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Adam Copeland | Owen Engbretson

FEDERAL RESERVE BANK of NEW YORK

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Abstract

Securities dealers play a central role intermediating funds in the U.S. short-term money markets. This intermediation involves risk, which can be mitigated by holding buffers of liquid securities. The cost of holding these buffers—the liquidity risk premium—is driven by the opportunity cost of holding money and so is influenced by monetary policy. We use detailed data on the pricing of repurchase agreements (repo), the main contract used to provide secured funding in the money markets, to measure by how much changes in monetary policy affect the liquidity risk premium embedded in repo pricing. The results imply that both changes in administrative rates and in aggregate reserves have effects on this risk premium and that this relationship is nonlinear. Using the average values of rates and reserves in 2024, the estimated coefficients predict that a 100-basis-point increase in the interest rate on reserve balances results in a 0.9 basis point increase in the liquidity risk premium—a 10 percent increase in the spread charged by securities dealers to their clients. The same effect on this risk premium can be achieved by a $429 billion decrease in the aggregate reserves.

JEL classification: G23, E58
Key words: repo, liquidity risk premium, rate pass-through, short-term funding

Copeland, Engbretson: Federal Reserve Bank of New York (emails: adam.copeland@ny.frb.org, owen.engbretson@ny.frb.org). The authors thank Nina Boyarchenko, Michael Fleming, Matt Plosser, and seminar participants at the Federal Reserve Board for helpful comments.

Short-term funding trades are often considered to be relatively low-risk, low-reward transactions. However, even when the funding is secured by high quality collateral and provided at a short maturity, material risks arise when entering into these transactions.[1] To mitigate these risks, market participants generally put aside a buffer of liquid securities, which is a cost that should be reflected in the pricing of funds, a driver of pricing that we term a *liquidity risk* premium. The cost of holding these buffers varies with the opportunity cost of holding money, and so it is influenced by monetary policy. This paper studies this connection, estimating how monetary policy influences the cost of short-term funding.

We accomplish this by analyzing secured funding trades in the U.S. that are documented as repurchase agreements (repo), which is the usual legal framework used for these types of transactions.[2] Using confidential trade-level data, we construct the spreads that dealers charge to intermediate funds in repo from 2020 onward. We then estimate that monetary policy, through both changes in interest rates and in aggregate reserves, meaningfully affects these spreads through changes in the liquidity risk premium. Consequently, this analysis highlights that that Federal Reserve influences short-term rates in two ways: through the usual pass-through channel and through the liquidity risk premium effect.

The analysis is centered on the service that dealers provide by intermediating funds in money markets and the risks they face. We focus on dealers because they serve as the main intermediaries in these markets. In general, dealers source secured funding from cash-rich clients, such as money market funds and pension funds, who are looking for a safe return on their holdings of cash. Dealers then provide secured funding to levered clients, such as hedge funds, who pursue an array of strategies.

In this role, dealers face risks from both trades. When lending funds, there are two ways through which a dealer is exposed to default risk even though it holds securities as collateral. First, these securities may fall in value and then no longer fully offset the cash principal amount of the repo. Second, in the event of default, quickly liquidating the securities so as to recover the cash principal amount likely forces the dealer to accept a price discount, which may then result in the dealer not fully recovering the cash principal amount.

When borrowing funds, the dealer is exposed to rollover risk as the cash-rich client pro-

[1] See TMPG (2025) for a distillation these risks.

[2] Garbade (2006) describes how repurchase agreements grew to be a main legal instrument used by securities dealers to seek financing.

viding funding may decide to not renew the trade. In this case, the dealer will be forced to scramble and find a replacement source of funding, so as to enable the dealer to continue to intermediate funds. This rollover risk exists whether or not the dealer provides maturity transformation, because there is long-term value in providing a steady source of funding to a client. As such, dealers are motivated to quickly find replacement sources of funding, even at (temporarily) disadvantageous rates. Naturally, if the dealer is also providing maturity transformation by borrowing short-term funds and lending long-term funds, then the rollover risk is accentuated because the dealer is obligated to continue to provide funding to the levered client.

Both the default and rollover risks incentivize the dealer intermediary to hold a buffer of liquid securities. The cost of holding this liquid buffer should be reflected in the pricing of the funds borrowed and lent. Furthermore, this liquidity risk premium will vary with the opportunity cost of holding cash, as noted in Nagel (2016) and Drechsler et al. (2017). Given the difficulties involved with separately identifying this liquidity risk premium from confounding factors in the cross-section, we rely on time-series variation. Changes in monetary policy—both in terms of rates and the aggregate level of reserves—drive changes in the opportunity cost of holding cash, which, in turn, allows for the estimation of changes in the liquidity risk premium, as reflected in dealers' pricing. The advantage of this time-series approach is the plausibility of the empirical analysis's identifying assumption—changes in monetary policy are exogenous to the spread that dealers charge to intermediate funds.

The empirical exercise is to construct the spread that dealers earn from intermediating funds using repo and then measure how this spread changes in response to changes in monetary policy. The main data analyzed come from the U.S. Treasury's Office of Financial Research's (OFR) centrally cleared repo collection. The focus is on repo trades using Treasury securities—these trades play a central role in U.S. short-term funding markets and so are representative of the general price of funding in the money markets.[3] Overnight Treasury repo is by far the dominate maturity in the market, and so the analysis considers this maturity, a step that also simplifies the empirical analysis by removing estimation obstacles inherent with longer-term trades, such as expectations over future interest rates.

Finally, we filter out repo trades used to source collateral so as to obtain a clean measure of funding in repo. This filter uses data on repo pricing and the theory presented in Duffie

[3]Further, short-term funding trades using other securities, such as agency mortgage-backed securities or corporate debt, are typically priced off of Treasury repo.

(1996) and is a result in itself, as previous attempts to filter out repos used to source collateral have relied on rules around the type of Treasury delivered (e.g., repos involving on-the-run Treasuries are deemed to not be funding trades) or based on an ad hoc rule (e.g., the Secured Overnight Financing Rate (SOFR) trim that eliminates all trades in a day with rates in the lower tail of the distribution).[4]

From these filtered data, we construct two types of spreads: a client-to-client spread measuring the price charged by a dealer lending cash on a secured basis to a client minus the price charged to borrow, and an equivalent interdealer spread. We combine these spreads with variables capturing the Federal Reserve's rate-setting policy (the interest rate on reserve balances, IORB) and balance sheet policy (a measure of the Federal Reserve's liabilities), along with other variables used to control for exogenous changes in the Treasury repo markets. From an analysis of these data, the main results are that both an increase in short-term rates and a decrease in Federal Reserve liabilities (hereafter Fed liabilities) raise the liquidity risk premium, driving up the cost of intermediating funding. For the client-to-client spread, the estimates imply that a one standard deviation increase in IORB (226 bps) drives up the liquidity risk premium by 2.1 to 3.5 basis points. A one standard deviation increase in Fed liabilities ($750 billion) drives down the premium by 1.6 to 2.5 basis points. These are economically significant effects, as evidenced by the fact that the average spread that dealers charge clients to intermediate funding in the sample period is 7.5 basis points. Similar effects are found for interdealer spreads.

A second set of results analyzes how dealers alter their spreads in response to monetary policy. This is accomplished by considering the level of repo rates in different segments of the repo market and how these rates change in response to changes in monetary policy. The results demonstrate that the rates at which dealers borrow funds does not seem to reflect changes in the liquidity risk premium. Rather, the rates at which dealers lend funds react to changes in the liquidity risk premium. Putting these results together, the results imply that the levered entities that borrow funds from dealers absorb the change in cost related to the liquidity risk premium.

A main insight from the above results is that the Federal Reserve can affect the liquidity risk premium using two tools: changes in administrative rates or changes in its balance sheet. Over the 2022–23 monetary policy tightening period, the Federal Reserve both raised rates and

[4] See `https://www.newyorkfed.org/markets/reference-rates/sofr` for details on the SOFR trim.

lowered the total value of its liabilities, actions that worked together to raise the liquidity risk premium and thereby widen dealers' spreads. This paper's results, however, highlight that the Federal Reserve has the ability to achieve a variety of outcomes with respect to interest rates in the economy and the spreads that dealers charge to intermediate funding. Hence, the Federal Reserve can manage how financing conditions are affected even as it influences economic conditions. For example, in a situation where the Federal Reserve wants to bolster the economy and is concerned about a high level of financial sector leverage, a way forward would be to lower interest rates and decrease Fed liabilities. Lowering rates would bolster the economy (through the usual channels) and a large enough decrease in Fed liabilities would result in a widening of dealers' spreads, dampening overall financial sector leverage. To quantify how much Fed liabilities would need to decline to offset lower rates, the results imply that, using the values of rates and Fed liabilities at the end of the sample, a 100 basis point decrease in IORB and a $429 billion decrease in Fed liabilities have offsetting effects on the liquidity risk premium.

This paper contributes to the liquidity premia literature, with this paper being closest to Nagel (2016). That paper documents the empirical relationship between the opportunity cost of money and the liquidity premia of near-money assets. Building on their approach, this paper considers (1) the service of intermediating funds that dealers provide to clients and (2) how the cost of this service varies with the opportunity cost of money. Hence, whereas Nagel (2016) examines the movement in prices of near-money assets, this paper focuses on how an intermediary prices funding.[5] Further, this paper separates out the effects of monetary policy changes to interest rates from changes to the Federal Reserve's balance sheet.

The results from this paper are also consistent with the dynamic asset pricing model of Drechsler et al. (2018). In their model, the risk-tolerant agents, which most closely map to banks, take deposits from risk-adverse households and invest in risky assets. In our setting, dealers are acting as intermediaries, channeling funding from risk-adverse investors such as money market mutual funds, to risk-tolerant clients such as hedge funds. Our results are inline with their model's prediction that increases in the nominal rate increase the cost of taking leverage.

This paper also fits into the literature studying the pass-through of monetary policy in

[5]Nagel presents a low-frequency analysis, with the main results using monthly data from 1990 to 2010. In contrast, this paper presents a higher-frequency analysis, using high frequency data over a four year period.

money markets. Within this field, Eisenschmidt et al. (2024) is the closest work; they use confidential transaction level data to study how changes to the ECB's policy rate passes through to various segments of the European repo market. We also take advantage of detailed transaction level repo data, along with institutional knowledge of differences across repo segments, to study the interaction between monetary policy and repo rates. A main difference is that Eisenschmidt et al. (2024) focus on measuring dealers pricing power and how that margin influences rate pass-through, whereas we focus on the liquidity risk premium, a cost that dealers face, and how that cost is affected by monetary policy.

More broadly, this paper adds to the understanding of U.S. repo markets. Hu et al. (2021), Anbil and Senyuz (2022), Han et al. (2022), Huber (2023), and Paddrick and Ramírez (2025), for example, have studied triparty repo during normal times. Our paper adds to this work by demonstrating that the pricing of triparty repo trades does not reflect a liquidity risk premium; in future work, we aim to explore what this result implies about the nature of the relationships in triparty relative to other repo segments. This paper also complements Anbil et al. (2026), recent work that uses the same underlying data and focuses on documenting how the repo financing costs of hedge funds are affected by Treasury securities issuance, the amount of central bank reserves in the system, and leverage constraints faced by bank holding companies. Finally, this paper's analysis of centrally cleared repo pricing is timely, given the current focus on how the Securities and Exchange Commission's update to the central clearing regulations (see Section 2.1 for more details) is causing a significant migration of dealer-to-client Treasury repo to central clearing.

The rest of the paper is organized as follows. The following section introduces the data sources. Section 2 then details how the data are filtered for the analysis, lays out the main empirical analysis on intermediation funding spreads. Section 3 presents secondary results on repo rates, and Section 4 describes robustness results. Section 5 then discusses the overall importance of the results, with a focus on the 2022–23 monetary policy tightening cycle, and Section 6 concludes.

1 Data

The analysis relies upon two confidential datasets of repo activity, both of which are described in the following section.

1.1 Centrally cleared repo

The main data used in the analysis come from the U.S. Treasury's Office of Financial Research's (OFR) centrally cleared repo collection. These data are collected from the Fixed Income Clearing Corporation (FICC), which was the only central counterparty in the Treasury market in the sample period.[6] We use those trades that are cleared using FICC's DVP Service offering, which can be split into four segments: interdealer trades executed without a broker (ID No Broker), interdealer trades executed with a broker (ID Broker), dealer-to-client trades where dealers are lending funds (DtC Lend), and dealer-to-client trades where dealers are borrowing funds (DtC Borr).[7] Figure 2 presents a schematic of the Treasury repo market and highlights which segments of the market are included in this analysis.

The salient differences across the four segments are which entities hold the clearing and settlement risks of the trade. For the interdealer segments, FICC takes on the counterparty credit risk for the trade. FICC manages this risk through a variety of tools, including making margin calls on the dealers. For the dealer-to-client segments, FICC continues to employ a risk management process that include margins, but the dealer remains on the hook for the failure of the client to perform on its obligations.[8] In the DtC Borr segment, money market mutual funds (MMFs) are the dominant type of client, whereas in the DtC Lend segment, hedge funds are the dominant type. As a result, we would expect to find the strongest evidence of a liquidity

[6] As of December 2025, FICC was the sole CCP for Treasury repo in the U.S. Both the Chicago Mercantile Exchange and Intercontinental Exchange have indicated that they will enter as CCPs. In a December 2, 2025 press release, the CME Group announced that they intend to start a service to centrally clear Treasury transactions in the second quarter of 2026.

