Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

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Dan Li, Lubomir Petrasek, and Mary Tian

2025-034

Please cite this paper as:
Li, Dan, Lubomir Petrasek, and Mary Tian (2025). "Risk-averse Dealers in a Risk-free Market - The Role of Trading Desk Risk Limits," Finance and Economics Discussion Series 2025-034. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2025.034.

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

Dan Li, Lubomir Petrasek, Mary Tian [1]

May 2025

[1]We thank Stephen Zoulalian, Karl Patram, and Edward Wu for excellent research assistance. We thank David Bowman, Darrell Duffie, Ellen Correia Golay, Sebastian Infante, Francis Longstaff, Norman Schürhoff, Sebastien Plante (discussant), 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) for their comments. We thank David Lynch, David McArthur and Dennis Mawhirter for explaining the details of the Volcker data to us. The views of this paper do not represent the views of the Federal Reserve Board.

Abstract

Self-imposed risk limits effectively limit dealers' appetite for risks and their capacity to intermediate in Treasury markets in times of market stress. Using granular and high frequency regulatory data on US dealers' Treasury securities trading desk positions and desk-level Value-at-Risk limits, we show that dealers are more inclined to reduce their positions as they get closer to their internal risk limit, consistent with such limit being meaningful and costly for traders to breach. Dealers actively manage their inventories away from their limits by selling longer-term securities and requiring higher compensation to take on additional risks. During the height of the Covid-crisis in 2020, dealer desks that were closer to their VaR limits sold more Treasury securities to the Fed and accepted lower prices in the emergency open market operations. Our findings complement studies that link post-GFC bank regulations to market liquidity by showing that self-imposed risk limits can explain the risk-averse behavior by dealers, and provide a micro-foundation for the link between market volatility and market liquidity in dealer-intermediated OTC markets. In times of crisis, policy prescriptions such as deregulation alone may not be sufficient to induce risk-taking by dealer intermediaries. Moreover, to address market functioning issues, policy actions that address the funding costs of intermediaries would not be as effective as policies that remove risks from intermediary balance sheets directly.

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 the 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 order flow met hesitant dealers. Even primary dealers, committed market makers of these securities, exhibited an increased reluctance to "lean against the wind" and buy Treasuries. Indeed, dealers sought to reduce their inventory of Treasury securities during the crisis even as Treasury yields rose (Figure 1), contributing to the selling pressure.

Many attribute this perplexing apathy of dealers to the slew of post-Global Financial Crisis (GFC) bank regulations, prominently the Volcker rule and the Supplementary Leverage Ratio (SLR). Indeed, a growing body of research suggests that intermediary balance sheet issues may have manifested across a variety of markets since these rules were implemented (Bao et al., 2018; Du et al., 2018). However, the Volcker rule that prohibits dealers from proprietary trading explicitly exempts US Treasury securities, in addition to exempting market-making activities. It seems plausible that that enhanced capital regulations, especially the U.S. SLR, had an impact on dealers' Treasury market making activities. Indeed, the SLR is "risk blind"— it treats traditional risk-free assets like Treasury securities similarly to their riskier corporate debt counterparts, which makes intermediation in low-margin high-volume risk-free markets particularly costly (Duffie, 2018).

Yet, this narrative remains incomplete. The SLR itself is slow-moving, with the on-balance sheet exposure being calculated as the average of the the daily values over the entire quarter. A temporary increase in dealer inventories has only a modest effect on the quarterly regulatory ratio. The SLR is also insensitive to risk—a sudden rise in market volatility does not alter the SLR. In addition, banks had substantial headroom under the SLR in March 2020, especially in comparison to the subsequent years, when the Treasury market was relatively calm. Furthermore, high frequency evidence in Vissing-Jorgensen (2021) points to the timing of a reversal of price pressure in Treasury market in 2020 lining up well with a large increase in the Federal Reserve's daily Treasury purchases on March 19, weeks before regulatory reliefs that temporarily exempted Treasuries and reserves from the calculation of SLR for banks were announced.

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.

For risk limits set by management to be credible and effective in controlling risks, two things have to be true. 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 carries non-trivial costs to traders. The cost could be reputational or pecuniary.[1] We provide robust empirical evidence that breaching the limit carries substantial costs to traders.

The schemes of internal risk limits that trading desks are subject to are quite elaborate, with potential limits on market risks, counterparty risks and liquidity risks; the actual schemes vary

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

substantially across firms and business lines.[2] We focus on a particular type of risk limit that is universally adopted by almost all Treasury securities trading desks — the Value-at-Risk (VaR) limit. In addition to being universally adopted by all desks, VaR is also considered as the primary risk limit that traders pay attention to. By design, VaR captures the magnitude of potential tail losses, and is highly sensitive to sharp changes in market volatility and is intrinsically counter-cyclical (Adrian and Shin, 2013). A static portfolio would have substantially higher VaR should market volatility rise. VaR-type risk measures thus differ substantially from risk measures that focus on the size of positions, such as the SLR. We show in a stylized model that a risk-free trader with a VaR limit behaves in a way that is observationally equivalent to a risk-averse trader with standard utility function.

Our unique data on desk-level risk limits have a few advantages. By observing the upper bound on VaR and its actual usage at the trading desks level, we can measure dealer intermediation capacity directly, rather than inferring it.[3] The high frequency panel data allow us to empirically identify effect of risk limits on risk-taking behavior at the trading desk level, rather than looking at market aggregate. We further take advantage of richness of our data to construct instrumental variables using changes in the limits on non-Treasury market making desks and examine exogenous sources of variation in limit usage on Treasury market making desks.

We show that dealers avoid breaching desk VaR limits by managing down their inventory away from the limit, and in particular, by acquiring less inventory or selling existing inventory, with newer inventory being sold first. On average, as VaR limit usage doubles, dealers decrease the change in their net positions by about 10 percent over the following week. Such aversion to breaching the limit is most prominent in March 2020, when dealers rush 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.

Notably, since VaR calculations reflect portfolio risk after taking into account offsetting positions and hedges, one would expect the net positions of dealers to be more important to manage than gross positions, in order to keep their VaR in check. Our findings confirm that dealers' net positions

[2]For 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.

