

Risk-averse Dealers in a Risk-free Market – The Role of Trading Desk Risk Limits

Dan Li, Lubomir Petrasek, Mary Tian ¹

October 2025

¹We thank Stephen Zoulalian, Karl Patram, and Edward Wu for excellent research assistance. We thank David Bowman, Darrell Duffie, Ellen Correia Golay, Itay Goldstein, Edith Hotchkiss (discussant), Sebastian Infante, Francis Longstaff, Marco Machiavelli, Sebastien Plante (discussant), Norman Schürhoff, Annette Vissing-Jorgensen, Liying Wang (discussant), and seminar participants at the Federal Reserve Board (Feb. 2024), University of Lausanne (Mar. 2024), Northern Finance Association Conference (Sep. 2024), and Fixed Income and Financial Institutions Conference (Oct. 2024). We thank David Lynch, David McArthur, and Dennis Mawhirter for their insights on the nuances of the Volcker data. The views of this paper do not represent the views of the Federal Reserve Board.

Abstract

We show that self-imposed risk limits significantly constrain dealers' risk-taking and Treasury market intermediation, especially during market stress. Dealers near Value-at-Risk (VaR) limits reduce positions and demand higher compensation for risk. During March 2020, constrained dealers sold more Treasuries to the Fed at lower prices and provided less liquidity to clients. An aggregate measure of dealer VaR constraints closely tracks Treasury market illiquidity. Our findings offer a micro-foundation for the volatility–liquidity link and show that, in crises, policy actions that remove risk from intermediary balance sheets may be more effective at supporting Treasury market functioning than regulatory relief.

JEL Classification: G01, G23, E52

Keywords: Dealer Intermediation Capacity, Treasury Market, Risk Limits, Regulation, Market Liquidity

1 Introduction

In March 2020, the US Treasury market, long heralded as the paragon of liquidity and a haven of safety, experienced surprising turbulence when foreign central banks and institutional investors such as mutual funds rushed to liquidate their most liquid assets in the face of the global pandemic (Vissing-Jorgensen, 2021; Falato et al., 2021; Kruttli et al., 2025). Prices and liquidity of Treasury securities declined sharply as one-sided client selling pressure met limited dealer intermediation. Even primary dealers, the designated market makers in Treasury securities, were reluctant to absorb inventory and “lean against the wind”. Indeed, dealers actively reduced their Treasury holdings during the crisis, even as yields rose (Figure 1), amplifying selling pressure.

A prominent explanation for this apparent reluctance points to post-Global Financial Crisis (GFC) bank regulation, particularly the Volcker Rule and the Supplementary Leverage Ratio (SLR). A growing literature documents that intermediary balance-sheet constraints may have affected market liquidity across asset classes following these reforms (Bao et al., 2018; Du et al., 2018). However, the Volcker Rule explicitly exempts U.S. Treasury securities and market-making activities. While the SLR plausibly affects Treasury intermediation—because it is risk-blind and treats Treasuries similarly to riskier assets (Duffie, 2018)—this explanation is incomplete.

The SLR is slow-moving by construction: on-balance-sheet exposures enter the ratio as quarterly averages, so temporary increases in dealer inventories have limited immediate impact. Moreover, the SLR is insensitive to changes in market volatility, which surged in March 2020. Banks also had substantial headroom under the SLR during this period, particularly relative to later years when Treasury markets were more stable. Consistent with this interpretation, Vissing-Jorgensen (2021) shows that the reversal of Treasury price pressure in March 2020 coincided closely with the Federal Reserve’s large-scale daily Treasury purchases beginning on March 19—well before the announcement of temporary regulatory relief exempting Treasuries and reserves from the SLR.

Moreover, the reluctance of dealers to embrace risk in times of crisis, even amidst the haven of the most risk-free assets, predates regulatory oversight. Stress in the Treasury markets in March 2020 shows a remarkable resemblance with historical events. For example, nearly a century ago, in September 1939, dealers were unable to intermediate a surge in sales of Treasury securities

at the onset of World War II, requiring the Federal Reserve to conduct large scale purchases of Treasury securities to preserve orderly market conditions and alleviate pressures at dealers (Duffie, 2023). Similarly, using mis-pricing of derivatives relative to the underlying securities as a proxy of intermediary balance sheet cost, Fleckenstein and Longstaff (2020) document that such cost was similar in magnitude in the decades before 2007 and after 2007, and argue that “we must consider other factors besides post-crisis capital regulation in order to fully explain the mispricing...”

Our study reveals that dealers are inherently risk averse — they employ internal risk limits, which effectively constrain their risk absorption capacity. These limits, typically imposed by firms’ risk management function, are set at the trading-desk level, and portfolio risks relative to these limits are scrutinized daily. Dealer firms set such limits to address the principal-agent problems between the firms and their traders (Holmström, 1979; Adrian and Shin, 2013). Without such limits, traders who enjoy proportional benefit from the upside of their trades and limited downside risks would be incentivized to engage in reckless and high-risk strategies. Although dealers are often modeled as risk neutral, binding VaR limits generate behavior that is observationally equivalent to risk aversion. When desks approach their VaR limits, they reduce inventory and require higher compensation for bearing additional risk.

For risk limits set by management to be credible and effective in controlling risks, two conditions must hold. First, the limits have to be predetermined and difficult to change. We show that internal risk limits are persistent—that they do not change often. Even when limits occasionally get relaxed, especially during market stress events, such limit changes typically require multiple layers of approval and are frequently insufficient to fully offset the demands on dealer risk taking. Second, breaching limits must be costly for traders. The cost could be reputational or pecuniary.¹ Our empirical results are consistent with such cost being no-trivial.

Trading desks are subject to multiple risk constraints—including market, counterparty, and liquidity risk limits—which vary across firms and business lines.² We focus on VaR limits because they are nearly universal among Treasury trading desks and represent the primary binding con-

¹Indeed, casual conversations with large bank compliance personnel suggest that banks do impose substantial dollar fines on limit breaches.

²For example, derivatives trading desks tend to have limits with regards to various portfolio greeks (delta, vega, gammas). Forex trading desks have limits of risk exposure with respect to each foreign currency exposure.

straint. VaR captures tail risk and is highly sensitive to changes in market volatility, making it intrinsically countercyclical(Adrian and Shin, 2013). Unlike size-based constraints such as the SLR, VaR responds immediately to increases in volatility even for static portfolios. We formalize this intuition in a simple model showing that a risk-neutral trader subject to a VaR constraint behaves equivalently to a risk-averse trader with a standard utility function.

Our analysis uses novel supervisory data from the Volcker Rule reporting framework, which provides desk-level information on VaR limits and their utilization. These data allow us to measure dealer intermediation capacity directly rather than inferring it from prices or quantities.³ The high-frequency panel structure enables us to identify the effect of binding risk limits on trading behavior at the desk level, rather than at the aggregate market level.

We show that dealers proactively manage their inventory to avoid breaching desk VaR limits. Specifically, when VaR limit usage doubles, dealers reduce the change in their net positions by about 10 percent, on average, over the subsequent week. This adjustment is achieved by acquiring less inventory or selling existing inventory, with newer inventory being sold first. Such aversion to breaching the limit is most prominent in March 2020, when dealers rushed to off-load Treasury securities to the Federal Reserve. Our VaR-based result provides a micro-foundation for the negative link between market volatility and dealer intermediation capacity.

Since VaR calculations measure portfolio risk after taking into account offsetting positions and hedges, gross positions are potentially less sensitive to VaR limits than net positions. Our findings confirm that the size of dealers' gross positions is indeed less affected by VaR constraints than their net positions. These findings also suggest that policy recommendations aimed at alleviating dealer gross balance sheet pressures may have limited effectiveness during market stress. For example, mandatory central clearing or a relaxation of the minimum SLR would provide relief from size-based regulatory constraints without alleviating risk-based constraints.

We further take advantage of richness of our data to analyze intra-firm variation in VaR constraints and positions across trading desks at dealers with several Treasury trading desks, as well as examine the role of non-VaR-based risk limits. The data also allow us to construct instrumental variables using changes in the limits on non-Treasury market making desks and examine exogenous

³Duffie et al. (2023) infer a capacity limit on intermediary positions based on historical maximum level of positions.

sources of variation in limit usage on Treasury market making desks.

Given the debate about the role of the SLR, we offer an assessment of the relative importance of VaR and the SLR constraints. In our sample, proximity to the minimum SLR is not significantly related to the changes in Treasury desks' positions at the daily-to-weekly frequencies. This finding is not surprising, given that Treasury securities holdings enter the SLR denominator as the daily average over the entire quarter. The slow-moving nature of the SLR should therefore make it less likely that a short-term increase in dealer intermediation would make the SLR requirement binding. However, although it is a slow-moving metric, balance sheet shocks could still affect dealer constraints under the SLR, especially if they are expected to persist. We follow [Favara et al. \(2024\)](#) and use drawdowns on corporate revolving credit facilities of the bank holding companies under which our sample dealers operate to construct a proxy for higher-frequency SLR shocks that could leave a longer-lasting imprint on dealer balance sheets. The analysis of the credit line drawdowns suggests that SLR shocks may also play some role in limiting dealers' Treasury intermediation. However, the analysis confirms that VaR limits are the primary constraint affecting dealers' Treasury market-making.

To further demonstrate that large Treasury market dealers faced significant constraints due to their internal VaR limits in March 2020, we conduct an event study. We compare how trading desks were differently inclined to reduce their inventories through selling to the Federal Reserve during the emergency open market operations from March to June. Our analysis shows that dealers closer to their VaR limits were more inclined to sell to the Fed in the subsequent days and months. These dealers also offloaded larger amounts of Treasury securities to the Fed's balance sheets, both in absolute quantity and relative to their overall intermediation activities. The sensitivity of dealers' sales to the Fed relative to the tightness of their VaR constraint was stronger in March, than from April to June.

In addition to selling more to the Fed, more constrained dealers also submitted more aggressive offers in auctions — they were willing to sell their Treasury bonds to the Fed at cheaper prices. Dealers bid 0.8 cents lower in prices when their limit usage doubled. We find that the aggressiveness of dealers' auction offers was particularly sensitive to their VaR limit usage for longer-maturity bonds. These bonds contribute disproportionately to the VaR of the portfolio and generate the

most relief from VaR limits when disposed of from dealers' portfolios. Such evidence of cross-sectional differences further points to VaR limits, instead of risk-blind size-based constraints, as being the more relevant constraint during periods of market illiquidity.

We examine next how VaR limits affect dealers' provision of liquidity to clients, and whether these effects can be alleviated by Federal Reserve asset purchases. We first confirm that during the COVID-crisis period, dealers were less likely to provide liquidity to clients (buy from clients) if they were closer to their VaR limit. In particular, dealer buy volume from clients decreased by 15.2 percent for every 100 percent increase in limit usage. However, after controlling for VaR limit usage, dealers who sold more to the Fed were more likely to purchase from clients, especially in March 2020. During that month, dealer buy volume from clients increased by 8.5 percent for every 100 percent increase in dealer sale volume to SOMA.

Therefore, by alleviating the balance sheet constraints of dealers and taking bonds off dealers' inventory, the SOMA purchase operations were effective in incentivizing dealers to provide more liquidity to clients. Interestingly, dealers who were able to sell more bonds to the Fed were able to provide more immediacy to their clients both for Treasury securities that were purchased by the Fed and those that were not. This suggests that dealers were not merely passing on bonds from clients to the Fed. Since dealer balance sheets are fungible, Fed support in some bonds has positive spill-over effects on other bonds — the extra capacity vacated from selling some bonds to the Fed allowed dealers to provide more immediacy to clients in other bonds.

We then explore how risk aversion among dealers translates to customers' transaction costs. We show that as dealers approach their VaR limit, they seek greater compensation for taking on any additional risk. We show that dealer average future profit and loss (P&L) scaled by their desk VaR, increases with the tightness of their VaR constraints. Moreover, the effect is entirely driven by P&L generated from new trades, rather than existing positions. Notably, as limit usage doubles, dealers require on average about 9 percentage points higher P&L per unit of VaR to take on new positions over the following week. Since the flip side of dealer profitability from new trades is client transaction cost, this result provides a direct link between dealer constraint and market illiquidity.

Finally, we develop an aggregate measure of Treasury market dealer VaR constraints using individual dealer VaR limit tightness and each dealer's recent share of customer transactions as

weights. This aggregate measure exhibits a strong correlation with established measures of Treasury market illiquidity for both average and tail measures of illiquidity, even after market volatility is controlled for. Furthermore, consistent with [Duffie et al. \(2023\)](#), we find that the impact of our aggregate dealer VaR constraint measure on Treasury market illiquidity is skewed and more pronounced when markets are illiquid.

2 Related Literature

Our findings challenge the classic micro-structure assumption that dealers are risk neutral. We argue that the apparent “risk averse” behavior of dealers in times of stress, even in “risk-free” asset market, is consistent with them optimizing under constraints. [Duffie \(2023\)](#) extends the dealership model of [Amihud and Mendelson \(1980\)](#) to include an explicit constraint on dealer inventory, and shows that the simple extension allows the model to generate dealer bid-ask quotes that are significantly wider when dealer inventory is near capacity. Consistent with the literature, we show in a simple stylized model that “risk neutral” dealer optimizing under an upper limit on portfolio Value-at-Risk is observationally equivalent to the decision faced by a risk-averse dealer with CRRA utility function.

We contribute to the vast literature of OTC market intermediary behavior and its effects on market liquidity by offering a peek behind the curtain of the real world of dealer trading desks and internally-set risk limits. Such risk limits allow us to measure the spare capacity of dealers under the limits directly, rather than inferring it. We document some stylized facts about desk-level VaR limits, how persistent they are, their general level of usage and how it varies across time and across desks. [Anderson et al. \(2023\)](#) look at several risk limits used by corporate bond trading desks and show that they affect corporate bond spreads and transaction costs.

Motivated by the sharp price movements and surprising hiccups in Treasury market functioning in March 2020, we focus on Treasury securities trading desks of major dealers and attempt to gain a deeper understanding of the choices they make and the constraints they face in different market environments and how dealer decisions translate into market outcomes such as market liquidity. Our study complements the literature that studies the behavior of various institutional investors of Treasury securities during the March 2020 market stress. [Falato et al. \(2021\)](#) and [Kruttili et al.](#)

(2025) document large sales of Treasury securities by mutual funds and hedge funds, respectively. Using data on both the price and quantity of liquidity in the Treasury market, [Goldberg \(2020\)](#) is able to decompose liquidity into supply and demand. He estimates that investors' demand for liquidity soared, while dealer liquidity supply declined notably during the onset of the pandemic in March 2020. We provide micro-level evidence that attributes the lack of dealer liquidity provision to their internal risk limit.

In addition, our paper is related to the growing literature on intermediary constraint and market liquidity. On the theory side, [Gârleanu and Pedersen \(2007\)](#) study the aggregate effects of risk management practices on market liquidity and asset prices. Empirically, [Lewis et al. \(2021\)](#) show that intermediary balance sheet constraints explain the cross-section of mispricing for safe assets. [He et al. \(2021\)](#) highlight the importance of intermediaries' balance sheet costs in explaining the disruptions in March 2020 in the Treasuries market. In particular, they point to the SLR as a potential source of dealer balance sheet constraint. [Breckenfelder and Ivashina \(2021\)](#) exploit the persistence in client-dealer relationship associated with home country bias and show that European corporate bond mutual funds with closer ties to banks with constrained leverage ratios experienced more outflow and selling pressure. Our research provides evidence that trading desk risk limits present another source of significant dealer constraint and documents how dealers manage their trading portfolios and set their required returns to avoid breaching such limits. We stress that the internal risk constraint and the regulatory constraint are not mutually exclusive. Both types of constraint could be at work simultaneously. Indeed, [Duffie et al. \(2023\)](#) show that a variety of aggregate dealer capacity measures can explain Treasury market liquidity beyond what can be explained by market volatility. Instead of looking at market aggregates, we focus on the cross-section of dealers and individual trading desks, and attempt to establish micro-level links between capacity constraints due to internal VaR limits and dealers' provision of liquidity.

Our findings are also consistent with the literature documenting the effectiveness of Federal Reserve open market purchases in alleviating Treasury market stress. Indeed, by carefully tracing out the timeline of Treasury securities price movement during the COVID crisis and the announcement and actual implementation of various policy actions, [Vissing-Jorgensen \(2021\)](#) identified a causal link between the Federal Reserve's Treasury purchases and market stabilization, and ruled

out other potential confounding factors. [Vayanos and Vila \(2021\)](#) show in a model of investors with preferred habitat and risk-averse arbitrageurs, QE style central bank intervention can be effective in lowering term premium. We show that “risk averse” behavior by market makers could be linked to their internal risk management and Fed asset purchases were effective in alleviating this particular friction and thawing the Treasury market in 2020. We show that dealers more constrained by the VaR limit are more likely to sell bonds to the Fed and offer more aggressively in auctions, and those who were selling more to the Fed were able to offer more immediacy to clients. Thus, the SOMA purchase program was highly effective in stabilizing the market by providing direct relief of dealers’ balance sheet constraints.

