LTCM Redux? Hedge Fund Treasury Trading, Funding Fragility, and Risk Constraints*

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July 2024

Abstract

We exploit the 2020 Treasury market shock to analyze how external and internal constraints impact arbitrageurs. Using regulatory filings, we find that hedge funds reduced arbitrage activities and increased cash holdings, despite stable credit and low contemporaneous redemptions. Creditors' regulatory and liquidity constraints were not propagated to hedge funds through repo—Treasury arbitrageurs' predominant financing source. Fund-creditor borrowing data reveal more regulated dealers provided, and more important clients received, higher funding. Value-at-risk reported by funds suggests internal risk constraints were binding. Our results support theoretical predictions that arbitrageur risk constraints and precautionary liquidity management can amplify market instability even when contemporaneous financing remains resilient.

JEL classification: G11, G23, G24, G01

Keywords: Hedge funds, Treasury markets, arbitrage, value-at-risk, risk constraints, liquidity, creditor constraints, relative value

*We thank Viral Acharya, Vikas Agarwal, Yu An, George Aragon, Darrell Duffie, Andrew Ellul, Matthias Fleckenstein, 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, Eric Richert, Noah Stoffman, Gregory Udell, Annette Vissing-Jorgensen, Min Wei, Joshua Younger, and seminar participants at Baylor University, Boston College, Cornell University, Federal Reserve Board, Federal Reserve Bank of Chicago, Federal Reserve Bank of Dallas, FSOC, Indiana University, London Business School, National University of Singapore, Securities Exchange Commission, UCLA, University of Houston, University of Massachusetts-Amherst, University of New South Wales, University of Oklahoma, University of Reading, University of Western Australia, 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, FIRS, Short-Term Funding Markets Conference, Northeastern University Finance 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 been widely discussed since the collapse of Long-Term Capital Management (LTCM) in 1998.[1] Hedge funds may be subject to external and internal constraints that limit their liquidity provision, especially during periods of market stress. During crises, hedge fund arbitrage can be subject to external financing constraints because dealer banks may be unwilling or unable to provide stable financing due to their own regulatory or liquidity constraints (Brunnermeier and Pedersen, 2009; Adrian and Shin, 2010), and investors may run on the fund and redeem their capital (Shleifer and Vishny, 1997). Consequently, hedge funds can impose internal limits on their risk taking to reduce the probability of shortfalls (Lo, 2001). However, theory suggests that such internal constraints may themselves be destabilizing during a crisis by limiting hedge funds' risk-bearing capacity and 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. 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 address this gap by collating a novel, granular regulatory dataset and exploiting the shock to the U.S. Treasury (UST) market in March 2020—a crisis of unprecedented volatility and illiquidity that instigated an extraordinary Federal Reserve intervention in UST markets. This episode 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] To our knowledge, ours is the first study to offer a granular view into hedge fund financing

[1] LTCM suffered massive losses in their arbitrage trades following a series of systematic shocks and was unable to continue to finance its 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.

and risk management during a crisis. We also analyze the uncleared bilateral repo funding market (i.e., borrowing via repurchase agreements between two parties without involving a central counterparty or custodian), which we find is the main source of funding for fixed income arbitrageurs.[3] Despite its importance, this funding market has previously remained opaque due to data limitations. Using data on other repo market segments, such as tri-party or centrally-cleared repo, in place of uncleared bilateral repo data could lead to misleading conclusions (Gorton, Metrick, and Ross, 2020).[4]

During the March 2020 crisis, UST yields increased as investors around the world rushed to sell U.S. Treasuries amid a sudden economic shutdown, calling into question the safe haven status of U.S. Treasuries. UST arbitrage spreads that hedge funds generally bet will converge widened, presenting seemingly profitable opportunities for arbitrage trading.[5] 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 stress by liquidating their arbitrage positions. Analyzing granular data on hedge fund positions, we find that just prior to March 2020, hedge fund aggregate long and short UST exposures were around \$1.4 trillion and \$0.9 trillion, respectively. In March 2020, the average hedge fund with UST holdings significantly reduced its gross exposures and arbitrage activity in UST markets, decreasing both long and short exposures by around 25%. By the end of March 2020, these funds also held 20% higher cash holdings and smaller, more liquid portfolios. In our analyses, we do not find evidence that UST-trading hedge funds exploited the market dislocation and provided

[3]Our novel dataset is primarily constructed using the U.S. Securities and Exchange Commission's (SEC) Form PF, which large hedge funds are required to file following its adoption as part of the Dodd-Frank Act of 2010.

[4]Gorton, Metrick, and Ross (2020, p. 1) state, "Unlike tri-party, bilateral repo is the home of hedge funds, many types of offshore institutions, and other unregulated cash pools." They find that centrally-cleared and uncleared repo behaved differently from each other during the global financial crisis (GFC). Uncleared bilateral repo is the largest of the repo markets (Hempel, Kahn, Mann, and Paddrik, 2023).

[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 crisis sold off sharply (Schrimpf, Shin, and Sushko, 2020). See Figure A1 and the Online Appendix for an overview of hedge fund fixed income arbitrage strategies.

liquidity during the March 2020 crisis. Instead, our results show that hedge funds were net liquidity consumers during the UST market stress.

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 repo did not significantly change in March 2020 for the average UST-trading hedge fund. In fact, we find that the daily aggregate repo lending volumes to hedge funds by the largest dealers increased intramonth. We also find that repo borrowing terms like maturity and collateral haircuts did not become more adverse.[6] Our findings that borrowing remained stable while portfolio exposures decreased are consistent with hedge funds maintaining their borrowing capacity on dealer balance sheets and hoarding liquidity during March 2020. In addition to debt financing, we find that hedge funds' contemporaneous equity financing was also stable as investor redemptions remained limited in March 2020.

We analyze the external financing channel further using granular data to test specific mechanisms proposed in the literature on why hedge fund repo borrowing might be curtailed during a crisis. Our analyses address the question of whether there was credit rationing due to constraints on dealer intermediation capacity such that hedge funds had unmet borrowing demand during the March 2020 crisis. 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 (e.g., Duffie (2020); Schrimpf, Shin, and Sushko (2020); He, Nagel, and Song (2022)). Given its dependence on dealer-provided funding, hedge fund arbitrage can potentially be limited by dealer balance sheet constraints, particularly during times of market 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

[6] 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.

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.[7]

We use three different proxies from the literature to capture creditor constraints. The first two measure creditor regulatory constraints: an indicator for a creditor's inclusion in the set of global systemically important banks (G-SIBs) (i.e., the large banks that are subject to enhanced regulations) and a continuous measure of a creditor's proximity to the Basel III leverage ratio threshold.[8] The third measure captures creditor liquidity constraints by exploiting the large and heterogeneous credit line drawdowns by non-financial firms during the crisis (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' repo lending to connected hedge funds during March 2020. Our findings are inconsistent with hedge funds' credit constraints being the driver of their step back from UST liquidity provision during the UST market stress. Debt financing remained surprisingly stable in March 2020.

These results may seem surprising given discussions on how amplified funding constraints during crisis periods impact market liquidity provision. Even with potentially constrained balance sheet capacity, dealers did not significantly step back from repo lending to connected hedge funds. Analyzing hedge fund-creditor relationships provides insight into why uncleared bilateral repo proved so resilient during the crisis. We find that dealers favor hedge fund clients with whom they have done more business and clients likely to generate more revenue

[7] 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.

[8] The Basel III leverage ratio is a non-risk-weighted bank capital requirement, U.S. implementation of which is the Supplementary Leverage Ratio (SLR). 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).

via greater activity in fixed income markets. Our findings highlight the discretionary aspect of these credit relationships. The value dealers derive from relationships with large hedge funds may make them reluctant to curtail the flow of credit to these clients during market stress. Also, during March 2020, the larger, bank-affiliated broker-dealers—which, in the post-GFC period, have been 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.[9]

We next examine how hedge funds' internal risk constraints 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 their portfolio risk and dynamically adjust their portfolio exposures to avoid losses over pre-specified VaR limits (Jorion, 2000b; Lo, 2001). According to theory, internal risk constraints can effectively induce risk-neutral arbitrageurs to behave as if they were risk-averse by curtailing their appetite for risk or risk-bearing capacity (Gârleanu and Pedersen, 2007; Shin, 2010; Adrian and Shin, 2014). In March 2020, UST-trading hedge funds experienced returns of -10%, which substantially exceeded their average VaR.[10] We find that the funds with greater risk appetite (i.e., the funds with looser ex ante risk constraints) as measured by the average VaR carried over the preceding 12-month period—provided more liquidity during the March 2020 crisis. Further, the funds that were closer to (or exceeding) their VaR constraints before the start of the crisis provided less liquidity in March 2020. The economic magnitude of the effect is substantial. Among large arbitrageurs, a one standard deviation lower risk-bearing capacity translates to a 12% higher sell-off in arbitrage positions. This evidence illustrates empirically, for the first time, the importance of internal risk constraints for arbitrageurs' ability and willingness to provide liquidity during a crisis.

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

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

We also analyze the role of investor flows in limiting hedge funds' arbitrage. Outflows remained relatively modest for UST-trading hedge funds in March 2020. Outflows during the quarter amounted to less than 2% of net asset value on average, consistent with the long share restrictions employed by hedge funds stemming outflows.[11] These long share restrictions were likely stabilizing because hedge funds were not forced to engage in fire sales to meet immediate, large investor redemptions. However, we find evidence that suggests that hedge funds' expectations of future outflows (post-March 2020) following the sharply negative returns in March 2020 drove some of the UST sell-off by hedge funds during the crisis. First, hedge funds with longer share restrictions and historically less volatile flows held onto disproportionately more UST arbitrage positions in March 2020.[12] Second, the flow-performance relationship is strongly positive in our sample and becomes even stronger with the March 2020 crisis. Consistent with the theoretical predictions of Shleifer and Vishny (1997), the anticipation of future redemptions likely made arbitrageurs more cautious during the crisis, and hence less effective in bringing about market efficiency.

Finally, we conduct a series of robustness and subsample analyses. In particular, hedge funds that sold more of their UST arbitrage positions in March 2020 had significantly worse returns post-March 2020. This result is inconsistent with hedge funds liquidating their UST positions in March 2020 due to opportunistic motives—such as taking advantage of more profitable investment opportunities—or due to anticipated quantitative easing or asset purchases by the Federal Reserve. Also, we find that UST hedge funds, regardless of the size of their pre-March 2020 UST exposure, stepped back from UST arbitrage during the March turmoil. This indicates that hedge funds with relatively small ex ante UST exposures and predominant focus on other asset classes did not step up UST liquidity provision in March

[11] 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.

[12] Ours is the first analysis to harness both the long and short UST exposures of a hedge fund and test the effect of share restrictions on arbitrage trading during a crisis. Previous studies on redemption risk and share restrictions have been primarily limited to analyzing hedge funds' equity holdings, which can be observed at the hedge fund adviser-level through 13-F filings (Ben-David, Franzoni, and Moussawi, 2012; Aragon, Spencer, and Shi, 2019; Agarwal, Aragon, and Shi, 2019). However, 13-F does not cover short equity positions, preventing the direct test of models of arbitrage trading like Hombert and Thesmar (2014).

2020 to exploit the widened arbitrage spreads. Analyzing the subsample of UST hedge funds predominantly engaged in Treasury cash-futures basis trading, we find basis traders' posted margin was substantially higher relative to other UST funds during March 2020. The basis trader hedge funds likely faced greater margin pressure stemming from their exchange-traded short futures positions, which are subject to automated daily mark-to-market and require immediate liquidity infusions or position liquidations.