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

are indeed more affected by their VaR constraint than their gross positions. A size-based constraint such as the SLR, which does not net long and short positions, would have the opposite implication for dealer behavior, with gross positions being more important to manage than net positions. These findings also suggest that some policy recommendations that are aimed at alleviating dealer gross balance sheet pressures could have only limited effectiveness during market stress. For example, mandatory central clearing or a relaxation of the minimum SLR could provide relief from size-based regulatory constraints without alleviating risk-based constraints.

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 time 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 a upper limit on portfolio Value-at-Risk is observational 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 Kruttli 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 on-set 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 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 arbitragers, 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 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 (Kruttli 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 setting, 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, despite profitable trading opportunities. 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 risk-neutral trader with VaR limit could be observational 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 presents an event study of dealer behavior after Fed purchases in March 2020. Section 7 examines the effects of internal risk limits on dealer profitability and aggregate market liquidity. Section 8 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:

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

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:

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

$\mathrm{VaR}_\alpha(W) = \inf\{x \in \mathbb{R} : P(W - W_0 \geq -x) \geq \alpha\}$, where α is the confidence level, typically set at 95% or 99%. $\mathrm{VaR}_\alpha(W)$ 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 $\overline{\mathrm{VaR}}_\alpha(W)$.

This optimization problem can be solved using Lagrangian transformation

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

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 $\overline{\mathrm{VaR}}_\alpha(W)$.

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 $VaR = Z_\alpha * \sigma_W$, where σ_W is the standard deviation of portfolio value next period W. Z_α is the is the z-score corresponding to the confidence level α.

We can re-write the constraint in Equation 2 as

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

$$\iff \sigma_W \leq \frac{\overline{\mathrm{VaR}}_\alpha(W)}{Z_\alpha}$$

$$\iff \frac{\sigma_W^2}{2} \leq \frac{\overline{\mathrm{VaR}^2}_\alpha(W)}{2 * Z_\alpha^2} \tag{5}$$

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

$$\text{Maximize} \quad \mathcal{L}(W,\gamma) = E(W) + \gamma(\frac{\overline{\mathrm{VaR}^2}_\alpha(W)}{2 * Z_\alpha^2} - \frac{\sigma_W^2}{2})$$
$$= \gamma\frac{\overline{\mathrm{VaR}^2}_\alpha(W)}{2 * Z_\alpha^2} + E(W) - \frac{\gamma}{2}\sigma_W^2 \tag{6}$$

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

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 are 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 7.

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 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, dealers affiliated with large bank-holding companies are required to report daily metrics for each of their trading desks on Form FR VV-1. This report collects detailed data from trading desks, including a daily time series of various risk limits and their usage, profit & loss and its attribution to risk factors, and trading positions and transactions.

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. As an additional check, we also review the list of exemptions from the the "Volcker Rule" on proprietary trading that the desk claims. Many Treasury trading desks claim the the "trading in domestics 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, we also examine a broader set of 40 desks that list Treasury securities in their desk descriptions, even if Treasury market making is not necessarily their main focus.[4]

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. If

[4]Many of these additional desks are repo desks, hedging desks, municipal desks, credit desks, or derivatives desks that may trade Treasury securities to support these activities.

several VaR limits are identified on a given desk, take the VaR limit with usage corresponding to the reported VaR measure.

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 smallat 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 remained small at 3% (0%).

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:

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

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 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 entail. 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.

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. 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.

We use the data to construct several inventory measures: (1) the net position, measured as the absolute value of the difference between the long and short securities and derivative positions; (2) the gross position, measured as the sum of long and short securities and derivative positions; (3) the long positions; (4) the short positions. Because these measures combine both securities and derivatives positions, we require that the derivative positions be measured as securities equivalents or at their notional value (rather than the market value). Therefore, the combined measures are only available through 12/31/2020. In addition, we construct measures based on securities positions only: (1) net securities positions; (2) gross securities positions; (3) long securities positions; and (4) short securities positions. These measures are based on the market value of securities holdings, and are available for the entire sample period.

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 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.

4.4 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 position including securities and derivatives is \$350.5 billion at the Treasury trading desks in the sample, and the average gross position is \$3,020.4 billion. The long and short positions are \$1,676.7 billion and \$1344.0 billion, respectively. Derivatives exposures account for most of the combined positions. Securities positions alone are notably smaller, with the average desk carrying a net securities potions of \$4.95 billion, and a gross securities position of \$26.7 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 \$0.98 million.

Total PnL scaled by VaR is -0.34 on average. The last row in Table 1 shows the SLR distance, which is a measure of excess capital that bank holding companies held in excess of the minimum SLR requirement. The average SLR distance is 2.4%, with a range of between 0.23% and 13%. Of note, most desks in the sample are affiliated with bank holdings companies with a minimum SLR requirement of 5%.

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 today 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:

$$\Delta Log(\text{Position})_{it,t+h} = \alpha_i + \alpha_t + \beta Log(\text{Limit Usage})_{it} + c + \epsilon_{it}, \tag{8}$$

where $\Delta Log(\text{Position})_{it,t+h} = Log(\text{Position})_{i,t+h} - Log(\text{Position})_{i,t}$, the difference in the log of desk i's positions between day t to day $t+h$. Limit Usage is defined as $VaR_{it}/\overline{VaR}_{it-1}$, with $\overline{VaR}_{it-1}$ 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. Since offsetting long and short positions typically have little effect on VaR calculations, the net position is likely to be most directly affected by the VaR limit. We find that Treasury market-making desks' VaR constraints have a negative and statistically significant effect on changes in net positions one day ($h = 1$), one week ($h = 5$), and two weeks ahead ($h = 10$). The coefficient of -0.046 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 4.6 percent. The magnitude of the impact grows to 9.1 and 11.6 percent over a horizon of one week and two weeks later, respectively (columns 2 and 3). The results are similar for net securities positions, which do not include derivatives – a 100 percent increase in a desk's VaR limit usage implies a decrease in net position change the next day of 3.1 percent.

The effect of VaR limit usage on gross positions (Panel b) are also negative and statistically significant, though the magnitudes are smaller than that for net positions. To further illustrate these results, 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.