This paper provides micro-level evidence that complements [Adrian and Shin \(2013\)](#), who document a negative relationship between banks’ leverage and VaR, and that banks deleverage substantially during market downturns. Their findings, while focusing on slower-moving lending by banks through business cycles, is consistent with what we find for faster-moving activities at trading desks. The authors document that banks keep the ratio of their VaR- to-equity roughly constant and develop a contracting model allowing bank creditors to impose a VaR limit that is proportional to the banks’ equity. Such contracting arrangement alleviates the risk-shifting moral hazard of the bank, and can effectively bound the bank’s probability of failure below a fixed threshold, irrespective of the risk environment. The paper mirrors our finding that trading desks not only universally adopt a VaR-type risk limit, but they also take the internally imposed limit seriously.

While we do not model or empirically test why dealer banks impose occasionally binding risk limits on their trading desks, agency problems between traders and bank shareholders or creditors resemble the contracting frictions discussed in [Holmström \(1979\)](#) and applied to dealers in [Adrian and Shin \(2013\)](#). Traders are typically awarded a proportion of the trade profits, but have limited liability and are not expected to absorb large losses. Such compensation schemes potentially lead to excessive risk taking. Desk-level VaR-type limit is a natural way for dealer firms to alleviate the agency problem. Similar types of risk management practices exist in other forms of delegated portfolio management. For example, large hedge funds typically have VaR-type risk limits for their traders as well ([Kruttili et al., 2025](#)). In the context of bank lending, lenders typically impose a variety of accounting-based debt covenants to facilitate monitoring and reduce risk taking by

borrowers (see for example [Dichev and Skinner \(2002\)](#)) .

As in the case of most contracting settings, where it is not feasible or too burdensome to incorporate state-contingency into the contract, an ex-ante commitment by dealer firms to rigid risk limits may come at the expense of forgoing profitable trading opportunities during market downturns. In the context of hedge funds, it is well documented that they typically retreat when market volatility rises ([Boyson et al., 2010](#); [Aragon and Strahan, 2012](#)). Such evidence and our finding of dealer behavior during the COVID crisis offer additional support to [Shleifer and Vishny \(1997\)](#). Therefore, agency problems within asset managers or dealer firms induce procyclical risk appetite and renders such financial intermediaries unsuitable to serve as “buyers of last resort”.

The rest of this paper is organized as follows. Section 3 illustrates in a simple model how a risk-neutral trader with VaR limit could be observationally equivalent to trader with risk-aversion. Section 4 describes the data. Section 5 shows main results about dealer inventory and dealer VaR usage. Section 6 examines the interaction between risk limits and regulatory constraints. Section 7 presents robustness results. Section 8 presents an event study of dealer behavior after Fed purchases in March 2020. Section 9 examines the effects of internal risk limits on dealer profitability and aggregate market liquidity. Section 10 concludes.

3 Illustrative Model of the Duality Problems

The simple model below illustrates the duality between portfolio optimization under a Value-at-Risk constraint and optimization under risk aversion. In a standard two-period optimization setting, the decision of a risk-averse investor maximizing next period utility under no risk constraint is observationally equivalent to the decision of a risk neutral investor maximizing next period wealth W under a VaR constraint.

- **Portfolio Optimization Under CARA Risk Aversion (Primal Problem)**

In this scenario, a trader with CARA (Constant Absolute Risk Aversion) utility optimizes her investment portfolio, which generates a next period wealth of W . The utility function is defined as $U(W) = -e^{-\gamma W}$, where γ is the risk aversion coefficient.

Maximizing this utility leads to mean-variance optimization:

$$\text{Maximize } U = E[W] - \frac{\gamma}{2}\sigma^2(W) \quad (1)$$

where σ^2 is the variance of the portfolio.

- **Optimization under Risk-neutrality and Value-at-Risk Constraint (Dual Problem)**

In this alternative scenario, the trader is risk-neutral. She maximizes next period wealth W , subject to a VaR risk limit:

$$\begin{aligned} &\text{Maximize } E[W] \\ &\text{s.t. } \text{VaR}_\alpha(W) \leq \overline{\text{VaR}}_\alpha(W). \end{aligned} \quad (2)$$

$\text{VaR}_\alpha(W) = \inf\{x \in \mathbb{R} : P(W - W_0 \geq -x) \geq \alpha\}$, where α is the confidence level, typically set at 95% or 99%. $\text{VaR}_\alpha(W)$ is the highest value of next period wealth loss so that the probability of wealth falling less than that value is more than α . The risk limit stipulates that the portfolio VaR should be lower than a pre-set ceiling value of $\overline{\text{VaR}}_\alpha(W)$.

This optimization problem can be solved using Lagrangian transformation

$$\text{Maximize } \mathcal{L}(W, \lambda) = E(W) + \lambda(\overline{\text{VaR}}_\alpha(W) - \text{VaR}_\alpha(W)) \quad (3)$$

where $\lambda \geq 0$ and λ is the Lagrange multiplier associated with the inequality constraint in Equation 2, and it can be interpreted as the shadow cost of portfolio VaR getting closer to its limit $\overline{\text{VaR}}_\alpha(W)$.

Proposition 1. *The primal problem and dual problem above are observationally equivalent.*

Proof. Assume that the next period wealth W follows a normal distribution centered around current period wealth W_0 . The VaR of the portfolio $\text{VaR} = Z_\alpha * \sigma_W$, where σ_W is the standard deviation of portfolio value next period W . Z_α is the z-score corresponding to the confidence level α .

We can re-write the constraint in Equation 2 as

$$VaR_\alpha(W) = Z_\alpha * \sigma_W \leq \overline{VaR}_\alpha(W) \quad (4)$$

$$\begin{aligned} &\iff \sigma_W \leq \frac{\overline{VaR}_\alpha(W)}{Z_\alpha} \\ &\iff \frac{\sigma_W^2}{2} \leq \frac{\overline{VaR}_\alpha^2(W)}{2 * Z_\alpha^2} \end{aligned} \quad (5)$$

The Lagrangian function of the optimization problem can be alternatively written as

$$\begin{aligned} \text{Maximize } \mathcal{L}(W, \gamma) &= E(W) + \gamma \left(\frac{\overline{VaR}_\alpha^2(W)}{2 * Z_\alpha^2} - \frac{\sigma_W^2}{2} \right) \\ &= \gamma \frac{\overline{VaR}_\alpha^2(W)}{2 * Z_\alpha^2} + E(W) - \frac{\gamma}{2} \sigma_W^2 \end{aligned} \quad (6)$$

$\gamma \geq 0$ and γ is the Lagrange multiplier associated with the new inequality constraint in Equation 5. Since $\gamma \frac{\overline{VaR}_\alpha^2(W)}{2 * Z_\alpha^2}$ is a constant, the two optimization problems in Equation 1 and Equation 6 are observationally equivalent. \square

This simple model shows that while dealers may not be “risk-averse” per se, the existence of internal risk limit may effectively induce trading behavior that is observationally equivalent to a “risk averse” trader. The model is not meant to capture all aspects of a dynamic optimization problem, but to offer a conceptual framework that links dealer risk-attitude, Value-at-Risk, risk limit, and dealer wealth (P&L). As a byproduct of the framework, in Appendix A, we show how the shadow cost of breaching risk limit λ can be empirically estimated using dealer P&L, VaR, and VaR limit. The estimation is carried out in Section 9.

We next turn to data to show that dealers indeed exhibit risk-averse behavior in the intermediation of Treasury securities — they reduce risk taking when they are close to their risk limit.

4 Data

4.1 Trading desk risk limit data

Our main data comes from the Volcker Rule collection. To insulate banks from the volatility and potential large losses originated from capital markets activities, the Dodd–Frank Act includes a prohibition known as the “Volcker Rule” on proprietary trading by U.S. banks. The rule allows

exemptions for hedging, market-making, and various financial instruments such as foreign exchange and government securities. To facilitate the monitoring of compliance with the Volcker rule, the Dodd-Frank Act requires that all banks with significant trading operations report daily quantitative metrics for each of their trading desks on Form FR VV-1. This report collects detailed data from all affiliated trading desks, including those that claim exemptions from the Volcker prohibition on proprietary trading. The report provides a daily time series of various risk limits and their usage, profit & loss and its attribution to risk factors, and trading positions and transactions. The mandatory nature of the reporting, management certification and examiner controls all together insure a high accuracy of the FR VV-1 data. Appendix C provides further details about the data collection process and data quality.

4.1.1 Treasury market-making desks

While Treasury securities are exempted from the “Volcker Rule” on proprietary trading, they are not excluded from regulatory reporting on Form FR VV-1. We identify Treasury trading desks by searching for terms such as “Treasury” and “U.S. Government” in the desk name and description. For desks identified by word search, we manually cross-check that the desk description is indicative of Treasury securities market making. As an additional check, we also review the list of exemptions from the “Volcker Rule” on proprietary trading that the desk claims. Treasury trading desks typically claim the “trading in domestic government obligations” and/or the “market making-related activity” exemption, which helps us narrow the sample of desks that are primarily engaged in such activities. Altogether, we identify a sample of 18 “prime” Treasury trading desks affiliated with 10 large banks during the sample period from 01/01/2015 to 03/31/2023.

As a robustness check in Section 7.3, we examine a broader set of 40 desks, which includes all desks that list Treasury securities in their name of desk description, even if the desk description suggests that Treasury market making is not their main focus. Many of these additional desks are derivatives market making desks, repo desks, hedging desks, municipal desks, or credit desks that may trade Treasury securities to support these activities. Additional information about the sample of Treasury trading desks can be found in Appendix C.

4.1.2 Internal risk limits

The “Volcker Rule” defines internal risk limits as constraints that determine the amount of risk that a trading desk is permitted to take at a point in time. Internal risk limits are not set by regulation, but rather defined by the banking entity itself for a specific trading desk as part of its internal risk management. The limits are typically expressed in terms of risk measures, such as Value-at-Risk, but may also be expressed in terms of other observable criteria, such as the number of open positions. We focus on the limits that are expressed in terms of Value-at-Risk (VaR), as all trading desks engaged in market-making related activities are required to have such limits. We explore alternative risk limits, such as the DV01 limits in our robustness analysis.

To identify VaR limits, we search for limit names that include VaR. For each limit, firms report the limit size, representing an upper bound on the risk measure, as well as the actual value of usage in dollars, corresponding to the observed value of the risk measure at the end of the day. In a separate field, firms also report the VaR, defined as the risk of future financial loss in the value of the trading desk’s aggregated positions at the 99% confidence level over a 1-day holding period.

To validate the VaR limit, we compare its usage to the reported VaR. If several VaR limits are identified on a given desk, we take the VaR limit with usage corresponding to the reported VaR measure. Although each firm uses its internal models to calculate VaR, there are minimum requirements for such models and firms must be able to justify to the satisfaction of supervisors any methodological choices.⁴ Importantly, regardless of the differences in how firms calculate VaR, the relevant internal constraints are those set by each firm using its own methodology.

To provide some empirical validation of desks’ reported values of VaR, we estimate a hypothetical VaR for each desk and compare it to their reported values in the data. The estimates suggest a notable amount of uniformity in desks’ reported VaR.⁵ Furthermore, Section 7.4 shows that our

⁴Appendix C provides additional information about the reporting requirements for VaR measurements.

⁵Our methodology in estimating VaR is based on [Duffie et al. \(2023\)](#), though our estimates are more granular at the desk-level. In particular, we run quantile regressions for daily PnL at the 1st percentile to estimate a one-day, 99th percentile VaR. The PnL regression model includes one-day lags of VIX, MOVE, and the PnL realized variance as explanatory factors. We find that the correlation between desks’ reported VaR and estimated VaR is 0.55 across all desks over the full sample period of 1/1/15-3/31/23. Moreover, the R-squared from the panel regression of desks’ reported VaR on estimated VaR, with desk fixed effects, is 72 percent, indicating that the standardized estimation across desks can explain 72 percent of the variation in desks’ reported VaR. The t-stat on the regression coefficient is statistically significant at the 1 percent level.

main findings are robust to differences in quantitative measurements across firms.

Internal risk limits are crucial for controlling risk exposure and ensuring trading activities align with the firm’s overall risk appetite. Although the limits are primarily an internal risk management tool, the limits are subject to supervisory review and oversight on an ongoing basis. As such, the risk limits and their usage are closely monitored by not only traders and bank management, but also bank supervisors.

Like other risk limits, VaR limits are highly persistent and change very infrequently. This ensures that the limits are a credible deterrent against excessive risk taking. In our sample period, the unconditional probability of VaR limit staying the same on a given day is 99.5%. The probability of the limit increasing (decreasing) on a given day is small at 0.29% (0.24%). Even in March 2020, when more dealer firms modified their risk limits in light of market conditions, the probability of an increase (decrease) of VaR limit on a given day remained small at 3% (0%). As detailed in Appendix C, increasing these limits requires a structured approval process involving various levels of management, including at senior levels.

4.1.3 Limit usage measure

VaR and VaR limit are both expressed in terms of dollar amount. To capture the level of capacity utilization and compare them across dealers, we define *Limit usage* ratio as:

$$Limit\ usage = VaR/VaR\ limit, \tag{7}$$

where VaR corresponds to the limit usage, as reported by each firm for the applicable VaR limit. This ensures that any differences in methodologies to estimate VaR would symmetrically affect both the VaR and its limit.

Figure 2 shows on the left the time series of the average VaR *Limit usage* ratio. The average *Limit usage* ratio spiked in March 2020, approaching one. Despite decreasing in early April, VaR *Limit usage* at Treasury trading desks remained elevated until June.

Figure 2 plots on the right the average limit size and usage (the VaR) of the sample desks. During March 2020, the average VaR on Treasury trading desks shot up. Although firms reacted

by also gradually increasing the size of the limit, the increases in limit size generally lagged the VaR increases and were not large enough to fully offset the increases in VaR. This chart suggests that the VaR limit occasionally becomes binding, even for the average desk.

There are a couple of properties of VaR measure that are particularly relevant for our analysis. First, VaR is intrinsically counter-cyclical. Volatilities in the prices of the underlying assets translate almost one-to-one to the desk VaR, even if the desk portfolio is held constant. Second, VaR measure accounts for correlations across positions. Therefore, long and short positions of similar exposure provide off-sets in their VaR contribution. This is different from constraints that limit the gross amount of exposure. Finally, since VaR is a risk measure, it is sensitive to the amount of risks each trading position entails. For example, a Treasury bond with longer tenor contributes more to portfolio VaR than a bond with the same par value but shorter tenor. We explore such cross-sectional differences in our empirical analysis.

4.1.4 Trading positions

To meet client demand, Treasury market-making desks maintain an inventory of securities and derivatives positions. The inventory is effectively constrained by the internal risk limits at each desk. We use the size of these positions to measure the desks' market-making activities, and examine the effect of internal risk limits on Treasury market-making.

Positions are a key outcome variable for the paper. The Volcker data contains several measures of trading desk positions: The market value of long and short securities positions, and either the market or the notional value of long and short derivative positions. Our baseline results are based on the market value of long and short securities positions, which is reported consistently throughout the entire sample period. The market value of securities positions is plotted in the left panel of Figure 3.⁶ Prior to 12/30/2020, derivative positions were reported at the notional value, with option values delta-adjusted, and interest rate derivatives reported as 10-year bond equivalent values. Since 2020, derivative positions have been reported at market value, which tends to be small and is not comparable to the market value of securities positions.

⁶Online Appendix Figure 1 compares the sum of the long securities positions at Treasury trading desks from the Volcker data with a measure of Treasury securities holdings from the Complex Institution Liquidity Monitoring Report (Form FR 2052a).

We use the data to construct several inventory measures: (1) the net securities position, measured as the absolute value of the difference between the long and short securities positions; (2) the gross securities position, measured as the sum of long and short securities positions; (3) the long securities positions; (4) the short securities positions. In addition, we construct measures based on the combined securities and derivatives positions: (1) net combined positions; (2) gross combined positions; (3) long combined positions; and (4) short combined positions. These measures are based on the combined market value of securities holdings and the notional value of derivative positions. Because the notional value of derivatives positions is only reported through 12/31/2020, the combined measures are only available through that date.

4.2 SLR data

In addition to internal risk limits, we examine whether Treasury market-making activities are constrained by regulatory capital requirements at the bank holding company level, particularly the Supplementary Leverage Ratio (SLR). The SLR is a non-risk weighted capital requirement, measured as the ratio of a banking organization's Tier 1 capital to total leverage exposure. As such, it is particularly affected by high-volume, low-risk activities such as Treasury market intermediation.

Large U.S. banks are required to maintain an SLR of 3%; additionally, Global Systemically Important Banks (G-SIBs) are subject to an additional 2% enhanced SLR (eSLR) buffer, bringing their total SLR requirement to 5%. All but three of the sample firms, which are all foreign bank subsidiaries, are subject to the eSLR of 5%. We obtain the quarterly SLR data from the bank holding companies' consolidated financial statements (Form FR Y-9C). We measure the excess capital under the SLR rule as the *SLR distance*, the difference between the actual SLR and the minimum SLR requirement for the bank holding company in each quarter. We measure the *SLR distance* since the SLR requirement became binding on 01/01/2018.

