
$DistAboveRiskLimit_{h,t}$	The difference between the VaR in period t and the $RiskLimit_{h,t-1}$. (m)	PF Q40
$FreeCashEq_{h,t}$	Unencumbered cash and cash equivalents. Includes Treasury and agency securites not posted as collateral.† (m)	PF Q33
$Cash_{h,t}$	Cash and cash equivalents, excluding government securites. (m)	PF Q30
$NAV_{h,t}$	Net asset value, or the amount of investor equity, of the hedge fund.	PF Q9
$GAV_{h,t}$	Gross asset value, akin to balance sheet assets, of the hedge fund.	PF Q9
$LeverageRatio_{h,t}$	Balance sheet leverage, i.e. the ratio of gross asset value to net asset value, of the hedge fund.	PF Q8, Q9
$PortIlliq_{h,t}$	The weighted average time (in days) it would take to liquidate the hedge fund's portfolio, assuming no fire sale discounting.	PF Q32
$ShareRes_{h,t}$	The weighted average time (in days) it would take for the investors of the hedge fund to withdraw all the fund's NAV.	PF Q50
$FinDur_{h,t}$	The weighted average maturity (in days) of the hedge fund's borrowing.	PF Q46(b)
$MgrStake_{h,t}$	The percent of the net asset value of the hedge fund owned by the managers or their related persons.	ADV Schedule D, Section 7.B.(1), Q14
$NetRetQ_{h,t}$ ($NetRetM_{h,t}$)	Net-of-fee quarterly (monthly) returns of the hedge fund.	PF Q17
$NetFlows_{h,t}$	Net investor flows to the hedge fund, estimated as $NetFlows_{h,t} = \frac{NAV_{h,t} - NAV_{h,t-1} \times (1+r_{h,t})}{NAV_{h,t-1}}$ (m)	PF Q9, Q17
$OpenPositions_{h,t}$	Number of open positions in the hedge fund's portfolio. (m)	PF Q34
$GNE_{h,t}$	Gross notional exposure estimated by summing long and short asset class exposures. (m)	PF Q30
$PortfolioGNE_{h,t}$	Gross notional exposure estimated by summing long and short exposures to non-cash asset classes. (m)	PF Q30
$Strategy_h$	Investment strategy of the hedge fund (Credit, Equity, Event Driven, Macro, Relative Value, Multi-strategy, or Other). See Online Appendix for classification methodology.	PF Q20

Continued on the next page.

Table A3: Variable definitions (continued)

Variable Name	Description	Source
$EqTurnover_{h,t}$	Sum of absolute value of all equity transactions of hedge fund adviser. (m)	PF Q27
$FITurnover_{h,t}$	Sum of absolute value of all fixed income transactions of hedge fund adviser. (m)	PF Q27
$USTTurnover_{h,t}$	Sum of absolute value of all UST transactions of hedge fund adviser. (m)	PF Q27
$UST_Gross_{h,t}$	Sum of long and short notional exposures to U.S. Treasury securities, including derivatives. (m)	PF Q30
$UST_Long_{h,t}$	Long notional exposure to U.S. Treasury securities, including derivatives. (m)	PF Q30
$UST_Short_{h,t}$	Short notional exposure to U.S. Treasury securities, including derivatives. (m)	PF Q30
$USTArbitrage_{h,t}$	The long-short balanced share of a fund's U.S. Treasury securities notional exposure, including derivatives. (m)	PF Q30
$USTDirectional_{h,t}$	The unbalanced share of a fund's U.S. Treasury securities notional exposure, including derivatives. (m)	PF Q30
$RepoBorrowing_{h,t}$	Value of repurchase agreements through which the hedge fund has borrowed cash and lent securities. (m)	PF Q30
$RepoLending_{h,t}$	Value of repurchase agreements through which the hedge fund has borrowed securities and lent cash. (m)	PF Q30
$RepoBrrwTerm_{h,t}$	Average term (in days) of the hedge fund's $RepoBorrowing_{h,t}$. (m)	PF Q30
$RepoLendTerm_{h,t}$	Average term (in days) of the hedge fund's $RepoLending_{h,t}$. (m)	PF Q30
$RepoTotalCollateral_{h,t}$	Total collateral posted by the hedge fund in support of its $RepoBorrowing_{h,t}$. (m)	PF Q43(b)(ii)(A-C)
$RepoClearedCCP_{h,t}$	Estimated percentage (by value) of repo trades entered into by the hedge fund that were cleared by a CCP.	PF Q24(d)
$BasisTrader_h$	Indicator for hedge fund predominantly engaging in the cash-futures basis trade in its UST portfolio. See Online Appendix for classification methodology.	PF Q20, Q30
$TotalMCBorrowing_{h,t}$	Total borrowings of the hedge fund across its major creditors, i.e. those from whom it borrows amounts totalling 5% or more of its net asset value.	PF Q47
$NumCrdtrsPerHF_{h,t}$	The number of creditors lending to the hedge fund.	PF Q47
$HF_Crdtr_Credit_{h,p,t}$	Amount borrowed by hedge fund h from creditor p at the end of quarter t.	PF Q47
$CrdtrRankInHF_{h,p,t}$	Rank of creditor p based on hedge fund h's borrowing at the end of quarter t, normalized to the range $[0, 1]$.	PF Q47
$HFRankInCrdtr_{h,p,t}$	Rank of hedge fund h based on creditor p's lending at the end of quarter t, normalized to the range $[0, 1]$.	PF Q47
$IsCrdtrCustodian_{h,p,t}$	Indicator for whether creditor p is one of hedge fund h's custodians as of the end of quarter t.	ADV Schedule D, Section 7.B.(1), Q24/25

†In the data, "cash and cash equivalents" refer to cash, cash equivalents (e.g., bank deposits, certificates of deposits, money market fund investments), and US Treasury and agency securities.