5.2 Dealers adjust newer inventory more

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 (8) 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 3, proximity to the risk limits generally affects newer dealer inventory more strongly. As seen in panel (a), VaR limit usage has a significant effect on the one day ahead change in positions of securities assets and liabilities 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. However, the magnitudes of the impact on changes in newer inventory is generally larger. These findings suggest that dealers actively manage their inventories away from their internal risk limits by selling newer inventory first or acquiring less inventory from clients. The results for short positions (liabilities) are similar to those for long positions (assets), but smaller in magnitude.

5.3 VaR matters more than 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 two regression specifications with VaR limit usage and SLR distance, the excess capital under the SLR rule:

$$\Delta Log(\text{Position})_{it,t+h} = \alpha_i + \alpha_t + \beta_1 Log(\text{Limit Usage})_{it} + \beta_2(\text{SLR dist})_{i,qtr(t)-1} + c + \epsilon_{it}, \tag{9}$$

$$\begin{aligned}\Delta Log(\text{Position})_{it,t+h} =& \alpha_i + \alpha_t + \beta_1 Log(\text{Limit Usage})_{it} + \beta_2(\text{SLR dist})_{i,qtr(t)-1} + \\ & \beta_{int} Log(\text{Limit Usage}_{it}) * \text{SLR dist}_{i,qtr(t)-1} + c + \epsilon_{it},\end{aligned} \tag{10}$$

In equation (9), VaR limit usage and SLR distance are both included as independent variables, while equation (10) contains the addition of an interaction term between the two. 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 4, we run regression specifications over changes in net positions (panel a) and net securities positions (panel b), as well as changes in net securities positions in 2020 (panel c) for h = 1, 5, and 10 business days ahead. In most regressions, the coefficient on VaR limit usage is negative and statistically significant. In contrast, the coefficient on lagged SLR distance is always insignificant, as well as the coefficient on the interaction term between VaR limit usage and SLR distance. These results show that the effects of VaR limit on dealer inventory changes are not driven by the SLR.

Tables 5 and 6 provide further evidence that the effects on dealers' Treasury market-making activities are more consistent with binding VaR limits than the SLR requirement. Table 5 shows that VaR limit usage significantly affects changes in dealer gross positions, even after controlling for lagged SLR distance, which is insignificant in nearly all specifications. Table 6 documents that the effects of VaR limit usage on changes in net positions is significantly larger than its effects on changes in gross positions. In particular, if VaR limit usage were to double, dealers would be inclined to reduce the change in net positions the next day by 3.8 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 6.8 and 8.6 percent more than that in gross positions, respectively (columns 2-3).

These results are consistent with the fact that VaR calculations usually balance long and short positions, so one would expect the net position of dealers to be more important than gross positions in keeping VaR in check. On the other hand, a size-based constraint that does not net long and short positions, such as the SLR, would have predicted the opposite, with gross positions being more important to manage than net positions.

5.4 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 8). For desks without DV01 limits in place, we set the DV01 limit usage to zero.[5] In addition, we run a horse race between the VaR and DV01 limit usage.

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

Table 7 shows the estimates from the panel regressions for both net and gross securities 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 net 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. Moreover, 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.

5.5 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 using VaR limit changes at non-Treasury desks of the same firm. Changes in risk limits at these 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 $t-1$:[6]

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

$$\Delta(\text{VaR Limit})^{k,dec}_{t-2,t-1} = \frac{\sum_{j=dec}[\text{VaR Limit}_{j,t-1} - \text{VaR Limit}_{j,t-2}]}{\sum_{j=dec}(\text{VaR Limit})_{j,t-2}}. \tag{12}$$

Table 8 shows the second stage 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 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.

5.6 Robustness

We show that the negative relationship between dealers' VaR limit usage and their positions in Treasury markets is robust in several dimensions.

First, the relationship 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.

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

[6]We 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 $t-1$.

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 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.

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 b). 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 b, 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.

Finally, 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 (Limit Usage) is negative and statistically significant in all specifications for the expanded sample. The magnitudes 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 positions change the next day of 2.5 percent (column 1).

6 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 constrains to sell 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.

6.1 Quantities of dealer-sell 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 3 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 Fed 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 11 shows results from panel regressions that study the effect of log(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 5 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).

6.2 Prices of dealer-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 12 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 ($\Delta p = \texttt{Avg Price in Auction} - \texttt{Price}_{\texttt{dealer sell}}$).[7] 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 percentage points 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 12 allow us to test this hypothesis directly. Indeed, for bonds with more years to mature, dealer' 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".

[7] While 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.

6.3 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 13 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 pecent increase in limit usage implies dealers buy 15.2 percent lower 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 increased 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.

7 Market Liquidity and VaR Usage

7.1 Dealer profitability and VaR usage

How does dealer's 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 the pricing 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:

$$\frac{1}{h} \cdot \sum_{k=1}^{h} \left[\frac{\text{P\&L}}{\text{VaR}}\right]_{i,t+k} - \left[\frac{\text{P\&L}}{\text{VaR}}\right]_{i,t} = \alpha_i + \alpha_t + \beta \log(\text{Limit Usage})_{it} + c + \epsilon_{it}, \tag{13}$$

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 14 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 (column 1). 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 is 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.

7.2 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}):

$$\text{Limit Usage Index}_t = \sum_i \mathrm{w}_{it} \cdot \mathit{Log}(\text{Limit Usage})_{it} \cdot, \tag{14}$$

where

$$\mathrm{w}_{it} = \frac{\sum_{k=1}^{20} \text{Cust Trans Volumn}_{i,t-k}}{\sum_i \left[\sum_{k=1}^{20} \text{Cust Trans Volumn}_{i,t-k}\right]}. \tag{15}$$

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 τth percentile on the Limit Usage Index residual, while controlling for interest rate volatility (MOVE index):

$$Q(\tau)_{\text{Illiquidity},t} = \alpha + \beta_\tau(\text{Limit Usage Index residual})_t + \gamma(\text{MOVE index})_t + \epsilon_t, \tag{16}$$

Table 15 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.[8] 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

[8] We 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.

8 Conclusion

We provide direct, trading desk-level evidence that dealer internal risk limits in the form of VaR limits limit 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 wouldn't 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. The 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 65, 1789–1816.

Breckenfelder, J., Ivashina, V., 2021. Bank balance sheet constraints and bond liquidity. Tech. rep.

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. The 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 us treasury market. Tech. rep.