4.3 Credit line drawdowns

We use data on credit line drawdowns at the parent company level to allow for the possibility that such drawdowns affect BHC balance sheets and the *SLR distance*. The source of the data on credit

line drawdowns is the Federal Reserve Board’s Complex Institution Liquidity Monitoring Report, Form FR 2052a. Large U.S. banking organizations are required to report daily the outstanding draws on revolving credit facilities. Following Favara et al. (2024), we measure credit line drawdowns as changes in the outstanding draws on revolving credit facilities (*CreditDraws*), scaled by total assets, as reported on Form FR Y-9C as of the end of the previous quarter ($q-1$). We only include draws from non-financial corporate borrowers, to minimize any endogeneity concerns. Specifically, we define *Drawdown* over a period of h days as follows:

$$Drawdown_{t,h} = \frac{CreditDraws_t - CreditDraws_{t-h}}{TotalAssets_{q-1}}. \quad (8)$$

The right panel in Figure 3 plots drawdowns over the 5-day horizon ($h=5$). Drawdowns spiked during the dash for cash in 2020 and decreased in subsequent quarters as corporate borrowers paid down the outstanding lines.

4.4 Fed emergency SOMA purchases data

To support the smooth function of markets for Treasury securities and agency MBS, on March 15, 2020, the FOMC directed the Open Market Trading Desk (the Desk) to increase the System Open Market Account (SOMA) holdings of Treasury securities and agency mortgage-backed securities (MBS) by at least \$500 billion and at least \$200 billion, respectively. Auctions of \$40 to \$75 billion worth of Treasury securities per day were carried out from March 16th to March 23rd. On March 23rd, the FOMC further instructed the desk to increase the SOMA holdings of Treasury and agency MBS securities in the amounts needed to support the smooth functioning of both markets, essentially lending unlimited balance sheets to the market. The size of Treasury purchase operations stayed at \$75 billion per day until April 1st and only gradually decreased.

We download daily operation results from March 16, 2020 to June 11, 2020 from “[Treasury Securities Operational Details](#)” page posted by the Federal Reserve Bank of New York. Data include information on the date, CUSIP, allocated par amount and weighted average price for each securities eligible for the purchase operations. Each open market outright operation is a multiple-price, multiple securities, competitive reverse-auction (will refer it as auction for simplicity) and only

primary dealers are allowed to submit offers. [Duffie and Keane \(2023\)](#) offers detailed descriptions of how central bank asset purchases are conducted.

There are 6,410 unique CUSIP-Date combinations with non-zero allocations during this sample period and 347 unique CUSIPs overall. For a typical CUSIP in a given day with non-zero allocation, the Desk purchases about \$133.5 million worth of the bonds from dealers. The data does not reveal the identity of winning dealers in each auction. To infer the amount of bonds each dealer in our sample sold to SOMA, we merge this auction data with supervisory Treasury TRACE transaction reporting data. The detail of the merging process is explained in [Appendix B](#). We keep two versions of the merged data for our analysis. For quantity related analysis, we keep the data at dealer-day level. For price level analysis, we use transaction level (bond-dealer-day) data.

4.5 Descriptive statistics

[Table 1](#) shows the summary statistics for the different measures of dealer positions and internal risk limits at Treasury trading desks. The average net securities position is \$4.95 billion at the Treasury trading desks in the sample, and the average gross securities position is \$26.7 billion. Long and short securities positions are \$15.0 billion and \$11.7 billion, respectively. Combined positions are notably larger, with derivatives exposures accounting for most of the combined positions. The average desk has net combined positions of \$350.5 billion, and gross combined positions of \$3020.4 billion. Variations in positions both across desks and over time are large and the distribution is skewed to the right, with the three largest desks on average accounting for almost 60% of the combined gross securities position. Therefore, we focus our analysis on the log changes of each individual desk's positions.

The VaR usage is \$4.2 million on average, compared to the VaR limit of \$12.2 million. Thus, the limit usage is about 0.3 (30%) on average. As shown in [Figure 2](#), the limit usage varies significantly over time, approaching or exceeding one during the March 2020 Treasury market stress. There is also significant cross-sectional variation in VaR usage, which we will exploit in the analysis. For example, on March 13, just before Federal Reserve began its large scale asset purchases, the VaR limit usage on Treasury trading desks ranged between 0.15 and 1.08. Desks' total profit and loss

(PnL), that is trading revenue from existing and new trading positions, is on average \$1.01 million. Total PnL scaled by VaR is -0.35 on average. The SLR distance, a measure of excess capital that bank holding companies held in excess of the minimum SLR requirement, averages 2.4%, with an interquartile range of between 1.30% and 2.36%. Of note, most desks in the sample are affiliated with bank holding companies with a minimum SLR requirement of 5%. The last row in Table 1 shows that the outstanding draws on credit facilities average 2.21% of BHC assets over the sample period.

Panel B in Table 1 provides summary statistics for the Fed Emergency SOMA Purchases Data. There are 620 dealer-day observations for the period from March 16, 2020 to June 11, 2020. The probability of a dealer selling to SOMA on a given day is 0.82. Conditional on a sale taking place, the average par amount being sold to SOMA is \$6.05 million. On average, sales to SOMA account for 19% of the total customer sales (incl. SOMA), and for 25% of total dealer buys of Treasury securities from customers. The log of total dealer buy volume from customers (in millions of dollars) is 15.34 on average, with similar volumes for CUSIPs that were on the SOMA purchase list and those that were not.

5 Dealer Inventory and VaR Limit Usage

5.1 Baseline results

To examine the impact of dealer internal risk limits on dealer inventory, we utilize the following panel regression specification at the trading-desk level. For each Treasury market-making desk i , on day t , we estimate:

$$\Delta \text{Log}(\text{Position})_{it,t+h} = \alpha_i + \alpha_t + \beta \text{Log}(\text{Limit Usage})_{it} + c + \epsilon_{it}, \quad (9)$$

where $\Delta \text{Log}(\text{Position})_{it,t+h} = \text{Log}(\text{Position})_{i,t+h} - \text{Log}(\text{Position})_{i,t}$, the difference in the log of desk i 's positions between day t and day $t+h$. Limit Usage is defined as $\text{VaR}_{it}/\sqrt{\text{VaR}_{it-1}}$, with $\sqrt{\text{VaR}_{it-1}}$ being the upper limit of VaR for desk i , from day $t-1$. α_i and α_t are desk and time fixed-effects, respectively. We use VaR limit from day $t-1$ to address the potential endogeneity of desks changing

their limit size when they breach or are close to breaching it.

Our baseline results, shown in Table 2, examine the effects on net and gross positions. We find that Treasury market-making desks' VaR constraints have a negative and statistically significant effect on changes in net securities positions one day ($h = 1$), one week ($h = 5$), and two weeks ahead ($h = 10$). The coefficient of -0.031 in column (1) indicates that if the VaR limit usage doubles (increases by 100 percent), the change in net positions the next day decreases by 3.1 percent. The magnitude of the impact grows to 5.8 and 7.0 percent over a horizon of one week and two weeks later, respectively (columns 2 and 3). The magnitudes are even larger for net combined positions, which include derivatives – a 100 percent increase in a desk's VaR limit usage implies a decrease in positions of almost 10 percent one week later.

The effect of VaR limit usage on changes in gross positions (Panel B) is also negative and statistically significant, though the magnitudes are smaller than that for net positions. Since offsetting long and short positions typically have little effect on VaR calculations, gross positions are less sensitive to VaR limits than net positions, consistent with our findings.⁷ Table 3 documents that the magnitudes of the effects of VaR limit usage on changes in net positions are indeed significantly larger than their effects on changes in gross positions. The difference is also economically significant. In particular, if VaR limit usage were to double, dealers would be inclined to reduce the change in net securities positions the next day by 2.3 percent more than the change in gross positions (column 1). Over a horizon of one week and two weeks, dealers would be inclined to reduce the change in net positions by 3.5 and 3.8 percent more than that in gross positions, respectively (columns 2-3).

To further illustrate our main findings, Figure 4 shows the relationship between net (top panel) and gross (bottom panel) securities positions and VaR usage. The position changes are measured over a two-week period ($h = 10$) and averaged across VaR usage ranks. Consistent with the regressions, the charts show that dealers are more inclined to reduce their positions as they get closer to their internal risk limit, with the magnitudes of changes in net positions being larger than that for gross positions.

Finally, to close the loop, we verify that there is indeed a reduction in desks' limit usage as they

⁷However, the t-statistics and R squared values for regressions with gross positions are larger than that for net positions, as changes in gross positions in our sample are less volatile, relative to their magnitude, than the changes in net positions, as gross positions are less affected by client order flow.

approach their risk limits. That is, we formally test for evidence of mean-reversion in desks' limit usage. Table 1 in the Online Appendix shows that as a desk's limit usage increases towards its upper risk limit, it will reduce its usage by a notable amount in the following days. Taken together, these results show that desks that are closer to their risk limits effectively manage their inventory downwards in response to their constraints, thus bringing their risk limit usage back to desired levels.

5.2 Intra-Firm Variation across Trading Desks

Although internal risk limits are imposed at the desk level, they may reflect in part regulatory constraints and risk appetite at the firm-level. For example, dealers may adjust their trading desks' risk limits to reflect the firm's balance sheet costs, including regulatory constraints such as the SLR. In this section, we use firm-day fixed effects to control for such firm-level variation. We examine variations across desks within firms where Treasury market-making activities are split among several trading desks. About one-third of the sample desks are structured in this way. This sample allows us to examine whether risk limit usage explains the intra-firm variation in trading desk positions.⁸

Specifically, for firms with two or more active trading desks on a given day, we estimate the regression model in equation (9) with firm-time fixed effects. The results, shown in Table 4, reveal that VaR constraints explain the variation in desk-level Treasury positions even after accounting for firm-time fixed effects. The magnitude of the coefficients is comparable to the baseline regressions in Table 2, showing that the results are primarily driven by desk-level variation in risk limits. In other words, firm-level factors such as balance sheet constraints are not the main driver of market-making desk inventories. These findings further underscore the importance of internal risk limits at the trading desk level for Treasury securities market making. The Online Appendix Table 2 shows similar results for the broad sample of all Treasury trading desks, including those that do not have Treasury securities market making as their main function.

⁸We thank an anonymous referee for suggesting this analysis.

5.3 Dealers adjust newer inventory first

How do dealers go about managing their inventory subject to the VaR constraint? Do they first cut back on newer, more liquid inventory or do they first reduce older, less liquid inventory? Next, we examine whether β in equation (9) varies with inventory aging or the amount of time that securities assets (long positions) and liabilities (short positions) have been held in inventory. The analysis uses data on securities assets and liabilities, split by inventory age, which was collected until 12/31/20.

As shown in Table 5, proximity to the risk limits affects newer dealer inventory more strongly, though the effect is primarily in dealer long positions (columns 1 and 2). As seen in Panel (a), VaR limit usage has a significant effect on the one day ahead change in positions of securities assets that is less than 30 days, but is insignificant for inventory that is more than 30 days. Over longer horizons, such as one week and two weeks ahead (Panels b and c), there is statistical significance on both newer and older inventory, suggesting that constrained dealers ultimately adjust both newer and older inventory. Moreover, for dealers' holdings of securities assets, the magnitudes of the impact on changes in newer inventory are significantly larger than that on older inventory, as shown by the chi squared p-values in column (1), confirming that dealers prefer to adjust newer long inventory when approaching VaR limits.

Risk limits also affect dealers' holdings of securities liabilities (columns 3 and 4), as changes in short positions generally show a significant decline for both newer and older inventory. However, the difference in the coefficients between columns (3) and (4) are not statistically significant, suggesting that dealers may manage short positions differently from long positions when approaching VaR limits.

Overall, these findings show that dealers actively manage their inventories away from their internal risk limits by selling newer inventory first or acquiring less inventory from clients. Although we cannot distinguish between the two channels of inventory adjustment, these results suggest that the first response of trading desks to risk constraint tightness is to adjust their market-making activities rather than offload older inventory.

5.4 Instrumental variable analysis

One potential question is whether our estimated effect of VaR constraints on changes in position may be subject to endogeneity. In addition to dealer risk appetite and shocks to dealer risk-bearing capacity, the variations across dealers' VaR usage likely depend on factors such as dealers' Treasury market outlook and their Treasury exposures. These factors may also affect subsequent changes in dealer positions. For instance, dealers with a negative Treasury market outlook may be likely to reduce their Treasury positions as well as the risk limits at Treasury trading desks. While this source of variation is informative of dealer behavior, it is important to understand how factors exogenous to the Treasury market affect dealers' risk taking in Treasuries.

To examine this question, we construct instrumental variables (IV) using VaR limit changes at non-Treasury desks of the same firm. This approach allows us to isolate the causal effect of VaR usage on position changes, as changes in risk limits at non-Treasury desks do not depend on Treasury market conditions or dealers' Treasury positioning. They affect the risk limits at Treasury trading desks and their usage only because they are both driven by dealer-level changes in risk appetite. In particular, we construct two variables measuring the percent change in the sum of the limit size across all non-Treasury desks j at firm k that increased (*inc*) or decreased (*dec*) their VaR limits between day $t - 2$ and $t - 1$:⁹

$$\Delta(\text{VaR Limit})_{t-2,t-1}^{k,inc} = \frac{\sum_{j=inc} [\text{VaR Limit}_{j,t-1} - \text{VaR Limit}_{j,t-2}]}{\sum_{j=inc} (\text{VaR Limit})_{j,t-2}} \quad (10)$$

$$\Delta(\text{VaR Limit})_{t-2,t-1}^{k,dec} = \frac{\sum_{j=dec} [\text{VaR Limit}_{j,t-1} - \text{VaR Limit}_{j,t-2}]}{\sum_{j=dec} (\text{VaR Limit})_{j,t-2}}. \quad (11)$$

We find that limit size changes at non-Treasury trading desks have a statistically significant effect on Limit usage at Treasury desks. Table 6 shows the results of using these instrumental variables to estimate the effect of limit usage on changes in positions. Similar to the main results in Table 2, the coefficients remain negative and statistically significant for changes in both net and gross securities positions over horizons of one day, one week, and two weeks ahead. These results offer supporting evidence that our main findings are robust to endogeneity. In fact, the

⁹We calculate the percent change in limit size between day $t - 2$ and $t - 1$ since Limit Usage is defined as the ratio of *VaR* on day t relative to *VaR* limit on day $t - 1$.

coefficients estimated with instrumental variables are larger in magnitude than when estimated without, indicating the sensitivity of position changes to internal risk constraints is even larger. For instance, column (2) implies that if VaR limit usage were to double, the change in net securities positions over the next week decrease by 25.6 percent. Finally, consistent with our earlier findings, the relative impact of VaR constraints on net positions is larger than on gross positions.

6 Regulatory constraints

6.1 SLR

Given the slew of post-GFC bank regulations, a natural question is whether the effects of internal risk limits may in part reflect regulatory constraints, such as the SLR. We show this is not the case. Our findings suggest that there might be bounds in what certain policy recommendations, such as regulatory relief, could achieve in relieving dealer capacity constraints during times of market stress.

We test the following regression specification with VaR limit usage and SLR distance, the excess capital under the SLR rule, as well as their interaction term:

$$\begin{aligned} \Delta \text{Log}(\text{Position})_{it,t+h} = & \alpha_i + \alpha_t + \beta_1 \text{Log}(\text{Limit Usage})_{it} + \beta_2 (\text{SLR dist})_{i,qtr(t)-1} + \\ & \beta_{int} \text{Log}(\text{Limit Usage}_{it}) * \text{SLR dist}_{i,qtr(t)-1} + c + \epsilon_{it}, \end{aligned} \quad (12)$$

We regress on the lagged measure of SLR distance from the previous quarter to ensure there is no forward-looking information contained in the explanatory variable.

As shown in Table 7, we run regression specifications over changes in net and gross securities positions over the full sample period (Panel a) and in 2020 (Panel b). In most regressions, the coefficient on VaR limit usage is negative and statistically significant. In contrast, the coefficient on lagged SLR distance is almost always insignificant, as well as the coefficient on the interaction term between VaR limit usage and SLR distance. These results indicate that the effects of VaR limit on dealer inventory changes are not driven by the SLR.

6.2 High-Frequency SLR Proxy

Given the discussion about dealer regulatory constraints, the finding that the SLR constraint does not have a measurable effect on positions at Treasury market-making desks may seem surprising. However, the SLR is by design a slow-moving regulatory capital requirement. Treasury securities holdings enter the SLR denominator as the average value over the entire quarter, spreading out any short-term spikes. The slow-moving nature of the SLR should therefore make it less likely that a short-term increase in dealer intermediation would make the SLR requirement significantly more binding. In contrast, internal risk limits on Treasury trading desks must be satisfied daily.

Although it is a slow-moving metric, balance sheet shocks could still affect dealer constraints under the SLR in some circumstances, especially if they are expected to persist. In that case, the quarterly frequency of the SLR data would not make for a level playing field compared to the daily risk limit data. For example, Favara et al. (2024) argue that drawdowns on revolving lines of credit, such as those that occurred in 2020, could be expected to affect bank balance sheets over an extended period. They find evidence that credit line drawdowns interacted with the SLR constraint to limit dealer Treasury repo intermediation during 2020.¹⁰ Following Favara et al. (2024), we use the drawdowns on corporate revolving credit facilities of the bank holding companies under which our sample dealers operate to provide another assessment of the relative importance of the VaR and SLR constraints.