[7] We do not consider centrally cleared trades that settle on the triparty settlement platform, such as FICC's GCF Repo Service. The volumes centrally cleared on FICC DVP Service are much larger than the centrally cleared volumes on the triparty settlement platform. (Put in a statistic on relative volumes.)

[8] The name of the service through which these dealer-to-client trades are centrally cleared is Sponsored Services. Copeland and Kahn (2024) analyze this service, work that includes descriptive statistics, such as the types of clients engaging with this service, and an overview of how margins are computed.

risk premium to involve trades in the DtC Lend segment, where dealers retain counterparty credit risk exposure to their relatively risky hedge fund clients.

These trade-level data include detailed information, including the rate, principal amount, type of securities exchanged (CUSIP), maturity, the names of counterparties, and if an inter-dealer broker was used for trade execution.[9] We filter these data in two ways. First, we focus on repo trades that only involve U.S. Treasuries and that have an overnight maturity. Both Treasury and agency debenture securities are eligible for central clearing through FICC's DVP Service, but only a tiny share of trades involve debentures. Although these securities are comparable to Treasuries in terms of safety, agency debentures are typically less liquid.[10] For these reasons, we remove agency debentures from the analysis. The focus on overnight maturity is adopted to simplify the analysis, because studying longer-term maturities introduces difficulties around heterogeneous expectations, such as those formed about future interest rates. Fortunately, the overnight maturity is by far the dominant maturity.

The second filter addresses the complication that the data contain trades used to source funding, as well as those used to source securities. Our focus is on the pricing of repo used to source funding and to what degree the pricing of these funding trades reflects a liquidity risk premium.[11] To that end, we employ a filter that classifies repos into one of these two groups based on repo rates. Details of this filter, an analysis of the outcomes, and robustness results are provided in Appendix A. The basic intuition of the filter is that the pricing fundamentals for repo used to source funding differ from those driving the price of repos used to source securities. We leverage this difference to identify the Treasury securities that market participants are trying to acquire (to source) using repo, and then we remove these securities from the analysis.

The OFR began this collection in October 2019. To avoid the financial market disruptions of COVID-19 and its aftermath, our sample begins on April 1, 2021, after the Federal Reserve ended the Treasury exemption for the supplementary leverage ratio. The sample extends

[9]CUSIP is an identifier used to uniquely identify a type of security.

[10]Krishnamurthy (2010) reports on the difference in liquidity risk between the agency debt and Treasury securities during the 2007–09 financial crisis.

[11]The pricing of trades to source securities should also reflect the costs of holding a liquidity buffer. However, the price dynamics of these trades differs from those driving trades to source funding, and the rates for trades sourcing securities are quite volatile. This can be seen in Appendix Figure 7, which plots the aggregate daily time-series of average rates for trades used to source funds and for those used to source securities. Consequently, for this paper we focus solely on repos used to source funding.

through the end of December 2024. Filtering the data reduces the size of the FICC DVP dataset by 7.2 percent (see Appendix Table 14). From this filtered trade-level data, we aggregate to the level of date and CUSIP. This aggregation reduces some of the noise inherent at the trade level, and it provides a measures of repo rates at the same level at which pricing is provided in the market, such as on broker screens.

To provide a general sense of the relative sizes of each segment, we plot the total centrally cleared overnight Treasury repo funding volumes by segments, as well as by their shares of total activity in Figure 3. As highlighted in this figure, ID Broker is the largest segment, with a share of total activity ranging between 38 and 63 percent. The ID Broker, DTC Lend, and DTC Borr segments were roughly flat from the beginning of the same period through the second quarter of 2022, and then funding volumes began to rise. The DtC segments both grew faster than ID Broker, appreciatively closing the gap in volumes between the interdealer and dealer-to-client segments. The rise in the DtC segments mostly reflects the SEC's latest rule amendments that call for increased central clearing in Treasury repo. Unlike interdealer Treasury repo, the vast majority of dealer-to-client Treasury repo before 2023 were not centrally cleared. Hence, it is dealer-to-client trades that are migrating into central clearing and driving up total volumes in DtC Borr and DtC Lend. The ID No Broker segment remains small throughout the sample; it is not used in the analysis because the motivations for dealers to execute funding trades without an interdealer broker are not clear to us, except when two affiliated entities are executing a trade.

1.1.1 Triparty repo

The second data used in the analysis are triparty repo transactions. These are dealer-to-client trades where dealers are sourcing funds from a variety of cash-rich investors. These trades are not centrally cleared; rather 'tri' highlights that both the dealer and client clear and settle this trade on the books of a third party, a custodial bank that runs a platform that allows for efficient clearing and settling of repo funding trades. MMFs are the dominant type of client, and in this way these trades look similar to those in the DtC Borr segment described above. The triparty repo segment, however, has much larger daily outstanding volumes than DtC Borr and reflects activity for a larger set of client types. As a result, we consider these data more representative of the pricing faced by dealers when sourcing funds from clients. The Federal Reserve operates its Reverse Repo Operations (RRP) and Standing Repo Facility (SRF) in triparty; transactions resulting from market participants accessing these facilities have been removed from the data. (In the schematic presented in Appendix Figure 2, the triparty repo data used in our analysis is labeled "private TPR".)

These trade-level data include detailed information, including the rate, principal amount, the asset class of the securities exchanged, maturity, and names of both counterparties. The securities are only identified by asset class (and not by the unique security type) because triparty repo transactions are general collateral trades, whereby at the time of execution the counterparty delivering securities against cash promises to deliver securities within a predefined set. In the triparty repo segment, for transactions involving Treasuries, this predefined set is almost always any Treasury security.

Following the approach used with the centrally cleared data, we filter these data to include only those repos involving Treasuries and those with overnight maturity, where trades executed with the Federal Reserve are dropped.[12] These filters remove 77.5% of value-weighted trades, as measured by their cash principal amount (see Appendix Table 13 for a detailed breakdown.) Finally, we aggregate the data up to the level at which prices are quoted, resulting in a time-series of overnight repo rates for general collateral trades backed by (any) Treasury securities.

In terms of total activity, overnight Treasury repo volumes in the triparty and ID Broker segments are close in magnitude. The daily total value of triparty overnight Treasury repo hovers around \$500 billion at the beginning of the sample; it starts to steadily increase in the first quarter of 2023, reaching \$800 by the second half of 2024.

2 Empirical analysis of spreads

In this section, we present the main empirical analysis. We begin by describing the institutional details of how in practice dealers are putting aside capital to mitigate risks from intermediating funds. We then describe the empirical approach and report the results.

[12]The triparty segment includes substantial trading of repos involving agency mortgage-backed securities, as well as those involving equities and corporate debt. Volumes of outstanding repo activity by asset class are published at https://www.newyorkfed.org/data-and-statistics/data-visualization/tri-party-repo.

2.1 Institutional details on risk mitigation in repo

In this section we layout the institutional details of repo that link how dealers put aside capital to manage their counterparty credit risk exposures to the theoretical idea of holding a liquidity buffer, so as to better motivate the mechanism behind the paper's results. We begin with a general question: Are dealers even worried about counterparty credit risk when entering into Treasury repos with overnight maturity—the trades that are the focus of this paper? Both the short-maturity of these trades and the deep liquidity of the Treasury market could lead one to conclude that the counterparty credit risks inherent to these trades are inconsequential. Strongly refuting this idea, TMPG (2022) lays out in detail the counterparty credit risks inherent in Treasury repo and notes that these risks need to be well understood and managed with rigor.[13] In follow-up work, TMPG (2025) builds on these points and motivates an update to the set of best practices that Treasury market participants should follow, so as to mitigate counterparty credit risks in Treasury repo. Further, the Securities and Exchange Commission's (SEC) recent amendments to central clearing were designed in part to lower the build of up risks that can arise with noncentrally cleared Treasury repo.[14]

With the understanding that counterparty credit risks are quantitatively important, how are they managed in the interdealer repo segment? Interdealer Treasury repo trades are centrally cleared, with the result that the dealers' counterparty credit risk shifts from one another to the central counterparty (CCP), which is presumable quite safe. As a result, it is not clear how much capital dealers set aside on their balance sheet to mitigate risks arising from interdealer trades. The CCP, however, collects margin from dealers to mitigate its risks; it is this margin call that most clearly aligns with the theoretical concept of a liquidity buffer discussed above.[15]

[13] The Treasury Market Practices Group (TMPG) is a group of market professionals committed to supporting the integrity and efficiency of the Treasury, agency debt, and agency mortgage-backed securities (MBS) markets. This group is sponsored by the Federal Reserve Bank of New York.

[14] The SEC adopted rule changes in December 2023 that will result in all eligible Treasury repo transactions being centrally cleared beginning in June 2026 (that is, a central clearing mandate). See the SEC's final rule at: https://www.sec.gov/files/rules/final/2023/34-99149.pdf.

[15] Failure to deliver securities can occur for repos, even those that are centrally cleared, and so could be a reason for a dealer to hold a liquidity buffer. On normal business days, however, these fail-to-delivers are quite small. The CCP reports daily total statistics on fails-to-deliver at https://www.dtcc.com/charts/daily-total-us-treasury-trade-fails; the Office of Financial Research reports similar statistics based on data from primary dealers at https://www.financialresearch.gov/short-term-funding-monitor/datasets/nypd-single/?mnemonic=NYPD-PD_AFtD_T-A. Fleming and Keane (2021) analyze settlement fails

Based on conversations with market participants, the rate of return on the margin posted to the CCP is both low relative to market rates and slow-moving in response to changes to pricing in the market place. As a result, the margin a dealer is obligated to deliver is costly from an opportunity cost perspective. That said, the CCP determines how much margin the dealer needs to deliver based on a dealer's portfolio of trades with the CCP, a feature that could dampen the connection between the spread that dealers charge in the interdealer market and the cost of margins that is imposed by the CCP.

In the client-facing repo segment, the dealers retain counterparty credit risk to their clients.[16] In repos, this risk can be mitigated through the use of haircuts, where the haircut is the difference in value between the cash principal amount and the Treasury securities, and it is a measure of over-collateralization. In practice, when lending cash to clients against Treasuries, dealers often charge a haircut and so are over-collateralized. When borrowing cash from clients against Treasuries, dealers often pay a haircut and so are under-collateralized. Infante (2019) lays out this practice and posits that dealers might be able to negotiate haircuts such that the dealer comes out with extra liquidity, in that it charges a higher haircut than what it pays, for a given dollar of funding intermediated. If this is true in practice, then we might not find a liquidity risk premium in repo pricing.[17]

For overnight Treasury repo and over our sample period, however, it seems unlikely that dealers are negotiating haircuts so as to end up with extra liquidity when intermediating funding among clients. When borrowing cash from clients in triparty repo, dealers pay haircuts. The median haircut is 2%, which means that dealers receive \$98 in cash for every \$100 of Treasuries delivered.[18] When lending cash against Treasuries to levered clients, the available evidence (Baklanova et al. (2019); Hempel et al. (2023)) suggest that dealers are typically not charging haircuts, and so \$100 in cash is delivered against \$100 of Treasuries.[19] These data

in the cash Treasury market using confidential trade-level data; they find that central clearing substantially lowers this type of fails.

[16] As detailed above, this is true even for the dealer-to-client trades that are centrally cleared through the Sponsored Services program.

[17] In the interdealer segment, haircuts for repo trades are set to zero because is the CCP is managing these risks through margin calls and other risk management tools.

[18] Statistics on the distribution of haircuts in triparty repo are published at `https://www.newyorkfed.org/research/tri-party-repo`.

[19] As noted in Hempel et al. (2023) and TMPG (2025), the lack of haircuts (or zero haircuts) most likely means that dealers are using other tools to manage these counterparty credit risks.

on haircuts of overnight Treasury repo, then, imply that dealers are not ending up with extra liquidity when negotiating haircuts, and so they likely need to put aside capital to manage their exposures to clients when intermediating funds.

This claim is further supported when considering the client-facing trades that dealers centrally clear. The CCP makes a margin call based on the set of trades between the dealer and each client, and the current market practice is for the dealer to fund this obligation.[20] Having dealers fund the CCP's margin calls (for both the cash-lending and cash-borrowing trades), along with the dealer putting aside capital because of its exposure to the counterparty credit risk, are the main market behaviors and practices that align with the theoretical concept of dealers holding a liquidity buffer when intermediating funds between clients in repo.

2.2 Empirical approach

The main analysis considers three spreads, all of which capture differences between the rates dealers earn lending cash and the rates dealers pay to source cash. All rates reflect overnight Treasury repo transactions.

The first two spreads capture what dealers charge clients. The first spread uses dealer-to-client trades that are centrally cleared. Letting j index each CUSIP and t denote the date, let $r_{j,t}^{\text{DtCLend}}$ be the value-weighted mean rate in the DtC Lend segment, where dealers lend cash to levered clients. Let $r_{j,t}^{\text{DtCBorr}}$ be the value-weighted mean rate in the DtC Borr segment, where dealers borrow cash. Then our first spread is the difference between these two rates.