Duffie, D., Fleming, M. J., Keane, F. M., Nelson, C., Shachar, O., Van Tassel, P., 2023. Dealer capacity and u.s. treasury market functionality .

Duffie, D., Keane, F. M., 2023. Market-function asset purchases. Staff Reports .

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 .

Fleckenstein, M., Longstaff, F. A., 2020. Renting Balance Sheet Space: Intermediary Balance Sheet Rental Costs and the Valuation of Derivatives. The 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.

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. The Journal of Finance 68, 2341–2382.

Kruttli, 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. The 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

$$\text{Maximize } \mathcal{L}(W,\lambda) = E(W) + \lambda(\overline{\text{VaR}}_\alpha(W) - VaR_\alpha(W)) \tag{17}$$

We can alternatively maximize

$$\begin{aligned} \frac{\mathcal{L}(W,\lambda)}{\overline{\text{VaR}}_\alpha(W)} &= E(\frac{W}{\overline{\text{VaR}}_\alpha(W)}) + \lambda(1 - \frac{VaR_\alpha(W)}{\overline{\text{VaR}}_\alpha(W)}) \\ &= E(\frac{W_0 + \Delta PnL}{\overline{\text{VaR}}_\alpha(W)}) + \lambda(1 - \frac{VaR_\alpha(W)}{\overline{\text{VaR}}_\alpha(W)}) \\ &= \frac{W_0}{\overline{\text{VaR}}_\alpha(W)} + E(\frac{\Delta PnL}{\overline{\text{VaR}}_\alpha(W)}) + \lambda(1 - \frac{VaR_\alpha(W)}{\overline{\text{VaR}}_\alpha(W)}) \end{aligned} \tag{18}$$

where $\frac{\Delta PnL}{\overline{\text{VaR}}_\alpha(W)}$ is trading PnL scaled by portfolio VaR and $1 - \frac{VaR_\alpha(W)}{\overline{\text{VaR}}_\alpha(W)}$ 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 14.

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 Tables

Table 1: Summary Statistics

(a) Positions and VaR

	mean	sd	p25	p50	p75	count
Net position	350.5	1209.1	0.34	3.24	40.5	31641
Gross position	3020.4	5475.9	10.0	340.7	4097.2	31641
Long position	1676.7	2987.1	5.24	182.4	2145.5	31657
Short position	1344.0	2609.4	4.72	157.1	1740.2	31686
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
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	0.98	4.27	-0.068	0.21	1.21	45840
Total PnL / VaR	-0.34	37.1	-0.047	0.18	0.55	42378
SLR dist	2.40	2.37	1.30	1.61	2.36	29863

(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 for 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), total profit and loss (PnL) in millions of dollars, total PnL scaled by VaR, and SLR distance (in percent). Gross (securities) positions are the sum of long and short (securities) positions. Net (securities) positions are the absolute value of the difference between long and short (securities) positions. Positions include cash and derivative assets. Securities positions include only cash assets. The sample period is 1/1/15-12/31/20 for positions and 1/1/15-3/31/23 for securities positions. 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 positions			Net securities positions		
	(1) h=1	(2) h=5	(3) h=10	(4) h=1	(5) h=5	(6) h=10
log(Limit Usage)	-0.046***	-0.091***	-0.116***	-0.031***	-0.058***	-0.070***
	(0.017)	(0.021)	(0.023)	(0.011)	(0.014)	(0.016)
Desk FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.131	0.127	0.144	0.129	0.125	0.132
N	12045	11986	11915	16838	16786	16721

(b) Gross positions

	Gross positions			Gross securities positions		
	(1) h=1	(2) h=5	(3) h=10	(4) h=1	(5) h=5	(6) h=10
ln_limit_usage_ratio2	-0.006***	-0.017***	-0.024***	-0.007***	-0.020***	-0.030***
	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Desk FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.136	0.146	0.154	0.132	0.153	0.154
N	12045	11986	11915	16838	16786	16721

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 positions (columns 1 through 3) include cash and derivative assets. Net and gross securities positions (columns 4 through 6) include only cash assets. Net (securities) positions are the absolute value of the difference between long and short (securities) positions. Gross (securities) positions are the sum of long and short (securities) 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 1/1/15-12/31/20 for positions (columns 1 through 3) and 1/1/15-3/31/23 for securities positions (columns 4 through 6). All regressions include desk and time fixed effects. Standard errors are robust.

Table 3: Effect of VaR Constraints on Dealer Long Positions (Assets) and Short Positions (Liabilities) of Different Vintages

(a) h=1

	(1) Assets ($\leq$30 day)	(2) Assets (>30 day)	(3) Liab ($\leq$30 day)	(4) Liab (>30 day)
log(Limit Usage)	-0.010***	-0.002	-0.008**	-0.003
	(0.003)	(0.002)	(0.003)	(0.003)
R^2	0.152	0.242	0.146	0.208
N	11428	11426	11434	11323

(b) h=5

	(1) Assets ($\leq$30 day)	(2) Assets (>30 day)	(3) Liab ($\leq$30 day)	(4) Liab (>30 day)
log(Limit Usage)	-0.034***	-0.018***	-0.013**	-0.017**
	(0.005)	(0.005)	(0.006)	(0.007)
R^2	0.168	0.150	0.150	0.165
N	11376	11374	11382	11260

(c) h=10

	(1) Assets ($\leq$30 day)	(2) Assets (>30 day)	(3) Liab ($\leq$30 day)	(4) Liab (>30 day)
log(Limit Usage)	-0.047***	-0.029***	-0.029***	-0.020**
	(0.006)	(0.008)	(0.007)	(0.010)
R^2	0.176	0.151	0.146	0.160
N	11309	11309	11315	11183

Table 3 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. The sample period is 1/1/15-12/31/20. All regressions include desk and time fixed effects. Standard errors are robust.