Overall, we show that creditor constraints did not spillover to hedge funds via borrowing relationships during the March 2020 crisis. Our findings show that even if contemporaneous external financing remains available during times of market stress, the internal risk constraints of hedge funds and precautionary liquidity management can significantly limit their role as liquidity providers. Our findings have important implications for the literature on the role of hedge funds' trading constraints and market resilience. There are three major contributions in this paper. First, we 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). Second, our findings highlight the importance of creditor-borrower relationships in repo markets when transactions are not centrally cleared and information about counterparties is valuable. We provide key evidence that the strength of relationships between hedge funds and broker-dealers matters for the resilience of repo funding and the liquidity of the corresponding (over-the-counter) OTC markets.[13] Third, we make significant contributions to our understanding of the importance of intermediaries, and hedge funds in particular, for asset prices.[14] Our paper significantly

[13]Predictions from the literature on relationship value in bank-firm lending (e.g., Petersen and Rajan (1994); Berger and Udell (1995)) do not necessarily apply in the context of relationships between hedge funds and broker-dealers as these are distinct in key ways (Kruttli, Monin, and Watugala, 2022).

[14]Key papers in this literature include Acharya, Lochstoer, and Ramadorai (2013); He and Krishnamurthy (2013); Kruttli, Patton, and Ramadorai (2015); Lewis, Longstaff, and Petrasek (2021). A novel contribution in our paper is the empirical analysis of the borrowing that supports arbitrageurs' trading activities using fund-creditor level data. Others have examined voluntarily-reported fund-level data from one fund or one fund-of-funds (Ang, Gorovyy, and Van Inwegen, 2011; Mitchell and Pulvino, 2012). An exception is Kruttli, Monin, and Watugala (2022), who analyze the impact of an idiosyncratic shock to one prime broker on hedge fund credit and counterparty relationships. In contrast, we analyze hedge fund borrowing during a systematic shock.

advances our understanding of hedge funds that engage in fixed income arbitrage and their impact on markets by providing both fund-level and fund-creditor-level analyses of their trading and funding.[15]

The remainder of this paper is structured as follows. We discuss the relevant theoretical literature and its testable implications in Section 2. We describe our data and empirical setting in Section 3. We present our main results on repo funding and dealer constraints in Section 4 and on internal risk and precautionary liquidity management in Section 5. We conclude in Section 6.

2 Theoretical literature and testable implications

In this section, we discuss the theoretical literature on the arbitrageur constraints that can affect hedge fund trading during a crisis and outline the testable implications. These models are presented by the authors as inspired by or applicable to the collapse of LTCM and for understanding arbitrageurs during future crises. For example, Brunnermeier and Pedersen (2009, p. 2224) state that, "An illustration of the importance of funding-liquidity management is the 'LTCM crisis.'"[16]

2.1 External funding constraints

A number of theoretical papers examine the implications of external funding constraints for arbitrageur behavior and market functioning. There are broadly two sources of external

[15] Others have analyzed price data to assess the risk and return of fixed income arbitrage strategies (e.g., Duarte, Longstaff, and Yu (2007)) or aggregate data to analyze a specific arbitrage strategy (e.g., Barth and Kahn (2021)). Hedge fund liquidity provision in equity markets, which differs significantly in terms of trading and financing from fixed income arbitrage, has been more widely studied (e.g., Khandani and Lo (2011); Aragon and Strahan (2012); Jylhä, Rinne, and Suominen (2014); Çötelioğlu, Franzoni, and Plazzi (2021); Glossner, Matos, Ramelli, and Wagner (2022)).

[16] Similarly, Shleifer and Vishny (2011, p. 37) write that, "The workings of our 1997 model and the Gromb-Vayanos (2002) model were seen in the collapse of Long Term Capital Management (LTCM) in 1998..." Gârleanu and Pedersen (2007, p. 193) state that, "While no formal empirical evidence is available, to our knowledge, our prediction is consistent with anecdotal evidence on financial market crises. For example, in August 1998 several traders lost money due to a default of Russian bonds and, simultaneously, market volatility increased."

funding for arbitrageurs like hedge funds: credit (debt) and investor capital (equity).

For example, Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) model arbitrageurs financing their trades through collateralized borrowing from dealers who set haircuts to manage counterparty risk. Brunnermeier and Pedersen (2009) show that this exposes arbitrageurs to funding liquidity risk, as haircuts increase when market liquidity deteriorates. Further, in the model of He, Nagel, and Song (2022), constraints on dealer balance sheets can affect repo lending to hedge funds. If these constraints bind, this model predicts that hedge funds receive less repo funding during the March 2020 crisis and/or face tighter funding terms. Also, hedge funds connected with more constrained dealers should experience a greater reduction in repo funding. Specifically, researchers have proposed two types of bank-dealer constraints that may limit the availability of funding: regulatory capital constraints—particularly those related to the Basel III leverage ratio (e.g., Duffie (2018); Schrimpf, Shin, and Sushko (2020))—and liquidity constraints (e.g., Acharya, Engle, and Steffen (2022)).

Another strand of the literature highlights arbitrageur dependence on equity capital provided by external investors and examines the implications of capital constraints on the limits to arbitrage (e.g., Shleifer and Vishny (1997); He and Krishnamurthy (2013)). Shleifer and Vishny (1997) first emphasized the role of fluctuations in investor capital for arbitrageurs. In their model, arbitrageurs rely on capital from outside investors, who receive signals about the fund manager's skills from the fund's past returns. When a manager bets on the price convergence of two assets, as in the case of relative value arbitrage, the prices can diverge in the interim, especially during market stress, in which case the fund can suffer a loss. An investor learning a fund manager's skill from returns may refuse to provide additional capital or even withdraw some of the fund's capital, forcing the fund to reduce its positions and realize losses. The testable prediction from this theoretical literature for our setting is that changes in hedge funds' Treasury arbitrage activity are positively associated with contemporaneous or expected investor flows, which in turn depend on past performance.

2.2 Internal controls to manage risk and liquidity

Researchers have modeled the internal controls that hedge funds impose to reduce shortfalls and mitigate funding fragility. We employ these models to consider the implications of imposing constraints on portfolio risk-taking and investor redemptions.

2.2.1 Internal constraints on risk-taking

A theoretical literature shows how internal risk constraints can prevent liquidity provision of financial institutions during crisis periods, thus amplifying market illiquidity and volatility. Gârleanu and Pedersen (2007) posit that while VaR-based risk management may be beneficial at the fund level, the aggregate effects of such fund-level constraints may be detrimental to market liquidity and raise the possibility of feedback effects that amplify market illiquidity. While tighter internal risk management and smaller portfolio positions can benefit each individual fund wishing to withstand a crisis, it can increase the time taken to find counterparties with unused risk-bearing capacity, potentially further reducing asset prices and liquidity. Shin (2010) describes how 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. Adrian and Shin (2014) provide the microfoundations for VaR constraints in a contracting framework with risk-shifting moral hazard. Financial intermediaries subject to a tighter VaR constraint would be forced to de-risk more during times of market stress.

These models predict that funds entering the March 2020 crisis close to or above their internal risk constraints would have less capacity to provide liquidity during the crisis. The increased volatility in March 2020 would have further pushed risk in these funds closer to or further above their limits, likely constraining their capacity to take on additional risk and potentially forcing them to deleverage and sell off positions. By contrast, a hedge fund with an ex ante high risk-bearing capacity would be better placed to hold onto its trades or even expand liquidity provision and increase risk-taking (i.e., put “risk on”) during the crisis.

Overall, while understanding the impact of risk constraints on arbitrageur liquidity provision is critical, this channel has been unstudied due to a lack of data and appropriate empirical setting. We are the first to empirically test and provide evidence for this channel.

2.2.2 Redemption restrictions

Hombert and Thesmar (2014) expand on the model of Shleifer and Vishny (1997) by incorporating a hedge fund's choice to impose share restrictions to manage redemption risk and ensure that convergence trades (arbitrage trades) do not have to be sold off with realized losses to meet investor outflows. Such share restrictions limit how much capital investors can withdraw over a given period regardless of the fund's performance. Longer, that is, tighter restrictions prevent investors from quickly withdrawing capital from the fund, allowing arbitrage positions to converge before they must be liquidated to honor redemptions. Hombert and Thesmar (2014) predict that funds with shorter, that is, looser share restrictions are subject to more redemption risk than funds with longer share restrictions, which reduces their arbitrage activity, especially during market turmoil.

3 Data and empirical setting

3.1 Hedge fund data

Our hedge fund data are primarily from Form PF for the period from 2012 to 2020. 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).[17] Table 1 presents summary statistics for the key variables of interest. Appendix Table A2 summarizes the variable definitions. Our baseline sample is the

[17] 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).

set of hedge funds with gross UST exposure of at least \$1 million on average over the last three months of 2019. While our findings are robust to varying this threshold, we apply this threshold for two reasons. On the one hand, we want to ensure that our regressions are not affected by funds with very small UST exposures. On the other hand, we want the threshold to be sufficiently low to capture hedge funds that had small UST trading positions before March 2020 but then substantially increased their UST trading during the crisis.

Table 1 Panel A reports the hedge fund characteristics. The variables $VaRConstraint_{h,t}$ and $DistAboveVaRConstraint_{h,t}$ are based on each fund's reported VaR. The VaR quantifies for each fund and month the potential loss (as a percentage of NAV) over a one-month horizon with a probability of 5%. Therefore, our measures reflect the current state of a hedge fund's portfolio composition.[18] A detailed description of the processing of the VaR data is in the Online Appendix. A hedge fund's internal risk management often targets a certain level of risk, such as a maximum portfolio VaR (Gârleanu and Pedersen, 2007; Shin, 2010). While we do not directly observe the exact constraint, it can be approximated using the average reported VaR by a fund because, due to option-like compensation schemes, traders generally have incentives to use up their allocated risk capacity to generate higher returns. As such, the average VaR carried by a hedge fund over a period is a proxy for the target VaR constraint of that fund. The higher the average VaR carried by a hedge fund, the higher the fund's risk appetite or risk-bearing capacity.[19] Portfolio and market shocks can temporarily push a hedge fund away from its average VaR in either direction, leading to fluctuations in the fund's remaining risk-bearing capacity. We construct two measures based on these observations.

[18] A key strength is that our measures do not rely on a hedge fund having a long historical time series of reported realized returns, which would not reflect portfolio compositions at a given point in time and would instead yield backward-looking measures appropriate for ex post analysis as in Gupta and Liang (2005). Only funds that calculate VaR for their risk management are required to report it on Form PF.

[19] In general, the source of risk constraints for hedge funds is driven by its internal risk appetite and the desire to manage risk. By contrast, risk constraints at regulated institutions such as banks are frequently driven by externally imposed regulatory capital requirements in addition to risk management.

The first measure is a hedge funds month-end VaR averaged over a rolling 12-month window:

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

The higher the $VaRConstraint_{h,t}$ of a fund, the higher its risk-bearing capacity. The second measure is the difference between a fund's current VaR and its $VaRConstraint_{h,t}$ at the end of the preceding period:

$$DistAboveVaRConstraint_{h,t} = VaR_{h,t} - VaRConstraint_{h,t-1}. \tag{2}$$

The higher the $DistAboveVaRConstraint_{h,t}$ of a fund, the lower its *remaining* risk-bearing capacity at that point in time. As shown in Table 1 Panel A, the mean $VaRConstraint_{h,t}$ is 4.7%, which implies that the average fund's risk constraints are such that 5% of the time it expects to lose 4.7% of its NAV in a month. We present in the Online Appendix how $VaRConstraint_{h,t}$ varies with other fund characteristics.

$DistAboveVaRConstraint_{h,t}$ has a mean of 0.1% and a median of 0.0%, consistent with hedge funds typically maintaining constant fund-level VaR levels. The 10^{th} and 90^{th} percentiles are -1.4% and 1.7%, respectively, indicating that deviations from the typical risk targets can occur. We find that $DistAboveVaRConstraint_{h,t}$ is generally uncorrelated with the characteristics of a hedge fund and with aggregate fixed income arbitrage spreads and macro variables (see Online Appendix Table B.6). The data are consistent with the idea that traders stay close to their target risk constraints with possible temporary and random deviations, which are equally likely to be positive or negative.