Online Appendix for "LTCM Redux? Hedge Fund Treasury Trading and Funding Fragility"

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March 2023

A Background and data

A.1 Value-at-risk (VaR) measure

Form PF Question 40 requires a qualifying hedge fund to report detailed information about its fund-level value-at-risk (VaR) calculation if the fund "regularly calculates" VaR. Information reported includes confidence level, time horizon in days, and VaR level as a percentage of the fund's NAV for each month in the reporting period. Details about the calculation method (historical simulation, parametric, Monte Carlo simulation, or other), length of historical lookback period, and weighting method (if any) are also reported. If a fund calculates VaR for multiple combinations of confidence intervals, horizons, and historical observation periods, then information about each of these combinations is reported.

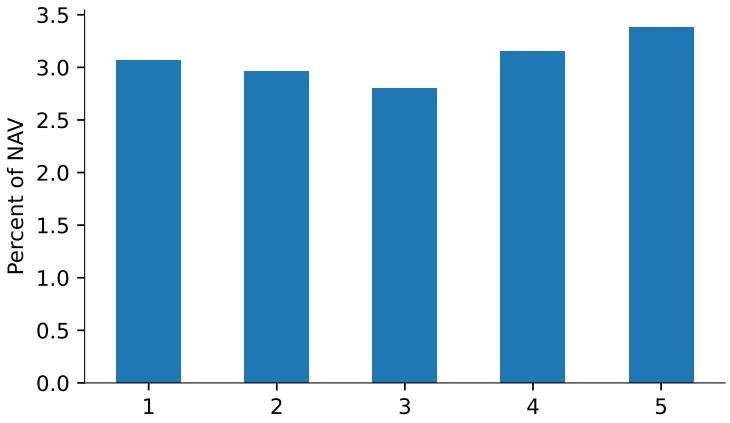
To make reported VaRs comparable across funds, we use the following method to convert reported VaRs to the same confidence level and time horizon. Let $VaR(\alpha_1, T_1)$ and $VaR(\alpha_2, T_2)$ be a fund's VaR (expressed as a percentage of NAV) for two potentially different confidence levels, α_1 and α_2, and two potentially different time horizons, T_1 and T_2. Under the assumption that the fund's continuously compounded daily returns are independent and identically normally distributed with zero mean and constant variance, we can show that

$$VaR(\alpha_2, T_2) = \frac{z_{\alpha_2}}{z_{\alpha_1}} \sqrt{\frac{T_2}{T_1}} VaR(\alpha_1, T_1), \tag{A.1}$$

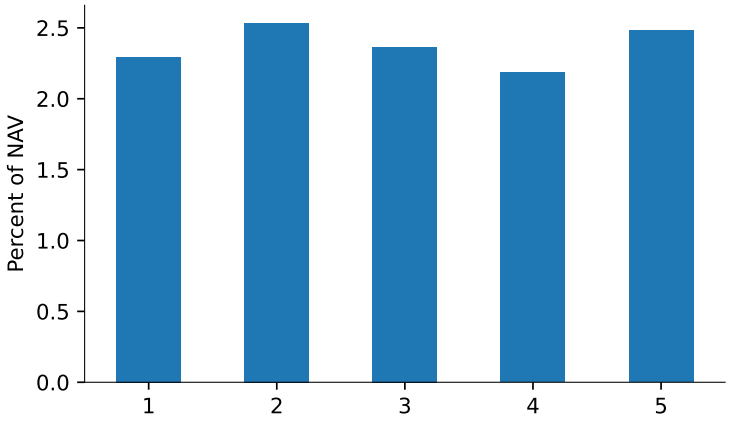
*Kruttli: Indiana University. Email: mkruttli@iu.edu. Monin: The Board of Governors of the Federal Reserve System. Email: phillip.monin@frb.gov. Petrasek: The Board of Governors of the Federal Reserve System. Email: lubomir.petrasek@frb.gov. Watugala: Indiana University. Email: sumudu@iu.edu.

where z_{α_i} is the quantile of the standard normal distribution, i.e. $z_{\alpha_i} = \Phi^{-1}(\alpha_i)$. By writing the fund's reported VaR as $VaR(\alpha_1, T_1)$ and setting $\alpha_2 = 0.05$ and $T_2 = 21$ trading days, we use (A.1) to convert all reported VaRs to a confidence level of 5% and a monthly time horizon. If a fund reports VaRs for multiple combinations of confidence levels, horizons, and historical observation periods, then all VaRs are first converted and are then averaged to obtain a single, fund-month level VaR.

Figure A.1 shows the average hedge fund risk limit—the 12-month moving average VaR—for five creditor groups sorted into quintiles based on total amount lent to hedge funds. Average risk limits of hedge funds are similar across creditor groups. Figure A.2 depicts how funds' risk limits vary with different fund characteristics that we include as controls in the regressions of the main draft. As expected, a higher risk limit is correlated with higher return volatility and returns. Further, hedge funds with a high risk limit are generally smaller, consistent with smaller funds being willing to take on more risk due to growth aspirations. The higher risk limit is also reflected in shorter share restrictions. Higher risk limit funds employ less leverage, which is likely related to their smaller size, and the fact that smaller funds find it more challenging to borrow from creditors, as shown in Section 3.3 of the main draft. Corresponding to the reduced funding, their UST arbitrage positions relative to their gross UST positions are also smaller. Interestingly, funds with a higher manager stake have a higher risk limit, which suggests that a fund's risk limit is related to a managers' predisposition for taking on risk.