Table 4: Regulatory Constraints and Net Positions

(a) Net positions

	h=1		h=5		h=10	
	(1)	(2)	(3)	(4)	(5)	(6)
log(Limit Usage)	-0.029	-0.045	-0.088***	-0.111**	-0.129***	-0.175***
	(0.027)	(0.040)	(0.033)	(0.050)	(0.035)	(0.052)
lagged SLR dist	-0.002	0.012	-0.007	0.013	-0.020	0.021
	(0.025)	(0.033)	(0.032)	(0.042)	(0.036)	(0.046)
log(Limit Usage) × lagged SLR dist		0.007		0.010		0.021
		(0.012)		(0.016)		(0.016)
R^2	0.121	0.121	0.127	0.127	0.140	0.140
N	6160	6160	6113	6113	6057	6057

(b) Net securities positions

	h=1		h=5		h=10	
	(1)	(2)	(3)	(4)	(5)	(6)
log(Limit Usage)	-0.037**	-0.033	-0.057***	-0.070***	-0.072***	-0.071**
	(0.015)	(0.022)	(0.019)	(0.027)	(0.022)	(0.031)
lagged SLR dist	0.001	-0.000	-0.010	-0.005	-0.019	-0.019
	(0.013)	(0.014)	(0.016)	(0.018)	(0.017)	(0.019)
log(Limit Usage) × lagged SLR dist		-0.002		0.006		-0.000
		(0.007)		(0.009)		(0.010)
R^2	0.122	0.122	0.116	0.116	0.115	0.115
N	10947	10947	10907	10907	10857	10857

(c) Net securities positions 2020

	h=1		h=5		h=10	
	(1)	(2)	(3)	(4)	(5)	(6)
log(Limit Usage)	-0.061	-0.063	-0.136***	-0.139**	-0.135**	-0.120
	(0.039)	(0.052)	(0.051)	(0.070)	(0.055)	(0.076)
lagged SLR dist	-0.003	-0.003	-0.128	-0.128	-0.114	-0.117
	(0.092)	(0.091)	(0.122)	(0.122)	(0.135)	(0.135)
log(Limit Usage) × lagged SLR dist		0.001		0.002		-0.008
		(0.015)		(0.022)		(0.024)
R^2	0.124	0.124	0.113	0.113	0.118	0.118
N	2232	2232	2228	2228	2223	2223

Table 4 shows the effects of dealer regulatory constraint, SLR distance, and log(Limit Usage) on the log change in net positions (panel a), log change in net securities positions (panel b), and the log change in net securities positions in 2020 (panel c). Net (securities) positions are the absolute value of the difference between long and short (securities) positions. Net positions include cash and derivative assets. Net securities positions include only cash assets. 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 for regressions in panel (a) is 1/1/18-12/31/20; in panel (b) is 1/1/18-3/31/23; and in panel (c) is 1/1/20-12/31/20. All regressions include desk and time fixed effects. Standard errors are robust.

Table 5: Regulatory Constraints and Gross Positions

(a) Gross positions

	h=1		h=5		h=10	
	(1)	(2)	(3)	(4)	(5)	(6)
log(Limit Usage)	-0.010***	-0.009**	-0.029***	-0.031***	-0.043***	-0.045***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.006)	(0.008)
lagged SLR dist	0.000	-0.002	0.001	0.002	0.002	0.005
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.006)
log(Limit Usage) × lagged SLR dist		-0.001		0.001		0.001
		(0.001)		(0.002)		(0.002)
R^2	0.122	0.122	0.123	0.123	0.133	0.133
N	6160	6160	6113	6113	6057	6057

(b) Gross securities positions

	h=1		h=5		h=10	
	(1)	(2)	(3)	(4)	(5)	(6)
log(Limit Usage)	-0.009***	-0.011**	-0.029***	-0.033***	-0.040***	-0.043***
	(0.003)	(0.005)	(0.004)	(0.007)	(0.005)	(0.008)
lagged SLR dist	-0.001	-0.001	-0.002	-0.000	-0.010	-0.009
	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)
log(Limit Usage) × lagged SLR dist		0.001		0.002		0.002
		(0.002)		(0.003)		(0.003)
R^2	0.127	0.127	0.153	0.153	0.152	0.152
N	10947	10947	10907	10907	10857	10857

(c) Gross securities positions 2020

	h=1		h=5		h=10	
	(1)	(2)	(3)	(4)	(5)	(6)
log(Limit Usage)	-0.020***	-0.014*	-0.047***	-0.035**	-0.057***	-0.046***
	(0.007)	(0.008)	(0.011)	(0.014)	(0.013)	(0.017)
lagged SLR dist	-0.015	-0.016	-0.034	-0.036	-0.069**	-0.071**
	(0.016)	(0.016)	(0.027)	(0.027)	(0.031)	(0.031)
log(Limit Usage) × lagged SLR dist		-0.003		-0.006		-0.005
		(0.002)		(0.004)		(0.005)
R^2	0.133	0.134	0.172	0.173	0.181	0.181
N	2232	2232	2228	2228	2223	2223

Table 5 shows the effects of dealer regulatory constraint, SLR distance, and log(Limit Usage) on the log change in gross positions (panel a), log change in gross securities positions (panel b), and the log change in gross securities positions in 2020 (panel c). Gross (securities) positions are the sum of long and short (securities) positions. Gross positions include cash and derivative assets. Gross securities positions include only cash assets. 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 for regressions in panel (a) is 1/1/18-12/31/20; in panel (b) is 1/1/18-3/31/23; and in panel (c) is 1/1/20-12/31/20. All regressions include desk and time fixed effects. Standard errors are robust.

Table 6: Net positions relative to gross positions

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

Table 6 shows the effect of log(Limit Usage) on the log change in the ratio of net positions to gross positions (columns 1 through 3) and on the log change in the ratio of net securities positions to gross securities positions (columns 4 through 6). Net (securities) positions are the absolute value of the difference between long and short (securities) positions. Gross (securities) positions are the sum of long and short (securities) positions. Net (gross) positions include cash and derivative assets. Net (gross) securities positions include only cash 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 1/1/15-12/31/20 for positions (columns 1 through 3) and 1/1/15-3/31/23 for securities positions (columns 4 through 6). All regressions include desk and time fixed effects. Standard errors are robust.

Table 7: Interest rate risk limits

(a) Net positions

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

(b) Net securities positions

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

(c) Gross positions

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

(d) Gross securities positions

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

Table 7 shows the effects of limits on interest rate risk, measured as log(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). 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(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 1/1/15-12/31/20 for positions (panel a and c), and 1/1/15-3/31/23 for securities positions (panel b and d). All regressions include desk and time fixed effects. Standard errors are robust.