While a hedge fund's VaR can fluctuate from month to month, we find that such fluctuations revert to a mean that is stable at the fund level. The explained variation (R-squared) from regressing the monthly fund-level VaR on fund fixed effects is 86.2%. For $VaRConstraint_{h,t}$, the equivalent exercise yields an R-squared of 91%. This result suggests that over our sample period, there are no strong trends within a hedge fund's VaR time series. Consistent with the interpretation of the $VaRConstraint_{h,t}$ as a measure of a fund's targeted level of risk, temporary deviations from the mean VaR appear to revert quickly. We plot hedge funds' risk capacity before the onset of the crisis in Figure 1, which presents the time series of (a) $VaRConstraint_{h,t}$ and (b) $DistAboveVaRConstraint_{h,t}$ for the pre-crisis period from January 2013 up to February 2020. Both figures plot the median with the interquartile range as a shaded region. The median $VaRConstraint_{h,t}$ stays close to 4% over the pre-crisis period but shows a large cross-sectional variation ranging from below 2% to over 5%. The median $DistAboveVaRConstraint_{h,t}$ stays close to zero throughout the time series, showing that at any given point in time, roughly half the funds are above their typical risk levels and half are below.

The 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. On the other hand, the variable $Cash_{h,t}$ 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 NAV (i.e., equity) and $Leverage_{h,t}$—the ratio of hedge fund $GAV_{h,t}$ (i.e., total gross assets) to $NAV_{h,t}$—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 period's 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] The weighted average time-

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

to-maturity of a fund's borrowing is denoted as $FinDur_{h,t}$. Panel A also provides statistics on monthly and quarterly returns, quarterly flows, monthly number of a hedge fund's open positions, monthly portfolio gross notional exposure (GNE), and monthly turnover variables.

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] Table 1 Panel B provides the summary statistics on the hedge funds' UST exposure. The gross notional UST exposure held by a hedge fund at a given point, $UST\_Gross_{h,t}$, 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 absolute values of a fund's long and short UST exposures, which we observe separately and are denoted as $UST\_Long_{h,t}$ and $UST\_Short_{h,t}$, respectively. The net UST exposure is given by the difference of the two, denoted as $UST\_Net_{h,t}$, and can be positive or negative. On average, the $UST\_Net_{h,t}$ is \$846.0 million showing that the average $UST\_Long_{h,t}$ is larger than the average $UST\_Short_{h,t}$. The variable $USTArbitrage_{h,t}$ captures the portion of $UST\_Gross_{h,t}$ that is long-short balanced and is our proxy for the UST arbitrage activity of a fund. Explicitly, we define $USTArbitrage_{h,t} = 2 \times min(UST\_Long_{h,t}, UST\_Short_{h,t})$ to capture prominent UST arbitrage trades like the on-the-run/off-the-run and the cash-future basis trade. The variable $USTDirectional_{h,t}$ captures the magnitude of the unbalanced directional UST exposure and is equal to $abs(UST\_Net_{h,t})$. The arbitrage and directional exposures add up to a hedge fund's total gross exposures, $UST\_Gross_{h,t} = USTDirectional_{h,t} + USTArbitrage_{h,t}$.

Table 1 Panel C provides 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

[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 Online Appendix section A.5.

of a hedge fund (see Appendix Figure A1). This reliance on repo is one of the major distinctions between fixed income- and equity-oriented hedge funds. 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. It is noteworthy that hedge funds' repo borrowing is predominantly in term repo, as opposed to overnight repo, and therefore, rolled over relatively infrequently. Repo borrowing is over-collateralized, with the average ratio of total collateral to borrowing of 118%. The type of repo borrowing can vary along two dimensions: (i) centrally cleared versus uncleared and (ii) bilateral repo versus 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 on average.[22] Indeed, most hedge funds in our sample exclusively transact in uncleared bilateral repo market with no reported activity in triparty or cleared repo.

Table 1 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. $NumCrdtrsPerHF_{h,t}$, the number of creditors from which a hedge fund borrows simultaneously, is on average 4.5. The average amount a hedge fund borrows from one creditor at the end of quarter, $HF\_Ctpty\_Credit_{h,p,t}$, is \$1.3 billion. In about half of the cases, a hedge fund's creditor is also its custodian.

3.2 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 hetero-

[22]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/).

geneity in broker-dealer constraints: $isGSIB_{p,t}$, $DistanceToLRT_{p,t}$, and $DrawnDelta_{p,t}$.[23] The first captures a dealer's status as a 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 eight domiciled in the United States. We define $isGSIB_{p,t}$ as an indicator variable 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 Online Appendix Table A.1, we list all G-SIB institutions, including the timeline of G-SIB classifications, using information from the FSB and the NY Fed.[24]

The BCBS 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 disclosure of bank leverage ratios by the first quarter of 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.[25] 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 LRT as follows:

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

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

[24]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.

[25]In the U.S., 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. U.S. banks subject to the SLR have an LRT of 3%, while U.S. G-SIBs are subject to an enhanced SLR of 5%.

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.[26] These data include information such as a dealer's daily total repo lending to hedge funds and help us to cross-check the findings from our main analysis, which is at a 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, which we source from S&P Market Intelligence.

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

3.3 Hedge fund UST activity and the March 2020 crisis

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.

Figure 3 Panels A to C show the dynamics of two Treasury arbitrage spreads that are representative of the spreads traded by fixed income hedge funds: the cash-futures basis and

[26] 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.

the on-the-run/off-the-run spread. Both spreads spike in March 2020, reaching their highest levels during our sample period. In Panel D, we plot the 10-year Treasury yield against the federal funds rate and S&P 500 Index returns. As discussed in Vissing-Jorgensen (2021) when describing this episode, the 10-year Treasury yield rose in the middle of March, despite falling stock returns and the Federal Reserve slashing the federal funds rate.

We first document the changes to hedge fund UST trading activity during the March 2020 crisis. The grey shaded line in Figure 2 shows that aggregate UST exposures fell significantly in March 2020. Figure 4 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 $\Delta y_{h,t}$ denotes the change in the outcome of interest. D_t is 1 for March 2020 and 0 otherwise. $Z_{h,t-1}$ denotes the set of lagged controls ($LogNAV$, $NetRet$, $NetFlows$, $PortIlliq$, $ShareRes$, $FinDur$, $MgrStake$, and $LeverageRatio$). μ_h denotes fund fixed effects. We double-cluster standard errors 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. In Panel A, we show results from analyzing 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. Columns (1) to (3) show that, in March 2020, hedge funds reduced UST exposure by around 20%, on both the long and the short sides. Columns (4) to (6) show that this change in March 2020 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' UST exposures in March 2020. Despite the widening of spreads during the Treasury market stress, hedge funds refrained from providing liquidity. In fact, they were net liquidity consumers.

Among the control variables in these regressions, we find that flows are generally positively related to UST exposure: columns (1) to (3) show a positive and significant coefficient on $NetFlows$, indicating that funds adjust their portfolios in response to investor inflows and outflows. Intuitively, because flows also affect NAV, columns (4) to (6) show that flows do not change UST allocations as a fraction of a fund's NAV. Most other control variables are not significantly related to UST exposures.

In Table 2 Panel B, we examine the changes to the directional exposure and arbitrage activity in UST portfolios in March 2020. The regression results in column (1) indicate that purely directional exposures, $USTDirectional$, dropped by close to 15%. Column (2) shows that hedge funds reduced their UST arbitrage portfolios by around 25%. The results in column (3) indicate that long-short balanced exposures declined disproportionately more than directional exposures in UST hedge fund portfolios in March 2020. Columns (4) to (7) show the changes to the arbitrage exposures of the set of UST hedge funds that had ex ante "moderate" or "large" arbitrage exposures.[27]

These estimates of decreases in hedge funds' notional UST exposures are based on end-of-month Treasury securities valuations. Since interest rates fell on net in March 2020, these valuations tend to underestimate the amount of UST selling by hedge funds. In Online Appendix Table B.2, we analyze the changes to valuation-adjusted and duration-adjusted

[27] 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.

UST exposures in March 2020. These regressions using valuation- and duration-adjusted UST exposures as the dependent variables yield qualitatively similar results. Further, in Online Appendix Table B.1, we show the robustness of the analysis of UST exposure changes to including several time series controls that proxy for the return to UST arbitrage strategies. These controls include the changes in the cash-futures basis spread, on-the-run/off-the-run spread, Treasury/TIPS spread (Fleckenstein, Longstaff, and Lustig (2014)), Bank of America / Merrill Lynch Option Volatility Estimate (MOVE), Hu, Pan, and Wang (2013) noise measure (HPW), yield slope (computed as the UST 10-year constant maturity rate minus the 2-year constant maturity rate), and the yield dispersion (computed as the average yield deviation relative to a fitted yield curve across Treasuries with maturities greater than 1 year). After including these time series controls, either contemporaneously or lagged, the coefficient on the March 2020 indicator remains negative and strongly significant.[28]

In Online Appendix Table B.3, we also show the March 2020 change in UST exposures separately for hedge funds with different levels of UST pre-crisis exposure. Hedge funds with the smallest pre-crisis exposures (of less than $100 million in gross exposures) likely increased long UST holdings to boost 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 Online Appendix Table B.11, analyzing data six months post-crisis, we find that hedge funds continued to reduce UST exposures even after the market turmoil subsided.

The UST market stress mostly subsided following the unprecedented Federal Reserve intervention on March 23, 2020, close to the end of the month and quarter. If hedge funds had sold off significantly more UST positions intra-month and bought back positions following the Federal Reserve intervention, our March 2020 coefficient estimates, which rely on month-end UST positions, would underestimate the extent of hedge funds' UST sell-off during the

[28] Outside of March 2020, changes in these aggregate time series variables do not predict large changes in hedge funds' UST positions. These proxies for returns from different UST arbitrage strategies correlate only weakly with each other, likely contributing to the weak predictive power of individual arbitrage spreads for hedge funds' aggregate UST exposures.

peak of the Treasury market stress.

We also analyze whether hedge funds sold off UST positions after the UST market turmoil subsided following the Fed intervention on March 23. Although intra-month Treasury holdings for hedge funds are not available, several key results support the interpretation that hedge funds predominantly sold their UST positions during the March 2020 crisis itself and not after the intervention. First, the large negative returns of UST trading hedge funds during March 2020, -10% on average (see Figure 4), appear inconsistent with hedge funds taking advantage of the crisis or waiting for arbitrage spreads to recover after the Federal Reserve intervention to sell Treasuries. If hedge funds retained or increased their UST arbitrage positions (as spreads widened) through the peak of the stress and then sold off their exposure significantly just after the Federal Reserve intervention, average UST hedge fund returns would have been flat or significantly positive in March 2020.

Second, Online Appendix Table B.7 presents evidence that hedge funds that sold more of their UST positions in March experienced significantly lower returns post-March. This finding is also inconsistent with the idea that the hedge funds that sold UST arbitrage positions during the March 2020 crisis did so to take advantage of other more profitable investment opportunities or large UST purchases by the Federal Reserve.

Third, aggregate daily hedge fund returns, calculated using data from commercial data sources and plotted in the Online Appendix Figure B.2, indicate sharp losses starting from March 9 for arbitrage hedge funds, prior to the March 23 Federal Reserve intervention, indicating it is likely that funds experienced VaR exceedance events and hit their risk and liquidity constraints such that funds had to take risk off during the March turmoil itself.

Fourth, data from the Commodity Futures Trading Commission (CFTC) on UST futures positions of levered funds also show that funds exited their short UST futures positions from the beginning of March 2020, which is consistent with the unwinding of the cash-futures basis trade during the crisis (see Online Appendix Figure B.3). Finally, our findings are also in line with anecdotal evidence from media and industry reports of hedge funds dumping

Treasuries during the UST market turmoil itself.[29,30]

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). Our estimate is in line with Vissing-Jorgensen (2021), who estimates that hedge funds had at least $183 billion in Treasury sales during the first quarter of 2020 using publicly available CFTC aggregated Treasury futures data and SEC private fund statistics.[31] The data that we use provide, to our knowledge, the most comprehensive view of hedge fund UST activity during March 2020.

The widening of arbitrage spreads, as observed in March 2020 (Figure 3), 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?

4 Repo funding, dealer constraints, and hedge fund UST liquidity provision

As discussed in Section 2.1, a prominent theme in the theoretical literature 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

[29] See, for example, the New York Times article: https://www.nytimes.com/2021/03/16/business/economy/fed-2020-financial-crisis-covid.html.