The second spread swaps out $r^{\text{DtCBorr}_{j,t}}$ for the value-weighted daily average for Treasury repo in the triparty repo segment, denoted r_t^{TPR}. Because triparty Treasury repo are general collateral trades, this rate is not indexed by j. An advantage of this rate is that it is a broader-based price of secured funding in short-term funding markets relative to $r_{j,t}^{\text{DtCBorr}}$. A disadvantage is that this second spread, unlike the first, does not account for any CUSIP-specific pricing differences that may occur.

The third spread focuses on interdealer trades. We use the trades from the interdealer brokered segment, where dealers execute trades anonymously using electronic platforms which,

[20]Copeland and Kahn (2024) provides a description of how margin calls are computed for the Sponsored Services. The market practice referred to here is described in the discussion of "indirect" central clearing in TMPG (2025). Central clearing practices are evolving.

among other features, relay timely information on pricing. This is the dominant segment; given its structure, it is likely to operate close to a perfectly competitive market. Because we do not know which counterparty to the trade initiated the transaction, we cannot directly compute spreads. Instead, we compute the value-weighted standard deviation of rates for a given CUSIP and date, denoted $\sigma_{j,t}^{\text{ID Broker}}$, and consider this statistic as a measure of the interdealer spread.

Summarizing, the three spreads considered are as follows:

$$\begin{aligned} S_{j,t}^{1} &= r_{j,t}^{\text{DtCLend}} - r_{j,t}^{\text{DtCBorr}}, && \text{(client-to-client)} \\ S_{j,t}^{2} &= r_{j,t}^{\text{DtCLend}} - r_{t}^{\text{TPR}} \text{ and,} && \text{(client-to-TPR)} \\ S_{j,t}^{3} &= \sigma_{j,t}^{\text{ID Broker}}. && \text{(interdealer)} \end{aligned} \tag{1}$$

The summary statistics of each spread are reported in Table 1. The first and second spreads have similar statistics, with means of 7.7 and 7.5 basis points. Furthermore, both are volatile, as captured by their standard deviations, which are 7.3 and 5.5 basis points, respectively. Given its interdealer focus, the third spread is understandably smaller at 1.8 basis points and relatively more volatile with a standard deviation of 2.3 basis points.

To provide a sense of the evolution of these spreads, we plot box-and-whisker boxes of $\{S^1, S^3\}$ for every quarter over the sample period in Figure 4. As illustrated in the figure, S^1 exhibits a steady rise from the second quarter of 2022 to the second quarter of 2023 and then fluctuates around 10 basis points over the remainder of the sample period. S^3 also grows over the sample period, with noticeable upticks in the second quarter of 2022 and the third quarter of 2024.

The focus of the paper is measuring by how much these spreads respond to time-varying changes in the opportunity cost of holding a liquidity buffer. In the literature, this opportunity cost is often captured using short-term funding rates where the time-series variation in these rates is understood to be driven by monetary policy. Given this paper's focus on short-term funding rates, we directly consider the two main tools the Federal Reserve currently uses to implement monetary policy and so manipulate the opportunity cost of money. These two tools are changes to (1) administrative rates and (2) the Federal Reserve's balance sheet, or quantitative easing and tightening.

To that end, we use two variables to capture the opportunity cost of money. The first is IORB, an administrative rate set by the Federal Reserve. We denote IORB as $\bar{r}_t$ and consider it as a risk-free rate of return benchmark for dealers; we note that increases in $\bar{r}_t$ drive up the opportunity cost of holding liquid buffers.[21]

The second variable captures the portion of Federal Reserve liabilities that reflect the total value of central bank reserves available to money market participants. To that end, we set this variable equal to the sum of bank balances held at Federal Reserve Banks and the total amount invested at the Federal Reserve's overnight reverse repo facility. We include the reverse repo facility usage because that amount of reserves is available to be invested in money markets, but it was placed at the Federal Reserve in response to market conditions. Of the liabilities not included, the most notable is the balance held in the Treasury general account (TGA). It is excluded because the Treasury's decision on how much to hold in its account is not driven by repo rates.[22] We call this second variable "Fed liabilities" and denote it L_t, where decreases in L_t drive up the opportunity cost of holding a liquid buffer.

Over the sample period, $\bar{r}_t$ varies substantially, with the 10th and 90th percentiles of its distribution equal to 15 and 540 basis points, respectively. This variation mainly reflects the large tightening of rates from 2022 to mid-2023. L_t varies between \$3.7 and \$5.5 trillion, where there is a steady decline in L_t starting in 2023 as the Federal Reserve shrunk its balance sheet when implementing a policy of quantitative tightening. Figure 1a plots each time-series.

We use regression analysis to capture by how much changes in the opportunity cost of money affect spreads. Formally, the main specification is as follows:

$$Y_{j,t} = \alpha + \beta_0 \bar{r}_t + \beta_1 L_t + \beta_2 \bar{r}_t \times L_t + \Omega' X_t + \eta_j + \varepsilon_{j,t}, \tag{2}$$

where $Y_{j,t}$ is one of the three spreads defined above, X is a matrix of time-varying controls, η_j is a CUSIP fixed effect, and ε is the error term. To account for the possibility that the liquidity

[21] The Federal Reserve also sets an administrative rate for its overnight reverse repo facility. That rate and IORB are almost always changed in tandem, and so either rate can be used for this analysis without any appreciable difference in the econometric results.

[22] The other excluded liabilities are Federal Reserve notes, FIMA reverse repo pool, and Other liabilities. These three components of Federal Reserve liabilities have very smooth profiles over the sample period and so are unlikely to affect the econometric results presented here. A visualization of the time-series of all components of Federal Reserve liabilities is provided in Chart 17 of SOMA (2024).

risk premium may have a nonlinear relationship with $\bar{r}_t$ and L_t, we include an interaction term in the specification. Given the large difference in scales between $\bar{r}_t$ and L_t, we standardize both variables and use these transformed variables in our estimation.

Our set of controls include variables that are known to affect repo rates but are exogenous to repo rates. The control variables are Treasury bill issuance, Treasury coupon issuance, total Treasury bills outstanding, change in the TGA, total Treasury redemptions, a forward-looking measure of volatility of Treasury yields, and indicator variables for end-of-month and end-of-quarter dates. Summary statistics of these variables are provided in Table 1

Past work has shown that Treasury bill and coupon issuance affect repo rates. Purchases of coupons are typically funded in repo, and so a large coupon issuance increases the demand for funding, pushing up repo rates. Purchases of bills are also funded in repo but to a much less extent. Rather, bill issuance affects repo rates because bills are a substitute product for Treasury repo as a cash investment tool. As a result, large bill issuance tends to decrease the amount of cash available in money markets, pushing up repo rates. Treasury issuance is determined with long-run goals in mind, including a main objective of being regular and predicable, making the two issuance measures plausibly exogenous to repo rates.[23]

The fact that money funds view Treasury repo and Treasury bills as substitutes also drives the inclusion of the stock of Treasury bills outstanding. The total supply of cash available for investment in repo could also be influenced by total redemptions, hence its inclusion as a control. The total balance the Treasury decides to hold in the TGA also affects the total supply of cash available in the money markets. As recently detailed in Vissing-Jorgensen (2025), the Treasury uses bill issuance to manage its balance in the TGA, accordingly, given the existing Treasury bill-related controls, we use the change in the TGA as a control.

For the expected volatility in Treasury yields, we use the volatility implied by swaptions with one-month expiration on two-year interest-rate swaps. An increase in volatility is associated with higher Treasury illiquidity, which could result in increases in the amount of capital set aside, for a given repo.[24] Through this mechanism, increases in expected volatility should increase the liquidity risk premium faced by dealers and so be reflected in the spreads that they

[23]The Treasury department publishes its debt management process goals on its website, `https://home.treasury.gov`. For a historical analysis of the Treasury department's shift to regular and predictable issuance, see Garbade (2007).

[24]Duffie et al. (2023) establishes the connection between Treasury illiquidity and Treasury yield volatility.

charge.

Finally, the end-of-month and end-of-quarter dummies are three-day windows. They are equal to 1 on the statement date, as well as on the day before and after, and so capture market dynamics that occur around the actual statement date.

2.3 Results

We estimate the regression specified in equation 2 for each spread and collect the results in Table 2. The focus is on how changes in the opportunity cost of holding capital, changes in $\{\bar{r}_t, L_t\}$, affect spreads. Because of the interaction term, this effect is nonlinear. As such, we compute the estimated effect on a change in $\bar{r}_t$ on spreads for different levels of L_t: The mean level of L_t, and the mean level of L_t plus or minus one standard deviation of L_t. We then compute the estimated effect of a change in L_t on spreads for three similarly calculated levels of $\bar{r}_t$. These estimated effects are reported in Table 3.

Starting with changes in rates, the results imply that the effect of a one standard deviation increase in $\bar{r}_t$ (226 basis points) has fairly uniform effects on the spreads charged by dealers to their clients (S^1 or S^2), ranging from 2.1 to 3.5 basis points. This effect is economically meaningful—indeed they are large—as the average of the spread charged by dealers to their clients is roughly equal to 7.5 basis points. Significant effects are also found for interdealer spreads (S^3). For the mean and low level of L_t, a one standard deviation change in $\bar{r}_t$ drives up the interdealer spread by 0.44 and 0.18 basis points, respectively, where the average interdealer spread is 1.77 basis points. No statistically significant effect was observed for a high level of L_t (\$5.5 trillion).

The result for interdealer spreads that changes in $\bar{r}_t$ are smaller for larger levels of L_t is intuitive, because changes in $\bar{r}_t$ could be less impactful on a dealer's opportunity cost of money when reserves are abundant. That said, for client-to-client spreads, the opposite trend is found; the estimated effects of a change in $\bar{r}_t$ are slightly larger for higher levels of L_t.

We also find significant effects for changes in L_t. For spreads that dealers charge clients (S^1 and S^2), the results imply that a one standard deviation increase in L_t (\$750 billion) ranges from -1.6 to -2.5 basis points across all levels of $\bar{r}_t$. Interdealer spreads are similarly impacted, with estimates of spreads falling by -0.52 basis points when $\bar{r}_t$ is low to -1.03 basis points when $\bar{r}_t$ is high.

These main results imply that the Federal Reserve significantly impacts the spreads charged by dealers intermediate funds through the liquidity risk premium channel. Furthermore, the Federal Reserve can influence the liquidity risk premium through two methods: changes to IORB and changes in the total amount of available reserves. To consider the relative effectiveness of each channel, we compute that at the end of our sample, best approximated as a (low L_t, high $\bar{r}_t$) state, a 100 basis point rise in $\bar{r}_t$ increases the client-to-client spread charged by dealers, S^1, by 0.93 basis points (a 10% increase to this spread, which averaged 9.33 basis points in 2024). To obtain a similar effect using liabilities, the Federal Reserve would need to decrease L_t by $429 billion.

We now briefly consider the estimated coefficients on the controls. The coefficients estimates for bill and coupon issuance are not statistically significant, suggesting that both borrowing and lending rates adjust in the same way on Treasury settlement dates. The coefficient on Treasury volatility is positive for all three spreads, which is in line with expectations. The estimated coefficient on Treasury bills outstanding is negative and significant across two of the three spreads. This result suggests that an increase in this stock squeezes the spreads that dealers charge. Both the amount of Treasury redemptions and the change in TGA balances do not have significant effects on spreads.

Turning to the dummy variables on statement dates, the estimates reveal there are month-end effects for all three spreads. For client-to-client spreads, the average month-end effect is a widening of 0.59 to 0.76 basis points, whereas for interdealer spreads, the effect is 0.14 basis points. The quarter-end effects are larger, with client-to-client spreads jumping up an additional 2.2 to 2.6 basis points and interdealer spreads widening an additional 1.1 basis points. These estimates fit into an existing literature that has documented increases in repo rates on quarter-end due to balance sheet constraints binding for dealers on these statement dates (see, for example, Correa et al. (2025), Aldasoro et al. (2022), and Kloks et al. (2024)).

3 Empirical analysis of rates

The main analysis above demonstrates that dealers widen the spreads they charge to intermediate funds when the opportunity cost of holding money increases. Furthermore, this liquidity risk premium is an economically meaningful cost to dealers. Given the focus on the spread charged by dealers, however, it is not clear how dealers are adjusting each of the rates behind the spread. In this section, we analyze which rates are being changed in response to changes in the opportunity cost of holding money.

We accomplish this by considering the level of Treasury repo rates for the cases where dealers lend cash to clients ($r_{j,t}^{\text{DtC Lend}}$) and where they borrow cash from clients (r_t^{TPR}). To account for the changes in short-term rates, each of these rates is considered as a spread to IORB. We then re-estimate equation 2 with the dependent variable being one of these two rates and the independent variables being the same as before. The results are collected in Table 4; as before, we compute the effect of a changes in $\bar{r}_t$ and L_t and report them in Table 5.

A striking pattern across the two regressions is that estimated coefficients for r_t^{TPR} are materially smaller in absolute value. Indeed, the estimated coefficients associated with changes in $\bar{r}_t$ and L_t imply that changes to the opportunity costs of holding money have little to no economic effect on rates in triparty repo; there is little evidence that the liquidity risk premium is material in this segment (see the second row of Table 5). In contrast, the rates dealers charge to lend cash to their (hedge fund) clients react substantially to changes in the opportunity cost of money (see the first row of Table 5). These results suggest that when dealers narrow or widen the spreads they charge to intermediate funds in response to changes in the liquidity risk premium, the adjustment comes almost entirely to rates charged to the clients borrowing cash. This asymmetric finding is consistent with a theory that dealer-to-client trading relationships differ across these two segments, a point discussed in more detail in Section 5.