Specifically, we obtain regulatory data on the credit line drawdowns from the Complex Institution Liquidity Monitoring Report (Form FR2052a). For each of the sample firms, we download daily data on the outstanding draws of credit facilities from non-financial corporations at the consolidated company level.¹¹ We calculate the credit line drawdowns as the change in the outstanding draws, scaled by the total bank holding company assets as of the end of the previous quarter. The drawdowns over the 5-day horizon are plotted in the right panel of Figure 3. We then use the credit line drawdowns as an explanatory variable, and also interact the drawdowns with the proximity to the minimum regulatory SLR to test whether banks that operate closer to the regulatory capital requirement reduce their positions by more in response to unexpected balance sheet shocks from

¹⁰They find no effect on Treasury securities holdings, unless they are financed in repo.

¹¹If reported separately, we combine the outstanding draws on unsecured and secured revolving credit facilities.

credit line drawdowns:

$$\begin{aligned} \Delta \text{Log}(\text{Position})_{it,t+h} = & \alpha_i + \alpha_t + \beta_1 \text{Log}(\text{Limit Usage})_{it} + \beta_2 (\text{Drawdown})_{it,t+h} + \beta_3 (\text{SLR dist})_{i,qtr(t)-1} + \\ & \beta_4 (\text{Drawdown})_{it,t+h} * \text{SLR dist}_{i,qtr(t)-1} + c + \epsilon_{it}, \end{aligned} \quad (13)$$

where $\text{Drawdown}_{it,t+h} = (\text{Outstanding Draws})_{i,t+h} - (\text{Outstanding Draws})_{i,t}$, is the change in the outstanding draws of credit facilities for firm i between day t and $t + h$, scaled by the total consolidated assets as of the end of the previous quarter.

Our analysis of the credit line drawdowns in Table 8 does not support the hypothesis that SLR constraints are a major driver of dealers' Treasury positions. As shown in Panel (a), the relationship between credit line drawdowns is generally insignificant over the sample period for both gross and net positions at most time horizons. It is negative and marginally significant only for gross securities positions at the 1-day time horizon, consistent with the hypothesis that balance sheet shocks resulting from credit line drawdowns may constrain Treasury intermediation. The interaction of the (lagged) SLR headroom with credit line drawdowns also tends to be insignificant, with the exception of gross securities position changes over the 1-day horizon, where the positive coefficient suggests that SLR constraints may be amplified by credit line drawdowns. Overall, these results do not support a major role for the SLR in limiting dealers' Treasury market making.

In contrast, the relationship between VaR limit usage and dealer positions remains negative and highly significant for both gross and net positions at most time horizons. As shown in Panel (b) of Table 8, these conclusions regarding the relative importance of SLR and risk-based constraints remain unchanged during the period of financial market stress in 2020.

7 Robustness

We show that our empirical results are robust in a variety of dimensions, including for long and short positions; for alternative measures of VaR limit usage; for a broad sample of Treasury desks; and to potential differences in definitions and measurement of reported VaR across firms.

7.1 Long and short positions

First, we show that the negative relationship between dealers' VaR limit usage and their positions in Treasury markets holds separately for both long and short positions. As seen in Table 9, an increase in VaR limit usage has a negative and statistically significant effect on changes in long positions (Panel a) and changes in short positions (Panel b) for horizons of one day, one week, and two weeks ahead. The magnitude of changes in long positions is larger than that of changes in short positions, indicating that dealers reduce their long positions more than short positions as they get closer to their internal risk limit.

7.2 Alternative VaR limit usage measures

In addition, our findings are robust to several alternative measures of trading desks' VaR limit usage: (a) Limit Usage (std) is a standardized measure of Limit Usage, equal to the difference between a desk's Limit Usage and its rolling mean, divided by its rolling standard deviation; (b) Limit Usage prc rank is the percentile rank of a desk's standardized Limit Usage, relative to its own distribution over the rolling window; (c) Limit Usage q2, q3, and q4 are desk-level quartile dummies, and are equal to one when a desk's Limit Usage prc rank is between 25 to 50, 50 to 75, and 75 to 100 percent, respectively. For all variables, the rolling window is the previous year.

As seen in row 1 of Table 10, the coefficient on Limit Usage (std) is negative and statistically significant for nearly all specifications, indicating that the more a desk's Limit Usage exceeds its rolling-average mean, the more the desk will reduce its positions. For instance, a one standard deviation increase in a desk's Limit Usage implies a 1.0 percent decrease in its change of net securities positions the next business day (Panel a). Similarly, the coefficient on Limit Usage prc rank (row 2) is negative and statistically significant – implying that the higher the percentile rank of a desk's Limit Usage, the more it will reduce its net positions.

Limit Usage quartile dummies (rows 3-5) also have a negative relationship with positions – most of the effect is coming from when a desk's Limit Usage is in the highest quartile (q4). For instance, a coefficient of -0.033 on Limit Usage q4 (Panel a, column 3) indicates that a trading desk will decrease its change in net securities positions the next day by 3.3 percent when its VaR limit

usage is in the highest quartile (q4) than when it's in the lowest quartile (q1). The magnitudes of the coefficients on the quartile dummies generally increase with the quartile, showing that Treasury desks decrease their net positions more as they get closer to their VaR limit. The results in Table 10 demonstrate that a desk's trading positions are not only sensitive to the level of its VaR limit usage, but also are sensitive to where its VaR limit usage falls relative to its own historical distribution.

7.3 Broad sample of desks

We show that our main results hold when we expand our definition of Treasury trading desks to all desks whose name and description contains terms such as "Treasury" and "U.S. Government." The sample of desks increases from 18 to 40. As shown in Panel (c) of Table 9, the coefficient on $\log(\text{Limit Usage})$ is negative and statistically significant in all specifications for the expanded sample. The magnitude of the effect is slightly smaller than for our prime market-making desk sample, though still economically meaningful – a 100 percent increase in a desk's VaR limit usage implies a decrease in net securities positions change the next day of 2.0 percent (column 1).

7.4 Firm sensitivity analysis

To address any potential differences in definitions and measurement across firms, we conduct a sensitivity analysis of the baseline results in Table 2, to including or excluding each firm. The results are shown in Figure 2 of the Online Appendix, which plots the range of coefficients from regressing the log change in positions on $\log(\text{Limit Usage})$, by excluding the firms in our sample, one at a time.

The sensitivity analysis shows that our main findings are robust to differences in quantitative measurements across firms. That is, the range of coefficients in the regressions each remain negative and statistically significant, for each firm that is dropped from the sample. All coefficients are statistically significant at least at the 5 percent level, with nearly all of them significant at the 1 percent level.

7.5 Non-VaR-based risk limits

Although VaR limits are the most prevalent type of risk limit at Treasury trading desks, many desks have other risk limits in place. The most common type of non-VaR limits are limits on the sensitivity of a desk’s positions to interest rate changes, as measured by DV01. Among the 18 desks in our sample, 11 desks have a DV01 limit in addition to the VaR limit. In this section, we examine whether the DV01 limits affect Treasury desk trading behavior and compare their effect on Treasury desk market-making with VaR-based limits. Similar to the analysis of VaR-based limits, we measure *DV01LimitUsage* as the ratio of DV01 over the corresponding limit size, and estimate panel regressions of changes in positions on the DV01 limit usage at the trading-desk level over different time horizons (Equation 9). For desks without DV01 limits in place, we set the DV01 limit usage to zero.¹² In addition, we run a horse race between the VaR and DV01 limit usage.

Table 11 shows the estimates from the panel regressions for both net and gross positions. The estimates for net positions shown in Panel (a) and (b) indicate that increases in the DV01 limit usage are associated with decreases in both net securities and combined positions. The effect of DV01 limit usage on net positions remains significant after controlling for the effect of VaR limit usage in columns (2), (4), and (6). However, the coefficient estimates on VaR limit usage are 2–5 times larger than those for DV01 limit usage, suggesting that VaR limits have a larger effect on Treasury desk’s net positions than interest rate risk limits.

In contrast, as shown in Panels (c) and (d), the effect of DV01 risk limits on gross positions is mostly insignificant or subsumed by the effect of VaR risk limits. Overall, these findings are consistent with net positions being subject to both interest rate and VaR risk limits. Gross positions are only subject to VaR risk limits, as positions that are hedged with respect to interest rate risk are still subject to basis risks. VaR models can be used to estimate and manage potential losses stemming from basis risks.

¹²The results are qualitatively similar if we estimate the regressions on a subsample of desks that have both DV01 and VaR limits in place.

8 Event Study: Did Fed Purchases Alleviate Dealer VaR Constraints?

To illustrate that desk level VaR limits were indeed binding in March 2020 and the months following, we conduct an event study of the effect of Federal Reserve asset purchases on dealer behavior. Specifically, we compare the likelihood, intensity and aggressiveness for dealers with different VaR constraints of selling Treasury securities to the Federal Reserve during the emergency SOMA operations from March 16, 2020 through June. The SOMA operations take bonds directly off dealers' balance sheets and allow dealers to reduce the VaR of their portfolio directly. Dealers, by having an "exit valve", should be more willing to serve their clients by taking bonds off their hands as well.

8.1 Quantities sold by dealers to the Fed and VaR limit usage

After the Federal Reserve began purchasing Treasuries on March 16, dealer inventories of Treasury securities decreased rapidly. We first document that Treasury securities declined more at dealers who were closer to their VaR constraint than at less constrained dealers. Using the Volcker data, Figure 5 contrasts two groups of desks based on the level of their VaR usage on March 13, 2020, the last business day before the announcement of the emergency SOMA operations. The more constrained desks, namely those with above median VaR usage on March 13, reduced their net positions significantly more than desks that were less constrained by their VaR limit.

Next, we examine directly whether the more constrained dealers sold more Treasury securities to the Fed SOMA portfolio. Table 12 shows results from panel regressions that study the effect of $\log(\text{Limit Usage})$ on different measures of probability and intensity of dealer sales to the Fed the following day. The VaR usage is aggregated to the dealer level by averaging across Treasury securities trading desks. Throughout the specifications, higher usage of the VaR limit on day $t - 1$ is associated with higher likelihood and intensity of sales by the dealer to the Fed on day t . For instance, a 100 percent increase in dealer VaR usage implies dealers were 16.7 percent more likely to sell Treasury securities to the Fed (Panel A). Such effect is particularly strong in the month of March, even when both dealer and day fixed effects are accounted for.

Figure 6 compares the cumulative sales to the Fed for the VaR constrained and unconstrained dealers. The constrained dealers are taken as those with above median VaR usage on March 13, where each dealer’s VaR usage is averaged across its Treasury trading desks. The chart shows that the high VaR usage dealers sold more in absolute volume to the Fed (upper panel) and as a fraction to the total amount of sales they made to customers (lower panel).

8.2 Prices at which dealers sell to the Fed and VaR limit usage

Do more constrained dealers submit more aggressive offers in SOMA auctions to alleviate their VaR constraint? Recall that SOMA purchase operations are multi-price auctions where offers are ordered in prices and the best offer (lowest dealer sell price) is accepted first and other offers are accepted sequentially until an ideal total size of allocation is reached. For the same bond, different dealers could be offering at different prices. We hypothesize that dealers closer to their VaR limits would be willing to offer more aggressively and accept lower prices in auctions. Table 13 shows results from regressions that link dealer offer aggressiveness to their VaR limit usage in the day prior. Dealer offer aggressiveness is measured as the difference between average price accepted in an auction and the dealer’s actual sell price to the Fed ($\Delta p = \text{Avg Price in Auction} - \text{Price}_{\text{dealer sell}}$).¹³ We show that dealers that are closer to their VaR limit offer more aggressively in auctions, and the effect is stronger in March 2020. In particular, a 100 percent increase in dealer limit usage implies dealers bid 0.8 cents lower (column 1).

Moreover, since the price risk of Treasury bonds scales with duration, bonds with more years to mature (remaining life) contribute more to the portfolio VaR. VaR-constrained dealers are therefore incentivized to get rid of long maturity bonds first. The granularity of the data in Table 13 allow us to test this hypothesis directly. Indeed, for bonds with more years to mature, dealer’s offer aggressiveness is more sensitive to its internal risk limit usage. For bonds with more than 10 years to maturity, every 100 percent increase in dealer limit usage implies dealers bid 2.1 cents lower (column 3). This differentiation across bonds implies that bonds contribute differently to dealers’ balance sheets constraint, and the constraint at work is therefore not “risk blind”.

¹³While dealer offers are not disclosed to the public, we infer dealer offers through reported transaction prices. These transactions are matched to the SOMA auctions using method documented in Appendix B.

8.3 Dealer liquidity provision to clients and Fed purchases

Does the ability to off-load bonds to the Federal Reserve translate to more dealer intermediation in the form of liquidity provision to clients? Since client order flow was overwhelmingly in the direction of sells, dealer liquidity supply during this period would be in the form of dealer buys from clients.

In Table 14 we regress dealer buy volume on prior day VaR limit usage and dealer sales to SOMA on the same day. The panel regression results suggest that higher VaR limit usage the day prior is associated with less client intermediation—more constrained dealers buy less from clients. That is, a 100 percent increase in limit usage implies dealers buy 15.2 percent less volume of bonds from clients (column 3). However, controlling for VaR limit usage, higher volume of dealer sales to SOMA is associated with higher volume of buys from clients. Every 100 percent increase in dealer sales volume to SOMA implies dealer buy volume from clients increases by 3.2 percent.

Having the Fed SOMA portfolio as an exit valve allows primary dealers to supply more liquidity to their clients. Not only are dealers able to buy more bonds from clients for bonds that are in the SOMA auction lists (column 1), dealers are able to buy more bonds not on the SOMA operation list from their clients (column 2), as their balance sheets become less constrained due to SOMA operations. Moreover, the effect of SOMA sales on dealer liquidity provision is primarily coming from the month of March, when market stress was the highest.

Our event study results suggest that the SOMA emergency purchase program was effective in providing liquidity to the market since the Fed was lending its balance sheets to primary dealers, who became less constrained themselves by selling their Treasury holdings directly into the SOMA portfolio and making room in their portfolio to provide more immediacy to clients.

9 Market Liquidity and VaR Usage

9.1 Dealer profitability and VaR usage

How do dealers' risk aversion affect market liquidity? In Section 5, we document that dealers adjust the size of their inventory as they approach the VaR limit. In this section, we show that dealers adjust how they price of their liquidity provision or potentially the type of bonds they intermediate,

effectively generating higher risk compensation when their VaR constraint is more binding. In particular, we estimate:

$$\frac{1}{h} \cdot \sum_{k=1}^h \left[\frac{\text{P\&L}}{\text{VaR}} \right]_{i,t+k} - \left[\frac{\text{P\&L}}{\text{VaR}} \right]_{i,t} = \alpha_i + \alpha_t + \beta \log(\text{Limit Usage})_{it} + c + \epsilon_{it}, \quad (14)$$

where the dependent variable is the average change in a desk’s profitability (scaled by VaR) over the next h business days. Higher future profitability per unit of risk can be achieved by dealers either setting higher prices for providing immediacy (by taking bonds into their inventory) or being more selective with new trades and only engage capital when the trade is sufficiently profitable.

The results in Table 15 show that as dealers’ VaR limit usage increases, they seek greater compensation, in terms of trading profitability, for taking on the increased risk of breaching their internal risk limits. In other words, a desk’s average future P&L scaled by its VaR increases with the tightness of its VaR constraint. The effects persist up to two weeks later (Panel c) and are statistically significant. Notably, the effect is driven entirely by P&L generated from desks’ *new* trading positions (column 2), rather than their existing positions (column 3). A 100 percent increase in a desk’s VaR limit usage corresponds with dealers requiring 7.4 percentage points higher P&L per unit of VaR to take on new positions over the next business day. P&L from new trades are mostly driven by markups, commissions clients paid, whereas P&L from existing trades could be driven by existing positions’ exposures to different risk factors. Therefore, our results on dealer profitability are indicative of dealer pricing behavior, rather than their ability to predict future market movement. Since the flip side of dealer profitability is client transaction cost, this result offers a direct link between dealer capacity constraints and client transaction costs.

A by-product of this profitability analysis is that it provides a rough estimate of the shadow cost of VaR constraint in dealer’s profit optimization problem— λ . Appendix A illustrates that λ can be proxied with the sensitivity of dealer’s wealth (P&L) scaled by VaR to the distance of dealer’s VaR to its limit. Our estimates indicate that λ is positive and therefore, the VaR constraint is active and meaningful.