[30] In the Online Appendix, we also analyze how hedge funds' UST trading typically responds to quantitative easing by the Federal Reserve outside of March 2020 (see Table B.12). In general, hedge funds' UST positions change little in response to quantitative easing, suggesting that hedge funds' UST demand is primarily driven by other factors. Hedge fund UST arbitrage trading is generally duration matched and not directional.

[31] By contrast, estimates based on publicly available quarterly U.S. Financial Accounts data published by the Federal Reserve, which covers only the subset of the hedge funds in Form PF domiciled in the U.S. and excludes offshore funds, tend to be lower. For example, He, Nagel, and Song (2022) find that this subset sold $30 billion in the first quarter of 2020.

(Gorton, Metrick, and Ross, 2020). In this section, we use unique data on hedge funds' bilateral repo financing to examine whether external constraints on repo funding limited hedge fund Treasury arbitrage in March 2020.

4.1 Repo funding during the COVID-19 shock

Table 3 presents results from analyzing hedge funds' repo activity using a panel regression specification similar to equation (5). Hedge funds' repo borrowing was surprisingly resilient on average during the March 2020 sell-off in Treasury markets. The estimates in column (1) 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 were able to maintain the allocated borrowing capacity on dealer balance sheets, potentially using previously non-financed securities to raise cash.

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 decrease UST positions. However, this result still leaves open the possibility that while repo borrowing amounts were unchanged, the terms of the bilateral repo transactions changed. Form PF data allow us to observe two important repo transactions terms 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 given that the average and median repo borrowing maturity,

$RepoBrrwTerm$, are 26 and 9 days, respectively. By contrast, the maturity of repo *lending* by hedge funds decreased by around 1 day. The average and median repo lending maturity, $RepoLendTerm$, are 12 and 4 days, respectively. Borrowing for longer periods and lending for shorter periods boosts hedge funds' access to cash. Columns (3) and (4) show the results from analyzing changes to 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 the March 2020 crisis 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 baseline 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 data yield a comprehensive view on the state of funds soon after, at the end of the month. However, several key observations using additional data support 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.[32] Finally, we analyze the *daily* time series of uncleared bilateral repo lending to asset managers collateralized by Treasuries by the top

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

G-SIB dealers from the regulatory dataset FR2052a.[33] We plot the data in Figure 5. There is a marked increase in repo lending at the beginning of March, with lending remaining elevated intra-month 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 UST hedge funds 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.

4.2 Dealer constraints and bilateral repo lending

There has been considerable debate on whether post-GFC regulations constrain bank-affiliated broker-dealers' provision of repo and intermediation in fixed income markets.[34] We next conduct a granular analysis on hedge fund repo borrowing using hedge fund-creditor (hedge fund-dealer) level data, focusing on whether dealers subject to enhanced regulations limited the supply of funding to connected hedge funds. 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-invariant and time-varying hedge fund characteristics.[35] We illustrate the methodology with an example hedge fund-dealer network

[33] 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). Other asset managers like mutual funds and pension funds are restricted in their borrowing activity.

[34] 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 markets (Bao, O'Hara, and Zhou, 2018; Boyarchenko, Eisenbach, Gupta, Shachar, and Van Tassel, 2020; Allahrakha, Cetina, Munyan, and Watugala, 2021).

[35] 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 separate from shocks to borrower demand. Others analyzing the impact of dealer constraints on the provision of repo examine a limited number of dealers and do not observe individual borrowers (e.g., Favara, Infante, and Rezende

in Figure 6. The panel regressions take the following 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 and 0 otherwise. $DealerConstraint_{p,t}$ is a measure that captures heterogeneity across dealers in terms of potential constraints to their intermediary role in 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. The 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 section 3.1).

First, we use a dealer's status as a global systemically important financial institution, $isGSIB$, as the $DealerConstraint$ measure capturing the set of dealers subject to the most

(2022)). Importantly, in our granular analysis using fund-creditor level borrowing data, we can control for borrowing demand.

stringent regulatory constraints. The findings reported in Table 4 are inconsistent with these constraints limiting dealers' funding provision during the March 2020 UST sell-off. During the crisis, G-SIBs provided disproportionately *higher* funding 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 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.[36] 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 LRT, $DistanceToLRT$, defined in Section 3.2, as the $DealerConstraint$ measure. A bank closer to its minimum LRT would have a smaller $DistanceToLRT$, and hence, potentially be more constrained by the leverage ratio requirement. The results are in Table 5 Panel A. The indicator variable *PostEffectiveDate* 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. Instead, we

[36] As we show in Online Appendix Table A.1, the set of primary dealers' parent companies largely overlaps with the set of G-SIB institutions.

find that the coefficients are insignificant. We do not find evidence that the distance to the LRT was a significant factor in the credit supplied to hedge funds during this episode.[37] We estimate the same regression for just the subsample of U.S. G-SIBs and obtain qualitatively similar results, as shown in Online Appendix Table B.5 Panel A.

Finally, we analyze whether the credit lines drawdown channel had a differential impact on repo funding provided to bank-dealer's hedge fund clients.[38] Here, we use $DrawnDelta$ as the $DealerConstraint$, which captures the change in how much corporations drew down the credit lines in bank p's C&I loan portfolio during quarter t. Table 5 Panel B presents the results. If the liquidity shocks from unexpected credit line drawdowns were passed on to hedge funds by bank-affiliated broker-dealers in March 2020, one would expect the coefficient on $March2020_t \times DrawnDelta_{p,t}$ to be negative and significant. However, we find that the coefficients on $March2020_t \times DrawnDelta_{p,t}$ are insignificant. We do not find evidence that credit line drawdown shocks were passed on to hedge fund clients during the March 2020 crisis. In Online Appendix Table B.5 Panel B, we show that the results are qualitatively similar when restricting the sample to just U.S. G-SIBs.

Overall, our findings indicate that dealers' regulatory and liquidity constraints were not passed on to hedge fund clients via repo funding during the March 2020 crisis.

4.3 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

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

[38] 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 pandemic and relate this channel to the underperformance of bank share prices compared to non-financial firms.

during a crisis, we use the empirical strategy discussed in Section 4.2 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 6. In Panel A shows the results of regressions including interaction variables that measure a hedge funds importance to a creditor and vice versa. The first interaction variable, $HFRankInCrdtr$, 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 $CrdtrRankInHF$ shows that the most important creditors of a hedge fund provided relatively higher funding than less important creditors, again indicating that the strength of the credit relationship matters. Because the interaction variable of interest varies at the fund-creditor-time level, these regressions can include both fund-time and creditor-time fixed effects to control for both fund-demand and credit-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.[39]

In Table 6 Panel B, we show results using 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, as shown in columns (3) to (8). By contrast, we find that the 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.

[39] 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.

5 Internal risk and liquidity management

5.1 Risk constraints

If shocks to external financing did not drive the hedge funds' sell-off in the Treasury market in March 2020, what did? As discussed in Section 2.2.1, theory suggests that during crises, hedge funds may curtail liquidity provision because of internal risk constraints. We next analyze how hedge funds' risk management affects their arbitrage trading during a crisis.

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

$$\Delta y_{h,t} = \beta_1 DistAboveVaRConstraint_{h,t-1} + \beta_2 D_t \times DistAboveVaRConstraint_{h,t-1} + \gamma_1 Z_{h,t-1} + \gamma_2 D_t \times Z_{h,t-1} + \mu_h + \theta_t + \epsilon_{h,t}, \tag{9}$$

$$\Delta y_{h,t} = \beta_1 DistAboveVaRConstraint_{h,t-1} + \beta_2 D_t \times DistAboveVaRConstraint_{h,t-1} + \beta_3 VaRConstraint_{h,t-1} + \beta_4 D_t \times VaRConstraint_{h,t-1} + \gamma_1 Z_{h,t-1} + \gamma_2 D_t \times Z_{h,t-1} + \mu_h + \theta_t + \epsilon_{h,t}, \tag{10}$$

where $\Delta y_{h,t}$ is the portfolio change of interest. Again, D_t is 1 for March 2020 and 0 otherwise. $Z_{h,t-1}$ denotes the same set of controls as in equation (5), which are also included in the regression interacted with D_t. We run the regression with just fund fixed effects or both fund and time fixed effects with qualitatively similar results. β_2 is the coefficient of interest and captures the differential effect between funds with a high and low risk-bearing capacity.

The results are in Table 7. In Panels A and B, the coefficient estimate on the interaction between the March 2020 indicator variable and the distance to the risk constraint, $March2020_t \times DistAboveVaRConstraint_{h,t-1}$, is negative and strongly significant for all specifications. These estimates show that hedge funds with a high VaR in February 2020 relative to their typical VaR over the previous year sold disproportionately more of their UST positions during March 2020. As shown in Panel B, including additional controls individually and interacted with $March2020$ yields qualitatively similar results. This effect is also economically significant. A one standard deviation higher $DistAboveVaRConstraint$ translates into a 8%-9% reduction in arbitrage positions, with a stronger effect of a 12% reduction for the largest arbitrage funds.

The results in Table 7 Panel C show that even when including both $DistAboveVaRConstraint$ and $VaRConstraint$ variables in the same regression, the coefficients on $March2020_t \times DistAboveRiskConstraint_{h,t-1}$ remain qualitatively the same. Intuitively, across the different dependent variables, the coefficient estimates show that hedge funds with loose VaR constraints were less likely to reduce their UST positions than hedge funds with a tight VaR constraints. The effect of the VaR constraint is also economically large. A one standard deviation increase in $VaRConstraint$ predicts that UST funds 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 constraints and the proximity to those constraints for hedge funds' ability and willingness to maintain their sizeable Treasury market exposures in March 2020.

5.2 Redemption risks

In this section, we analyze how redemption risks faced by hedge funds affected their UST trading by considering both contemporaneous and expected investor redemptions. We find that contemporaneous equity financing remained largely stable for hedge funds in March 2020. As shown in Appendix Table A1, the average outflow during this crisis was -1.8%. These outflows are modest compared to the distribution of historical flows shown in Table 1 Panel A. Long share restrictions likely helped to keep hedge fund equity financing resilient, consistent with the theoretical predictions of Hombert and Thesmar (2014). The median hedge fund in our sample receives at least 30 days of notice before the first 1% of the fund's NAV (equity) could be redeemed, which can prevent contemporaneous investor redemptions during a short-lived crisis.[40]

However, hedge funds might have sold their UST positions in March 2020 in part due to the anticipation of future outflows even though contemporaneous flows remained stable. In the theoretical model of Shleifer and Vishny (1997), funds may refrain from trading against mispricing due to concerns about future outflows (see Section 2.2.2). Further, anticipated redemptions may be a particular concern if a hedge fund suffers losses because external investors may learn about the manager's skill from current performance and adjust future flows accordingly (and bring about the flow-performance relationship).

Our findings are consistent with this prediction. First, we find that hedge fund share restrictions were likely stabilizing for hedge funds and the tightness of share restrictions mattered for how much arbitrage positions hedge funds sold off in March 2020. As shown in Table 8 Panel A, funds with longer share restrictions tended to reduce their Treasury trading by less in March 2020, with larger effects for the funds most focused on arbitrage trading.

Second, hedge funds with more volatile past investor flows sold more of their UST positions during the UST market stress. The magnitude of the coefficients on these standardized variables allows us to directly compare the economic significance of the effects of internal risk constraints, flow volatility, and share restrictions. The results in columns (5) to (7) in Panel B show that the economic effects of VaR constraints on arbitrage positions are comparable and in some cases larger than the effects of flow volatility and share restrictions.

Third, to test the hypothesis that the hedge fund UST sell-off was affected by expectations of future investor redemptions reacting to current losses, we analyze whether the cross-section of hedge fund losses in March 2020 predict the magnitude of fund outflows in the second and third quarter of 2020. Table 9 shows the results when we predict quarterly flows with lagged returns computed over a rolling window of four quarters. As shown in columns (1) to (4), returns predict future flows. The results hold for both continuous returns and

[40] By 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 (2022); Li, Li, Macchiavelli, and Zhou (2021)).

when fund-quarter observations are sorted into quintiles based on their returns. In Online Appendix Tables B.8 and B.9, we show that these results are robust to computing hedge fund performance on a risk-adjusted basis and over 12 instead of 4 quarters, respectively. Interestingly, when interacting the returns with a post-March 2020 indicator variable, we find an even stronger flow-performance relationship. This result suggests that investors pay particular attention to a hedge fund's performance during crisis periods. A crisis can uncover skill in the cross-section of hedge funds, with investor capital flowing to the most skilled asset managers (Berk and Green, 2004).