The pattern of smaller estimated effects in triparty repo extends to month-end and quarter-end dates. In fact, it is remarkable that tri-party repo rates are estimated to move up by only 0.012 basis points on quarter-ends; In the dealer-to-client segment the combined quarter-end effect is more than 4 basis points.

4 Robustness results

In this section, we present two sets of robustness results. The first set presents evidence of liquidity risk premium affecting repo rates using cross-sectional variation. The second set presents results showing that the benchmark results are robust to time-aggregation, or aggregating the data from a daily frequency to a 30-day block frequency.

4.1 Estimating the liquidity risk premium in the cross-section

We now consider whether the liquidity risk premium can be measured using cross-sectional variation, an approach that complements the benchmark results that rely on time-series variation. We rely on institutional knowledge of repo markets to claim that the changes in the liquidity risk premium should have a larger effect on pricing for trades involving clients versus those involving other dealers. This assertion mainly relies on the fact that interdealer trades are centrally cleared using the standard service that results in counterparty risk being fully transferred to the central counterparty, which has a safe risk profile. In contrast, when trading with clients, the dealer retains counterparty credit risk to the client.[25] This risk is particularly salient for funding trades where the dealer is lending cash because these levered clients (often hedge funds) often present relatively risky counterparty credit risk profiles.

The empirical approach is to compare relative changes in pricing across segments given changes in monetary policy. We consider two specifications. The first is a comparison of client-to-client spreads, S^1, versus interdealer spreads, S^3. Letting $1_{x=y}$ be an indicator variable equal to 1 when the conditional statement is true, and $m \in \{1,3\}$, the regression estimated is as follows:

$$S^m_{j,t} = \alpha_0 + \left(\alpha_1 + \beta_0 \bar{r}_t + \beta_1 L_t + \beta_2 \bar{r}_t \times L_t\right) \cdot 1_{S^m_{j,t} = S^1_{j,t}} + \eta_j + \zeta_t + \varepsilon^m_{j,t}. \tag{3}$$

Note that the day fixed effects, ζ_t, soak up the time-series variation, such as the changes in the Treasury control variables used in the benchmark specification (such as Bills issuance and UST expected volatility). The variables of interest, $\{\beta_0, \beta_1, \beta_2\}$, measure whether client-to-client spreads have a differential response to changes in the opportunity cost of holding money compared to interdealer spreads.

The second specification mirrors the first but considers the level of rates. Letting $r^1_{j,t} = r^{\text{DtC Lend}}_{j,t}$ and $r^2_{j,t} = r^{\text{ID Broker}}_{j,t}$, where this latter rate is the value-weighted average rate in the ID

[25] As discussed in Section 1.1, dealers retain counterparty credit risk to the client for trades that are centrally cleared through the Sponsored Services program, which is the source of the data for the DtC Borr and DtC Lend segments.

Brokered segment for a given CUSIP j and date t. The regression estimated is as follows:

$$r^m_{j,t} = \alpha_0 + \left(\alpha_1 + \beta_0 \bar{r}_t + \beta_1 L_t + \beta_2 \bar{r}_t \times L_t\right) \cdot 1_{r^m_{j,t} = r^{\text{DtC Lend}}_{j,t}} + \eta_j + \zeta_t + \varepsilon^m_{j,t}, \tag{4}$$

where $m \in \{1,2\}$.

Given the liquidity risk premium is expected to be larger for client-facing trades, we expect that changes to $\bar{r}_t$ or L_t to have larger relative effects on the pricing of those trades. Indeed, this is what the results imply.[26] As reported in Table 6, a one standard deviation increase in $\bar{r}_t$ increases client-to-client spreads by 1.7 to 2.8 basis points relative to interdealer spreads. Further, a one standard deviation increase in L_t decreases client-to-client spreads by 0.3 to 1.4 basis points relative to interdealer spreads.

Similarly, increases to $\bar{r}$ increase $r^{DtCLend}$ more than $r^{IDBroker}$ and changes to L_t have larger effects on $r^{DtCLend}$ relative to $r^{IDBroker}$. These results provide additional evidence on the economic importance of the liquidity risk premium in pricing of funding and the Federal Reserve's ability to change this risk premium through monetary policy.

4.2 The robustness of the results to time-aggregation

In this section, we consider if the benchmark results hold for a higher level of temporal aggregation of the data. This exercise is motivated by the fact that changes to the liquidity risk premium could be driven by lower frequency changes in the opportunity cost of money. If so, it is useful to see how the results compare when using lower frequency data. This approach also has the advantage of smoothing through daily idiosyncratic shocks. We aggregate the data temporally by constructing 30 business-day blocks over the sample period. If there is a change in IORB within a 30-day block, then that block is split at the point when IORB is changed. Hence, within any block of time there is a constant $\bar{r}_t$. Within a block, each spread is averaged, as are L_t and the control variables.

We re-estimate the main specification laid out in equation 2 using the temporally-aggregated data and find the main results to continue to hold. The estimated coefficients are reported in Appendix Table 12, and the estimated effects on each spread are reported in Table 7. For the two client-to-client spreads, the estimated effects of a change in $\bar{r}_t$ or a change in L_t are close

[26]The estimated coefficients for both regressions are reported in Appendix Table 11.

to the benchmark results.

For the third, interdealer spread, the estimated effects are generally larger in magnitude. The statistical significance of the effects for changes in r_t are weaker; the estimated changes to the liquidity risk premium are not significantly different from zero for a 90% confidence interval. Effects for a change in liabilities are larger in magnitude across all levels of IORB when compared to the baseline results and retain their statistical significance.

The fact that the benchmark results continue to largely hold in this robustness exercise provides confidence both in the economic importance of the results and the interpretation that the results are capturing changes in the liquidity risk premium.

5 Discussion

The interpretation of the estimated coefficients presented above is that the cost of intermediating funds depends upon the opportunity cost of money. This liquidity risk premium varies with both the administrative rate set by the Federal Reserve and the total amount of liabilities held by the Federal Reserve. Over the latest tightening cycle, the FOMC has changed both the IORB and the total amount of Fed liabilities. We compute the cumulative impact of both tools separately, as well as their total cumulative impact, from April 2021 to December 2024. These estimates are plotted in Figure 1 alongside the the time-series of IORB and Fed liabilities.

Over the sample period, IORB has increased from 15 to 540 basis points, with large steps up in 2022. At the end of the sample, in the last half of 2024, there are three decreases in IORB. Fed liabilities are hump-shaped; starting at about $4 trillion, they rise steeply in 2021 to almost $6 trillion. They then stay roughly flat through the beginning of 2023, before steadily falling through 2024, reaching $3.5 trillion by December 2024. The estimated cumulative effects naturally mirror their respective monetary policy tools; however, the magnitudes slightly differ because of the estimated nonlinear effects. For example, a $1 billion change in Fed liabilities has a larger estimated effect on the liquidity risk premium when IORB is low compared to when IORB is high.

In Table 8 we report snapshots of the estimated cumulative effects in December for each year in the sample period, alongside the monthly averages of IORB, Fed liabilities, and the observed client to client spread (S^1) in the data. These calculations reveal that from April to

Dec of 2022, the steep rise in Fed liabilities and small changes to IORB, resulted in a substantial decrease of 3.87 basis points to the liquidity risk premium. As reference, the observed client-to-client spreads in December 2021 were 2.42 basis points. From this point onward, both monetary tools increase the liquidity risk premium, so that by December 2024, the total cumulative effect is 5.17 basis points, a swing of 9.04 basis points from December 2021. In line with these estimated increases in cost, we observe that the client-to-client spread observed in the data rose 8.18 basis points from December 2021 to December 2024.

Changes to IORB have the largest effect on the risk premium between December 2021 and December 2022, which is not surprising given that this administrative rate was raised by almost 400 basis points over the year. Fed liabilities fall steadily from December 2022 to December 2024, pushing up the liquidity risk premium alongside the changes to IORB. Despite the fact that Fed liabilities falls to their lowest point in December 2024 ($3.4 trillion), the total cumulative impact of Fed liabilities is estimated to remain slight negative, at -0.2 basis points. This result reflects the nonlinear relationship between monetary policy and the liquidity risk premium. The increases in Fed liabilities at the beginning of the sample, when IORB was low, had larger effects on the risk premium relative to the decreases in Fed liabilities at the end of the sample, when IORB was high.

Defining the monetary tightening period observed in our sample period to occur from early 2022 through the first half of 2023, then the Federal Reserve used both of its monetary tools to increase the opportunity cost of money and so to push up the liquidity risk premium. A main insight from the results, however, is the possibility of a wider range of outcomes on how the Federal Reserve impacts the financial sector. For example, in a situation where the Federal Reserve wants to bolster the economy and is concerned about a high level of financial sector leverage, a way forward would be to lower interest rates and decrease Fed liabilities. Lowering rates would bolster the economy through the usual channels, and a large enough decrease in Fed liabilities would result in a widening of the spreads that dealers charge clients to intermediate funds, dampening overall financial sector leverage. To quantify how much Fed liabilities would need to decline to offset lower rates, the results imply that, using the values of rates and Fed liabilities at the end of the sample period, a 100 basis point decrease in IORB and a $429 billion decrease in Fed liabilities have offsetting effects on the liquidity risk premium.

The result in this paper—that dealers face larger costs to intermediate funds when the

Federal Reserve increases the opportunity cost of money—fits into the theoretical results of Drechsler et al. (2018), a dynamic asset pricing model that establishes a relationship between nominal rates and the level of risk premia. In their model, risk-tolerant agents take deposits from risk-adverse households and invest in risk assets. Because of the risks associated with this strategy, the risk-tolerant agents hold a liquidity buffer, which has an associated opportunity cost that varies with the nominal rate. As a result, their model predicts that increases in the nominal rate drive up the cost of holding a liquidity buffer and so dampen the amount of risk assets a risk-tolerant agent will purchase for a given dollar of deposits. This theoretical prediction of a decline in leverage taken is consistent with the empirical results in this paper showing that an increase nominal rates drives up the spreads that dealers charge to intermediate funding. Naturally, the general equilibrium effects derived in Drechsler et al. (2018) depend on movements in quantities, and in particular, the quantity of safe assets in the economy. A next step would be estimating the price elasticities associated with repo funding and so determining by how much the quantity of funding demanded reacts to changes in the spreads charged by dealers.

The results presented in Section 3 demonstrate that dealers adjust the spread they charge asymmetrically. In those relationships where dealers borrow cash, notably in triparty repo, rates tend to move one-for-one with changes in IORB or Fed liabilities; the estimated results imply that changes to either monetary policy tool have little to no effect on the spread of TPR rates to IORB. Conversely, in those relationships where dealers are lending cash, we find strong evidence that changes to IORB or Fed liabilities have positive and significant effect on the spread of repo rates to IORB. These results suggest that the nature of the relationship between dealers and each type of client are driven by different fundamental factors. Thus, although the observable characteristics of the transaction are the same across the two types of trades (e.g., we are only considering overnight funding Treasury repos), the different pricing dynamics in response to changes in IORB or Fed liabilities suggest the dealers are providing different services to each type of client. In future work, we aim to further analyze a dealer's relationship with each type of client. This understanding of the market microstructure is a crucial ingredient to determining the impact of a number of policy issues, such as the gains from expanded central clearing in Treasury repo markets or moving towards an all-to-all Treasury repo market.[27]

[27] See Group of Thirty Working Group on Treasury Market Liquidity (2021) for a detailed discussion of ex-

6 Conclusion

This paper studies how monetary policy affects the cost of short-term funding in the U.S. repo market. When dealers intermediate funding among clients, they take on counterparty credit risks. To mitigate these exposures, a dealer typically holds a buffer of liquid securities, the cost of which is a function of the opportunity cost of holding cash. We label this cost the liquidity risk premium and note this premium should vary with monetary policy. We then estimate by how much changes in monetary policy influence the liquidity risk premium and, consequently, the cost of providing short-term funding.

We conduct this empirical exercise using confidential, trade-level data from the OFR's centrally cleared repo collection. These data allow us to construct the spreads that dealers charge to intermediate funds among clients, as well as those charged to intermediate funds among dealers. We then use regression analysis to measure how much these spreads change when the Federal Reserve changes the opportunity cost of cash, either through changes in rates or through the total value of Federal Reserve liabilities. The results imply that the Federal Reserve can materially affect the cost of funding intermediation. Considering the intermediation of funding for clients, we estimate that a one standard deviation increase in rates drives up the liquidity risk premium by 2.1 to 3.5 basis points, a sizable amount given that average spread dealers charged is 7.5 basis points. Furthermore, a one standard deviation increase in central bank reserves drive down the liquidity risk premium by 1.6 to 2.5 basis points.

A main insight is that the Federal Reserve can affect the liquidity risk premium using two tools. Over the 2022–23 monetary policy tightening period, the Federal Reserve both raised rates and lowered the total value of its liabilities, actions that worked together to raise the liquidity risk premium and so widen dealers' spreads. This paper's results, however, highlight that the Federal Reserve can manage how financing conditions are affected even as it influences economic conditions. For example, in a situation where the Federal Reserve wants to bolster the economy and is concerned about a high level of financial sector leverage, a way forward would be to lower interest rates and decrease Federal Reserve liabilities. Lowering rates would bolster the economy, and a large enough decrease in liabilities would result in a widening of dealers' spreads, dampening overall financial sector leverage. To quantify how much the

panding central clearing in Treasury markets, and Chaboud et al. (2022) for an analysis of the gains to all-to-all trading in the U.S. Treasury secondary market.