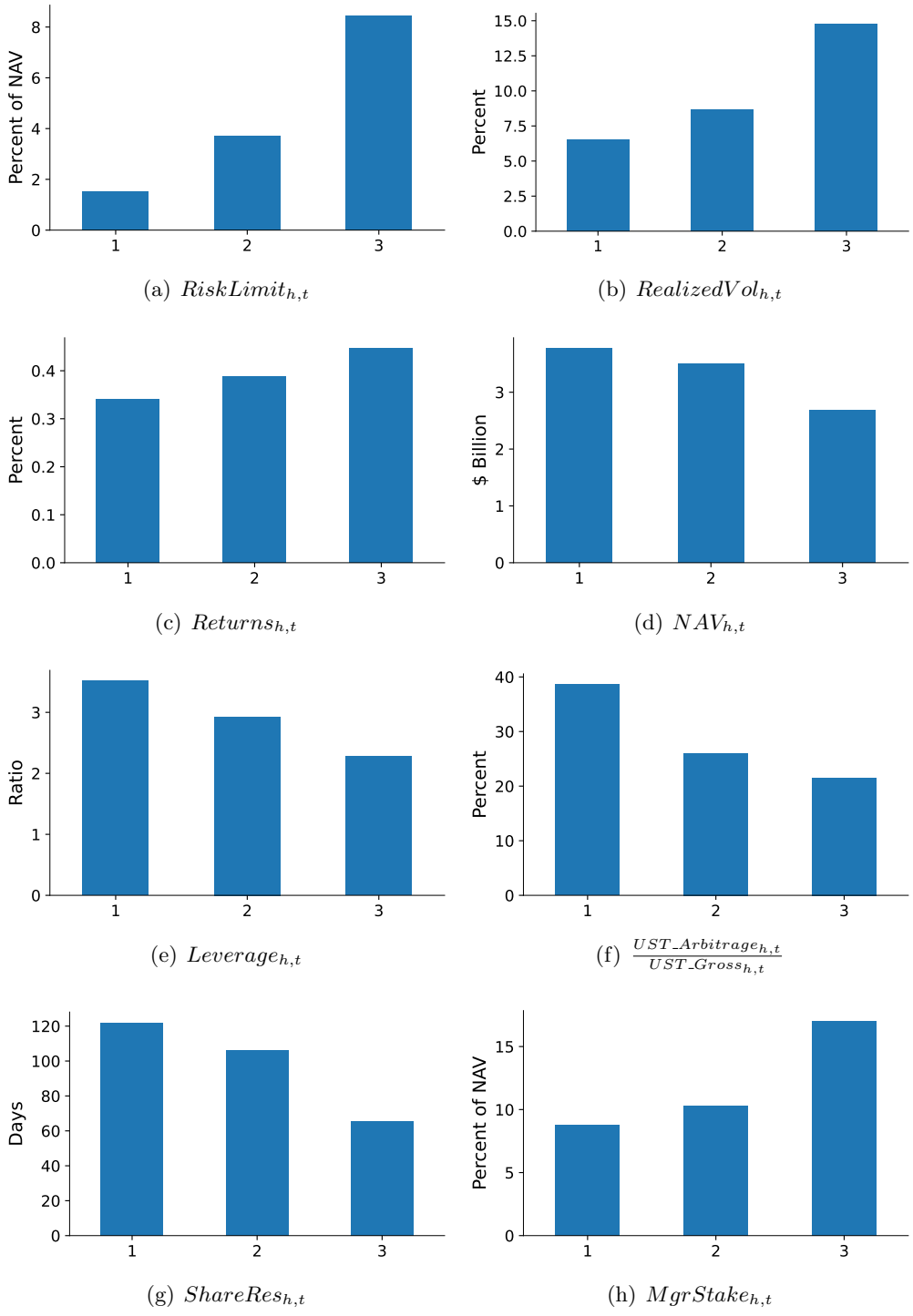
(a) Equal-weighted



(b) Lending-weighted

Figure A.1: Distribution of mean $RiskLimit_{h,t}$ across creditors

This figure shows the (a) equal-weighted and (b) lending-weighted mean $RiskLimit_{h,t}$ for each group of creditors sorted into quintiles by total amount lent to hedge funds each quarter.



(a) $RiskLimit_{h,t}$ (b) $RealizedVol_{h,t}$

(c) $Returns_{h,t}$ (d) $NAV_{h,t}$

(e) $Leverage_{h,t}$ (f) $\frac{UST_Arbitrage_{h,t}}{UST_Gross_{h,t}}$

(g) $ShareRes_{h,t}$ (h) $MgrStake_{h,t}$

Figure A.2: Hedge fund characteristics by $RiskLimit_{h,t}$ tercile

This figure presents histograms of the mean value of characteristics of hedge funds sorted into $RiskLimit_{h,t}$ terciles each quarter.

A.2 Overview of fixed income arbitrage strategies

In this section, we provide a high-level overview of the economics of hedge funds' fixed income arbitrage strategies. Figure A1 in the main paper illustrates the securities flows, cash flows, and exposures associated with trade open, trade maintenance, and trade close for a typical (a) long-short bond spread trade and (b) Treasury cash-futures basis trade.

Duarte, Longstaff, and Yu (2007) provide an overview of several arbitrage trading strategies of fixed income hedge funds and simulates their risk-return trade offs. Edward (1999) and Jorion (2000) discuss the liquidity risk, volatility risk, default risk, and other risks inherent in fixed income arbitrage trading in the context of the 1998 meltdown of Long-Term Capital Management (LTCM), which engaged in such bond spread trading until a systematic shock caused massive losses that threatened systemic stability and led to a Fed-arranged broker takeover of the fund's positions. Industry insiders and observers drew parallels between the 1998 LTCM episode and the impact of the March 2020 shock on fixed income hedge funds. There are indeed some parallels, but, as we describe when presenting the main results in the paper, also important differences between the two episodes.

A.2.1 Long-short bond spread trading

Long-short bond spread trading bets on the convergence of a particular bond spread—such as the on-the-run/off-the-run (ONR-OFFR) spread—due to theoretical or statistical predictions on the relative value of the two securities forming the spread. Details on the life cycle of a typical long-short bond spread trade are depicted in Figure A1(a). For such trades to be sufficiently profitable for a hedge fund, these arbitrage trades are typically significantly leveraged. Long UST securities positions are primarily financed via repurchase agreements (repo borrowing), while short UST securities positions are primarily sourced through reverse repo (repo lending).

Hedge funds engaging in such convergence trades generally go long the more illiquid security and short the more liquid security to earn a liquidity premium. In the case of the ONR-OFFR spread, this means going long the OFFR bond and short the ONR bond. In a typical market stress episode, liquidity risk spikes and such spreads widen. During such an episode, if a fund is unable to obtain sufficient capital or funding to hold onto spread convergence trades, the fund would have

to liquidate the trades at unfavorable prices in illiquid markets and realize losses.