Finally, the results in Online Appendix Table B.7 Panel B suggest that hedge funds that sold more of their UST in March 2020 experienced somewhat larger outflows after March 2020. Because such hedge funds also had significantly worse returns post-March 2020 (see Table B.7 Panel A), these results are in line with a strong flow-performance relationship.[41]

Overall, the evidence is consistent with concerns about future outflows also contributing to hedge funds' precautionary step back from Treasury arbitrage trades in March 2020, as theorized by Shleifer and Vishny (1997). Notably, we show that the economic significance of internal risk constraints for hedge funds' ability to hold on to arbitrage positions through a crisis is comparable to or exceeds that of anticipated redemptions.

5.3 Cash and liquidity management

Our results indicate that even while external financing remained stable, hedge funds refrained from providing liquidity in the Treasury market driven by their internal risk constraints. In this section, we test whether such "risk-off" behavior is observable in other investment decisions besides arbitrage exposures by analyzing changes to cash and portfolio liquidity.

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

[41]For hedge funds, the evidence for the flow-performance relationship is somewhat limited. Goetzmann, Ingersoll, and Ross (2003) find a negative flow-performance relationship using data from 1990 to 1995 from the U.S. Offshore Funds Directory database. By contrast, Agarwal, Green, and Ren (2018) and Liang, Schwarz, Sherman, and Wermers (2019) analyze data from 1994 to 2012 from commercial hedge fund databases and find a positive flow-performance relationship. We contribute to this literature by analyzing regulatory data and documenting a strong flow-performance relationship that becomes even stronger during the crisis period.

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, hedge funds held significantly higher cash and more liquid portfolios than at the beginning of the month. We show changes to both the $FreeCashEq$ and $Cash$ measures of cash holdings. $FreeCashEq$ increased by 26% in March 2020. Similarly, $Cash$, which includes cash both unencumbered and posted as collateral, 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. Column (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 and GAV 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 the risk constraints channel whereby hedge funds take risk off due to binding internal risk constraints.

These findings also contribute to our understanding of how a hedge fund manages its liquidity during a systematic stress period. In a systematic crisis, 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 for hedge funds during the March 2020 crisis contrast with the behavior of LTCM in 1998, which sold off its most liquid holdings first as the 1998 crisis began.[42] Analyzing the LTCM meltdown in 1998, Jorion (2000a, p. 288) concludes that: "...[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."

Given the contrast between LTCM's behavior in 1998 and our findings for UST hedge funds during March 2020, it is possible that the hedge funds in our sample learned from the experiences of LTCM and other subsequent hedge fund meltdowns, which influenced their liquidity management during March 2020. Indeed, as we show in the Online Appendix Table B.10, 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.[43]

5.4 Basis trading and futures margin pressure

In this section, we analyze differences in UST trading and funding of hedge funds that predominantly engaged in basis trading compared to other UST-trading hedge funds. Although we find that bilateral repo funding generally remained stable for hedge funds, not all fixed income strategies are exclusively funded via repo (see Appendix Figure A1 and the overview of hedge fund fixed income arbitrage strategies in the Online Appendix). The cash-futures basis trade, which is an arbitrage strategy popular with some large fixed income relative value hedge funds in the run up to the March 2020 crisis, 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

[42] 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 (2022), who show for the GFC and the March 2020 shock, respectively, that corporate bond mutual funds sold their relatively *more* liquid positions to meet investor redemptions.

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

strategies, such as on-the-run/off-the-run bond spread trading, which 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 futures margins are likely quite different. As discussed in Section 4.3, relationships and counterparty considerations matter in uncleared bilateral repo markets. By 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 crisis, 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 the Chicago Mercantile Exchange rose by 30% to 210% during March 2020. At the inception of the crisis, while UST securities declined in value, UST futures *appreciated* in value, and the resulting widening of the basis exposed arbitrageurs to margin calls. Since hedge funds that predominantly engage in the cash-futures basis trade likely faced greater margin pressure, we examine the differential impact of such immediate liquidity needs on these funds.

Figure 7 plots 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, classified as described in Online Appendix Section A.4. 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 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 shows results on the changes to UST exposures. The coefficients on $March2020_t \times$

$BasisTrader_h$ 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.

Table 11 Panel B shows the differences for basis traders in repo borrowing. Relative to other UST funds, basis traders increased repo borrowing in March 2020, which suggests greater liquidity needs due to margin pressure on futures positions. Consistent with the increase in borrowing levels, borrowing terms appear to have tightened for basis traders. The repo borrowing maturity 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 held for liquidity management (i.e., $FreeCashEq$) at the end of March 2020. However, the results in columns (3) and (4) show that basis traders' $Cash$, which includes both unencumbered cash *and* cash already posted as margin/collateral, was significantly higher than that of other UST hedge funds, which is consistent with greater margin pressure. We also 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.

6 Conclusion

Using novel and comprehensive regulatory data, we find that during the crisis in UST markets in March 2020, 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 representing potential profit-making opportunities? A common perception is that during crises, 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. Using an identification strategy that isolates credit supply effects from borrower demand or characteristics, we conduct a granular analysis of the dealer constraints channels proposed in the literature, through which hedge funds might face curtailed supply of repo funding, including dealer regulatory constraints and dealer liquidity constraints. However, we find that these dealer constraints were not propagated to hedge funds via bilateral repo during the March 2020 crisis. We document 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, hedge fund clients that generate greater revenue streams for a creditor received disproportionately more funding from that creditor.

We find that the reduction in hedge fund UST exposures is strongly related to internal risk and liquidity management considerations. Hedge funds with looser ex ante VaR constraints were able to hold onto more of their arbitrage positions during the crisis, and funds with less headroom relative to these constraints saw significantly larger selloffs. These empirical results are consistent with an internal risk constraints channel limiting arbitrageur liquidity provision. Further, we find that hedge funds' concern about future outflows of investor capital also hindered their liquidity provision in March 2020.

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 like the UST market. By analyzing the activity of hedge funds during this episode in UST markets and uncleared bilateral repo funding markets, we provide insights on how the risk management and funding structures of hedge funds affect the role they play in these markets. Our analysis shows that hedge fund arbitrage can be fragile during times of stress due to limited risk-bearing capacity, even if contemporaneous external financing remains stable. Our results highlight the need to expand researchers' focus beyond dealer constraints and to understand the internal structures and risk management strategies of arbitrageurs that impact liquidity and market functioning in these vital markets.

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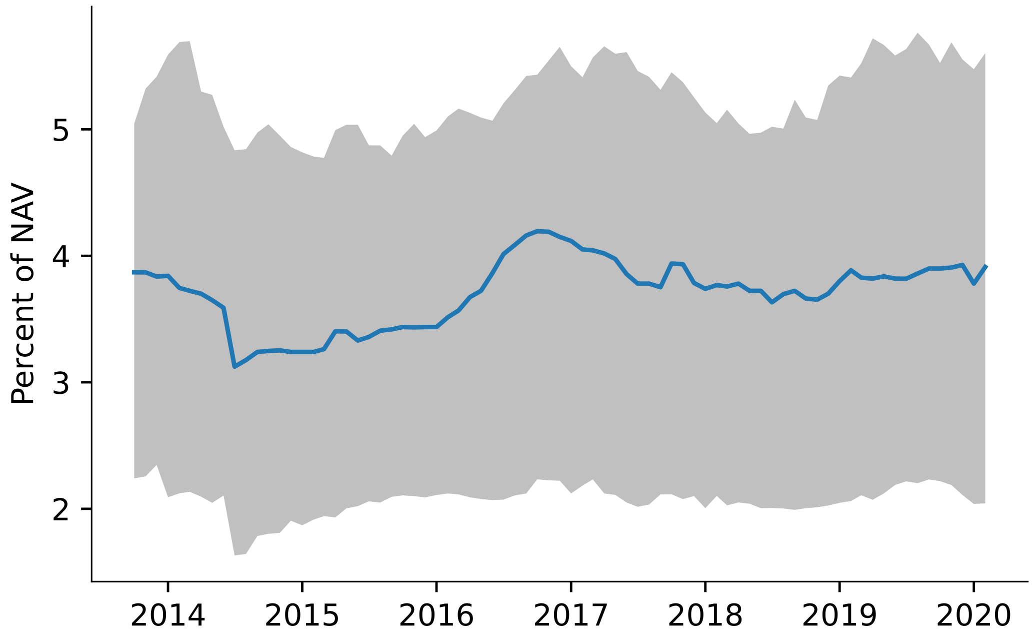
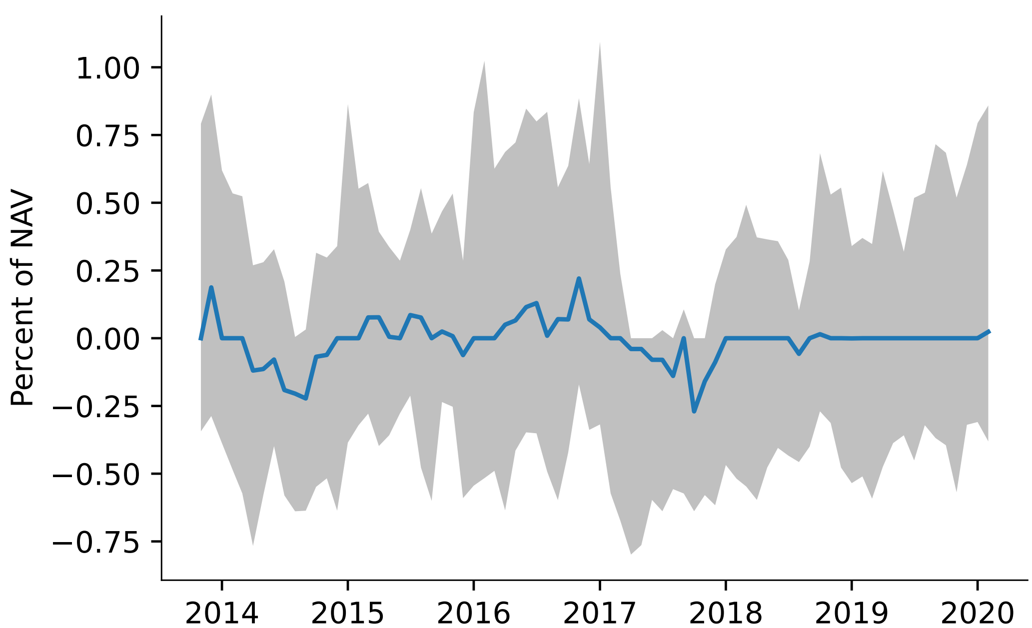


(A) $VaRConstraint_{h,t}$



(B) $DistAboveVaRConstraint_{h,t}$

Figure 1: Distribution of $VaRConstraint_{h,t}$ and $DistAboveVaRConstraint_{h,t}$

This figure illustrates the time series of the median (solid line) and 25^{th}-75^{th} percentile interquartile range (shaded area) of $VaRConstraint_{h,t}$ (Panel A) and $DistAboveVaRConstraint_{h,t}$ (Panel B) for the pre-crisis period up to February 2020.