9.2 Aggregate market liquidity and VaR usage index

Taking a macro view, we examine next the implications of trading desks' VaR limit usage for aggregate Treasury market liquidity. We first construct an aggregate measure, or an index, of dealers' Treasury market VaR constraints from desk-level VaR limit usage, weighted by a desk's market share of customer transaction volumes over the past 20 business days (w_{it}):

$$\text{Limit Usage Index}_t = \sum_i w_{it} \cdot \text{Log}(\text{Limit Usage})_{it}, \quad (15)$$

where

$$w_{it} = \frac{\sum_{k=1}^{20} \text{Cust Trans Volumn}_{i,t-k}}{\sum_i [\sum_{k=1}^{20} \text{Cust Trans Volumn}_{i,t-k}]} \quad (16)$$

It is well documented that Treasury market liquidity is highly sensitive to interest rate volatility. Our limit usage index is also positively correlated with interest rate volatility. To isolate the independent effect of limit usage on market liquidity, we first regress our limit usage index on a market-implied measure of bond market volatility, the MOVE index, and extract the residual. We then conduct quantile regressions of Treasury market illiquidity at the τ th percentile on the Limit Usage Index residual, while controlling for interest rate volatility (MOVE index):

$$Q(\tau)_{\text{Illiquidity},t} = \alpha + \beta_\tau(\text{Limit Usage Index residual})_t + \gamma(\text{MOVE index})_t + \epsilon_t, \quad (17)$$

Table 16 shows quantile regression results for two Treasury market illiquidity measures. In Panel (a), the measure is the average absolute residuals that result from fitting a smooth Treasury yield curve to the cross-section of yields every day.¹⁴ This measure of market illiquidity is used in D'Amico and King (2013) and Hu et al. (2013). The impact of VaR constraint on Treasury market illiquidity is skewed and more pronounced for higher percentiles of market illiquidity, consistent with Duffie et al. (2023), who show that market illiquidity changes in character at tail levels of illiquidity, becoming more sensitive to measures of dealer intermediation capacity. For instance, column 4 shows that for the 99th percentile, a one standard deviation increase in the Limit Usage

¹⁴We are grateful to Federal Reserve Board staff for providing the data based on internal calculations. Sample used in the yield curve estimation includes Treasury securities maturing in between 2 and 10 years, excluding on-the-run and first off-the-run securities.

Index residual corresponds with a 0.24 standard deviation increase in Treasury market illiquidity. Pseudo R^2 also increases with market illiquidity percentile, nearly doubling from the 50th percentile to the 99th percentile regression.

Interestingly, unlike [Duffie et al. \(2023\)](#), who only find significant relationship between their measure of dealer capacity and Treasury market illiquidity at extreme tails, we find significant relationship between dealer VaR constraints and Treasury market illiquidity both on average, through an OLS regression (column 1) and in the median, through quantile regression at 50% (column 2).

In Panel (b), the measure of Treasury market illiquidity is the on-the-run yield premia, defined as the spread between the 10-year on-the-run and off-the-run Treasury yield. Similarly, we find that the relationship between VaR constraints and Treasury market illiquidity is statistically significant for both average and tail measures of illiquidity. Both the coefficient on the Limit Usage Index residual and the pseudo R^2 increases with illiquidity percentile. Overall, our findings support the hypothesis that the tightness of internal risk limits at dealers adversely affect market liquidity, and particularly so in times of market stress.

10 Conclusion

We provide direct, trading desk-level evidence that dealer internal risk limits in the form of VaR limits constrain dealer willingness to take risk in the Treasury market, especially in times of market stress. Dealers avoid taking on additional inventory and require higher compensation per unit of risk when their trading positions are closer to their VaR limits. In March 2020, many primary dealer Treasury securities trading desks either breached or were close to breaching their VaR limit, severely limiting these desks' ability to provide liquidity to clients. We show that dealers that were closer to their VaR limit were more likely to sell Treasury securities to the Federal Reserve during the emergency SOMA operations authorized in late March 2020. All else equal, dealers that sold more to the Federal Reserve were able to provide more liquidity to clients, both in bonds that were on the list of Federal Reserve purchases and bonds outside the lists, suggesting that the bond purchase program was effective in alleviating dealer VaR constraint by taking bonds directly off their balance sheets.

Our work has important policy implications. We should be careful attributing “risk averse” dealer behavior to financial regulations such as the SLR. Self-imposed internal risk limits could be lurking in the background. Such insights could matter in assessing various options of structural reforms that aim at improving Treasury market liquidity. Deregulation could be limited in its potency in removing dealer balance sheet rigidity. Treasury market reforms that focus on reducing market’s reliance on dealers’ balance sheets (such as encouraging all-to-all trading) could potentially be more effective. Our research also offers insights into what market intervention methods are most useful in addressing market functioning problems during market stress. We show that in a crisis where intermediaries are risk averse, policies that address the funding costs of intermediaries would not be as effective as policies that remove risks from intermediary balance sheets directly. More work needs to be done to understand how different constraints that dealers face affect their behavior and how these constraints interact.

References

- Adrian, T., Shin, H. S., 2013. Procyclical leverage and Value-at-Risk. *Review of Financial Studies* 27, 373–403.
- Amihud, Y., Mendelson, H., 1980. Dealership market: Market-making with inventory. *Journal of Financial Economics* 8, 31–53.
- Anderson, C. S., McArthur, D. C., Wang, K., 2023. Internal risk limits of dealers and corporate bond market making. *Journal of Banking & Finance* 147, 106653.
- Aragon, G. O., Strahan, P. E., 2012. Hedge funds as liquidity providers: Evidence from the Lehman bankruptcy. *Journal of Financial Economics* 103, 570–587.
- Bao, J., O'Hara, M., (Alex) Zhou, X., 2018. The Volcker rule and corporate bond market making in times of stress. *Journal of Financial Economics* 130, 95–113.
- Boyson, N. M., Stahel, C. W., Stulz, R. M., 2010. Hedge fund contagion and liquidity shocks. *Journal of Finance* 65, 1789–1816.
- Breckenfelder, J., Ivashina, V., 2021. Bank balance sheet constraints and bond liquidity. ECB Working Paper 2589.
- Dichev, I. D., Skinner, D. J., 2002. Large sample evidence on the debt covenant hypothesis. *Journal of Accounting Research* 40, 1191–1217.
- Du, W., Tepper, A., Verdelhan, A., 2018. Deviations from covered interest rate parity. *Journal of Finance* 73, 915–957.
- Duffie, D., 2018. Financial regulatory reform after the crisis: An assessment. *Management Science* 64, 4835–4857.
- Duffie, D., 2023. Resilience redux in the U.S. Treasury market. Working Paper, Jackson Hole Symposium.

- Duffie, D., Fleming, M. J., Keane, F. M., Nelson, C., Shachar, O., Van Tassel, P., 2023. Dealer capacity and U.S. Treasury market functionality. Federal Reserve Bank of New York Staff Reports 1070.
- Duffie, D., Keane, F. M., 2023. Market-function asset purchases. Federal Reserve Bank of New York Staff Reports 1054.
- D’Amico, S., King, T. B., 2013. Flow and stock effects of large-scale Treasury purchases: Evidence on the importance of local supply. *Journal of Financial Economics* 108, 425–448.
- Falato, A., Goldstein, I., Hortaçsu, A., 2021. Financial fragility in the COVID-19 crisis: The case of investment funds in corporate bond markets. *Journal of Monetary Economics* pp. 35–52.
- Favara, G., Infante, S., Rezende, M., 2024. Leverage regulations and Treasury market participation: Evidence from credit line drawdowns. Working Paper.
- Fleckenstein, M., Longstaff, F. A., 2020. Renting balance sheet space: Intermediary balance sheet rental costs and the valuation of derivatives. *Review of Financial Studies* 33, 5051–5091.
- Gârleanu, N., Pedersen, L. H., 2007. Liquidity and risk management. *American Economic Review* 97, 193–197.
- Goldberg, J., 2020. Dealer inventory constraints during the COVID-19 pandemic: Evidence from the Treasury market and broader implications. Tech. rep., FEDS Notes.
- He, Z., Nagel, S., Song, Z., 2021. Treasury inconvenience yields during the COVID-19 crisis. *Journal of Financial Economics* .
- Holmström, B., 1979. Moral hazard and observability. *The Bell Journal of Economics* 10, 74–91.
- Hu, G. X., Pan, J., Wang, J., 2013. Noise as information for illiquidity. *Journal of Finance* 68, 2341–2382.
- Kruttili, M. S., Monin, P. J., Petrasek, L., Watugala, S. W., 2025. LTCM redux? Hedge fund Treasury trading, funding fragility, and risk constraints. *Journal of Financial Economics* 169, 104017.

- Lewis, K. F., Longstaff, F. A., Petrasek, L., 2021. Asset mispricing. *Journal of Financial Economics* 141, 981–1006.
- Shleifer, A., Vishny, R. W., 1997. The limits of arbitrage. *Journal of Finance* 52, 35–55.
- Vayanos, D., Vila, J.-L., 2021. A preferred-habitat model of the term structure of interest rates. *Econometrica* 89, 77–112.
- Vissing-Jorgensen, A., 2021. The Treasury market in spring 2020 and the response of the Federal Reserve. *Journal of Monetary Economics* 124, 19–47.

Appendix

A How to estimate shadow cost of breaching risk limit λ

Recall that the Lagrangian form of the optimization problem for the trader is

$$\text{Maximize } \mathcal{L}(W, \lambda) = E(W) + \lambda(\overline{\text{VaR}}_\alpha(W) - \text{VaR}_\alpha(W)) \quad (18)$$

We can alternatively maximize

$$\begin{aligned} \frac{\mathcal{L}(W, \lambda)}{\overline{\text{VaR}}_\alpha(W)} &= E\left(\frac{W}{\overline{\text{VaR}}_\alpha(W)}\right) + \lambda\left(1 - \frac{\text{VaR}_\alpha(W)}{\overline{\text{VaR}}_\alpha(W)}\right) \\ &= E\left(\frac{W_0 + \Delta PnL}{\overline{\text{VaR}}_\alpha(W)}\right) + \lambda\left(1 - \frac{\text{VaR}_\alpha(W)}{\overline{\text{VaR}}_\alpha(W)}\right) \\ &= \frac{W_0}{\overline{\text{VaR}}_\alpha(W)} + E\left(\frac{\Delta PnL}{\overline{\text{VaR}}_\alpha(W)}\right) + \lambda\left(1 - \frac{\text{VaR}_\alpha(W)}{\overline{\text{VaR}}_\alpha(W)}\right) \end{aligned} \quad (19)$$

where $\frac{\Delta PnL}{\overline{\text{VaR}}_\alpha(W)}$ is trading PnL scaled by portfolio VaR and $1 - \frac{\text{VaR}_\alpha(W)}{\overline{\text{VaR}}_\alpha(W)}$ is distance of VaR limit utilization from 1 (100%). Dealers optimize their trading position and bid-ask spread to trade-off between profitability per unit of risk and the shadow cost of getting close to the VaR utilization limit.

Therefore, λ can be loosely thought of as the sensitivity of dealer profitability to VaR usage distance. We estimate λ in reduced form in Table 15.

B Matching SOMA Operation data and Treasury TRACE

We match Treasury transactions in the supervisory TRACE to the SOMA auctions data in March through June, 2020 to identify the quantities and prices of Treasuries that primary dealers sold to the Federal Reserve Board.

We take transactions that are "Dealer sell to customer" in principal capacity by a primary dealer and a par amount no less than 1/2 of a million to SOMA auction operations on the same day, for the same CUSIP. The match is done sequentially from level 1 through level 3, with level 1 being

the most precise and level 3 being the least.

1. In level 1 match, we require the size of the transaction to match exactly the size of the bond awarded in the SOMA auction. We further require that the timestamp of the trade to be within $[-10, 30]$ minutes of the auction timestamp. When there are multiple trades that match the auction record, we pick the trade that has a timestamp closer to the auction time. Roughly a quarter of all auctions can be matched uniquely to a transaction in TRACE.
2. In Level 2 match, we allow TRACE transaction quantities to be smaller than the auction sizes and several transactions add up to the sizes of the auction . We find that roughly 37% of all SOMA auctions can be matched to a series of TRACE transactions, whose par amount add up exactly to the quantity awarded in the auction, and another 30% can be matched to a series of transactions that add up to a quantity smaller than the auction amount.
3. In Level 3 match, we take the set of transactions of the same CUSIP and sort them by transaction prices, we add up the trade volume from the one with the highest prices down until we exhaust the auction volume. Only 7% of SOMA auctions are matched this way.

The end results of the match are trades that are dealer sell to the Fed during the period from March 16 to June 11th, 2020. We then match this data to our Volcker data at dealer-day level for analysis.

C Volcker Rule data collection (Form FR VV-1)

This appendix provides information about Regulation VV Quantitative Measurements Data—the Volcker Rule data collection on Form FR VV-1—as it relates to our main variables. Complete instructions and the current and historical reporting Forms FR-VV1 can be found at: https://www.federalreserve.gov/apps/reportingforms/Report/Index/FR_VV-1.

The Volcker data is a detailed, regulatory daily data collection from trading desks supervised by the Board of Governors of the Federal Reserve System. The reporting is mandated by the Dodd-Frank Act, which specifies the reporting and recordkeeping requirements. Reporting is mandatory for banking entities with significant trading operations. By law, these banks are required to (i)

furnish periodic reports to the Board regarding a variety of quantitative measurements of their covered trading activities, and (ii) create and maintain records documenting the preparation and content of these reports. On an ongoing basis, banking entities must carefully monitor, review, and evaluate all furnished quantitative measurements. The data are intended to provide regulators with a view of desks' trading activities and positions in order to monitor their compliance with the Volcker Rule. Questions raised by FR VV-1 data data may prompt further supervisory inquiries or examinations. The CEO of the banking entity must, annually, attest in writing to regulators that the bank has in place processes to establish, maintain, enforce, review, test and modify the compliance program and ensure the accuracy of the quantitative measurements data.

Each banking entity must furnish the following quantitative measurements:

1. *Trading desk information:* The report collects detailed daily data from trading desks supervised by the Board of Governors of the Federal Reserve System. A trading desk is an unambiguously defined group of traders or trading accounts that implements a well defined business strategy operating within a clear risk management structure. Trading desks are defined by the bank but subject to the regulatory approval. The trading desk information schedule includes the trading desk name, identifier, type of activity (e.g., underwriting, market-making, hedging, trading in domestic Government obligations...) and description of the general strategy. Importantly, although there are exceptions from the Volcker prohibition on proprietary trading for certain activities—including market making, hedging, and trading in government securities—the Volcker metrics contain information about both the non-exempt and the exempt activities, including Treasury market making. This information is collected so supervisors can evaluate whether the trading activities of trading desks engaged in market making-related activities are consistent with the requirements governing permitted market making-related activities.

- *Identification of Treasury trading desks:* Because Treasury trading desks are not explicitly identified in the data collection, we use available information on trading desk activity descriptions and the list of exemptions claimed by each desk to identify a sample of Treasury market-making desks and a broader sample of Treasury trading desks. The sample desks are identified by a key word search for terms including “Treasury”, “UST”, “U.S.

Government” and variations of these words in both the desk name and desk descriptions. All desks identified in this way are included in the broad sample of 40 Treasury trading desks. In addition, Treasury market making desks typically rely on two sets of exceptions from the Volcker rule on proprietary trading – the market making exception and the trading in domestic Government obligations exemption. We require that Treasury market making desks claim either one or both of these exceptions. Finally, we manually cross-check that the desk description is indicative of Treasury securities market making. Some typical desk descriptions for market making desks read as follows: “The desk provides market making services in US Treasuries.” “The Desk utilizes the Market Making-Related Exemption and makes markets as a primary dealer in U.S. Treasuries.” “The desk performs market-making activities and provides liquidity in US government securities.” In contrast, we exclude from the main sample desks with descriptions that indicate that Treasury securities market making is not its main focus. For example: “The Desk utilizes the Market Making-Related Exemption and makes markets in forwards, options, and treasury futures.” “Desk trades with clients mostly in IRS, basis swaps, and may transact in UST, futures and exchange traded instruments.” “The desk engages in market making and hedging for Rates and Treasury ETFs.” While these desk may trade Treasury securities, Treasury market making is not their main focus.

2. *Value-at-Risk*: Trading desks must report daily VaR measurements, namely the risk of future financial loss in the value of the trading desk’s aggregated positions at the 99% confidence level over a 1-day holding period, based on current market conditions. Banking entities should compute and report VaR consistently with regulatory capital requirements for market risk. As described under Section 205 of the Market Risk Rule, internal models for calculating its VaR-based measure must use risk factors sufficient to measure the market risk inherent in all covered positions. The market risk categories must include, as appropriate, interest rate risk, credit spread risk, equity price risk, foreign exchange risk, and commodity price risk. The bank must be able to justify to the satisfaction of the Federal Reserve Board the omission of any risk factors from the calculation of its VaR-based measure. The VaR-based measure

must be based on a historical observation period of at least one year. Banks are required to validate and demonstrate the reasonableness of its process for measuring correlations, weighting schemes and other methodologies.

3. *Internal Risk Limits and their Usage:* Internal Limits are the constraints that define the amount of risk and the positions that a trading desk is permitted to take at a point in time, as defined by the banking entity for a specific trading desk. Usage represents the value of the trading desk's risk or positions that are accounted for by the current activity of the desk. Internal limits and their usage are key compliance and risk management tools used to control and monitor risk taking. Trading desks must report information on the internal risk limits schedule, including the type of limit (VaR, position limit, sensitivity limit, stress scenario, inventory aging, and other), risk limit identifier, description, limit size, and limit usage. Reporting of VaR risk limits is required for all trading desks engaged in market making-related activities.¹⁵ We focus our analysis on VaR limits and their usage. Other risk limits, including those on position size or sensitivities, are only reported to the extent that they apply to a given desk.