Table 8: 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*	-0.256***	-0.245**	-0.006	-0.069***	-0.077***
	(0.073)	(0.095)	(0.103)	(0.013)	(0.022)	(0.026)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	16816	16764	16699	16816	16764	16699

Table 8 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, 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 9: Robustness

(a) Long Positions

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

(b) Short Positions

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

(c) Net Positions - all UST market-making desks

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

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 positions (columns 1 through 3) and on the log change in net securities positions (columns 4 through 6) for all UST market-making desks. Net (securities) positions are the absolute value of the difference between long and short (securities) positions. Positions include cash and derivative assets. Securities positions include only cash 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 1/1/15-12/31/20 for positions (columns 1 through 3) and 1/1/15-3/31/23 for securities 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 positions

	h=1			h=5			h=10		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Limit Usage (std)	-0.007			-0.017*			-0.038***		
	(0.007)			(0.009)			(0.010)		
Limit Usage prc rank		-0.046			-0.099***			-0.153***	
		(0.030)			(0.037)			(0.039)	
Limit Usage q2			-0.028			-0.073**			-0.078**
			(0.023)			(0.030)			(0.032)
Limit Usage q3			-0.019			-0.085***			-0.079**
			(0.024)			(0.030)			(0.032)
Limit Usage q4			-0.039			-0.062**			-0.108***
			(0.024)			(0.030)			(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

(b) Net securities positions

	h=1			h=5			h=10		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Limit Usage (std)	-0.010**			-0.016**			-0.023***		
	(0.005)			(0.006)			(0.007)		
Limit Usage prc rank		-0.044**			-0.073***			-0.093***	
		(0.018)			(0.024)			(0.026)	
Limit Usage q2			-0.007			-0.041**			-0.064***
			(0.015)			(0.020)			(0.022)
Limit Usage q3			-0.011			-0.028			-0.032
			(0.016)			(0.020)			(0.022)
Limit Usage q4			-0.033**			-0.059***			-0.078***
			(0.015)			(0.019)			(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

Table 10 shows the effect of alternative measures of Limit Usage on the log change in net positions (Panel a) and the log change in net securities positions (Panel b). Net (securities) positions are the absolute value of the difference between long and short (securities) positions. Net positions include cash and derivative assets. Net securities positions include only cash 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 1/1/15-12/31/20 for positions (panel a) and 1/1/15-3/31/23 for securities positions (panel b). All regressions include desk and time fixed effects. Standard errors are robust.

Table 11: 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***	0.117***		0.321***	0.751***	
	(0.022)	(0.039)		(0.113)	(0.244)	
March=0 $\times$ $\log(\text{Limit Usage})_{t-1}$			0.030			0.068
			(0.038)			(0.190)
March=1 $\times$ $\log(\text{Limit Usage})_{t-1}$			0.127***			0.373*
			(0.047)			(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***	0.100***		0.104***	0.140***	
	(0.010)	(0.023)		(0.016)	(0.036)	
March=0 $\times$ $\log(\text{Limit Usage})_{t-1}$			0.027			0.041
			(0.022)			(0.036)
March=1 $\times$ $\log(\text{Limit Usage})_{t-1}$			0.059**			0.085**
			(0.026)			(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(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. Limit Usage is defined as the ratio of VaR relative to VaR limit from the day before. Standard errors are robust.

Table 12: Dealer SOMA Offer Aggressiveness and VaR limit Usage

	$\Delta p =$ `Avg Price in Auction` $-$ `Price`$_{\texttt{dealer sell}}$					
	Full Sample			Sample of Level 1 and 2 Match		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Limit Usage)$_{t-1}$	0.008***			0.009***		
	(0.002)			(0.002)		
March=0 $\times$ log(Limit Usage)$_{t-1}$		0.006***			0.006***	
		(0.001)			(0.001)	
March=1 $\times$ log(Limit Usage)$_{t-1}$		0.009**			0.012***	
		(0.004)			(0.004)	
Bond Life<5Yrs $\times$ log(Limit Usage)$_{t-1}$			0.001			0.001
			(0.001)			(0.001)
Bond Life$\in$[5,10)Yrs $\times$ log(Limit Usage)$_{t-1}$			0.007*			0.007*
			(0.004)			(0.004)
Bond Life$\geq$10Yrs $\times$ log(Limit Usage)$_{t-1}$			0.021***			0.026***
			(0.008)			(0.007)
constant	-0.002	-0.002	-0.002	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(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(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' 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 13: 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(Limit Usage)$_{t-1}$	-0.146***	-0.124**	-0.152***	-0.149***	-0.129**	-0.156***
	(0.055)	(0.063)	(0.046)	(0.054)	(0.061)	(0.044)
log(Dealer Sell to SOMA)	0.048***	0.032	0.032**			
	(0.016)	(0.021)	(0.013)			
March=0 × log(Sell to SOMA)				0.038**	0.015	0.017
				(0.017)	(0.019)	(0.013)
March=1 × log(Sell to SOMA)				0.085***	0.096**	0.085***
				(0.018)	(0.038)	(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(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. 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 non-zero SOMA auction volume 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 14: Dealer Profitability and VaR constraint

(a) h=1

	(1) Total	(2) New	(3) Existing
log(Limit Usage)	0.109***	0.074***	0.025
	(0.018)	(0.014)	(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***	0.092***	0.029
	(0.015)	(0.012)	(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***	0.102***	0.031
	(0.015)	(0.012)	(0.019)
R^2	0.232	0.174	0.180
N	16772	16771	16771

Table 14 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 15: Treasury Market Illiquidity Quantile Regressions