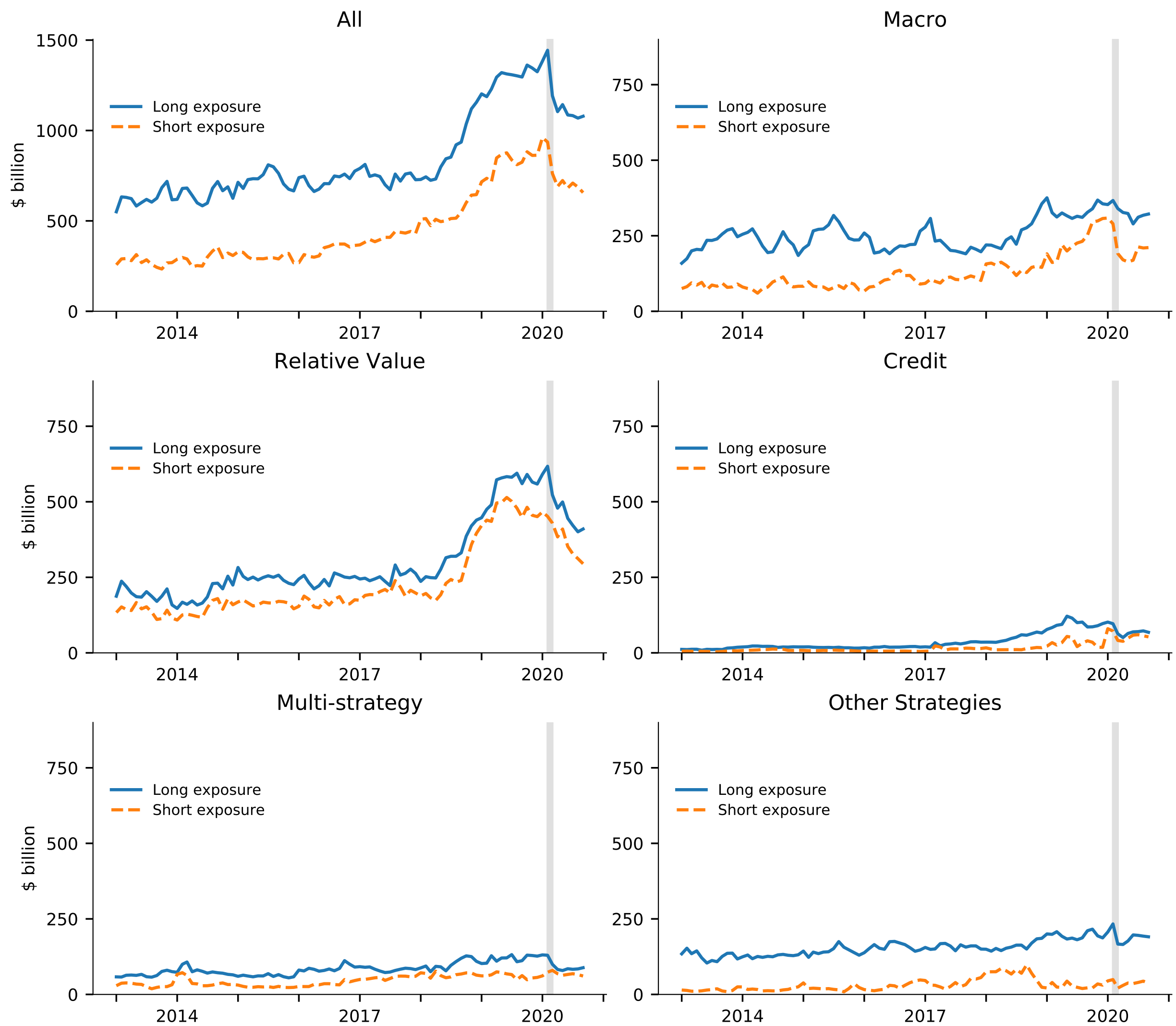


Figure 2: Hedge fund U.S. Treasury exposures

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.

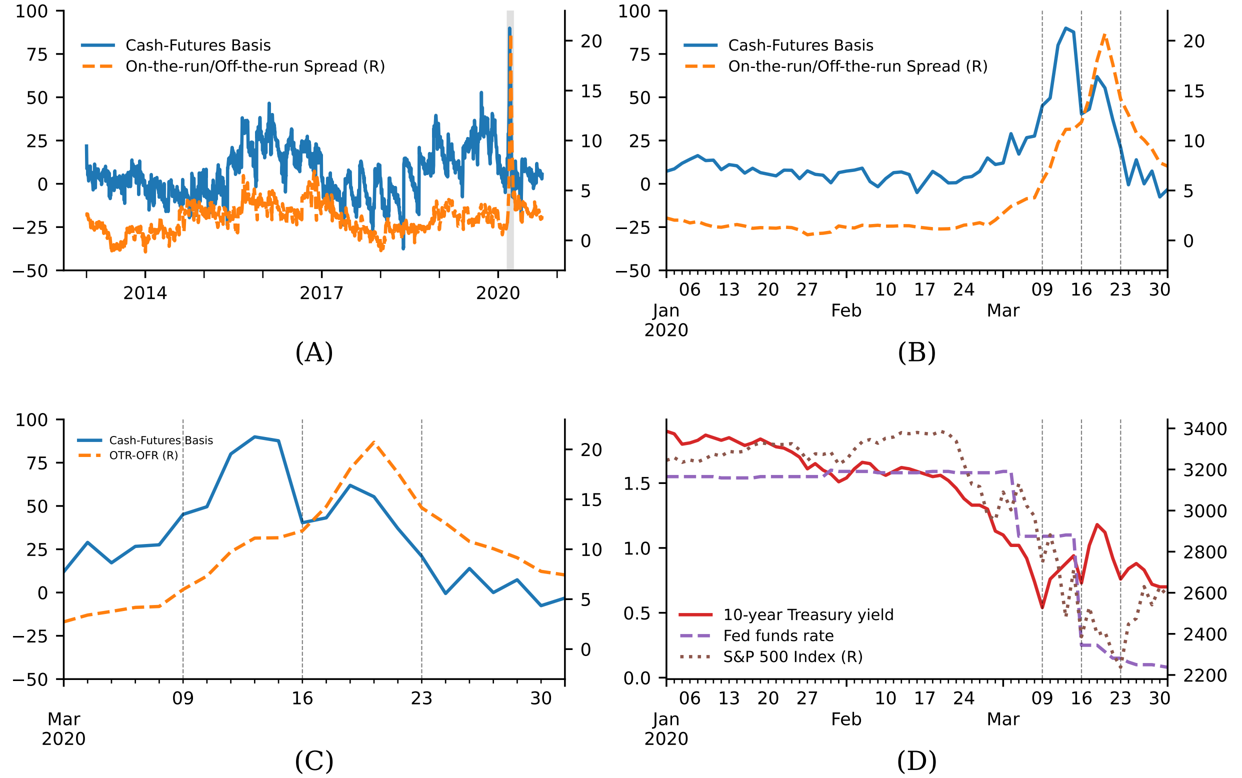


Figure 3: U.S. Treasury arbitrage spreads and interest rates in March 2020

Panels A, B, and C show the cash-futures basis and on-the-run/off-the-run spreads in basis points from January 2013 to September 2020 (Panel A), from January to March 2020 (Panel B), and for March 2020 (Panel C). Panel D shows the 10-year Treasury yield (left y-axis in %), federal funds rate (left y-axis in %), and S&P 500 Index (right y-axis) in March 2020. March 2020 is shaded gray in Panel A. In Panels B, C, and D, the vertical dashed lines denote the inception of the crisis (March 9) and the trading dates on which the Federal Reserve bond purchases were announced (March 16 and 23).

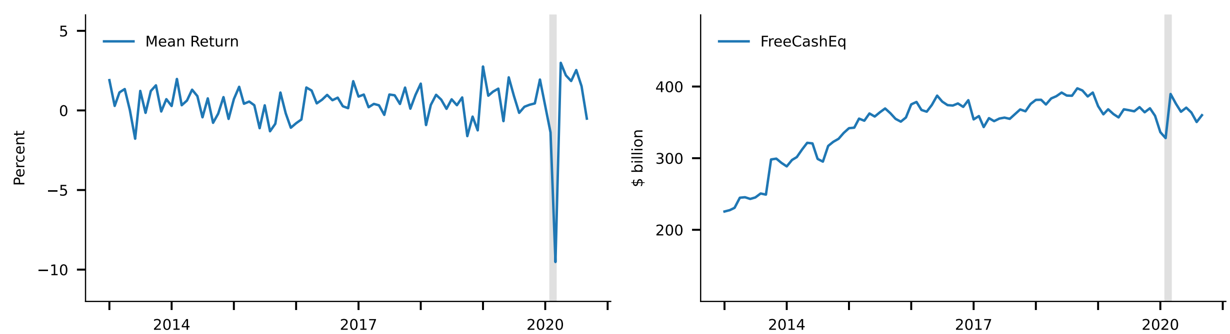


Figure 4: Hedge fund returns and cash held for liquidity management

This figure presents the times series of returns and unencumbered cash and cash equivalents from January 2013 to September 2020 for UST trading hedge funds. The figure on the left shows the monthly mean returns, net-of-fees. The figure on the right shows aggregate holdings of unencumbered cash and cash equivalents ($FreeCashEq$). March 2020 is shaded gray.

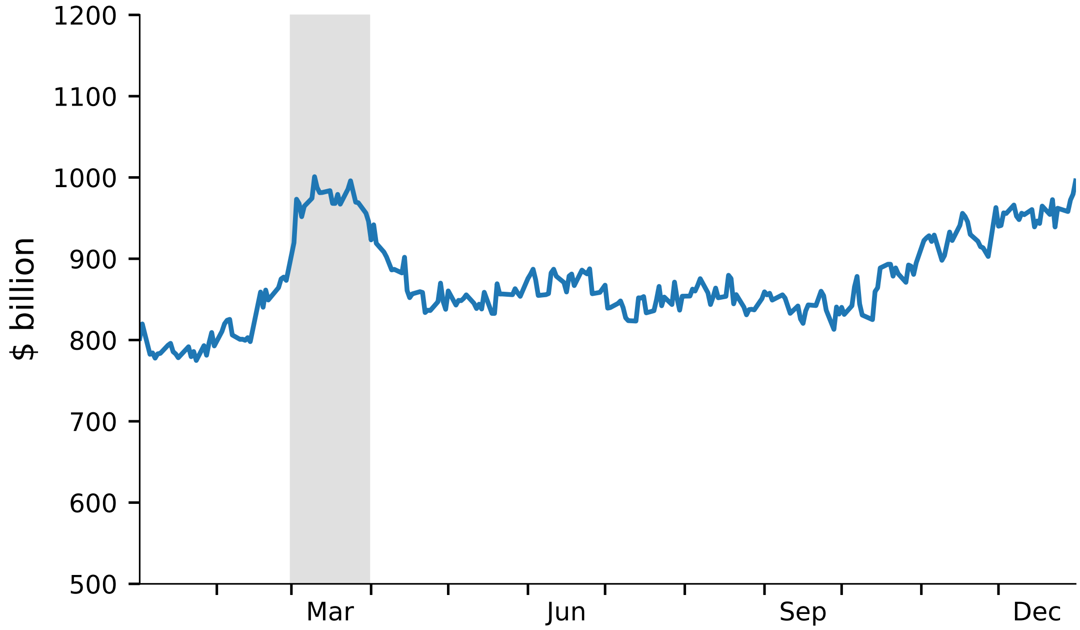


Figure 5: Daily UST bilateral repo lending by the top 10 G-SIB dealers in 2020

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, J.P. Morgan, Morgan Stanley, UBS, and Wells Fargo. March 2020 is shaded gray.

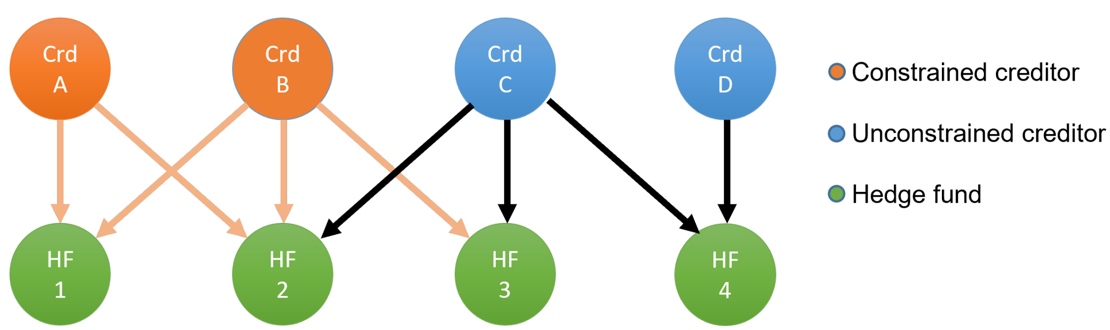


Figure 6: Empirical strategy for analyzing hedge fund-creditor bilateral repo data

This figure illustrates the identification strategy we use to analyze the 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.