- *Changes to Internal Risk Limits:* Changes to internal risk limits are infrequent to ensure that the limits are a credible deterrent against excessive risk taking. Increasing these limits involves a structured approval process involving various levels of management, including at senior levels. Regulation VV requires banks to have established written authorization procedures, including escalation procedures that require review and approval of any trade that exceeds a trading desk's limit(s), demonstrable analysis of the basis for any increase to a trading desk's limit(s), and independent review of such demonstrable analysis and approval.¹⁶ In addition to providing daily risk limits reports to management, banks are also required to maintain and make available to supervisors upon request records regarding any limit breaches or any temporary or permanent increases to any limit(s). The limits and their changes are subject to supervisory review and oversight by

¹⁵Except to the extent the VaR metric is demonstrably ineffective for measuring and monitoring the risks of a trading desk based on the types of positions traded by, and risk exposures of, that desk.

¹⁶<https://www.ecfr.gov/current/title-12/chapter-II/subchapter-A/part-248>

the Board of Governors on an ongoing basis.

4. *Positions:* Desks report the daily value of all securities and derivatives positions managed by the trading desk, including the market value of all long securities positions, short securities positions, and the notional value of all derivatives receivables and payables reported as 10-year bond equivalents. After 12/31/2020, derivatives positions are reported at their market value rather than the notional value, and we do not use the reported market values of the derivatives positions because they are not indicative of the portfolio exposure.
5. *Inventory Aging:* Inventory aging measures the age profile of the trading desk's assets and liabilities. The inventory aging schedule provides each trading desk's aggregate assets and liabilities classified according to the amount of time that those assets and liabilities have been held, calculated as the "current date" less the "trade date." Banks should apply a First In, First Out (FIFO) method in measuring the age profile. This schedule is only available until 12/31/2020.
6. *Profit and loss information:* Reported is the trading desk's daily comprehensive profit and loss from all sources, and the attribution of the profit and loss to either new or existing positions. New positions result from the current day's trading activity, including purchases and sales of financial instruments and any amendments to existing positions. Existing positions are those held by the trading desk as of the end of the previous day. The profit and loss report is comprehensive, including profits from commissions and fee income and expenses, market gains or losses associated with the transactions, and profits and losses attributable to changes in risk factors, actual cash flows, carry, valuation adjustments, or other factors.

D Tables

Table 1: Summary Statistics

(a) Positions and VaR						
	mean	sd	p25	p50	p75	count
Net securities position	4.95	9.01	0.23	2.15	6.41	43310
Gross securities position	26.7	39.2	2.25	13.8	30.0	43310
Long securities position	15.0	21.4	1.15	7.98	17.8	43313
Short securities position	11.7	18.9	0.67	4.73	13.2	43323
Net combined position	350.5	1209.1	0.34	3.24	40.5	31641
Gross combined position	3020.4	5475.9	10.0	340.7	4097.2	31641
Long combined position	1676.7	2987.1	5.24	182.4	2145.5	31657
Short combined position	1344.0	2609.4	4.72	157.1	1740.2	31686
VaR	4.20	6.25	0.82	2.26	4.73	42483
VaR limit	12.2	12.1	5	10	15	41904
Limit Usage	0.30	0.20	0.16	0.26	0.40	41814
Total PnL	1.01	4.35	-0.088	0.24	1.28	44217
Total PnL / VaR	-0.35	37.3	-0.049	0.19	0.56	41950
SLR dist	2.40	2.37	1.30	1.61	2.36	29863
Credit draws	2.21	2.66	0.66	0.99	2.81	25935

(b) SOMA event study						
	mean	sd	p25	p50	p75	N
Probability of Selling to SOMA	0.82	0.38	1.00	1.00	1.00	620
Log(Par Amount of Sale to SOMA, million\$)	6.05	2.04	5.00	6.33	7.53	521
Sales to SOMA/ Total Sales to Customer	0.19	0.19	0.02	0.13	0.33	609
Sales to SOMA/Total Buys from Customer	0.25	0.30	0.03	0.14	0.39	610
Log (Dealer Buy from Customer), Cusip in SOMA list	14.46	1.76	14.00	14.89	15.51	610
Log (Dealer Buy from Customer), Cusip not in SOMA list	14.55	1.54	14.18	15.05	15.51	610
Log (Total Dealer Buy from Customer)	15.34	1.37	14.97	15.81	16.23	610

Table 1 Panel (a) shows summary statistics of Treasury trading desks for the levels of the positions variables (in billions of dollars), VaR and VaR limit (in millions of dollars), Limit Usage (defined as the ratio of VaR relative to VaR limit from the day before). Net positions are the absolute value of the difference between long and short positions. Gross positions are sum of long and short positions. Securities positions include only cash assets. Combined positions include cash and derivative assets. The sample period is 1/1/15-3/31/23 for securities positions and 1/1/15-12/31/20 for combined positions. Total profit and loss (PnL) is in millions of dollars, or scaled by VaR . SLR distance is distance in percent between the observed and the required SLR. Credit draws are draws on revolving credit facilities at the BHC level, as percent of total BHC assets. Panel (b) shows summary statistics for data used in the SOMA event study, for the period 03/16/20-06/11/20.

Table 2: Dealer Desk Positions and VaR Constraints (Baseline)

(a) Net positions						
	Net securities positions			Net combined positions		
	(1) h=1	(2) h=5	(3) h=10	(4) h=1	(5) h=5	(6) h=10
log(Limit Usage)	-0.031*** (0.011)	-0.058*** (0.014)	-0.070*** (0.016)	-0.046*** (0.017)	-0.091*** (0.021)	-0.116*** (0.023)
Desk FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.129	0.125	0.132	0.131	0.127	0.144
N	16838	16786	16721	12045	11986	11915

(b) Gross positions						
	Gross securities positions			Gross combined positions		
	(1) h=1	(2) h=5	(3) h=10	(4) h=1	(5) h=5	(6) h=10
log(Limit Usage)	-0.007*** (0.002)	-0.020*** (0.003)	-0.030*** (0.003)	-0.006*** (0.001)	-0.017*** (0.002)	-0.024*** (0.003)
Desk FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.132	0.153	0.154	0.136	0.146	0.154
N	16838	16786	16721	12045	11986	11915

Table 2 shows the effect of log(Limit Usage) on the log change in net positions (Panel a) and on the log change in gross positions (Panel b). Net and gross securities positions (columns 1 through 3) include only cash assets. Net and gross combined positions (columns 4 through 6) include cash and derivative assets. Net positions are the absolute value of the difference between long and short positions. Gross positions are the sum of long and short positions. Limit Usage is defined as the ratio of VaR relative to VaR limit from the day before. Regression results are shown for positions change over $h = 1, 5,$ and 10 business days. The sample period is 1/1/15-3/31/23 for securities positions (columns 1 through 3) and 1/1/15-12/31/20 for combined positions (columns 4 through 6). All regressions include desk and time fixed effects. Standard errors are robust.

Table 3: Net Positions Relative to Gross Positions

	Net/Gross securities positions			Net/Gross combined positions		
	(1)	(2)	(3)	(4)	(5)	(6)
	h=1	h=5	h=10	h=1	h=5	h=10
log(Limit Usage)	-0.023** (0.011)	-0.035** (0.014)	-0.038** (0.015)	-0.038** (0.017)	-0.068*** (0.021)	-0.086*** (0.022)
R^2	0.130	0.125	0.132	0.132	0.128	0.145
N	16838	16786	16721	12045	11986	11915

Table 3 shows the effect of log(Limit Usage) on the log change in the ratio of net securities positions to gross securities positions (columns 1 through 3) and on the log change in the ratio of net combined positions to gross combined positions (columns 4 through 6). Net and gross securities positions include only cash assets. Net and gross combined positions include cash and derivative assets. Net positions are the absolute value of the difference between long and short positions. Gross positions are the sum of long and short positions. Limit Usage is defined as the ratio of VaR relative to VaR limit from the day before. Regression results are shown for positions change over $h = 1, 5,$ and 10 business days. The sample period is 1/1/15-3/31/23 for securities positions (columns 1 through 3) and 1/1/15-12/31/20 for combined positions (columns 4 through 6). All regressions include desk and time fixed effects. Standard errors are robust.

Table 4: Dealer Desk Positions and VaR Constraints with Firm-by-Day Fixed Effects

(a) Net positions						
	Net securities positions			Net combined positions		
	(1) h=1	(2) h=5	(3) h=10	(4) h=1	(5) h=5	(6) h=10
log(Limit Usage)	-0.028 (0.024)	-0.061* (0.032)	-0.080** (0.033)	-0.059* (0.031)	-0.117*** (0.038)	-0.141*** (0.040)
FirmXDay FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.475	0.472	0.500	0.486	0.492	0.513
N	5379	5350	5316	4267	4238	4204

(b) Gross positions						
	Gross securities positions			Gross combined positions		
	(1) h=1	(2) h=5	(3) h=10	(4) h=1	(5) h=5	(6) h=10
log(Limit Usage)	-0.009** (0.004)	-0.024*** (0.006)	-0.034*** (0.008)	-0.009*** (0.003)	-0.019*** (0.006)	-0.023*** (0.007)
Firm X Day FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.496	0.500	0.500	0.506	0.498	0.503
N	5379	5350	5316	4267	4238	4204

Table 4 shows the effect of $\log(\text{Limit Usage})$ on the log change in net positions (Panel a) and on the log change in gross positions (Panel b). The regressions are estimated with firm-day fixed effects. Net and gross securities positions (columns 1 through 3) include only cash assets. Net and gross combined positions (columns 4 through 6) include cash and derivative assets. Net positions are the absolute value of the difference between long and short positions. Gross positions are the sum of long and short positions. Limit Usage is defined as the ratio of VaR relative to VaR limit from the day before. Regression results are shown for positions change over $h = 1, 5,$ and 10 business days. The sample period is $1/1/15-3/31/23$ for securities positions (columns 1 through 3) and $1/1/15-12/31/20$ for combined positions (columns 4 through 6). All regressions include firm-by-day fixed effects. Standard errors are robust.

Table 5: Effect of VaR Constraints on Dealer Long (Assets) and Short (Liabilities) Positions of Different Vintages

(a) h=1				
	(1) Assets (≤ 30 day)	(2) Assets (> 30 day)	(3) Liab (≤ 30 day)	(4) Liab (> 30 day)
log(Limit Usage)	-0.010*** (0.003)	-0.002 (0.002)	-0.008** (0.003)	-0.003 (0.003)
R^2	0.152	0.242	0.146	0.208
N	11428	11426	11434	11323
chi p-value	0.011		0.204	

(b) h=5				
	(1) Assets (≤ 30 day)	(2) Assets (> 30 day)	(3) Liab (≤ 30 day)	(4) Liab (> 30 day)
log(Limit Usage)	-0.034*** (0.005)	-0.018*** (0.005)	-0.013** (0.006)	-0.017** (0.007)
R^2	0.168	0.150	0.150	0.165
N	11376	11374	11382	11260
chi p-value	0.016		0.711	

(c) h=10				
	(1) Assets (≤ 30 day)	(2) Assets (> 30 day)	(3) Liab (≤ 30 day)	(4) Liab (> 30 day)
log(Limit Usage)	-0.047*** (0.006)	-0.029*** (0.008)	-0.029*** (0.007)	-0.020** (0.010)
R^2	0.176	0.151	0.146	0.160
N	11309	11309	11315	11183
chi p-value	0.049		0.419	

Table 5 shows the effect of log(Limit Usage) on the log change in securities assets (columns 1 to 2) and securities liabilities (columns 3 to 4), separated by inventory age. Limit Usage is defined as the ratio of VaR relative to VaR limit from the day before. Panels (a), (b) and (c) show regression results for securities change over $h = 1, 5,$ and 10 business days, respectively. “chi p-value” shows the p-value from a chi-squared test on the statistical significance in the difference between the coefficients in columns (1) versus (2), shown in column (1), and that in columns (3) versus (4), shown in column (3). The sample period is 1/1/15-12/31/20. All regressions include desk and time fixed effects. Standard errors are robust.

Table 6: Instrumental Variable Analysis with Limit Changes at Non-Treasury Desks

	Net securities positions			Gross securities positions		
	(1) h=1	(2) h=5	(3) h=10	(4) h=1	(5) h=5	(6) h=10
fitted log(Limit Usage)	-0.134* (0.073)	-0.256*** (0.095)	-0.245** (0.103)	-0.006 (0.013)	-0.069*** (0.022)	-0.077*** (0.026)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	16816	16764	16699	16816	16764	16699

Table 6 shows the second stage results of instrumental variable regressions using $\Delta(\text{VaR Limit})^{inc}$ and $\Delta(\text{VaR Limit})^{dec}$ to estimate the effect of log(Limit Usage) on the log change in net securities positions (Columns 1 through 3) and on the log change in gross securities positions (Columns 4 through 6). $\Delta(\text{VaR Limit})^{inc}$ and $\Delta(\text{VaR Limit})^{dec}$ is computed as the percent change from day $t - 2$ to $t - 1$ of the sum of *VaR* limit size across all non-Treasury desks at the same firm that increased and decreased their *VaR* limit sizes between day $t - 2$ to $t - 1$, respectively. Limit Usage is defined as the ratio of *VaR* relative to *VaR* limit from the day before. Regression results are shown for positions change over $h = 1, 5, \text{ and } 10$ business days. The sample period is 1/1/15-3/31/23. All regressions include time fixed effects. Standard errors are robust.

Table 7: Regulatory Constraints and Dealer Positions

(a) Full sample period						
	Net securities positions			Gross securities positions		
	(1) h=1	(2) h=5	(3) h=10	(4) h=1	(5) h=5	(6) h=10
log(Limit Usage)	-0.033 (0.022)	-0.070*** (0.027)	-0.071** (0.031)	-0.011** (0.005)	-0.033*** (0.007)	-0.043*** (0.008)
lagged SLR dist	-0.000 (0.014)	-0.005 (0.018)	-0.019 (0.019)	-0.001 (0.005)	-0.000 (0.006)	-0.009 (0.008)
log(Limit Usage) \times lagged SLR dist	-0.002 (0.007)	0.006 (0.009)	-0.000 (0.010)	0.001 (0.002)	0.002 (0.003)	0.002 (0.003)
Desk FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.122	0.116	0.115	0.127	0.153	0.152
N	10947	10907	10857	10947	10907	10857

(b) 2020						
	Net securities positions			Gross securities positions		
	(1) h=1	(2) h=5	(3) h=10	(4) h=1	(5) h=5	(6) h=10
log(Limit Usage)	-0.063 (0.052)	-0.139** (0.070)	-0.120 (0.076)	-0.014* (0.008)	-0.035** (0.014)	-0.046*** (0.017)
lagged SLR dist	-0.003 (0.091)	-0.128 (0.122)	-0.117 (0.135)	-0.016 (0.016)	-0.036 (0.027)	-0.071** (0.031)
log(Limit Usage) \times lagged SLR dist	0.001 (0.015)	0.002 (0.022)	-0.008 (0.024)	-0.003 (0.002)	-0.006 (0.004)	-0.005 (0.005)
Desk FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.124	0.113	0.118	0.134	0.173	0.181
N	2232	2228	2223	2232	2228	2223

Table 7 shows the effects of dealer regulatory constraint (SLR distance) and log(Limit Usage) on the log change in net and gross securities positions (Panel a) or the log change in net and gross securities positions in 2020 (Panel b). Net and gross securities positions include only cash assets. Net positions are the absolute value of the difference between long and short positions. Gross positions are the sum of long and short positions. Lagged SLR distance is defined to be the previous quarter's difference between a firm's SLR and the minimum SLR requirement as specified in the Basel III accord. Data for the SLR starts in 1/1/18. Limit Usage is defined as the ratio of VaR relative to VaR limit from the day before. Regression results are shown for positions change over $h = 1, 5,$ and 10 business days. The sample period is 1/1/18-3/31/23 in Panel (a), and 1/1/20-12/31/20 in Panel (b). All regressions include desk and time fixed effects. Standard errors are robust.