Federal Reserve's liabilities would need to decline to offset lower rates, the results imply that, using the average values of rates and Federal Reserve liabilities in 2024, a 100 basis point decrease in rates and a $429 billion decrease in liabilities would have offsetting effects on the liquidity risk premium.

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Table 1: Summary statistics

	Mean	SD	P10	Median	P90
Client-to-client spread	7.65	7.26	2.00	7.80	12.00
Client-to-TPR spread	7.51	5.45	2.16	8.12	11.82
Interdealer spread	1.77	2.32	0.47	1.29	3.35
IORB	326.75	225.83	15.00	465.00	540.00
Fed liabilities	4.75	0.75	3.65	5.02	5.54
Bills issued	0.07	0.09	-0.00	0.00	0.22
Coupons issued	0.02	0.05	-0.00	0.00	0.04
UST volatility	112.29	46.95	26.59	119.54	166.86
UST Bills outstanding	4.67	0.96	3.65	4.22	6.03
Change in TGA balance	-0.00	0.04	-0.03	-0.00	0.03
UST redemptions	82.36	97.42	0.00	0.00	224.18

Note: This table reports summary statistics of the main variables used in the analysis. SD is standard deviation, P10 and P90 are the 10th and 90th percentiles. Client-to-client spread is S^1, Client-to-TPR is S^2, and Interdealer spread is S^3, as defined in equation 1. All three spreads are in basis points. IORB is interest on reserves balances and is reported in basis points. Fed liabilities is the sum of bank balances held at Federal Reserve Banks and usage at the Federal Reserve's reverse repo facility and is in trillions of dollars. Bills issued and Coupons issued are the total value of U.S. Treasury bills and coupon securities issuance, respectively. UST Bills outstanding is the total value of U.S. Treasury bills that are outstanding and UST redemptions is the total value of Treasuries that are redeemed. Issuance, UST Bills outstanding, and UST redemptions are in trillions of dollars. UST volatility is measured using swaptions with one-month expiration on two-year interest-rate swaps. Change in TGA balance is the change in the balance held in the Treasury general account (at the Federal Reserve Banks).
Source: OFR centrally cleared repo data collection, FRBNY, U.S. Treasury, and authors' calculations.

Table 2: Liquidity risk premium for overnight Treasury repo, by segment

	Client-to-client	Client-to-TPR	Interdealer
IORB	2.414***	3.034***	0.184**
	(0.225)	(0.204)	(0.088)
Fed liabilities	-1.942***	-2.044***	-0.776***
	(0.288)	(0.255)	(0.086)
IORB x Fed liabilities	0.319*	0.434***	-0.256***
	(0.165)	(0.148)	(0.059)
Bills issued	-1.782	-2.837	-1.097
	(4.310)	(3.918)	(1.910)
Coupons issued	2.397	1.869	1.041
	(3.177)	(3.023)	(1.514)
UST volatility	0.312***	0.284***	0.360***
	(0.098)	(0.087)	(0.032)
Bills outstanding	-0.507	-1.241***	-0.320***
	(0.318)	(0.277)	(0.111)
Change in TGA balance	3.778	3.753	0.445
	(2.547)	(2.298)	(0.850)
UST redemptions	0.233	0.319	0.077
	(0.373)	(0.342)	(0.175)
Month end	0.761***	0.589***	0.136**
	(0.204)	(0.169)	(0.061)
Quarter end	2.634***	2.244***	1.121***
	(0.548)	(0.502)	(0.247)
Constant	6.462***	6.591***	1.688***
	(0.279)	(0.250)	(0.111)
Observations	221006	264614	352665
R-squared	0.191	0.352	0.138

Note: This table reported the estimated coefficients from three regressions. The columns refer to the spreads, $\{S^1, S^2, S^3\}$ respectively, as defined in equation 1. IORB x Fed liabilities denotes an interaction between IORB and Fed liabilities. See Table 1 Notes for all other definitions. IORB, Fed liabilities, UST volatility, Bills outstanding, and UST redemptions have been standardized. Month and quarter-end indicators are equal to 1 on the statement date as well as on the business date before and after the statement date. CUSIP fixed effects are included in the specification but not reported. Standard errors are clustered by date.

Table 3: Estimated effects on the liquidity risk premium

	Given an IORB change and:			Given a Fed liabilities change and:		
	low liab	avg liab	high liab	low IORB	avg IORB	high IORB
Client-to-client	2.094***	2.414***	2.733***	-2.261***	-1.942***	-1.622***
	(0.374)	(0.225)	(0.125)	(0.241)	(0.288)	(0.404)
Client-to-TPR	2.600***	3.034***	3.468***	-2.478***	-2.044***	-1.610***
	(0.339)	(0.204)	(0.110)	(0.223)	(0.255)	(0.353)
Interdealer	0.440***	0.184**	-0.073	-0.520***	-0.776***	-1.032***
	(0.142)	(0.088)	(0.047)	(0.070)	(0.086)	(0.130)

Note: Using the estimated coefficients reported in Table 2, this table reports the estimated effects of a change in IORB or a change in Fed liabilities on the liquidity risk premium, associated with client-to-client, client-to-TPR, and interdealer spreads. Reflecting the nonlinearities of the empirical relationship, changes in IORB are computed given: the mean level of Fed liabilities in the sample period (avg liab), one standard deviation below the mean level (low liab), and one standard deviation above the mean level (high liab). Similarly, the changes in Fed liabilities are computed given: the mean level of IORB (avg IORB), one standard deviation below the mean (low IORB), and one standard deviation above the mean (high IORB).

Table 4: Rate sensitivity for overnight Treasury repo, by segment

	DtC Lending - IORB	TPR - IORB
IORB	2.277***	-0.008***
	(0.349)	(0.002)
Fed liabilities	-1.763***	0.005**
	(0.422)	(0.002)
IORB x Fed liabilities	0.562**	0.001
	(0.253)	(0.001)
Bills issued	-1.044	0.019
	(7.069)	(0.034)
Coupons issued	5.025	0.027
	(5.666)	(0.029)
UST volatility	-0.091	-0.004***
	(0.153)	(0.001)
Bills outstanding	1.270***	0.027***
	(0.468)	(0.002)
Change in TGA balance	4.133	0.002
	(4.007)	(0.020)
UST redemptions	0.237	-0.001
	(0.632)	(0.003)
Month end	0.920***	0.004***
	(0.268)	(0.001)
Quarter end	3.279***	0.008**
	(0.825)	(0.004)
Constant	-3.828***	-0.105***
	(0.457)	(0.002)
Obs	270599	907
R-squared	0.438	0.621

Note: This table reported the estimated coefficients from two regressions. DtC Lending-IORB are the rates charged by dealers lending cash to their clients as a spread to IORB, and TPR-IORB are triparty repo rates as a spread to IORB. See Table 2 Notes for all other definitions. CUSIP fixed effects are included in the specification but not reported. Standard errors are clustered by date.

Table 5: Estimated effects on rates given changes in IORB and Fed liabilities

	Given an IORB change and:			Given a Fed liabilities change and:		
	low liab	avg liab	high liab	low IORB	avg IORB	high IORB
DtC Lending - IORB	1.715***	2.277***	2.839***	-2.325***	-1.763***	-1.200**
	(0.579)	(0.349)	(0.190)	(0.359)	(0.422)	(0.597)
TPR - IORB	-0.009***	-0.008***	-0.007***	0.004***	0.005**	0.006*
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)

Note: Using the estimated coefficients reported in Table 4, this table reports the estimated effects of a change in IORB or a change in Fed liabilities on: the rates that dealers charge to fund clients as a spread to IORB (DtC Lending - IORB), and the rates that dealers pay to borrow funds as a spread to IORB (TPR - IORB). See Table 3 Notes for all other definitions.

Table 6: Robustness: Estimated effects on the liquidity risk premium in the cross-section

	Given an IORB change and:			Given a Fed liabilities change and:		
	low liab	avg liab	high liab	low IORB	avg IORB	high IORB
Spreads, relative to interdealer	1.720***	2.254***	2.787***	-1.388***	-0.854***	-0.321**
	(0.126)	(0.066)	(0.079)	(0.111)	(0.085)	(0.125)
Rates, relative to interdealer	0.162**	0.300***	0.438***	-0.399***	-0.261***	-0.123*
	(0.067)	(0.032)	(0.040)	(0.089)	(0.067)	(0.071)

Note: Using the estimated coefficients reported in Appendix Table 11, this table reports the estimated effects of a change in IORB or a change in Fed liabilities on the relative liquidity risk premium. The first row considers the estimated effect on liquidity risk premium for client-to-client spreads relative to interdealer spreads. The second row considers the estimated effect on the rates dealers charge to lend cash to clients relative to interdealer rates. See Table 3 Notes for all other definitions.

Table 7: Robustness: Estimated effects on the liquidity risk premium on time-aggregated data

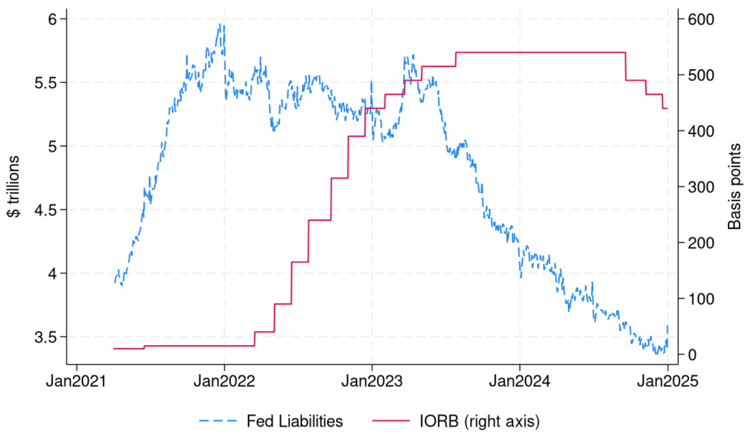
	Given an IORB change and:			Given a Fed liabilities change and:		
	low liab	avg liab	high liab	low IORB	avg IORB	high IORB
Client-to-client	2.497***	2.672***	2.847***	-2.407***	-2.232***	-2.057**
	(0.904)	(0.538)	(0.305)	(0.563)	(0.632)	(0.901)
Client-to-TPR	2.447**	3.057***	3.666***	-2.578***	-1.968***	-1.358
	(1.048)	(0.621)	(0.342)	(0.704)	(0.657)	(0.902)
Interdealer	0.728	0.346	-0.036	-1.479**	-1.861***	-2.243***
	(0.947)	(0.525)	(0.262)	(0.694)	(0.572)	(0.765)

Note: Using the estimated coefficients reported in Appendix Table 12, this table reports the estimated effects of a change in IORB or a change in Fed liabilities on the liquidity risk premium, associated with client-to-client, client-to-TPR, and interdealer spreads. See Table 3 Notes for all other definitions.

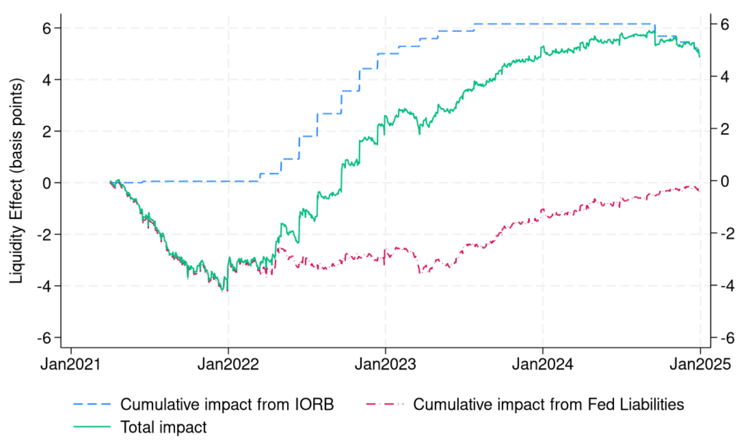
Table 8: Cumulative effect of monetary policy on the liquidity risk premium

	Total CE	IORB CE	Liab CE	Client-to-client spread	IORB	Fed liab
Dec 2021	-3.87	0.05	-3.92	2.42	15	5.8
Dec 2022	1.79	4.71	-2.92	7.62	412	5.3
Dec 2023	4.65	6.16	-1.51	10.66	540	4.3
Dec 2024	5.17	5.38	-0.20	10.6	458	3.4

Note: This table presents snapshots of the cumulative effect of monetary policy on the liquidity risk premium over the sample period. This cumulative effect is computed starting on April 1, 2021 through December 31, 2024. The cumulative effects reported above are the mean over December of each year in the sample period, excluding year-end dates. Total CE is the total cumulative effect of both changes in IORB and Fed liabilities, IORB CE are the cumulative effects from changes in IORB and Liab CE are the cumulative effects from changes in Fed liabilities. Client-to-client spread is the average over December of each year, excluding year-end dates. IORB and Fed liabilities are similarly calculated averages. The cumulative effects, spread and IORB are in basis points and Fed liabilities are in trillions of dollars.