(a) Yield curve fitting error

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

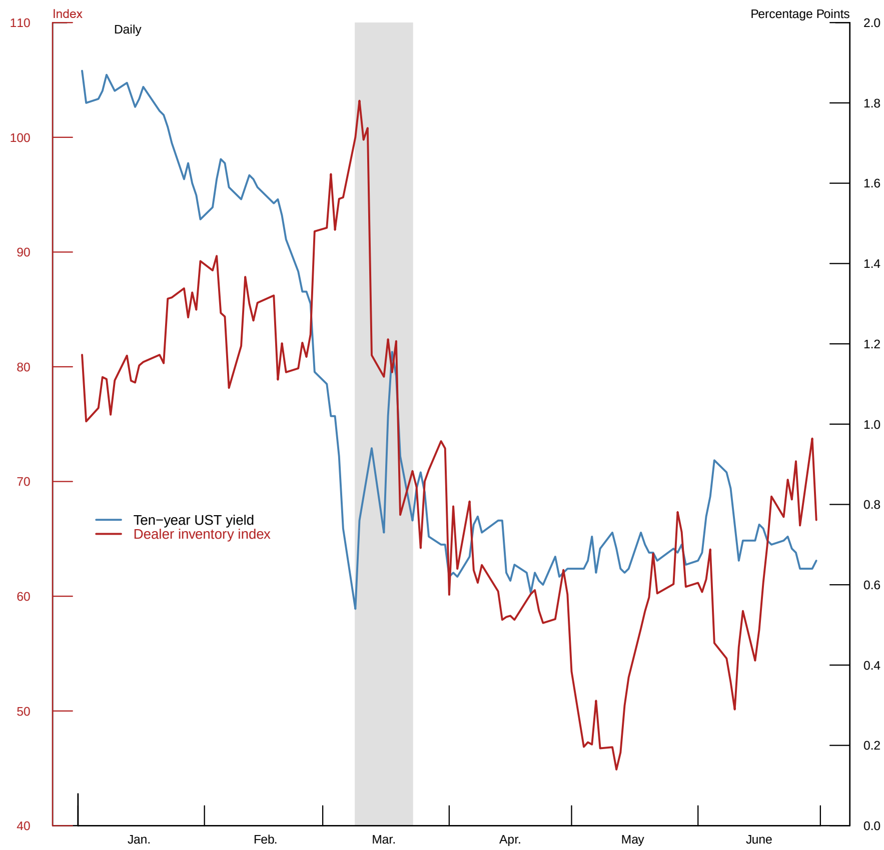
(b) 10 year Treasury on the run premia

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

Table 15 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(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.

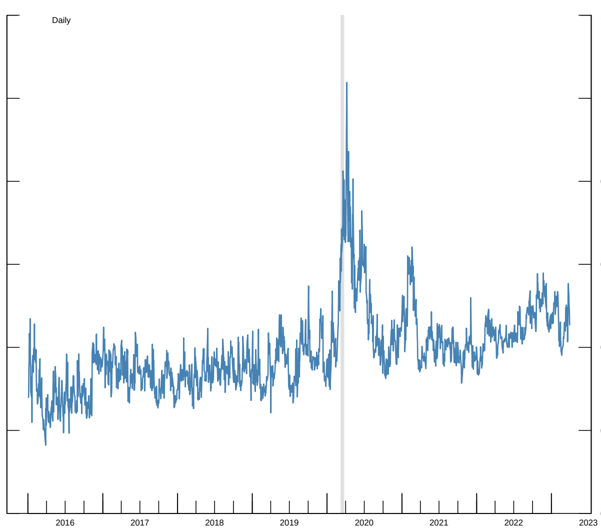
D Figures

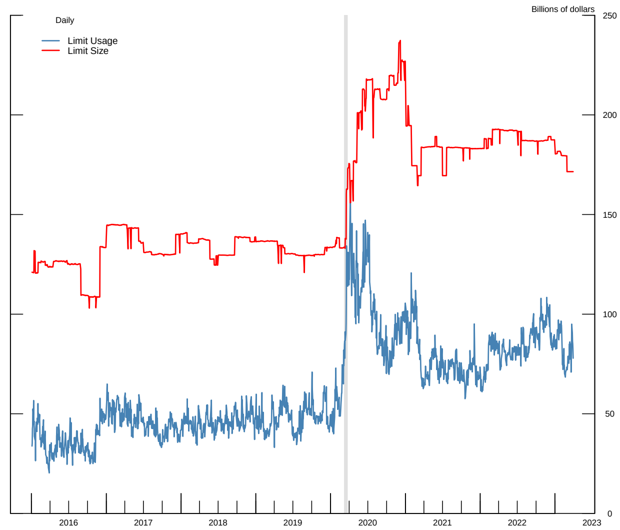
Figure 1: Dealer Inventory Index and 10-year Treasury Yield



The figure 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).

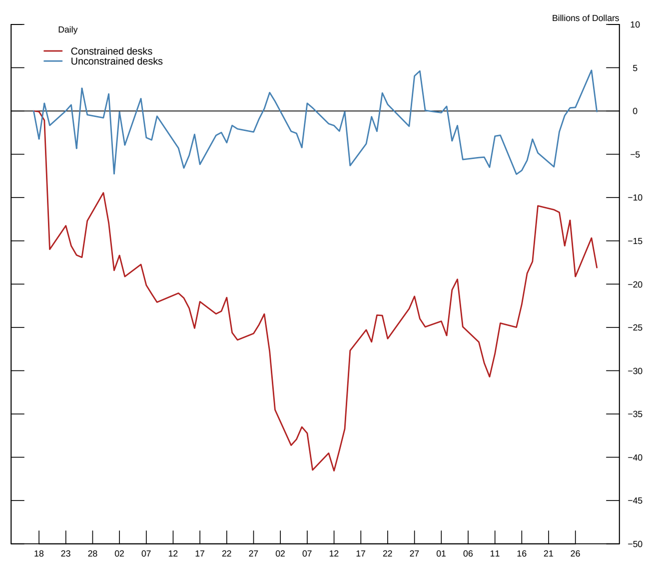
Figure 2: VaR Limit Size, Usage and Usage Ratio