Table 8: Credit Line Drawdowns and Dealer Positions

(a) Full sample period						
	Net securities positions			Gross securities positions		
	(1) h=1	(2) h=5	(3) h=10	(4) h=1	(5) h=5	(6) h=10
log(Limit Usage)	-0.032** (0.013)	-0.038** (0.018)	-0.055*** (0.020)	-0.007*** (0.003)	-0.022*** (0.004)	-0.029*** (0.005)
lagged SLR dist	0.000 (0.013)	-0.011 (0.017)	-0.014 (0.018)	-0.001 (0.004)	0.000 (0.006)	-0.008 (0.008)
drawdown	-0.199 (0.732)	-0.487 (0.361)	0.153 (0.238)	-0.536* (0.284)	-0.103 (0.154)	-0.101 (0.104)
lagged SLR dist \times drawdown	0.146 (0.437)	0.256 (0.204)	-0.142 (0.129)	0.304* (0.181)	0.030 (0.087)	0.044 (0.055)
Desk FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.163	0.161	0.168	0.171	0.186	0.193
N	8375	8339	8299	8375	8339	8299

(b) 2020						
	Net securities positions			Gross securities positions		
	(1) h=1	(2) h=5	(3) h=10	(4) h=1	(5) h=5	(6) h=10
log(Limit Usage)	-0.071** (0.028)	-0.103*** (0.039)	-0.151*** (0.040)	-0.011* (0.006)	-0.027*** (0.009)	-0.044*** (0.011)
lagged SLR dist	0.021 (0.078)	0.071 (0.113)	0.131 (0.113)	-0.002 (0.017)	-0.014 (0.026)	-0.028 (0.029)
drawdown	-1.179 (1.552)	-0.697 (0.531)	0.467 (0.306)	0.139 (0.275)	0.144 (0.132)	0.044 (0.094)
lagged SLR dist \times drawdown	0.916 (1.083)	0.440 (0.316)	-0.207 (0.165)	-0.045 (0.147)	-0.040 (0.063)	0.002 (0.042)
Desk FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.143	0.163	0.187	0.176	0.207	0.240
N	1715	1711	1706	1715	1711	1706

Table 8 shows the effects of credit line drawdowns and log(Limit Usage) on the log change in net and gross securities positions (Panel a) or the log change in net and gross securities positions in 2020 (Panel b). Net (Gross) securities positions are the difference (sum) of long and short securities positions. Securities positions include only cash assets. Credit line drawdowns are measured as changes in the outstanding draws on revolving credit facilities, as percentage of total assets over the previous quarter. The drawdowns are measured over the time horizons corresponding to the changes in positions. Limit Usage is defined as the ratio of VaR relative to VaR limit from the day before. Regression results are shown for positions change over $h = 1, 5,$ and 10 business days. The sample period is 1/1/18-3/31/23 in Panel (a), and 1/1/20-12/31/20 in Panel (b). All regressions include desk and time fixed effects. Standard errors are robust.

Table 9: Robustness

(a) Long Positions						
	Long securities positions			Long combined positions		
	(1) h=1	(2) h=5	(3) h=10	(4) h=1	(5) h=5	(6) h=10
log(Limit Usage)	-0.008*** (0.002)	-0.025*** (0.003)	-0.034*** (0.004)	-0.007*** (0.002)	-0.020*** (0.003)	-0.030*** (0.004)
R^2	0.134	0.153	0.161	0.133	0.143	0.154
N	16838	16786	16721	12045	11986	11915

(b) Short Positions						
	Short securities positions			Short combined positions		
	(1) h=1	(2) h=5	(3) h=10	(4) h=1	(5) h=5	(6) h=10
log(Limit Usage)	-0.005* (0.003)	-0.013*** (0.004)	-0.023*** (0.005)	-0.005*** (0.001)	-0.009*** (0.003)	-0.015*** (0.003)
R^2	0.131	0.140	0.136	0.135	0.142	0.144
N	16825	16773	16706	12047	11989	11921

(c) Net Positions - all UST market-making desks						
	Net securities positions			Net combined positions		
	(1) h=1	(2) h=5	(3) h=10	(4) h=1	(5) h=5	(6) h=10
log(Limit Usage)	-0.020*** (0.008)	-0.045*** (0.010)	-0.063*** (0.012)	-0.025** (0.011)	-0.053*** (0.014)	-0.075*** (0.016)
R^2	0.062	0.063	0.069	0.066	0.064	0.067
N	32560	32438	32292	23471	23349	23201

Table 9 shows the effect of log(Limit Usage) on the log change in long positions (Panel a) and on the log change in short positions (Panel b). Panel (c) shows the effect of log(Limit Usage) on the log change in net securities positions (columns 1 through 3) and on the log change in net combined positions (columns 4 through 6) for all UST market-making desks. Net positions are the absolute value of the difference between long and short positions. Securities positions include only cash assets. Combined positions include cash and derivative assets. Limit Usage is defined as the ratio of VaR relative to VaR limit from the day before. Regression results are shown for positions change over $h = 1, 5,$ and 10 business days. The sample period is 1/1/15-3/31/23 for securities positions (columns 1 through 3) and 1/1/15-12/31/20 for combined positions (columns 4 through 6). All regressions include desk and time fixed effects. Standard errors are robust.

Table 10: Robustness - Limit Usage Rank Transformation

(a) Net securities positions

	h=1			h=5			h=10		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Limit Usage (std)	-0.010** (0.005)			-0.016** (0.006)			-0.023*** (0.007)		
Limit Usage prc rank		-0.044** (0.018)			-0.073*** (0.024)			-0.093*** (0.026)	
Limit Usage q2			-0.007 (0.015)			-0.041** (0.020)			-0.064*** (0.022)
Limit Usage q3			-0.011 (0.016)			-0.028 (0.020)			-0.032 (0.022)
Limit Usage q4			-0.033** (0.015)			-0.059*** (0.019)			-0.078*** (0.021)
R^2	0.129	0.131	0.128	0.124	0.125	0.124	0.131	0.131	0.131
N	16649	16469	16832	16597	16417	16781	16532	16352	16713

(b) Net combined positions

	h=1			h=5			h=10		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Limit Usage (std)	-0.007 (0.007)			-0.017* (0.009)			-0.038*** (0.010)		
Limit Usage prc rank		-0.046 (0.030)			-0.099*** (0.037)			-0.153*** (0.039)	
Limit Usage q2			-0.028 (0.023)			-0.073** (0.030)			-0.078** (0.032)
Limit Usage q3			-0.019 (0.024)			-0.085*** (0.030)			-0.079** (0.032)
Limit Usage q4			-0.039 (0.024)			-0.062** (0.030)			-0.108*** (0.032)
R^2	0.131	0.133	0.131	0.125	0.127	0.125	0.143	0.145	0.143
N	11853	11673	11882	11794	11614	11823	11723	11543	11752

Table 10 shows the effect of alternative measures of Limit Usage on the log change in net securities positions (Panel a) and the log change in net combined positions (Panel b). Net positions are the absolute value of the difference between long and short positions. Net securities positions include only cash assets. Net combined positions include cash and derivative assets. Limit Usage (std) is a standardized measure of Limit Usage, equal to the difference between a desk's Limit Usage and its rolling mean, divided by its rolling standard deviation. Limit Usage prc rank is the percentile rank of a desk's standardized Limit Usage, relative to its own distribution over the rolling window. Limit Usage q2, q3, and q4 are desk-level quartile dummies, and is equal to one when a desk's Limit Usage prc rank is between 25 to 50, 50 to 75, and 75 to 100 percent, respectively. For all variables, the rolling window is the previous year. Regression results are shown for positions change over $h = 1, 5,$ and 10 business days. The sample period is 1/1/15-3/31/23 for securities positions (Panel a) and 1/1/15-12/31/20 for combined positions (Panel b). All regressions include desk and time fixed effects. Standard errors are robust.

Table 11: Interest Rate Risk Limits

(a) Net securities positions						
	h=1		h=5		h=10	
	(1)	(2)	(3)	(4)	(5)	(6)
log(DV01 Limit Usage)	-0.007** (0.003)	-0.006** (0.003)	-0.013*** (0.004)	-0.011*** (0.004)	-0.015*** (0.004)	-0.012*** (0.004)
log(Limit Usage)		-0.029*** (0.011)		-0.054*** (0.014)		-0.066*** (0.016)
R^2	0.129	0.129	0.125	0.126	0.132	0.133
N	16838	16838	16786	16786	16721	16721

(b) Net combined positions						
	h=1		h=5		h=10	
	(1)	(2)	(3)	(4)	(5)	(6)
log(DV01 Limit Usage)	-0.025** (0.010)	-0.019* (0.010)	-0.055*** (0.013)	-0.045*** (0.013)	-0.061*** (0.014)	-0.047*** (0.014)
log(Limit Usage)		-0.038** (0.017)		-0.073*** (0.022)		-0.097*** (0.023)
R^2	0.131	0.131	0.127	0.128	0.144	0.145
N	12045	12045	11986	11986	11915	11915

(c) Gross securities positions						
	h=1		h=5		h=10	
	(1)	(2)	(3)	(4)	(5)	(6)
log(DV01 Limit Usage)	-0.001 (0.000)	-0.000 (0.000)	-0.001 (0.001)	-0.000 (0.001)	-0.002* (0.001)	-0.001 (0.001)
log(Limit Usage)		-0.006*** (0.002)		-0.020*** (0.003)		-0.030*** (0.003)
R^2	0.131	0.132	0.151	0.153	0.150	0.154
N	16838	16838	16786	16786	16721	16721

(d) Gross combined positions						
	h=1		h=5		h=10	
	(1)	(2)	(3)	(4)	(5)	(6)
log(DV01 Limit Usage)	-0.003*** (0.001)	-0.002** (0.001)	-0.005*** (0.001)	-0.003* (0.002)	-0.005*** (0.002)	-0.002 (0.002)
log(Limit Usage)		-0.006*** (0.001)		-0.016*** (0.002)		-0.023*** (0.003)
R^2	0.135	0.137	0.142	0.146	0.149	0.154
N	12045	12045	11986	11986	11915	11915

Table 11 shows the effects of limits on interest rate risk, measured as $\log(\text{DV01 Limit Usage})$ on the log change in net positions (Panel a and b) and the log change in gross positions (Panel b and c). Securities positions include only cash assets. Combined positions include cash and derivative assets. Net positions are the absolute value of the difference between long and short positions. Gross positions are the sum of long and short positions. DV01 Limit Usage is defined as the ratio of DV01 relative to DV01 limit from the day before. Columns (2), (4), and (6) also include the $\log(\text{Limit Usage})$, defined as the ratio of VaR relative to VaR limit from the day before. The DV01 limit usage is assumed to be zero for desks without DV01 limits in place. Regression results are shown for positions change over $h = 1, 5,$ and 10 business days. The sample period is 1/1/15-3/31/23 for securities positions (Panel a and c), and 1/1/15-12/31/20 for combined positions (Panel b and d). All regressions include desk and time fixed effects. Standard errors are robust.

Table 12: Dealer Sales to SOMA

	Panel A					
	Probability of Sale			Log Amount of Sale		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{Limit Usage})_{t-1}$	0.167*** (0.022)	0.117*** (0.039)		0.321*** (0.113)	0.751*** (0.244)	
March=0 $\times \log(\text{Limit Usage})_{t-1}$			0.030 (0.038)			0.068 (0.190)
March=1 $\times \log(\text{Limit Usage})_{t-1}$			0.127*** (0.047)			0.373* (0.215)
Dealer FE		Yes	Yes		Yes	Yes
Time FE	Yes		Yes	Yes		Yes
R^2	0.244	0.451	0.616	0.499	0.331	0.750
N	619	619	619	520	520	520

	Panel B					
	Sales to SOMA/Total Sales to Cust.			Sales to SOMA/Total Buys from Cust.		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{Limit Usage})_{t-1}$	0.058*** (0.010)	0.100*** (0.023)		0.104*** (0.016)	0.140*** (0.036)	
March=0 $\times \log(\text{Limit Usage})_{t-1}$			0.027 (0.022)			0.041 (0.036)
March=1 $\times \log(\text{Limit Usage})_{t-1}$			0.059** (0.026)			0.085** (0.041)
Dealer FE		Yes	Yes		Yes	Yes
Time FE	Yes		Yes	Yes		Yes
R^2	0.370	0.244	0.555	0.306	0.210	0.451
N	608	608	608	609	609	609

Table shows the effect of $\log(\text{Limit Usage})$ on the probability and quantity of dealer sale to the Fed SOMA portfolio between March 16 and June 11th, 2020. In Panel A, the dependant variables for Columns 1 through 3 are the probability of sales and the dependant variables for Column 4 through 6 are the log volume of sales. Probability of sales is a dummy variable equal to 1 on days when a dealer sold bonds to the Fed SOMA portfolio. In Panel B, the dependant variable for Columns 1 through 3 are the ratio of dealer sales to SOMA to total dealer sales to customer that day and the dependant variable for Column 4 through 6 are the ratio of dealer sales to SOMA to total dealer buys from customer that day. Trading volumes in the denominators are restricted to CUSIPs with SOMA auctions that day. Data is aggregated to dealer-day level. Limit Usage is defined as the ratio of VaR relative to VaR limit from the day before. Standard errors are robust.

Table 13: Dealer SOMA Offer Aggressiveness and VaR Limit Usage

	$\Delta p = \text{Avg Price in Auction} - \text{Price}_{\text{dealer sell}}$					
	Full Sample			Sample of Level 1 and 2 Match		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{Limit Usage})_{t-1}$	0.008*** (0.002)			0.009*** (0.002)		
March=0 $\times \log(\text{Limit Usage})_{t-1}$		0.006*** (0.001)			0.006*** (0.001)	
March=1 $\times \log(\text{Limit Usage})_{t-1}$		0.009** (0.004)			0.012*** (0.004)	
Bond Life<5Yrs $\times \log(\text{Limit Usage})_{t-1}$			0.001 (0.001)			0.001 (0.001)
Bond Life \in [5,10]Yrs $\times \log(\text{Limit Usage})_{t-1}$			0.007* (0.004)			0.007* (0.004)
Bond Life \geq 10Yrs $\times \log(\text{Limit Usage})_{t-1}$			0.021*** (0.008)			0.026*** (0.007)
constant	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.053	0.053	0.054	0.070	0.070	0.072
N	11,012	11,012	11,007	10,244	10,244	10,239

Table shows the effect of $\log(\text{Limit Usage})$ on the aggressiveness of dealer's offer in SOMA auctions. Sample period is from March 16 to June 11th, 2020. Offer aggressiveness is measured as the difference between average prices of successful offers in the auction and the dealer's actual offer (dealer sell price). The higher this measure is, the less the dealer is willing to accept when selling to the Fed, the more aggressive is his offer. Column (1) through (3) use the full sample of transactions that are identified as dealer sell to the Fed (details of the matching method described in Appendix B). Column (4) through (6) use only the sample from level 1 and level 2 match, which match the transactions and SOMA auctions data with a high degree of confidence. Limit Usage is defined as the ratio of VaR relative to VaR limit from the day before. Standard errors are robust.

Table 14: Dealer Liquidity Provision to Clients and SOMA Operations

Log (Dealer Buy from Customer)						
	In SOMA (1)	Not in SOMA (2)	Total (3)	In SOMA (4)	Not in SOMA (5)	Total (6)
$\log(\text{Limit Usage})_{t-1}$	-0.146*** (0.055)	-0.124** (0.063)	-0.152*** (0.046)	-0.149*** (0.054)	-0.129** (0.061)	-0.156*** (0.044)
$\log(\text{Dealer Sell to SOMA})$	0.048*** (0.016)	0.032 (0.021)	0.032** (0.013)			
March=0 \times $\log(\text{Sell to SOMA})$				0.038** (0.017)	0.015 (0.019)	0.017 (0.013)
March=1 \times $\log(\text{Sell to SOMA})$				0.085*** (0.018)	0.096** (0.038)	0.085*** (0.015)
Dealer FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.884	0.851	0.908	0.885	0.853	0.910
N	510	510	510	510	510	510

Table shows the effect of $\log(\text{Limit Usage})$ and the SOMA operation on dealer's ability to supply liquidity to client by taking bonds off their hands. Sample period is from March 16 to June 11th, 2020. Transaction level data is aggregated at dealer-day level for this analysis. Dependant variables in Columns (1) and (4) are Log volume of trades that are dealer buy from customers for bonds that are in the list of bonds with non-zero SOMA auction volume that day. Dependant variables in Columns (2) and (5) are Log volume of trades that are dealer buy from customers for bonds that are not in the list of bonds with a SOMA auction that day. Dependant variables in Columns (3) and (6) are Log volume of trades that are dealer buy from customers for all bonds. Limit Usage is defined as the ratio of VaR relative to VaR limit from the day before. Standard errors are robust.

Table 15: Dealer Profitability and VaR Constraint

(a) h=1			
	(1) Total	(2) New	(3) Existing
log(Limit Usage)	0.109*** (0.018)	0.074*** (0.014)	0.025 (0.023)
R^2	0.213	0.153	0.178
N	16667	16665	16665

(b) h=5			
	(1) Total	(2) New	(3) Existing
log(Limit Usage)	0.118*** (0.015)	0.092*** (0.012)	0.029 (0.020)
R^2	0.228	0.162	0.180
N	16772	16771	16771

(c) h=10			
	(1) Total	(2) New	(3) Existing
log(Limit Usage)	0.130*** (0.015)	0.102*** (0.012)	0.031 (0.019)
R^2	0.232	0.174	0.180
N	16772	16771	16771

Table 15 shows the effect of log(Limit Usage) on average change in profitability over the next $h = 1, 5,$ and 10 business days. Total, new, and existing profitability is defined to be the ratio of profit and loss (PnL) from total, new, and existing positions, respectively, scaled by VaR . Total positions PnL is defined to be the sum of PnL from new and existing positions. Limit Usage is defined as the ratio of VaR relative to VaR limit from the day before. The sample period is 1/1/15-3/31/23. All regressions include desk and time fixed effects. Standard errors are robust.