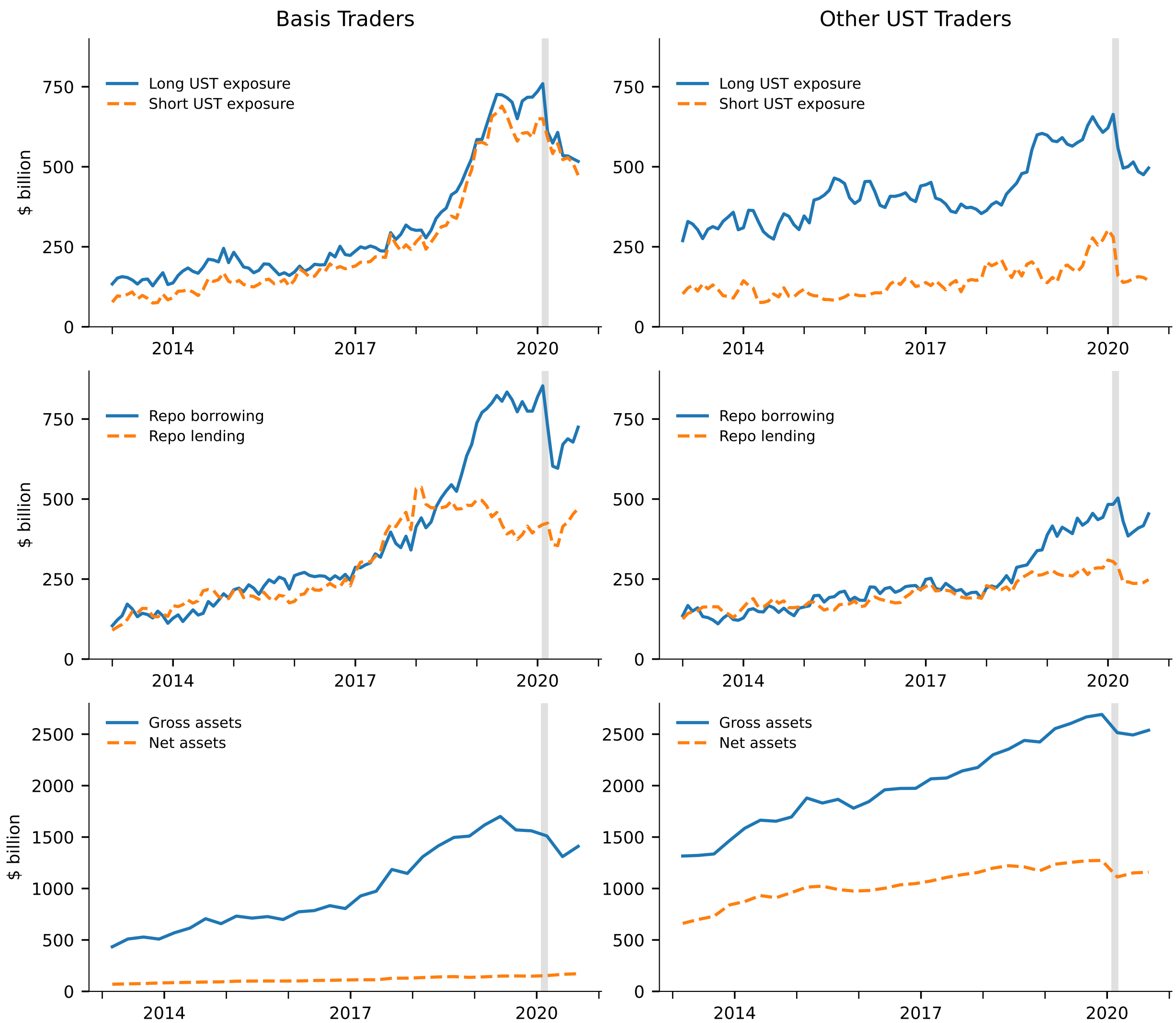


Figure 7: UST cash-futures basis trader versus other UST trader hedge funds

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 in 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 Appendix Table A2. 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	Std. Dev.	25th	75th	10th	90th
$VaRConstraint_{h,t}$ (%)	17,898	4.676	3.783	4.496	2.100	5.411	1.146	7.925
$DistAboveVaRConstraint_{h,t}$ (%)	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
$PortfolioGNE_{h,t}$ (m US$)	37,292	24,592.608	5,445.073	59,761.393	1,752.156	17,174.351	710.106	56,505.466
$EqTurnover_{h,t}$ (m US$)	33,292	9,792.620	1,302.997	22,957.386	141.588	7,999.925	0.191	19,414.891
$FITurnover_{h,t}$ (m US$)	33,292	21,610.450	2,824.357	42,959.217	411.433	15,878.278	56.848	85,010.462
$USTTurnover_{h,t}$ (m US$)	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	Std. Dev.	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	Std. Dev.	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	Std. Dev.	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 column header. The data are monthly from January 2013 to March 2020. Panel A shows changes in gross, long, and short UST notional exposures for our baseline sample. Panel B shows 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	
	$\Delta LogUSTDir$	$\Delta LogUSTArb$	$\Delta \frac{USTArb}{USTGross}$	$\Delta LogUSTArb$	$\Delta \frac{USTArb}{USTGross}$	$\Delta LogUSTArb$	$\Delta \frac{USTArb}{USTGross}$
	(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 column header. 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. 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, 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***	13.373***
	9.589	4.141	3.701	2.496	3.318	3.315
$IsGSIB_{p,t}$	-0.602	-5.143***	-6.230**	-2.516	14.215***	13.541***
	-0.464	-2.972	-2.315	-0.840	4.630	4.740
$LogHF\_Crdtr\_Credit_{h,p,t-1}$					-80.762***	-74.268***
					-27.208	-16.780
$CrdtrRankInHF_{h,p,t-1}$						-0.380
						-0.259
$HFRankInCrdtr_{h,p,t-1}$						-6.417**
						-2.448
$IsCrdtrCustodian_{h,p,t-1}$						5.500
						1.435
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's proximity to leverage constraints and revolver drawdown

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 %). In Panel A, the independent variable $DistanceToLRT_{p,t-1}$ measures the distance between a bank's leverage ratio and its required leverage ratio threshold (LRT). The data are quarterly from March 2015 (when banks started disclosing leverage ratios under the Basel III Accords) to March 2020. The indicator variable $PostEffectiveDate_{p,t}$ captures the effective date of the LRT requirement for each bank, which can differ across countries and institutions. In Panel B, 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 2013 to March 2020. In both panels, 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 "Other Controls" in column (5) are $CrdtrRankInHF_{h.p,t-1}$, $HFRankInCredtr_{h,p,t-1}$, and $IsCrdtrCustodian_{h,p,t-1}$. The independent variables, with the exception of the indicator variables, are standardized. The sample includes UST hedge funds that borrow predominantly through repo. 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: Creditor's proximity to leverage constraints

	(1)	(2)	(3)	(4)	(5)
$March2020_t \times DistanceToLRT_{p,t-1}$	-2.246	-1.580	0.922	-2.383	-2.172
	-1.283	-0.795	0.397	-0.942	-0.785
$PostEffectiveDate_{p,t} \times DistanceToLRT_{p,t-1}$	0.569	0.709	-0.731	2.604	2.645
	0.234	0.267	-0.284	0.819	0.841
$DistanceToLRT_{p,t-1}$	1.801	1.907	3.086	-0.463	-0.234
	0.692	0.747	1.060	-0.124	-0.062
$PostEffectiveDate_{p,t}$	-0.481	-0.638	1.754	-6.614	-6.501
	-0.118	-0.141	0.410	-1.191	-1.148
$LogHF\_Crdtr\_Credit_{h,p,t-1}$				-85.796***	-80.445***
				-21.366	-14.992
Observations	7,385	7,385	7,385	7,385	7,385
R^2	0.042	0.232	0.329	0.531	0.532

Panel B: Creditor's revolver drawdown

	(1)	(2)	(3)	(4)	(5)
$March2020_t \times DrawnDelta_{p,t}$	-0.599	0.970	3.313	-0.176	-0.093
	-0.255	0.399	1.368	-0.110	-0.054
$DrawnDelta_{p,t}$	1.136	1.136	0.351	0.529	0.500
	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
Observations	4,527	4,527	4,527	4,527	4,527
R^2	0.057	0.308	0.405	0.585	0.585

For both panels

	(1)	(2)	(3)	(4)	(5)
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: 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. The specifications include combinations of fund, quarter, and creditor fixed effects where indicated. The independent variables, with the exception of the indicator variable $March2020_t$, are standardized. The standard errors are clustered at the creditor and time level. 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
$\times LogHF\_Crdtr\_Credit_{h,p,t-1}$		5.230		16.279		-0.433
$LogHF\_Crdtr\_Credit_{h,p,t-1}$		-20.478***		-29.627***		-18.497***
		-7.544		-9.521		-6.091
Fund $\times$ Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Creditor $\times$ 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)
$March2020_t$	-0.159	0.659					0.467	0.172
$\times LogEqTurnover_{h,t-1}$	-0.074	0.379					0.258	0.095
$LogEqTurnover_{h,t-1}$	2.372	0.060					-0.276	0.070
	1.343	0.028					-0.119	0.031
$March2020_t$			5.773*	7.470***			7.275***	
$\times LogFITurnover_{h,t-1}$			1.876	3.359			2.858	
$LogFITurnover_{h,t-1}$			2.625	12.735**			12.779**	
			0.959	2.267			2.282	
$March2020_t$					6.479	10.527***		10.413***
$\times LogUSTTurnover_{h,t-1}$					1.347	3.438		3.138
$LogUSTTurnover_{h,t-1}$					-0.588	-0.342		-0.347
					-0.495	-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 $\times$ Creditor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Creditor $\times$ 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	0.293	0.480	0.293	0.483	0.293	0.480	0.483	0.480

Table 7: Internal risk constraints 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 column header. 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 VaR constraint

					$\Delta LogUSTArb$		
	$\Delta LogUST\_Gross$	$\Delta LogUST\_Long$	$\Delta LogUST\_Short$	$\Delta LogUSTDir$	All	Moderate	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$DistAboveVaRConstraint_{h,t-1}$	-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***
$\times DistAboveVaRConstraint_{h,t-1}$	-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 VaR constraint, with controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$DistAboveVaRConstraint_{h,t-1}$	-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***
$\times DistAboveVaRConstraint_{h,t-1}$	-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 of and proximity to VaR constraint, with controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$DistAboveVaRConstraint_{h,t-1}$	-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
$VaRConstraint_{h,t-1}$	-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***
$\times DistAboveVaRConstraint_{h,t-1}$	-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***
$\times VaRConstraint_{h,t-1}$	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 8: Internal risk constraints, 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 column header. 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	Mid	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$NetFlowVol_{h,t-1}$	0.168	0.668	-0.477	0.887	0.242	-0.100	0.753
	0.386	1.327	-0.540	1.050	0.207	-0.063	0.407
$ShareRes_{h,t-1}$	2.427	4.088**	-4.352	2.812	-3.381	-2.914	-1.906
	1.292	2.306	-1.304	1.182	-0.961	-0.772	-0.413
$March2020_t$ $\times NetFlowVol_{h,t-1}$	-1.805	-5.162***	-13.503***	-4.464**	-6.589*	-9.487***	-8.929**
	-1.126	-3.177	-3.728	-2.290	-1.824	-2.696	-2.286
$March2020_t$ $\times ShareRes_{h,t-1}$	-0.621	-7.986***	12.217***	-9.822***	-3.859	9.115*	19.511***
	-0.430	-4.426	4.142	-4.349	-0.993	1.823	3.697
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	17,809	16,002	12,271	17,794	10,512	7,241	5,049
R^2	0.031	0.035	0.043	0.016	0.038	0.053	0.062