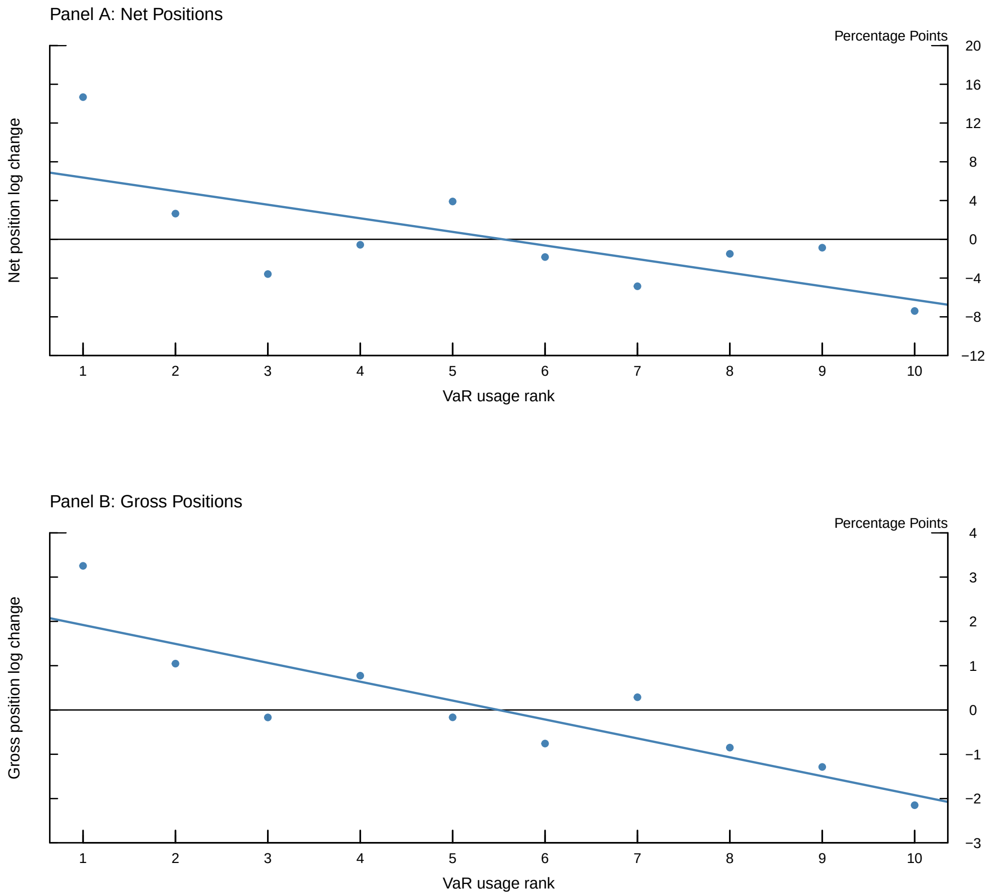
The left figure plots the times series of average limit usage, defined as the ratio of VaR usage and the VaR limit. The right figure plots the times series of average limit size and limit usage for the VaR limit. The shaded area indicates the period of Treasury market stress from March 9 to March 23,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

Figure 3: Inventory Change since March 16, 2020 by Proximity to VaR Constraint



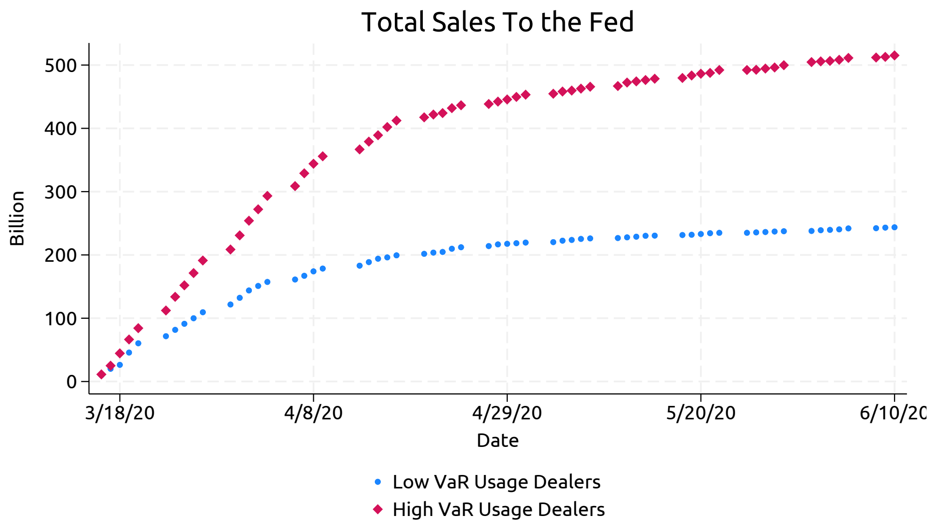
The figure plots the times series of average cumulative changes since March 16, 2020 in net securities positions on UST trading desks that were relatively constrained/unconstrained by their VaR limit. More (less) constrained desks are taken as those with above (below) median VaR usage as of March 13,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

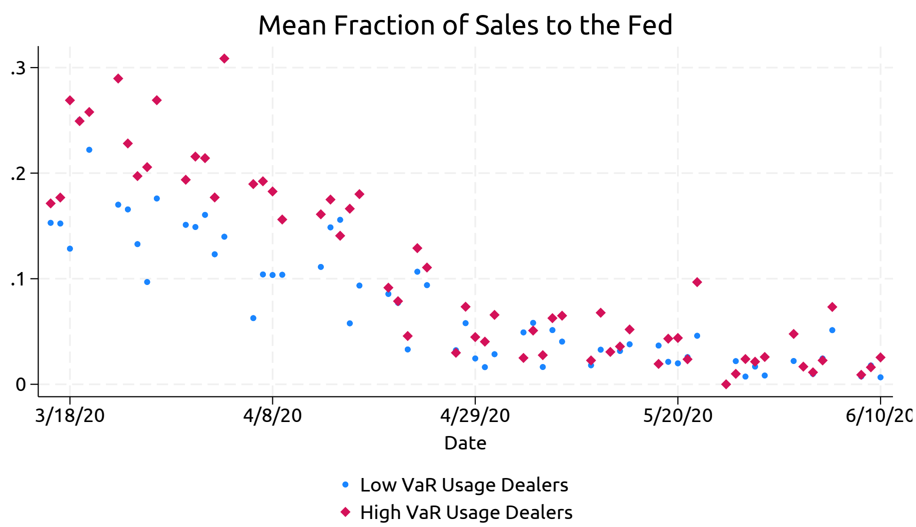
Figure 4: Position Changes against VaR Usage



The 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: Sales of Treasury Securities to the Fed During Open Market Operation since March 16, 2020, Grouped By VaR limit Usage





Upper panel shows 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. Lower panel shows the average fraction of dealer sales to clients that day that were sold to the Fed, over time.