In addition to liquidity risk, trade maintenance exposes a fund to repo rollover risk. Under extreme conditions, the dealer may refuse to roll over the repo loan funding the long side of the trade. Newly rolled-over loans might have higher haircuts if Treasury collateral is suddenly more volatile, a higher interest rate, or a lower borrowing amount if the value of the collateral (bond price) has gone down. Each of these possibilities increases the cost of carrying the trade.

A.2.2 UST cash-futures basis trading

The UST cash-futures basis trade became popular in the years preceding March 2020. In essence, it is a cross-market arbitrage constructed by shorting a Treasury futures contract and going long a Treasury security deliverable into that contract, funding the long position with repo borrowing.[1] We find that there was a significant increase in repo borrowing between early 2018 and February 2020, indicating a marked increase in long UST securities holdings (see Figure B.1). Before early 2018, aggregate hedge fund repo borrowing and lending exposures were generally matched, as one would observe with long-short bond spread trading strategies such as trading on-the-run/off-the-run spreads or yield spreads. The divergence between hedge fund repo borrowing and lending between early 2018 and February 2020 was likely driven by a significant increase in UST cash-futures basis trading.

In a UST cash-futures basis trade, a hedge fund goes long the (cheapest-to-deliver) Treasury security and goes short the corresponding Treasury futures contract. The futures leg does not require reverse repo, so the divergence between hedge fund repo borrowing and lending is consistent with reports of a significant increase in UST cash-futures basis trading. Typically, this is a low volatility, low yield convergence trade that is operationally intensive and requires leverage to be worthwhile. The trade is profitable as long as the actual cost of carrying the cash position (the "repo rate" or the cost of repo borrowing for the hedge fund) is below the implied cost of carry on the futures (the "implied repo rate").

As with many other spread trades hedge funds engage in, UST cash-futures basis trades are also primarily "short liquidity," and perform worst in states of the world in which liquidity is scarce.

[1] The long Treasury security in a cash-futures basis trade is typically a Treasury note. We will use the term "bond" when describing the economics of the trade.

Maintaining the trade exposes a fund to repo rollover risk and margin risk, described further below. In addition to liquidity risk, this trade is exposed to basis risk, i.e., the risk that the underlying asset price dynamics diverge from the futures price dynamics.

Details on the basis trade are depicted in Figure A1(b), which follows a typical trade's lifecycle. The transactions and cash flows at initiation are shown on the left. The cash flows include initial margin on the short futures contract and net cash needed above repo borrowings to complete the purchase of the bond. Given low haircuts on Treasury repo and low margin levels on futures, these initial cash outlays are low relative to the exposure of the trade. Thus, the UST cash-futures basis trade is very highly leveraged. As the figure suggests, it is also an operationally intensive trade.

Maintaining the trade to realize its gains exposes the fund to two risks: rollover risk and margin risk. Although the fund would prefer to use term repo with maturity matched to the expiry of the futures, shorter-term or overnight repo is common and exposes the fund to the risk of not being able to continue financing the bond. Under extreme conditions, the dealer may refuse to roll over the repo loan. Newly rolled-over loans might have higher haircuts if Treasury collateral is suddenly more volatile, a higher interest rate, or a lower borrowing amount if the value of the collateral (bond price) has gone down. Each of these possibilities increases the cost of carrying the bond. The second risk is margin risk. If futures prices increase rapidly or volatility leads to higher margin requirements, the fund might have to make variation margin payments to satisfy margin calls. It is worth noting that if cash and futures prices move in lockstep, margin payments may be made using increased repo borrowings from the appreciating collateral. However, if futures prices increase more than bond prices, i.e., if the futures basis widens, as they did in March 2020, there may be net cash demands on the fund related to margin payments. In such a case, the hedge fund would have to immediately meet the margin call to hold on to the basis trade position or liquidate the position at unfavorable prices and realize a loss.

Finally, at trade close on the right, the fund closes its repo and delivers the Treasury into the futures contract. The fund may alternatively choose to roll the trade to the following futures expiry.

A.3 Basis trader classification

We use the following methodology to classify a hedge fund as predominantly engaging in the UST cash-futures basis trade as opposed to other UST trading strategies. The classification recognizes

that a basis trade has broadly balanced long and short UST notional exposures, but the long "cash" side is a physical bond while the short "futures" side is a derivative. As such, only the long side is funded via repo, while the short side is not. This generally contrasts with other UST arbitrage strategies such as on-the-run/off-the-run spread trading where the long and short side of the trade is funded via more balanced repo borrowing and repo lending, respectively.

The algorithm begins by subsetting funds to those whose strategy allocation according to Form PF Question 20 includes some allocation to either "Relative Value, Fixed Income Sovereign" or "Macro, Global Macro." We then classify a fund in this set as a Basis Trader if, during the height of the basis trade between January 2018 and February 2020 (inclusive), its balanced UST position, $USTArbitrageNE$, is positively and significantly correlated at the 5% level with its *net* repo exposure ($RepoBorrowing - RepoLending$). Finally, we manually inspect the results of the algorithm for consistency.

A.4 Converting reported U.S. Treasury exposures to 10-year bond equivalents

Funds supplement their reporting of notional exposures to U.S. Treasury securities on Form PF Question 30 by reporting the duration, weighted average tenor (WAT), or 10-year bond equivalent values for both their long and short exposures. To facilitate comparisons across funds, we convert entries of WAT and duration to 10-year bond equivalent values.

Our method begins with the observation (see section A.4.1) that one can approximate the modified duration of a semi-annual coupon bond at par value given its yield and remaining maturity according to the formula:

$$ModDur(y, \tau) \approx \frac{1}{y}\left(1 - \frac{1}{(1 + \frac{1}{2}y)^{2\tau}}\right), \tag{A.2}$$

where y is the yield-to-maturity (expressed as a decimal) and τ is the remaining time-to-maturity of the bond in years. For zero-coupon bonds such as T-bills, the modified duration is computed as

$$ModDur(y, \tau) = \frac{\tau}{1 + \frac{y}{k}}, \tag{A.3}$$

where k is the compounding frequency per year. Thus, we use $k = 12$ for the 4-week T-bill, $k = 6$ for the 8-week T-bill, $k = 4$ for the 13-week T-bill, and so on.