(a) Monetary policy changes over the sample period



(b) Cumulative impact on the liquidity risk premium

Figure 1: Estimated effect of monetary policy on the liquidity risk premium
Panel a displays the evolution of IORB and size of Federal Reserve liabilities as measured by the amount of reserves that banks hold at Federal Reserve Banks plus amount of cash placed that the Federal Reserve overnight reverse repo facility. Panel b displays the cumulative effect of monetary policy on the liquidity risk premium as implied from the estimated results, where the cumulative effect is set to zero at the beginning of the sample. A decomposition is also provided, separately showing the effect of changes to IORB and Fed liabilities on the liquidity risk premium.
Source: FRBNY and authors' calculations.

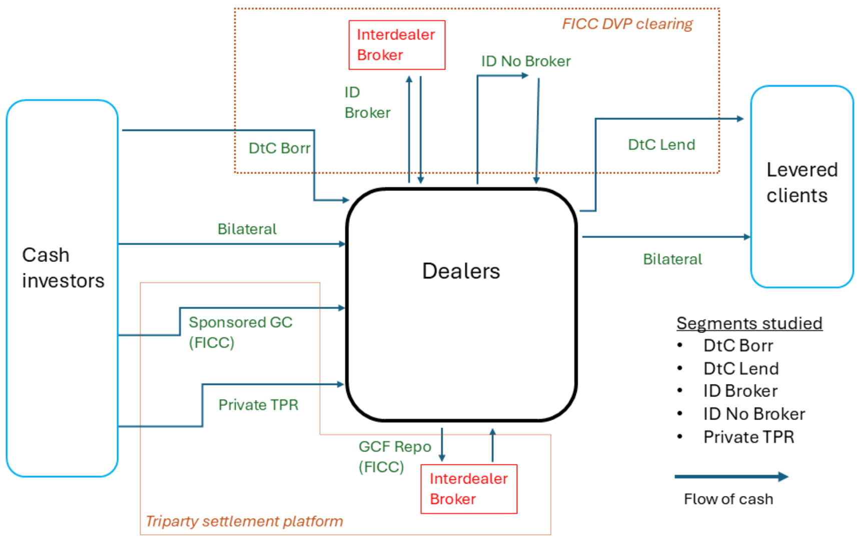
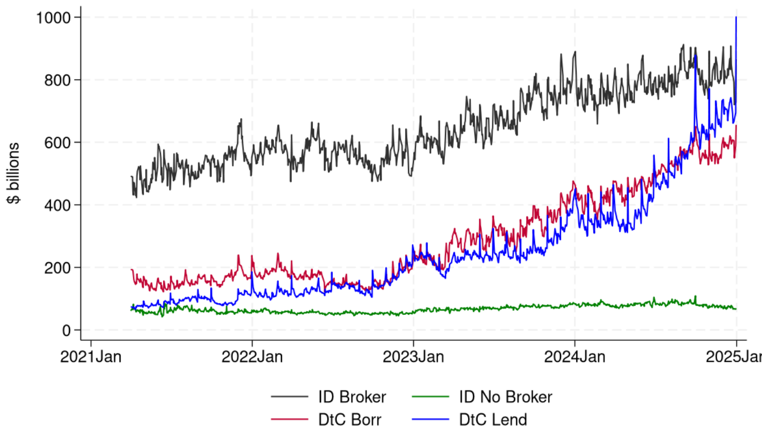
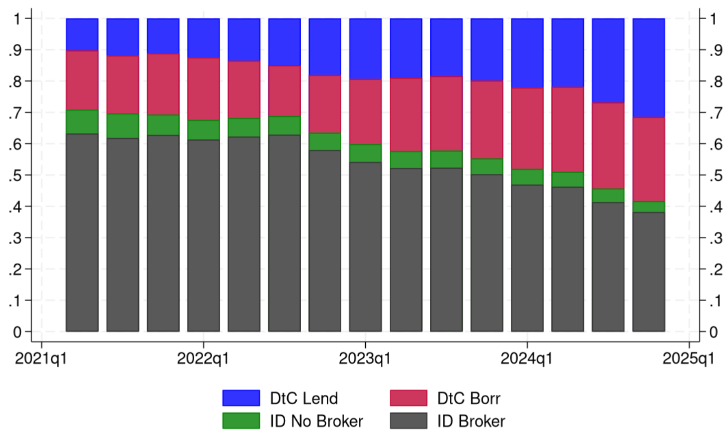


Figure 2: Schematic of the Treasury repo market

This figure is a schematic of the segments of the Treasury repo market. The Federal Reserve's Standing Repo Facility and Reverse Repo Facility are not shown, but transactions involving those facilities settle on the triparty settlement platform.



(a) Volumes, daily



(b) Shares, quarterly

Figure 3: Centrally cleared overnight Treasury funding repo, by segment

This figure displays aggregated volumes and shares of centrally cleared overnight Treasury funding repo over the sample period. Volumes are aggregated to the daily frequency (Panel a) and shares of total activity are computed at the quarterly frequency (Panel b). ID stands for interdealer and Broker indicates whether an interdealer broker was used to execute the trade. DtC Lend are dealer-to-client trades where the dealer is lending cash against Treasuries and DtC Borr are dealer-to-client trades where the dealer is borrowing cash against Treasuries. Funding trades are identified using the C-E filter described in Appendix A.
Source: OFR centrally cleared repo data collection and authors' calculations.

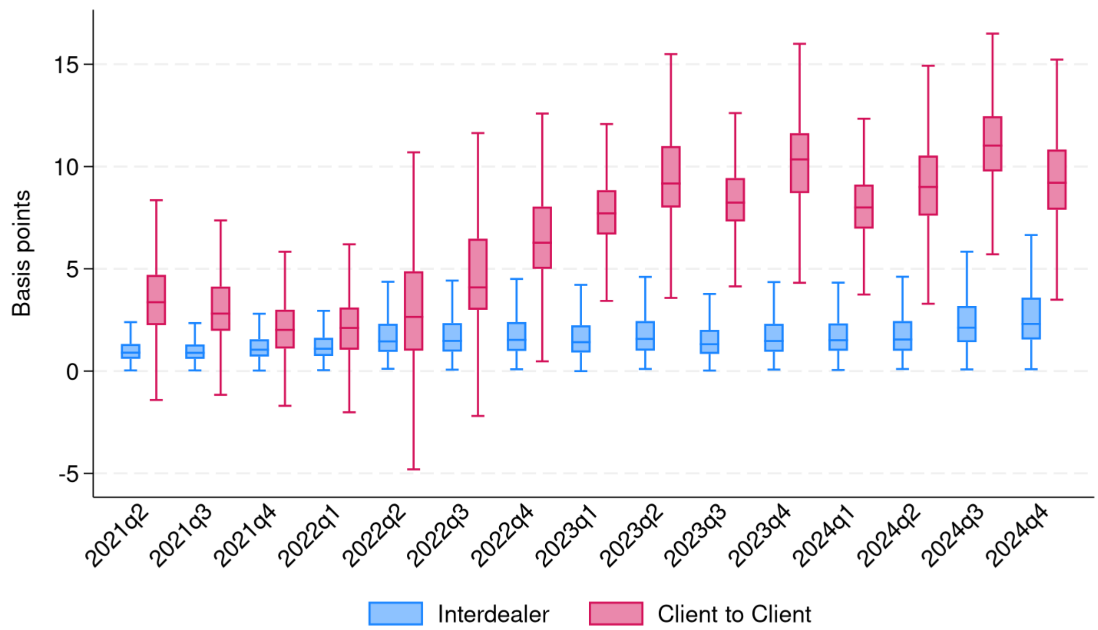


Figure 4: Distribution of spreads by quarter

This figure is a box-and-whiskers plot of interdealer and client-to-client spreads by quarter over the sample period. Each box displays the 25th, 50th, and 75th percentiles of the distribution of spreads in each quarter. The lower whisker is equal to the 25th percentile minus 1.5 times the interquartile range. The upper whisker is similarly defined.

Source: OFR centrally cleared repo data collection and authors' calculations.

Appendices

A Filtering the data for specials

In this section we describe the filter used to classify which CUSIPs are on special, hereafter the *C-E filter*. We then provide an example of how this filter works as well as general statistics on the outcomes over the sample period. Lastly, we consider the robustness of the classification outcomes of the filter.

A.1 Filter description

Repurchase agreements are generally used by market participants to engage in two types of trades: sourcing funds and sourcing collateral. When used to source funds, the repo rate of a trade reflects the value of cash, or short-term funds, in the market. When used to source collateral, the repo rate reflects the value of the securities acquired. Hence, the drivers of rates across these two types of trades are different and should, in most cases, result in different negotiated rates.

The rates for a funding trade reflect the supply and demand of cash in the market, and so typically track the Federal Reserve's administrative rates of the interest of reserve balances or the reverse repo facility rate, as these are often the outside option for the cash-providing counterparty of the repo. As detailed in Duffie (1996) and Jordan and Jordan (1997), the negotiated rates for collateral trades are less than the going rate for funding. The intuition is that the securities-providing counterparty is compensated for delivering securities in demand with a cash-loan at a below-market interest rate. This counterparty can then lend the cash out in the marketplace and earn a higher return, for example in a repo. For these collateral-driven repos, how far below the negotiated rate is from the prevailing funding rate reflects the demand and supply of the specific securities in question. In practice, negative rates of large absolute value are often observed in the data.

We use this intuition to develop a filter that classifies repos into those sourcing collateral, labeled specials, and those sourcing funds. Given the trading behavior described above, relative to specials, funding repo rates will be both higher than specials and also more closely grouped together, where this second feature arises because these trades are driven by the same factors. These differences are visually highlighted when comparing average rates by CUSIP, where CUSIPs are ranked from low to high based on rate. The line connecting these average rates has an elbow shape. Moving from low to high rates, at first there are both small and large differences between adjoining CUSIPs, as these low rates reflect collateral trades where the drivers are security-specific. After a point, however, the rates reflect the value of cash, and so the differences between any adjoining CUSIPs are consistently relatively small. This dynamic creates the elbow shape of the line connecting the rates.[28] The C-E filter leverages this idea by looking for a threshold rate where all CUSIPs with higher average rates are labeled funding and all those CUSIPs with lower average rates are labeled specials.

We implement this filter using the paper's main data set—data from the OFR's centrally cleared repo collection where the transactions are cleared by the FICC's DVP service (see the description provided in Section 1.1). We use only the interdealer brokered trades so as to reduce concerns about differences in information known about the value of securities or cash in the market place, as both counterparties to the trade are dealers specialized in this type of trading. Furthermore, in this segment trades are executed anonymously using broker screens, and so relationships between dealers are not relevant and both counterparties to the trade can see the latest pricing on the broker's electronic platform. The interdealer broker segment contains a substantial amount of activity, allowing us to classify almost all Treasury securities traded and cleared by the FICC DVP service on any particular day.[29]

Using the interdealer brokered trades, for every date, we calculate the value-weighted average rate, r_j, for each CUSIP j, where we denote the set of all CUSIPs traded as J and the total number of CUSIPs as K. (Because each day is considered in isolation, we do not subscript variables by a date index.) CUSIPs are then ordered by the average rate, such that $J = \{j_1, j_2, \cdot, j_K | r_{j_1} \leq r_{j_2} \leq \ldots \leq r_{j_K}\}$. Given there is still some volatility in the data, we further aggregate by partitioning the CUSIPs into 100 ordered buckets, $\{I_1, I_2, \ldots, I_{100}\}$ where each bucket is a percentile of the CUSIPs rate distribution. As such, if there are 500 CUSIPs

[28] This shape is also characterized as an inverted hockey stick.

[29] In our sample, there are 10,605 instances where on a particular day a CUSIP is not cleared in the ID Broker segment but is cleared in the DtC Lend, DtC Borr, or ID No Broker segments. This is 2.5 percent of all (CUSIP x date) instances in the data. In terms of dollars, these instances are less than 0.01% of total volumes in DtC Lend and DtC Borr, and less than 0.3% of total volume in ID No Broker. These CUSIP x date instances will be classified as funding by the C-E filter.

traded on a particular day, each bucket would be composed on 5 CUSIPs, where I_1 would include $\{j_1, j_2, j_3, j_4, j_5\}$ and so forth. We label the weighted average rate of I_n as $\hat{r}_n$, and note that $\hat{r}_1 \leq \hat{r}_2 \leq \ldots \leq \hat{r}_{100}$. Finally, we calculate the difference in rates between buckets, as $\Delta\hat{r}_n = \hat{r}_n - \hat{r}_{n-1}$ where $n = 2, 3, \ldots, 100$.

Finally, we use $\Delta\hat{r}_n$ to find a threshold ordered bucket around which CUSIPs are classified as specials or funding. The threshold is defined based on the first occurrence of two consecutive $\Delta\hat{r}_n$s that are small, or less than 1 basis point. Formally, the rule is to find i^* such that

$$i^* = \{\min i \in [2, 100] \text{ such that } \Delta\hat{r}_i < 1 \ \& \ \Delta\hat{r}_{i+1} < 1\}. \tag{5}$$

We then define all repos involving CUSIPs in $\{I_1, I_2, \ldots, I_{i^*-1}\}$ as specials. All other CUSIPs are labeled funding repos.