Panel B: Internal risk constraints, funding, and redemption risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$VaRConstraint_{h,t-1}$	-1.319	0.125	-3.796	0.621	-0.069	4.705	4.931
	-0.851	0.050	-0.804	0.224	-0.012	0.682	0.636
$DistAboveVaRConstraint_{h,t-1}$	-0.587	0.489	-1.138	-1.357	1.074	2.306	2.329
	-0.818	0.619	-0.741	-1.154	0.615	1.053	0.969
$GSIB\_BrrwShare_{h,t-1}$	-0.333	0.777	-5.079	1.088	-5.743	-7.282	-8.973
	-0.147	0.248	-1.081	0.264	-1.064	-1.124	-1.057
$NetFlowVol_{h,t-1}$	0.018	0.816	-0.732	0.907	0.197	-0.176	1.535
	0.032	0.926	-0.550	0.748	0.111	-0.084	0.570
$ShareRes_{h,t-1}$	1.942	2.717	-5.549	1.382	-5.748	-4.593	-2.988
	1.234	1.282	-1.457	0.512	-1.385	-1.065	-0.572
$March2020_t$ $\times VaRConstraint_{h,t-1}$	16.262***	18.967***	22.712***	9.325***	52.864***	38.004***	24.269***
	8.233	7.349	4.795	3.048	12.355	7.735	5.460
$March2020_t$ $\times DistAboveVaRConstraint_{h,t-1}$	-9.094***	-11.584***	-4.711**	-9.004***	-8.702**	-10.643***	-17.174***
	-4.887	-5.790	-2.277	-3.497	-2.587	-2.795	-4.922
$March2020_t$ $\times GSIB\_BrrwShare_{h,t-1}$	-4.635	9.028	45.096***	18.610***	41.404***	55.018***	70.084***
	-1.097	1.652	6.014	2.779	5.194	5.649	7.494
$March2020_t$ $\times NetFlowVol_{h,t-1}$	-0.760	-18.892***	-19.004***	-6.684	-27.913***	-36.882***	-12.822
	-0.235	-4.882	-3.316	-1.583	-3.810	-4.266	-1.232
$March2020_t$ $\times ShareRes_{h,t-1}$	15.128***	6.193**	21.328***	-2.676	2.164	21.596***	33.600***
	6.768	2.205	4.216	-0.724	0.425	3.404	4.297
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	10,232	9,577	7,586	10,232	6,963	4,994	3,454
R^2	0.049	0.049	0.067	0.023	0.058	0.079	0.091

Table 9: Flow-performance relationship

This table presents results of the panel regression model, where the dependent variable is a hedge fund's quarterly flow, $NetFlows$. The independent variable is the return of a UST hedge fund over a lagged 4-quarter rolling window. Alternatively, we sort hedge funds into quintiles based on their returns over a lagged 4-quarter rolling window and include indicator variables for the quintiles. In columns (3) and (4), the return measures are interacted with a post-March 2020 indicator variable that takes the value 1 for the first and second quarter of 2020. The data are from January 2013 to June 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, 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 $p < 0.01$.

	(1)	(2)	(3)	(4)
$NetRet12m_{h,t-1}$	1.030***		0.967***	
	3.923		3.265	
$NetRet12m\_Quint2_{h,t-1}$		1.344***		1.115**
		2.904		2.172
$NetRet12m\_Quint3_{h,t-1}$		2.334***		2.235***
		4.741		4.047
$NetRet12m\_Quint4_{h,t-1}$		2.826***		2.694***
		4.631		3.955
$NetRet12m\_Quint5_{h,t-1}$		2.838***		2.723***
		3.761		3.358
$PostMar2020_t \times NetRet12m_{h,t-1}$			1.251***	
			4.878	
$PostMar2020_t \times NetRet12m\_Quint2_{h,t-1}$				3.714***
				4.167
$PostMar2020_t \times NetRet12m\_Quint3_{h,t-1}$				1.578
				1.480
$PostMar2020_t \times NetRet12m\_Quint4_{h,t-1}$				3.550***
				3.104
$PostMar2020_t \times NetRet12m\_Quint5_{h,t-1}$				5.419***
				3.971
Controls	Yes	Yes	Yes	Yes
Controls $\times PostMar2020_t$	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	6,738	6,738	6,738	6,738
R^2	0.378	0.379	0.383	0.385

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 column header. 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

	$\Delta LogFreeCashEq$	$\Delta \frac{FreeCashEq}{NAV}$	$\Delta LogCash$	$\Delta \frac{Cash}{NAV}$	$\Delta LogPortIlliq$
	(1)	(2)	(3)	(4)	(5)
$March2020_t$	25.708***	6.284***	23.001***	8.817***	-10.540***
	18.866	36.677	20.196	27.559	-8.403
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***	-13.898***	-12.778***	-0.004
	-44.125	-43.468	-8.262	-25.313	-18.068	-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 vs. 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 column header. The data are from January 2013 to March 2020. In 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 column 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

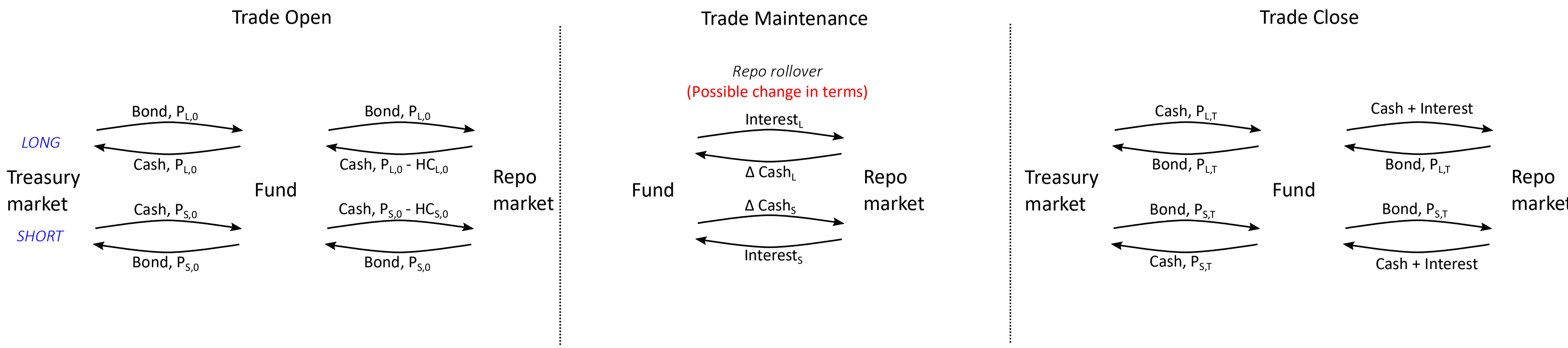
					$\Delta LogUSTArb$		
	$\Delta LogUST\_Gross$	$\Delta LogUST\_Long$	$\Delta LogUST\_Short$	$\Delta LogUSTDir$	All	Moderate	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$March2020_t$	4.938	0.120	4.325	-9.176	9.161	22.586***	22.612***
$\times BasisTrader_h$	1.243	0.028	0.630	-1.328	1.233	3.308	3.193
Controls	Yes	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

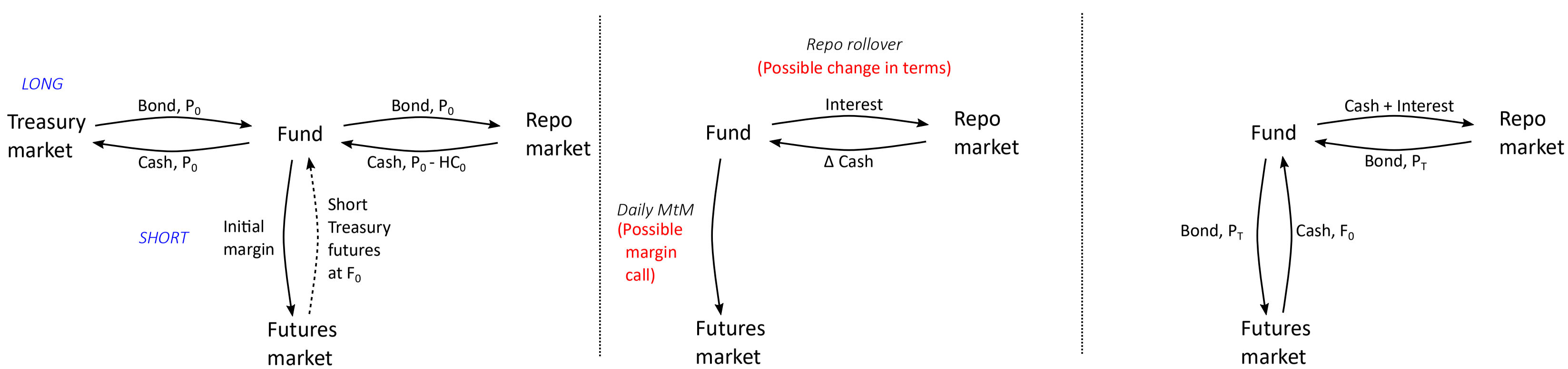
	Exposure		Maturity		Haircut
	$\Delta LogRepoBorrowing$	$\Delta LogRepoLending$	$\Delta RepoBrrwTerm$	$\Delta RepoLendTerm$	$\Delta \frac{RepoTotalCollateral}{RepoBorrowing}$
	(1)	(2)	(3)	(4)	(5)
$March2020_t$	23.206***	-6.666	-3.355***	-0.414	1.361**
$\times BasisTrader_h$	4.174	-1.054	-5.801	-0.355	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***	15.264***
$\times BasisTrader_h$	-4.976	-2.856	2.869	4.338	3.442
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 long-short bond spread trade (Panel A) and Treasury cash-futures basis trade (Panel B). 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: 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 column header. 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 $p < 0.01$.

	$NetRetM$ (1)	$NetRetQ$ (2)	$NetFlows$ (3)
$March2020_t$	-6.629***	-9.764***	-1.774***
	-37.528	-23.587	-5.989
$ShareRes_{h,t-1}$	0.055	0.027	1.197
	0.761	0.182	1.388
$PortIlliq_{h,t-1}$	-0.142	-0.109	-2.010***
	-1.319	-0.204	-3.364
$FinDur_{h,t-1}$	0.042	0.393	0.516*
	0.874	1.298	1.812
$LogNAV_{h,t-1}$	-0.402***	-1.172**	-7.698***
	-2.714	-2.316	-7.408
$NetRet_{h,t-1}$	0.025	1.329*	-0.990**
	0.193	1.785	-2.347
$NetFlows_{h,t-1}$	-0.021	-0.582***	3.054***
	-0.570	-3.293	6.573
$MgrStake_{h,t-1}$	-0.076*	-0.173	0.709
	-1.731	-1.344	1.450
$Leverage_{h,t-1}$	0.081	0.126	-0.634
	1.347	0.610	-1.405
Fund FE	Yes	Yes	Yes
Observations	21,659	7,630	7,618
R^2	0.194	0.548	0.344

Table A2: Variable definitions

This table presents definitions of the main variables. 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 3.

Variable Name	Description	Source
$VaRConstraint_{h,t}$	The 12-month rolling average VaR with a time horizon of one month and a probability of 5%. (m)	PF Q40
$DistAboveVaRConstraint_{h,t}$	The difference between the VaR in period t and the $VaRConstraint_{h,t-1}$. (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 Q8
$LeverageRatio_{h,t}$	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
$NetFlowVol_{h,t}$	Volatility of net investor flows over the last four quarters.	PF Q9, Q17
$OpenPositions_{h,t}$	Number of open positions in the hedge fund's portfolio. (m)	PF Q34
$PortfolioGNE_{h,t}$	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 A2: 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
$USTDirectional_{h,t}$	The unbalanced share of a fund's U.S. Treasury securities notional exposure, 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
$RepoBorrowing_{h,t}$	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
$HFRankInCrdtr_{h,p,t}$	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
$CrdtrRankInHF_{h,p,t}$	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
$IsCrdtrCustodian_{h,p,t}$	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 U.S. Treasury and agency securities.