Our analysis also requires the monthly time series of the Treasury yield curve. We obtain month-end historical constant maturity Treasury rates from the Federal Reserve's H.15 data and linearly interpolate between maturities to form a yield curve estimate. In particular, we use (A.2) to produce a time-varying estimate of the modified duration of the 10-year Treasury note.

To convert reported duration values to 10-year bond equivalent values, we use the following formula:

$$USTexposurein10yrBE = \frac{ReportedDuration}{DurationOf10yrUST} * (ReportedUSTExposure) \tag{A.4}$$

Finally, to convert from WAT to 10-year bond equivalent values, we first convert WAT to duration and then use (A.4). To convert WAT to duration, we use the interpolated U.S. Treasury yield curve to find the approximate yield-to-maturity for a Treasury with WAT remaining years to maturity. The duration is then approximated using (A.2) if WAT is greater than one, or computed using (A.3) if WAT is less than or equal to one.

A.4.1 Derivation of (A.2)

Consider a semi-annual coupon bond with yield-to-maturity y and coupon C with $2n$ remaining semi-annual coupon payments. Write the price P of the bond in terms of two components: the present value of an annuity represented by the coupon payments, and the present value of the par value payment at maturity. The price P per \$100 of par can be written as:

$$P = C\left[\frac{1 - \frac{1}{(1+y/2)^{2n}}}{y/2}\right] + \frac{100}{(1+y/2)^{2n}}. \tag{A.5}$$

Computing the modified duration by taking the derivative with respect to y, we obtain

$$ModDur = -\frac{1}{P}\frac{\partial P}{\partial y} = \frac{\frac{2C}{y^2}\left[1 - \frac{1}{(1+y/2)^{2n}}\right] + \frac{n(100-2C/y)}{(1+y/2)^{2n+1}}}{P} \tag{A.6}$$

For a semi-annual coupon bond at par value, we have that $P = 100$ and $C = 100y/2$ (y is a decimal). Inserting this into the above, we obtain

$$ModDur = \frac{\frac{2\times 100y/2}{y^2}\left[1 - \frac{1}{(1+y/2)^{2n}}\right] + \frac{n(100-2\times 100y/2y)}{(1+y/2)^{2n+1}}}{100} \tag{A.7}$$

$$= \frac{1}{y}\left(1 - \frac{1}{(1+y/2)^{2n}}\right). \tag{A.8}$$

A.5 Average term of repo and reverse repo

As in the case of U.S. Treasury exposures, funds report on Form PF Question 30 the duration, weighted average tenor (WAT), or 10-year bond equivalent values for both their repo borrowing and repo lending. We use these values to estimate the average term of their repo borrowing and repo lending.

A repo can be viewed as a collateralized loan with a single payment of principal and interest at maturity. The duration and WAT of a repo is thus equal to its term, much like the duration and WAT of a zero-coupon bond is its maturity. Finally, we use this observation and (A.4) to convert a 10-year bond equivalent value to the repo term.

A.6 Investment strategy classification

Question 20 on Form PF contains 22 strategy categories to which hedge funds assign shares of their invested net asset value (NAV). Among these is an "Other" category into which funds can manually enter strategies that are not covered by the other 21 sub-strategies. The 22 strategy categories roll up to 8 broad strategies: equity, macro, relative value, event driven, credit, managed futures, investment in other funds, and other. We use these data to classify a hedge fund's broad strategy using a methodology consistent with Kruttli, Monin, and Watugala (2022) applied across the duration of the sample.

First, we inspect the strategies entered in the "Other" category and reclassify entries that are similar to other listed broad strategies. For example, a description of "Relative Value Fixed Income" is reclassified from "Other" to "Relative Value."

Next, the data are normalized so that the sum of each hedge fund's allocation across the 22 strategy categories equals 100% of their NAV. These normalized values are aggregated to the broad

strategy categories, and then further aggregated across all the fund's filings over time. A hedge fund is considered to use a given broad strategy if more than 50% of its aggregated, normalized assets are allocated to that broad strategy. If there is not a broad strategy to which more than 50% of the normalized assets are allocated, then the fund is classified as a multi-strategy fund.

A.7 Dealer classification

Table A.1 presents information on G-SIB designations and primary dealer subsidiaries at the parent bank holding company level. We use the G-SIB designations for our analysis on lending to hedge funds and broker-dealer constraints in Section 3.2 of the main draft.

Table A.1: G-SIB and primary dealer classifications

This table presents G-SIB and primary dealer classifications as of December 2019. The source for the G-SIB classifications is the Financial Stability Board (https://www.fsb.org/work-of-the-fsb/policy-development/addressing-sifis/global-systemically-important-financial-institutions-g-sifis/) and for primary dealers is the New York Fed (https://www.newyorkfed.org/medialibrary/media/markets/Dealer_Lists_1960_to_2014.xls and https://www.newyorkfed.org/markets/primarydealers#additions-and-removals).