A.2 Results from applying the filter

We begin by demonstrating how the C-E filter works on a typical day in the sample period. We then provide statistics on the outcome of this filter, such as total daily volumes and daily average rates of specials and funding repos over the sample period.

We consider April 1, 2022. On that day, there were 425 CUSIPs cleared in the interdealer brokered segment and a total of $635.6 billion in repo activity. Using the filter described above, 100 ordered buckets were constructed, and for each bucket the value-weighted average rate is computed. These average rates, ranked from low to high, are illustrated in Appendix Figure 5 and the resulting profile is elbow-shaped, as discussed above. Changes in this rate between adjoining ordered buckets are computed ($\Delta\hat{r}_n$); this change along with the natural log of this change are illustrated in Appendix Figure 6. The log transformation better illustrates the evolution of $\Delta\hat{r}_n$ as we move from the I_1 to I_{100} because it is easier to see when the log change is less than 0 (or $\Delta\hat{r}_n < 1$). As shown in Appendix Figure 6b, the first instance where two consecutive rate changes are below 1 basis point occurs with the ordered buckets 9 and 10.[30] The result is that on this day, CUSIPs designated as special are those in $\{I_1, I_2, \ldots, I_7\}$ (this set contains 29 CUSIPs and a daily total of $80.5 billion in repo activity); all other CUSIPs are considered to be funding (those in I_8 and all higher ordered buckets).

[30]The repo rate change associated with ordered bucket 9 is between ordered buckets 8 and 9.

This filter is applied to every day in our sample period. The classification of CUSIPs into specials and funding results in two groups of rates with significantly different time-series properties, as illustrated in Appendix Figure 7. This figure shows that specials rates are more volatile than funding rates and so likely to be driven by different economics factors—for example, unlike for funding, rates on specials tend to spike downwards around FOMC announcement dates.

The resulting classification of CUSIPs into these two types is applied across all four segments of the centrally cleared data. The total daily volumes for specials and funding are plotted for the interdealer segment in Appendix Figure 8 and accompanying average numbers across all segments are reported in Appendix Table 9. Overall, specials trading is found to be concentrated in the interdealer brokered segment, where on average there is \$53 billion in daily activity as opposed to less than \$15 billion overall in the other three segments. This allocation of specials trades in the interdealer segment is stable over the sample period, in contrast to the allocation of funding trades, which has risen.

For both the DtC Borr and DtC Lend segments, the C-E filter designates the vast majority of total trading to be for funding purposes. This outcome is in line with what is known about these segments. MMFs seeking to invest cash dominate the DtC Borr segment and so we expect this segment to be composed almost entirely by funding trades. Similarly, existing works argue that DtC Lend will be dominated by funding trades between dealers and hedge funds (see, for example, Barth and Kahn (2025)).

We then look at the number of CUSIPs classified as funding versus specials and find that in the sample period, on average 39 CUSIPs traded special each day whereas an average of 407 CUSIPs are used each day for funding purposes. Over the sample period, these numbers are fairly stable, as illustrated in Appendix Figure 9.

Finally, we consider the make-up of CUSIPs that are specials. On-the-run (OTR) CUSIPs as well as those designated as cheapest-to-deliver (CTD) are often sought after by market participants. As a result, these CUSIPs should trade special in repo. We examine how these CUSIPs are classified by the C-E filter and find that roughly half of specials activity value-wise are composed of OTR or CTD CUSIPs. As a result, a significant amount of specials activity involves CUSIPs that are off-the-run and not CTD. Furthermore, 22 percent of all funding activity involves CUSIPs that are OTR or CTD. Hence, there is a substantial amount of overnight Treasury repo activity involving OTR or CTD CUSIPs where the negotiated rates are close to the average funding rate in the marketplace. Overall then, these results argue that using OTR or CTD as a way to label specials trading is likely to result in inaccurate outcomes.

A.3 Robustness of the two consecutive rule

A central feature of the C-E filter is the definition of i^* based on there being two consecutive instances where $\Delta\hat{r}_n$ is less than a basis point (see equation 5). We explored rules where i^* is based on three, four, and more consecutive instances of $\Delta\hat{r}_n < 1$ and found little change. We measure the impact of the different rules by computing the average daily total of funding of overnight Treasury repo in the sample period as well as the total funding volume of overnight Treasury repo across the sample period. If the benchmark cutoff rule is accurately identifying the threshold beyond which all CUSIPs are used for funding purposes, then average rates beyond the threshold should be quite close to one another because they are driven by the same factors. As such, cutoff rules based on two, three, four or more instances of $\Delta\hat{r}_n < 1$ should return a similar classification outcome of CUSIPs into specials and funding.

These statistics are presented in Appendix Table 10. Comparing the first and second rows demonstrates that moving from using the first instance where $\Delta\hat{r}_n < 1$ to using two consecutive instances results in a drop in daily total volume of \$0.012 trillion and a drop of \$14.2 trillion in total volume. Subsequent moves from two to three instances or three to four instances, result in much smaller differences in these two volume measures. The much smaller reductions in volumes that result from moving beyond two consecutive instances of $\Delta\hat{r}_n$, the benchmark rule used in this paper, suggest little is gained from using these alternative rules.

B Sample construction

This section provides details on how the value of trades filtered out in order to construct the final datasets used in the analysis. The goal is to have sample of Treasury repo trades with overnight maturity. The sample period used in this section is January 2020 to December 2024.

We begin with the triparty repo data, which capture all the triparty repo trades that are executed on a particular day. The raw data capture different types of trades that settle on the triparty settlement platform, and so we begin by selecting only those trades that are labeled as triparty repo transactions. We label this set of trades as "initial" and consider the total sum of the cash principal amount of all these transactions as the full set of triparty repo trades. The first set of filters applied involve dropping (i) trades with open maturity, (ii) trades with optionality on maturity (e.g., evergreen trades), (iii) trades where the rates are not fixed (e.g., rates are set as a spread to a benchmark rate), (iv) trades which are being cleared with the central counterparty (i.e., Sponsored GC transactions), or (v) trades where "TEST" appears in the name of either counterparty. These constraints decreased the total value of trades considered by 14.9 percent, as shown in the "Cleaning" row of Appendix Table 13.

We then keep only those trades with an overnight maturity, where the maturity of the trade is computed based on business days. As such, a repo trade with a start date on Friday and an end date on the following Monday, is considered to have overnight maturity. This restriction only drops the total value of all trades by 1.6 percentage points (see the "Overnight only" row in Appendix Table 13. This small decline reflects both the dominance of overnight trades in triparty repo and the flow nature of the data, where trades only show up in the data on their date of execution.

Finally, only those trades that involve Treasury securities and do not involve the Federal Reserve are kept. Trades with the Federal Reserve reflect market participants using the Standing Repo Facility or the Overnight Reverse Repo facility. This final restriction drops the total value of trades by 61 percentage points. Taken all together, the total value of repo trades considered in the analysis is 22.5 percent of the initial total value of repo trades, where once again these trades capture the flow of triparty repo transactions executed over the four-year sample period.

We now turn to the OFR repo data, which capture all the outstanding repo trades being cleared and settled on their FICC DVP service. To arrive at the initial set of trades from the raw data, we remove duplicate observations of the same economic trade, drop forward starting trades, and only keep observations recording when a trade was initially settled. There are duplicate observations in the sense that if Dealer A executes a trade with Dealer B using an interdealer broker, then that trade shows up four times in the data. For our purposes, we only want this trade to count once, hence we remove three out of the four instances. The initial settlement constraint transforms the data from a measure of the stock of trades outstanding to a measure of flow, which aligns with the triparty repo data. This distinction is not that important for this paper given its focus on overnight trades, where the stock and flow measures are the identical.

Starting with this initial set of trades, we then keep only trades with overnight maturity, when maturity is computed using business days. This approach removes only 2 percent of total trades by value. We then focus on Treasury repo, which removes 0.1 percentage points of trades by value—this trades involved agency debentures. Finally, we use the C-E filter to identify which trades were entered into for funding purposes. Keeping these trades reduces total trades by 5.1 percentage points. Overall, the filters we employ only shrink the trades considered for analysis by 7.2 percent. Appendix Table 13 captures how these filters successively shrink the value of total trades consider for the analysis.

C Additional results

In this section, we present additional empirical results.

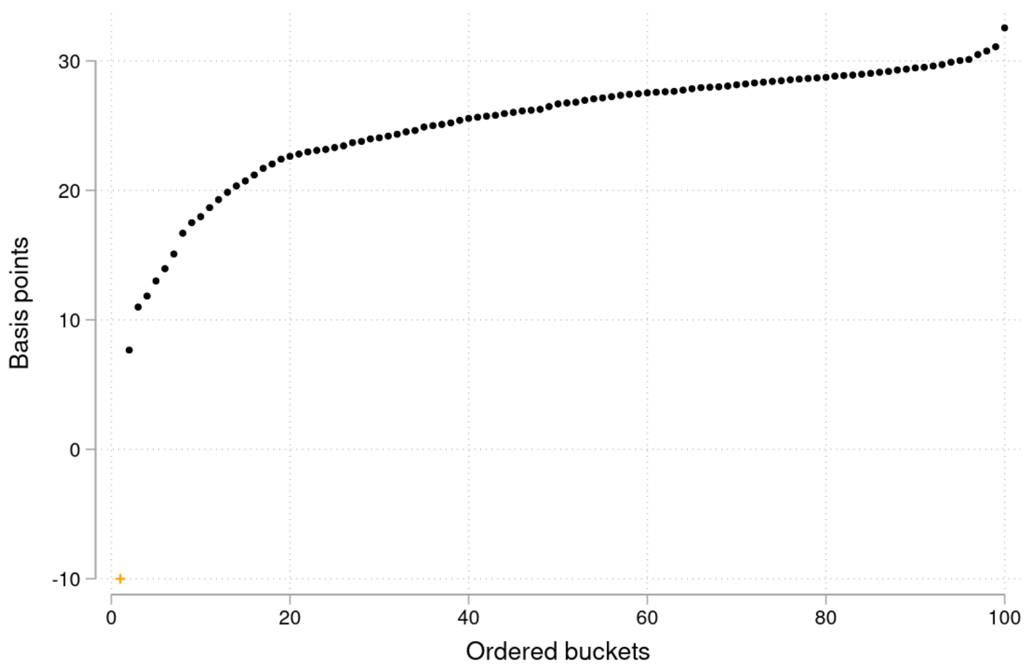
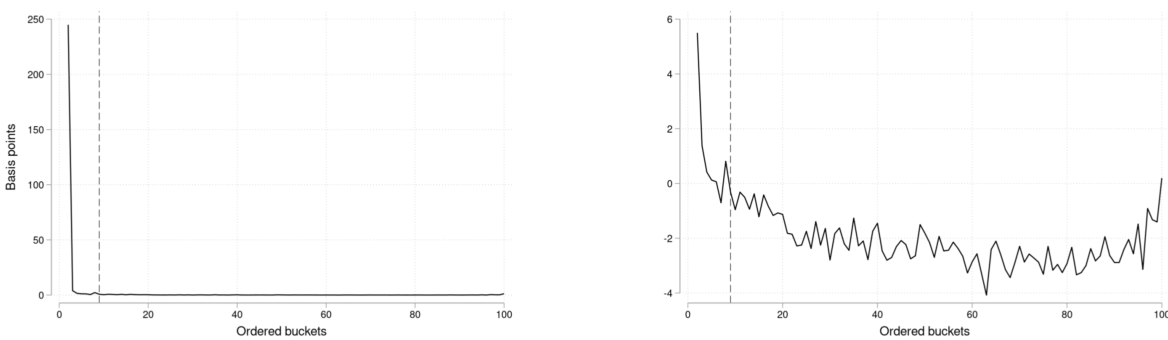


Figure 5: Average rates by ordered buckets, for April 1, 2022

This figure shows the weighted average rate by bucket on April 1, 2022, where the buckets are ranked from lowest to highest average rate. The rate for the first bucket is highlighted with an orange '+' marker as its rate of -55 bps has been replaced with -10 for illustrative purposes.

Source: OFR centrally cleared repo data collection and authors' calculations.



(a) Change in rate across ordered buckets

(b) Log of rate change across ordered buckets

Figure 6: Cutoff rule, for April 1, 2022

Panel a shows the change in rates between adjoining ordered buckets. Panel b shows the natural log of this change. The cutoff rule looks for the first instance where two consecutive changes are less than 1 basis point. For the log of the change, this means two consecutive values less than zero. In both figures, the cutoff rule is illustrated with vertical dashed line, at the 9th ordered bucket.

Source: OFR centrally cleared repo data collection and authors' calculations.