Table 16: Treasury Market Illiquidity Quantile Regressions

(a) Yield curve fitting error				
	(1)	(2)	(3)	(4)
	OLS	50th	75th	99th
MOVE	0.719*** (0.014)	0.646*** (0.020)	0.723*** (0.028)	1.418*** (0.089)
Limit Usage Index residual	0.253*** (0.014)	0.181*** (0.025)	0.235*** (0.031)	0.238*** (0.043)
R^2	0.583			
Pseudo R^2		0.274	0.378	0.502
N	2023	2023	2023	2023

(b) 10 year Treasury on the run premia				
	(1)	(2)	(3)	(4)
	OLS	50th	75th	99th
MOVE	0.737*** (0.015)	0.839*** (0.021)	0.940*** (0.020)	1.027*** (0.087)
Limit Usage Index residual	0.085*** (0.015)	0.091*** (0.025)	0.090*** (0.016)	0.142** (0.067)
R^2	0.552			
Pseudo R^2		0.347	0.368	0.511
N	2026	2026	2026	2026

Table 16 shows results from quantile regressions for the 50th, 75th, and 99th percentiles of Treasury market illiquidity measures on interest rate volatility (MOVE) and Limit Usage Index residual (columns 2-4). OLS regression results are shown in column 1. Treasury market illiquidity is defined in Panel (a) as the average absolute nominal yield curve fit error for securities used in the curve estimation and maturing in between 2 and 10 years, excluding on-the-run and first off-the-run securities; defined in Panel (b) as the spread between the 10-year on-the-run and off-the-run Treasury yield. Limit Usage Index is a time-series average of individual desks' values of $\log(\text{Limit Usage})$, weighted by their market share of customer transaction volumes over the past 20 business days. Limit Usage Index residual is the residual from the OLS regression of Limit Usage Index on MOVE. Quantile regression standard errors are bootstrapped. All variables are standardized in the regressions. The sample period for the regressions is 1/1/15-3/31/23.

E Figures

Figure 1: Dealer Inventory Index and 10-year Treasury Yield

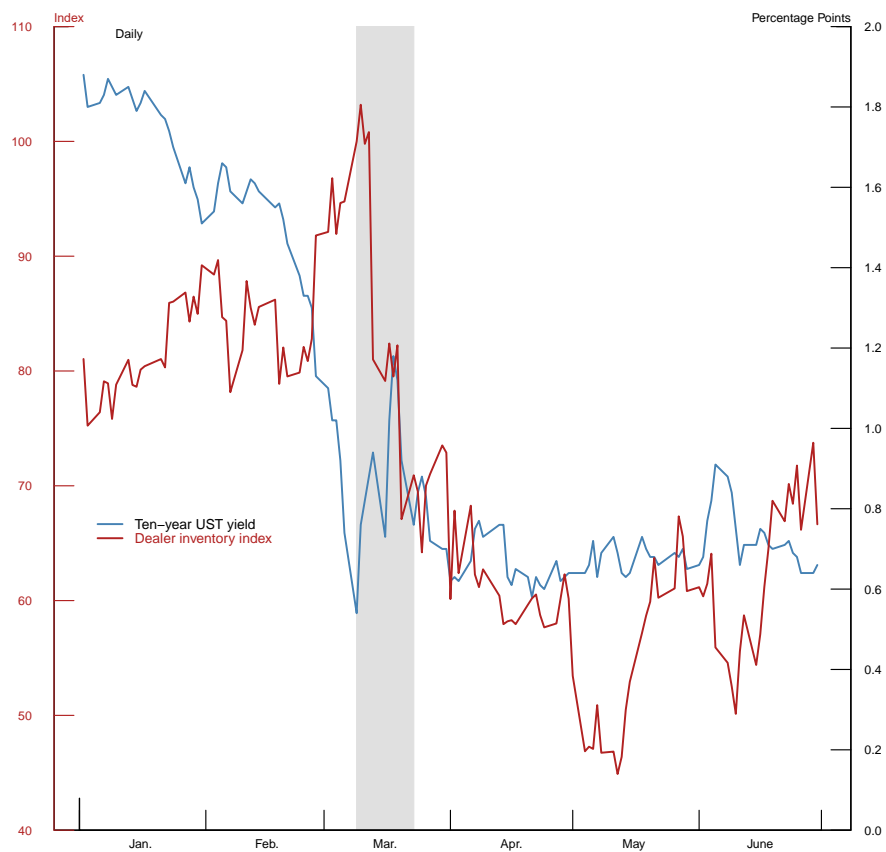
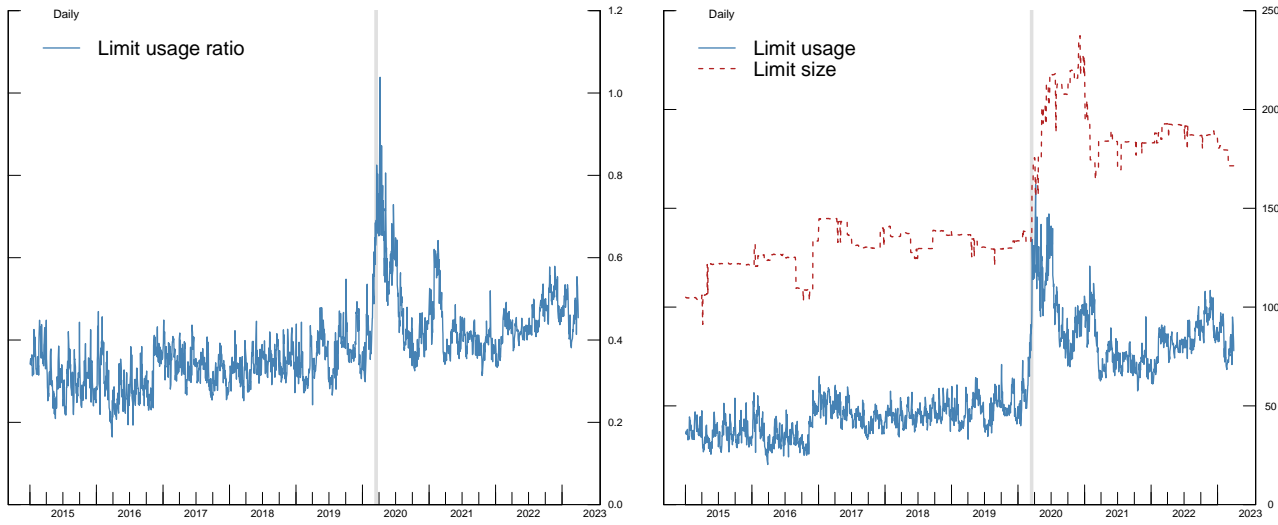


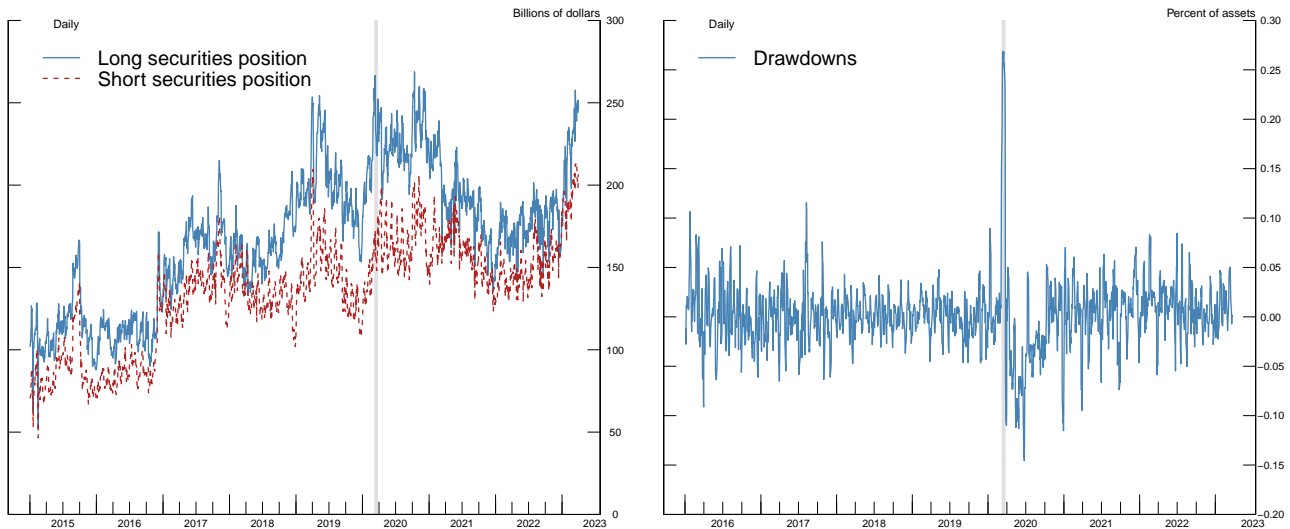
Figure 1 plots dealer Treasury inventory index and the 10-year Treasury yield during the first half of 2020. The dealer inventory index is measured as the sum of net securities positions at dealers' Treasury trading desks, indexed to 100 on March 9, 2020. The shaded area indicates the period of Treasury market stress from March 9 to March 23, 2020. Source: Board of Governors of the Federal Reserve System. Regulation VV Quantitative Measurements (FR VV-1).

Figure 2: VaR Limit Size, Usage and Usage Ratio



The left panel of Figure 2 plots the times series of average limit usage, defined as the ratio of VaR usage and the VaR limit. The right panel of Figure 2 plots the times series of average limit size and limit usage for the VaR limit. The shaded area indicates the period of Treasury market stress from March 9 to March 23, 2020. Source: Board of Governors of the Federal Reserve System. Regulation VV Quantitative Measurements (FR VV-1).

Figure 3: Trading Desk Positions and Bank Credit Line Drawdowns



The left panel of Figure 3 plots the times series of long and short securities positions at Treasury trading desks. The right panel of Figure 3 plots the times series of credit line drawdowns, measured as changes in the outstanding draws on corporate credit facilities over a 5-day horizon, as percentage of BHC assets. The shaded area indicates the period of Treasury market stress from March 9 to March 23, 2020. Source: Board of Governors of the Federal Reserve System. Regulation VV Quantitative Measurements (FR VV-1) and Complex Institution Liquidity Monitoring Report (FR 2052a).

Figure 4: Position Changes against VaR Limit Usage

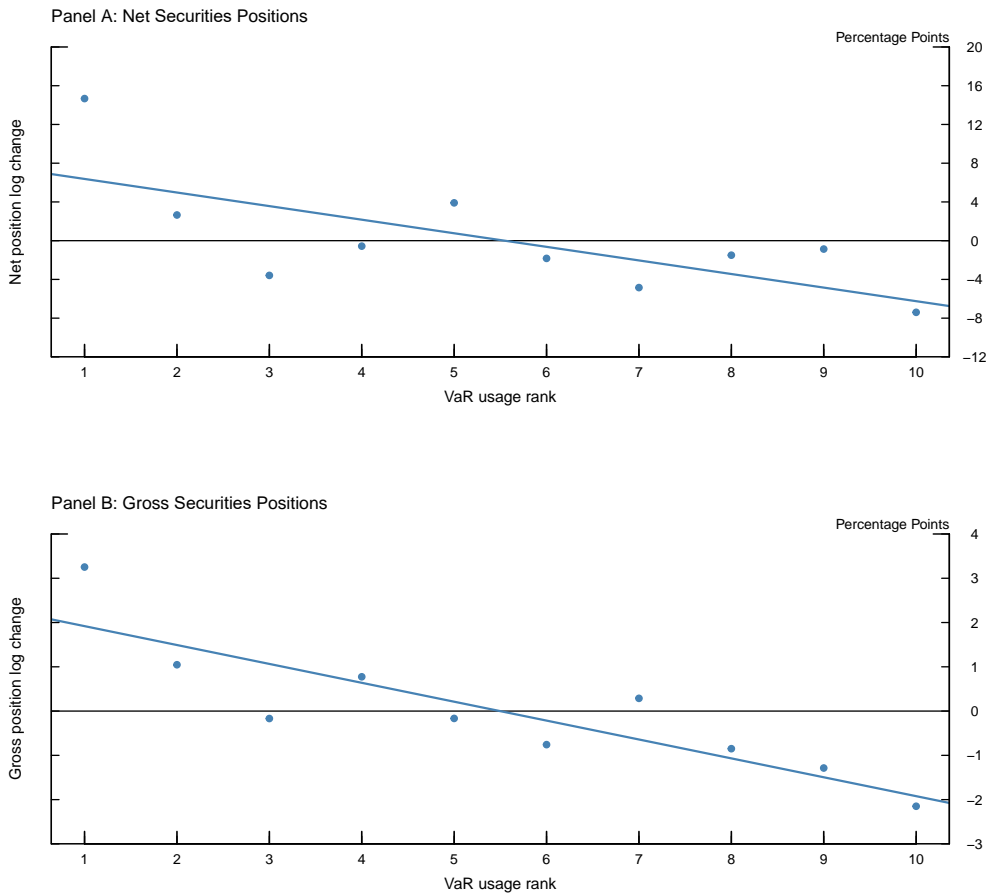


Figure 4 figure plots the average 10-day percentage changes in net and gross securities positions against VaR limit usage ranks. Inventory changes are averaged across decile ranks. Source: Board of Governors of the Federal Reserve System. Regulation VV Quantitative Measurements (FR VV-1).

Figure 5: Inventory Change since March 16, 2020 by VaR Limit Usage

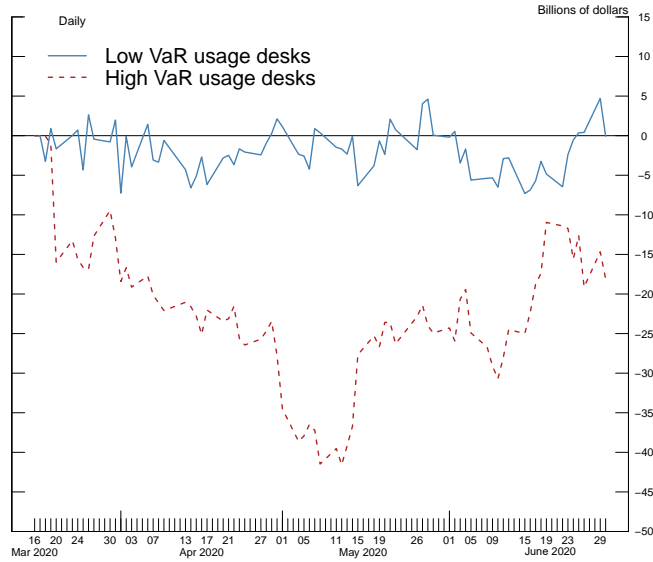
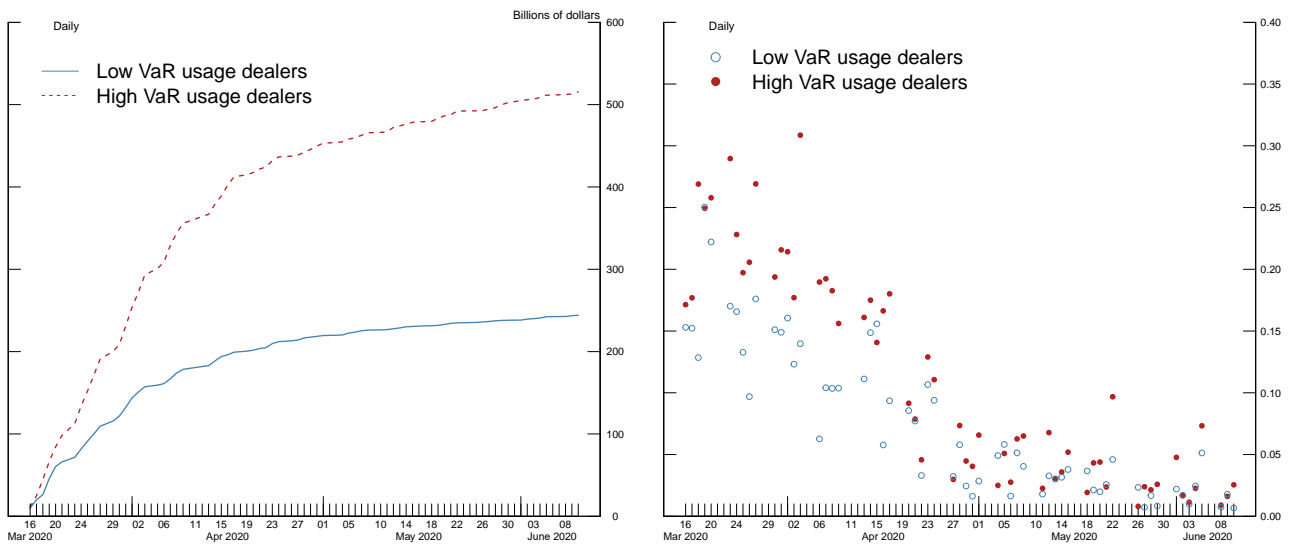


Figure 5 plots the times series of average cumulative changes since March 16, 2020 in net securities positions on UST trading desks that were relatively constrained/unconstrained by their VaR limit. High (Low) VaR usage desks are those with above (below) median VaR usage as of March 13, 2020. There are 6 desks in each group. Source: Board of Governors of the Federal Reserve System. Regulation VV Quantitative Measurements (FR VV-1).

Figure 6: Sales of Treasury Securities to the Fed During Open Market Operation since March 16, 2020, Grouped by VaR Limit Usage



The left panel of Figure 6 shows the cumulative total dollar volume of dealer sales of Treasuries to the Fed during open market operations. Dealers are grouped into Low VaR usage and High VaR usage groups based on ranking of their VaR limit usages as of March 13, 2020, averaged across Treasury securities trading desks. There are five dealers in each group. The right panel of Figure 6 shows the average fraction of dealer sales to clients that day that were sold to the Fed, over time.