Institution	Jurisdiction	G-SIB designated years	Primary dealer subsidiary
Amherst Pierpont	US		1
Agricultural Bank of China	CN	2014 -	0
Bank of America	US	2011 -	1
Bank of China	CN	2011 -	0
Bank of Montreal	CA		1
Bank of New York Mellon	US	2011 -	0
Bank of Nova Scotia	CA		1
Barclays	UK	2011 -	1
BBVA	ES	2012 - 2014	0
BNP Paribas	FR	2011 -	1
Cantor Fitzgerald	US		1
China Construction Bank	CN	2015 -	0
Citigroup	US	2011 -	1
Commerzbank	DE	2011	0
Credit Suisse	CH	2011 -	1
Daiwa Securities Group	JP		1
Deutsche Bank	DE	2011 -	1
Dexia	BE	2011	0
Goldman Sachs	US	2011 -	1
Groupe BPCE	FR	2011 -	0
Groupe Crédit Agricole	FR	2011 -	0
HSBC	UK	2011 -	1
Industrial and Commercial Bank of China	CN	2013 -	0
ING Bank	NL	2011 -	0
Jefferies Group	US		1
JP Morgan Chase	US	2011 -	1
Lloyds Banking Group	UK	2011	0
Mitsubishi UFJ FG	JP	2011 -	0
Mizuho FG	JP	2011 -	1
Morgan Stanley	US	2011 -	1
Nomura Holdings	JP		1
Nordea	SE	2011 - 2017	0
Royal Bank of Canada	CA	2017 -	1
Royal Bank of Scotland	UK	2011 - 2017	1
Santander	ES	2011 -	0
Société Générale	FR	2011 -	1
Standard Chartered	UK	2012 -	0
State Street	US	2011 -	0
Sumitomo Mitsui FG	JP	2011 -	0
Toronto Dominion	CA	2019 -	1
UBS	CH	2011 -	1
Unicredit	IT	2011 -	0
Wells Fargo	US	2011 -	1

B Additional figures and tables

This section presents additional tables. Figure B.1 illustrates the times series of aggregate repo borrowing and repo lending by all hedge funds and separately by hedge fund strategy. Repo lending fell substantially over the two months after the March 2020 turmoil, in line with the continued decrease in hedge UST exposures post-March 2020 and the reduction in precautionary cash holdings after the turmoil. Table B.1 shows estimates for the same regression specification as in Table 2 of the main draft but with additional time series variables added, namely, the Bank of America / Merrill Lynch Option Volatility Estimate (MOVE1), the yield slope, and the Hu, Pan, and Wang (2013) noise measure (HPW).[2] Table B.2 estimates changes in hedge funds' UST exposures but adjusted for changes in UST prices, and B.3 estimates changes in hedge funds' risk-adjusted UST exposures. In Table B.4, we examine if hedge funds of advisers incepted before the LTCM collapse managed their portfolio illiquidity differently. These results suggest that the experience of the LTCM collapse led to hedge funds reducing their portfolio illiquidity by more during March 2020. In contrast, LTCM increased their portfolio illiquidity during the crisis in 1998 by holding on to illiquid assets (Jorion, 2000). This decision was driven by the expectation that once the crisis is over, these illiquid assets will substantially increase in value. Table B.5 shows summary statistics for hedge funds for which at least 50 percent of their total borrowing is through repo. Table B.6 presents hedge fund UST activity in the months after March 2020.

[2]The yield slope is computed as the Treasury 10-year constant maturity rate minus 2-year constant maturity rate.

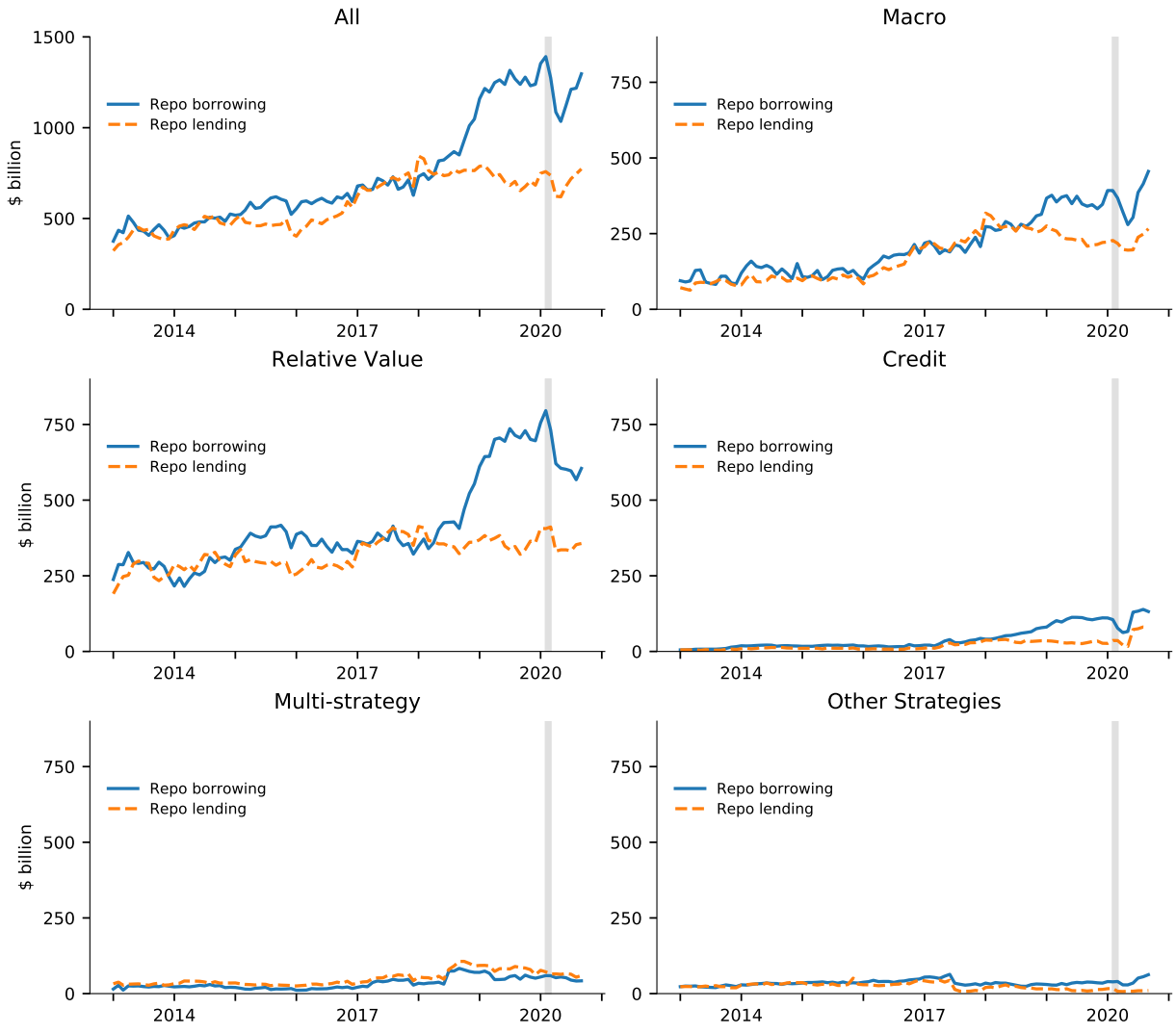


Figure B.1: Hedge fund repo exposures

This figure presents the times series of aggregate repo borrowing and lending exposures from January 2013 to September 2020 for all hedge funds and hedge funds separated into broad strategies: macro, relative value, credit, multi-strategy, and all other strategies. March 2020 is shaded gray.