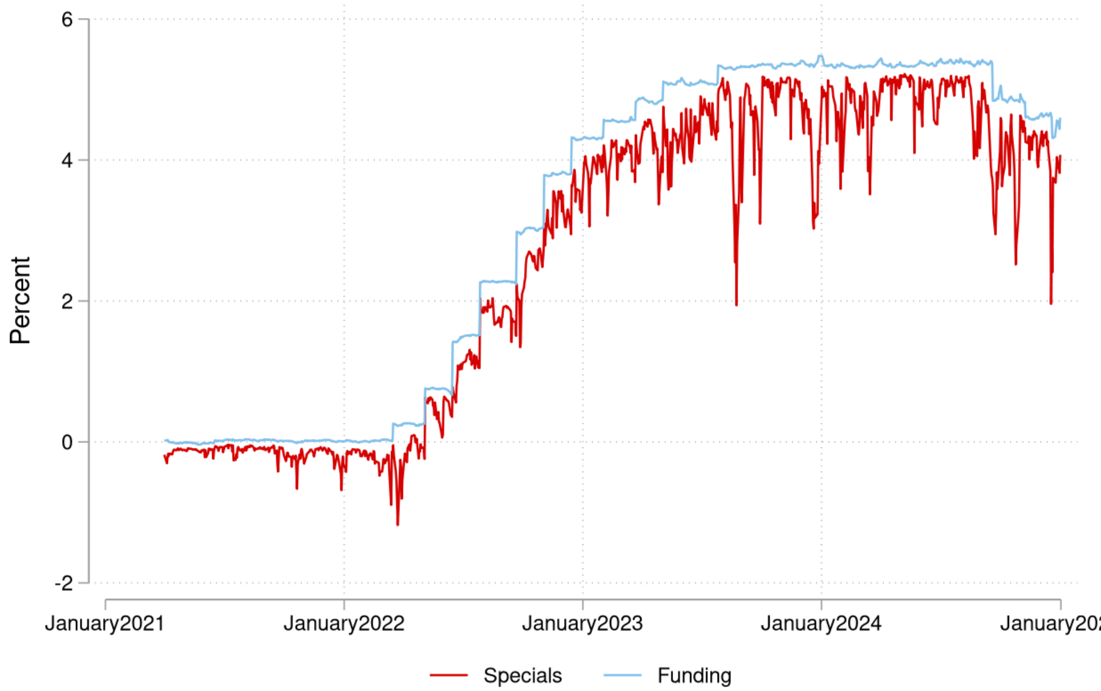


Figure 7: Average daily date of special and funding trades

This figure illustrates the average daily rate of overnight Treasury repo by type (special or funding) in the inter-dealer segment when brokers are used (ID Broker segment). The type classification is the outcome of the C-E filter.

Source: OFR centrally cleared repo data collection and authors' calculations.

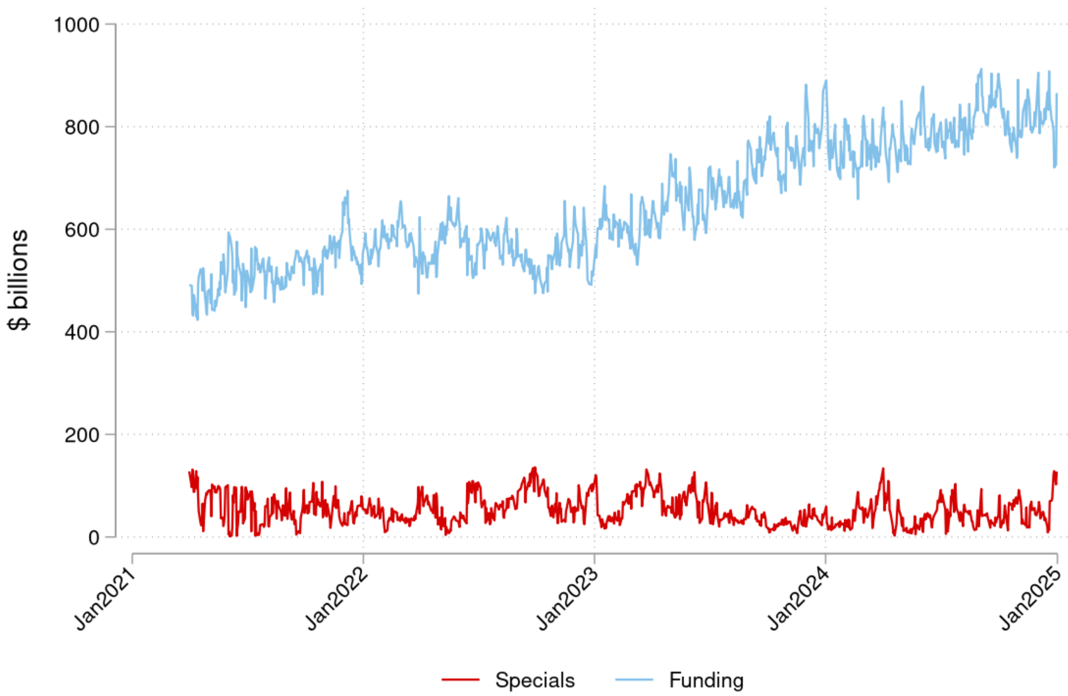


Figure 8: Daily volume of special and funding trades, interdealer segment
This figure illustrates total daily volumes of overnight Treasury repo by type (specials versus funding) for the brokered interdealer segment. The type classification is the outcome of the C-E filter.
Source: OFR centrally cleared repo data collection and authors' calculations.

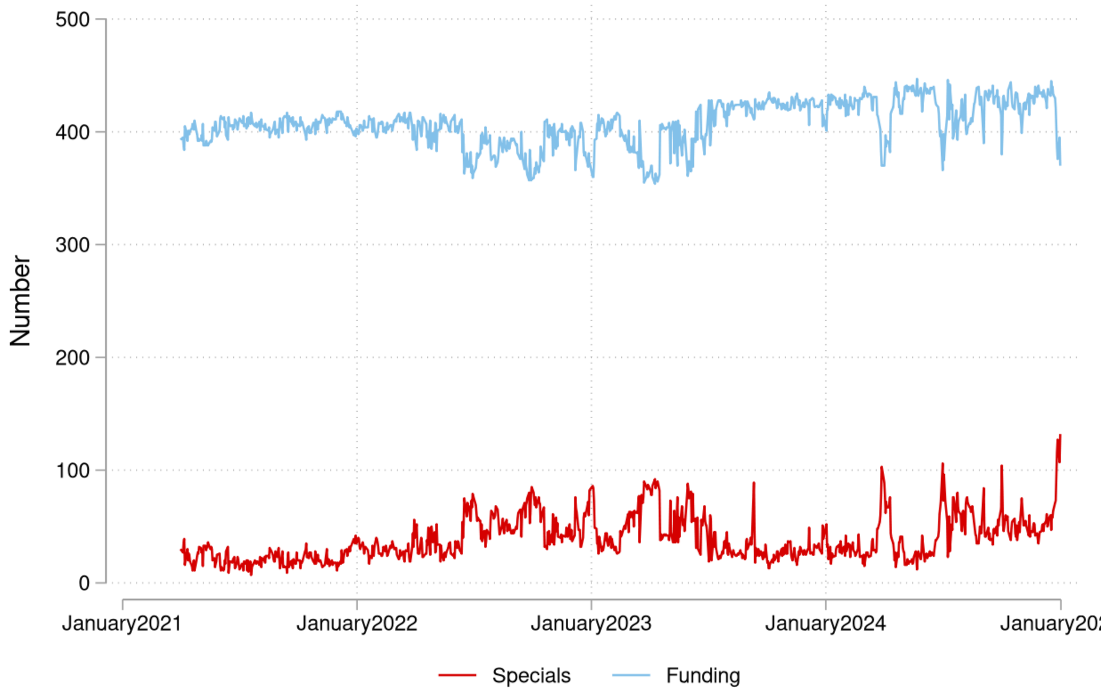


Figure 9: Number of special and funding CUSIPs over time
This figure shows the total number of CUSIPs used in overnight Treasury repo by type (specials versus funding). The type classification is the outcome of the C-E filter.
Source: OFR centrally cleared repo data collection and authors' calculations.

Table 9: Average daily total volume of special and funding overnight Treasury repo ($ billions)

Repo segment	Specials	Funding
ID Broker	52.68	645.98
ID No Broker	2.91	67.02
DtC Borr	5.88	290.36
DtC Lend	5.15	249.58

Note: This table reports the average daily total of overnight Treasury repo by segment and type, in billions of dollars. The type classification is the outcome of the C-E filter. ID is interdealer, DtC is dealer-to-client transaction, Borr designate cases where the dealer is counterparty to the trade that is borrowing cash, and Lend are cases where the dealer is lending cash. Broker and No Broker designate when an interdealer is used to execute the trade.
Source: OFR centrally cleared repo data collection and authors' calculations.

Table 10: Statistics on funding volumes for different cutoff rules

Cutoff Rule	Daily Average $ trillions	Total Sum $ trillions
Single	1.179931	1,464.294
Double	1.168803	1,450.484
Three	1.161281	1,441.149
Four	1.157343	1,436.263
Five	1.154595	1,432.852
Six	1.152655	1,430.445
Seven	1.15132	1,428.789
Eight	1.150167	1,427.357
Nine	1.149349	1,426.343
Ten	1.148826	1,425.693

Note: This table reports the summary statistics on funding volumes for overnight Treasury repo using different cutoff rules. The benchmark rule is two consecutive average rate changes for adjoining CUSIPs, which is denoted as Double. Single is a cutoff rule where the first average rate change below 1 basis point is the cutoff rule. Three is a cutoff rule where the threshold rate is the first time there are three consecutive average rate changes less than 1 basis point. Four through Ten are similarly defined.
Source: OFR centrally cleared repo data collection and authors' calculations.

Table 11: Measuring the liquidity risk premium using the cross section

	Spreads Client-to-client relative to interdealer	Rates DtC Lending relative to ID Broker
1(Clt)	4.910***	5.122***
	(0.069)	(0.053)
1(Clt) x IORB	2.254***	0.300***
	(0.066)	(0.032)
1(Clt) x Liabilities	-0.854***	-0.261***
	(0.085)	(0.067)
1(Clt) x IORB x Liabilities	0.534***	0.138***
	(0.082)	(0.045)
Constant	1.894***	-8.540***
	(0.025)	(0.013)
Obs	570,858	652,658

Note: This table reports the estimated coefficients from two regressions. The first regression considers the spreads dealers charge, and measures by how much changes in IORB and Fed liabilities affect client-to-client spreads relative to interdealer spreads. The second regression considers the rates dealers change, and measures by how much changes in IORB and Fed liabilities affect the rates dealers charge when lending cash to clients versus the rates dealers pay to borrow in the interdealer brokered market. Date and CUSIP fixed effects are included in the specification but not reported. Standard errors are clustered by date.

Table 12: Measuring the liquidity risk premium on time-aggregated data

	Client to Client	Client to TPR	Interdealer
IORB	2.672***	3.057***	0.346
	(0.538)	(0.621)	(0.525)
Fed liabilities	-2.232***	-1.968***	-1.861***
	(0.632)	(0.657)	(0.572)
IORB x Fed liabilities	0.175	0.610	-0.382
	(0.407)	(0.471)	(0.455)
Bills issued	-9.243	-6.875	-9.269
	(10.022)	(10.530)	(11.383)
Coupons issued	-0.348	0.432	1.139
	(2.767)	(2.852)	(2.713)
UST volatility	0.319	0.262	0.655***
	(0.261)	(0.268)	(0.215)
Bills outstanding	-0.349	-0.742	-0.448
	(0.774)	(0.812)	(0.727)
Change in TGA balance	-1.764	-1.347	-5.498
	(5.583)	(5.566)	(5.388)
UST redemptions	0.339	0.389	0.645
	(0.467)	(0.462)	(0.493)
Month end	0.002	-0.376	-0.371
	(0.612)	(0.561)	(0.517)
Quarter end	1.509*	1.394	1.879**
	(0.847)	(0.854)	(0.892)
Constant	7.450***	7.077***	3.391**
	(1.406)	(1.592)	(1.543)
Obs	2.0e4	2.1e4	26092
R-squared	0.357	0.406	0.278

Note: This table reports the estimated coefficients from three regressions. These results mirror those of Table 2 except that the data are not daily, but rather aggregated temporally with the construction 30-business-day blocks over the sample period. If there is a change in IORB within a 30-day block, then that block is split at the point when IORB is changed. Hence, within any block of time IORB is constant. See Table 2 Notes for all other definitions. CUSIP fixed effects are included in the specification but not reported. Standard errors are clustered by date.

Table 13: The impact of triparty repo sample construction

	Share of Total Value
Initial	100
Cleaning	85.1
Overnight only	83.5
Private UST only	22.5

Note: This table shows how successive constraints used to filter the triparty repo data decreased the sample size, as measured by the cash principal amount of a transaction, over the sample period of January 2020 to December 2024. "Cleaning" involves filtering out open trades, Sponsored GC repo trades, forward-starting trades, trades with optionality on maturity or rate, or trades executed to test operations. "Overnight only" means trades with an overnight maturity are kept."Private UST only" means trades involving US Treasury securities are kept and trades with the Federal Reserve are excluded. Trades involving Treasury STRIPS are not included.
Source: FRBNY and authors' calculations.

Table 14: The impact of OFR repo sample construction

	Share of Total Value
Initial	100
Overnight only	98.0
UST only	97.9
Funding only	92.8

Note: This table shows how successive constraints used to filter the OFR centrally cleared repo data decreased the sample size, as measured by the cash principal amount of a transaction, over the sample period of January 2020 to December 2024. To arrive at the initial dataset, duplicate observations of the same economic trade were removed and forward-starting trades were dropped. These constraints transform the data from a measure of stock (all trades that have not yet matured) to a flow. "Overnight only" means trades with an overnight maturity are kept. "UST only" means trades involving US Treasury securities are kept. "Funding only" means on trades designated as funding trades by the C-E filter are kept.
Source: OFR centrally cleared repo data collection and authors' calculations.