Table B.1: Hedge fund U.S. Treasury exposures with time series controls

This table presents results of the panel regression model given in equation (5) of the main draft with additional time series controls included. The dependent variables are shown in the first row. The data are monthly from January 2013 to March 2020. Panel B also show changes to arbitrage exposures for the set of UST hedge funds that had "moderate" or "large" arbitrage exposures over the last three months of 2019. The specifications include fund fixed effects. The standard errors are clustered at the fund and time level. The independent variables, with the exception of the indicator variable $March2020_t$, are standardized. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: U.S. Treasury exposure

	$\Delta LogUST_Gross$	$\Delta LogUST_Long$	$\Delta LogUST_Short$	$\Delta \frac{UST_Gross}{NAV}$	$\Delta \frac{UST_Long}{NAV}$	$\Delta \frac{UST_Short}{NAV}$
	(1)	(2)	(3)	(4)	(5)	(6)
$March2020_t$	-20.525***	-21.330***	-22.190***	-15.330***	-9.102***	-7.200***
	-13.089	-12.102	-7.287	-10.281	-8.637	-9.611
$MOVE1_t$	1.100**	1.937**	0.477	0.209	0.592*	-0.324
	2.144	2.624	0.339	0.446	1.790	-1.614
$YieldSlope_t$	-0.256	-0.632	1.009	-1.358***	-0.901**	-0.515***
	-0.522	-1.057	0.723	-2.862	-2.286	-2.710
HPW_t	-0.534	-0.363	-2.767***	-0.321	-0.357	0.018
	-0.823	-0.471	-2.906	-0.509	-0.749	0.079
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,849	16,874	12,978	18,801	18,801	18,801
R^2	0.016	0.016	0.018	0.018	0.017	0.015

Panel B: U.S. Treasury directional and arbitrage exposure

	All UST funds			Moderate UST arbitrage positions		Large UST arbitrage positions	
	$\Delta LogUSTDir$	$\Delta LogUSTArb$	$\Delta \frac{USTArb}{Gross}$	$\Delta LogUSTArb$	$\Delta \frac{USTArb}{Gross}$	$\Delta LogUSTArb$	$\Delta \frac{USTArb}{Gross}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$March2020_t$	-16.876***	-25.040***	-1.960***	-45.373***	-5.750***	-42.824***	-7.596***
	-6.351	-6.989	-3.536	-10.427	-5.648	-9.414	-6.314
$MOVE1_t$	1.551*	1.814	0.006	0.052	-0.189	-0.443	-0.149
	1.984	1.182	0.029	0.028	-0.530	-0.218	-0.344
$YieldSlope_t$	-0.131	0.832	0.066	0.015	-0.141	-0.273	-0.022
	-0.154	0.494	0.301	0.007	-0.392	-0.127	-0.063
HPW_t	-1.047	-3.150**	-0.145	-2.350	0.023	-1.479	-0.094
	-1.085	-2.384	-0.868	-1.442	0.090	-0.946	-0.287
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,834	11,053	18,849	7,642	9,155	5,322	6,186
R^2	0.007	0.014	0.005	0.017	0.006	0.017	0.008

Table B.2: Valuation-adjusted changes in U.S. Treasury exposures

This table presents results of the panel regression model given in equation (5) of the main draft. The dependent variables are shown in the first row and are the changes in UST gross, long, and short exposures, but adjusted for changes in UST prices. The data are monthly from January 2013 to March 2020. The specifications include fund fixed effects. The standard errors are clustered at the fund and time level. The independent variables, with the exception of the indicator variable $March2020_t$, are standardized. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

	$\Delta LogUST_Gross$	$\Delta LogUST_Long$	$\Delta LogUST_Short$	$\Delta \frac{UST_Gross}{NAV}$	$\Delta \frac{UST_Long}{NAV}$	$\Delta \frac{UST_Short}{NAV}$
	(1)	(2)	(3)	(4)	(5)	(6)
$March2020_t$	-24.518***	-23.343***	-26.464***	-17.009***	-10.922***	-14.436***
	-18.875	-12.965	-6.872	-11.924	-9.495	-10.594
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,394	16,667	12,828	18,079	16,306	12,532
R^2	0.023	0.025	0.036	0.016	0.016	0.016

Table B.3: Risk-adjusted changes in U.S. Treasury exposures

This table presents results of the panel regression model given in equation (5) of the main draft. The dependent variables are shown in the first row and are the changes in interest rate risk-adjusted UST gross, long, and short exposures. The data are monthly from January 2013 to March 2020. The specifications include fund fixed effects. The standard errors are clustered at the fund and time level. The independent variables, with the exception of the indicator variable $March2020_t$, are standardized. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

	$\Delta LogUST_Gross_10yEQ$	$\Delta LogUST_Long_10yEQ$	$\Delta LogUST_Short_10yEQ$	$\Delta \frac{UST_Gross_10yEQ}{NAV}$	$\Delta \frac{UST_Long_10yEQ}{NAV}$	$\Delta \frac{UST_Short_10yEQ}{NAV}$
	(1)	(2)	(3)	(4)	(5)	(6)
$March2020_t$	-17.090***	-15.039***	-33.105***	-10.606***	-4.826***	-5.882***
	-9.914	-6.845	-8.452	-10.715	-6.632	-11.906
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,341	16,512	12,633	18,293	18,293	18,293
R^2	0.015	0.013	0.017	0.021	0.017	0.018

Table B.4: Hedge funds that experienced LTCM

This table presents results of the panel regression model adapted from the specification in equation (9) of the main draft, with the interaction term being the variable $LTCMExp_h$, which captures if the fund's adviser was incepted before the LTCM crisis in 1998. The dependent variable is $\Delta LogPortIlliq_{h,t}$ (in %). The data are quarterly from March 2013 to March 2020. The specifications include fund and time fixed effects. The standard errors are clustered at the fund and time level. The independent variables, with the exception of the indicator variables $March2020_t$ and $LTCMExp_h$, are standardized. Controls are included separately and interacted with the $March2020_t$ variable. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

	$\Delta LogPortIlliq$			
	(1)	(2)	(3)	(4)
$March2020_t$	-7.298***	-7.004***		
	-14.268	-5.456		
$LTCMExp_h$	0.518		0.493	
	0.687		0.657	
$March2020_t \times LTCMExp_h$	-10.069***	-9.955***	-10.044***	-9.926***
	-9.235	-4.910	-9.334	-4.921
Controls	Yes	Yes	Yes	Yes
Controls $\times$ $March2020_t$	Yes	Yes	Yes	Yes
Fund FE	No	Yes	No	Yes
Time FE	No	No	Yes	Yes
Observations	7,625	7,625	7,625	7,625
R^2	0.022	0.093	0.028	0.099

Table B.5: Summary statistics for hedge funds primarily borrowing via repo

This table shows select summary statistics over the period from January 2013 to September 2020 for the UST hedge funds that borrow predominantly through repo on average over the last three months of 2019. This is the main sample of hedge funds used in the hedge fund-creditor level analysis on changes to repo borrowing. The N column shows the number of observations used to calculate the statistics in a particular row. The last four columns show percentiles.

	N	Mean	Median	Stdev	25th	75th	10th	90th
$\frac{RepoBorrowing}{TotalBorrowing}$ (%)	8,995	88.786	99.241	15.740	79.379	100.000	59.829	100.000
$TotalMCBorrowing_{h,t}$ (m US$)	2,189	8,738.516	1,027.546	26,954.468	314.389	4,320.877	107.501	21,159.939
$NumCrdtrsPerHF_{h,t}$	2,189	6.265	5.000	5.464	2.000	8.000	1.000	13.200
$HF_Crdtr_Credit_{h,p,t}$ (m US$)	13,819	1,267.736	351.938	2,818.642	132.387	1,087.282	61.780	2,946.323
$\Delta logHF_Crdtr_Credit_{h,p,t}$	11,121	1.370	0.381	52.724	-22.847	25.015	-60.263	62.666
$IsCrdtrCustodian_{h,p,t}$	13,819	0.296	0.000	0.457	0.000	1.000	0.000	1.000

Table B.6: Hedge fund UST trading and funding after the March 2020 shock

This table presents results of the panel regression model given in equation (5) of the main draft but including additional indicator variables for months and quarters after March 2020.The dependent variables are shown in the first row. The data are from January 2013 to September 2020. Panel A shows estimates for quarterly dependent variables, that is, returns, flows, size, and leverage. Panel B shows estimates for changes in monthly UST positions. Columns 5 to 7 show changes to arbitrage exposures for the set of UST hedge funds that had "moderate" or "large" arbitrage exposures over the last three months of 2019. The specifications include fund fixed effects. The standard errors are clustered at the fund and time level. All independent variables except date and quarter indicator variables are standardized. t-statistics are shown below the corresponding coefficient estimates. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Returns, flows, and leverage

	$NetRetQ$	$NetFlows$	$\Delta LogNAV$	$\Delta LogGAV$	$\Delta LeverageRatio$
	(1)	(2)	(3)	(4)	(5)
$March2020_t$	-9.643***	-1.905***	-14.048***	-12.743***	0.008
	-22.043	-5.838	-24.562	-17.621	0.339
$2020Q2_t$	6.601***	-3.324***	2.810***	-0.677	-0.179***
	5.896	-5.012	3.206	-0.705	-7.278
$2020Q3_t$	1.260**	-3.339***	-2.249***	-1.942***	0.068***
	2.166	-6.630	-3.473	-2.803	2.919
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Observations	8,361	8,349	8,356	8,356	8,356
R^2	0.556	0.335	0.231	0.176	0.135

Panel B: U.S. Treasury exposure

					$\Delta LogUSTArb$		
	$\Delta LogUST_Gross$	$\Delta LogUST_Long$	$\Delta LogUST_Short$	$\Delta LogUSTDir$	All	Moderate	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$March2020_t$	-19.486***	-19.172***	-22.019***	-15.602***	-24.883***	-45.354***	-41.942***
	-12.534	-9.979	-7.169	-7.739	-7.244	-10.842	-8.831
$April2020_t$	5.364**	2.889	-3.869	4.867*	-8.587	-10.005	9.815*
	2.555	1.340	-0.699	1.735	-1.479	-1.377	1.893
$May2020_t$	-4.204***	-3.082**	-12.824***	-7.746***	-12.203***	-12.306***	-3.292
	-4.162	-2.099	-5.400	-3.968	-4.874	-3.723	-0.809
$June2020_t$	-5.579***	-4.031***	-16.479***	-7.038***	-16.959***	-13.331***	-4.039
	-4.490	-3.010	-6.028	-3.332	-6.317	-3.926	-1.268
$July2020_t$	-6.547***	-9.836***	-6.005**	-19.833***	-0.546	3.277	-4.076
	-6.657	-5.384	-2.204	-8.978	-0.181	0.876	-1.310
$Aug2020_t$	-3.448***	-3.431***	-6.920***	1.174	-5.850***	-3.341	0.699
	-4.207	-3.960	-2.932	0.534	-2.786	-1.304	0.244
$Sept2020_t$	-4.080***	-3.145***	1.065	-1.154	4.132	-10.459***	-10.634***
	-5.004	-2.751	0.479	-0.670	1.519	-5.266	-4.607
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,776	18,495	14,293	20,761	12,075	8,401	5,872
R^2	0.015	0.016	0.015	0.007	0.013	0.016	0.017

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