Lender Preference, Borrower Market Power, and the Effect of RRP

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Abstract

I model and structurally estimate the equilibrium rates and volumes on the Triparty repo market to study how imperfect competition affects monetary transmission through this key financial market. Motivated by new facts that I document, I characterize the Triparty market as cash-lenders allocating their portfolios among differentiated cash-borrowers (dealers) who set repo rates. I find that even within this liquid and sophisticated market, because of cash-lenders' aversion to concentrated portfolios, dealers hold substantial market power and command over 80% of the total surplus. I show through counterfactual analyses that, between 2014 and 2017, the Federal Reserve's Reverse Repo Facility (RRP) aided the passthrough of policy rates by constraining dealers' market power. Without the RRP, dealers' markdown would have widened, leaving the Triparty repo rate 11 bps below the lower bound of the policy target and lowering the passthrough rate to the broader financial market by 7 bps.

JEL Classifications: E59, G20, L13
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1 Introduction

The transmission of monetary policy hinges on incentivizing private agents to set market rates in accordance with policy rates. This paper studies how imperfect competition affects the relationship between policy rates and market rates in the Triparty repo market. A key part of the money and bond market, the $2 trillion Triparty repo market underpins the working of a large volume of securities, including Treasury and Agency mortgage bonds (see the studies by Copeland et al. (2014), Krishnamurthy et al. (2014)). Every day in the Triparty repo market, experienced and sophisticated actors on both sides of the market borrow and lend cash using homogeneous repurchase agreements (repo). Nevertheless, when cash-lenders (e.g., BlackRock) lend to different dealers simultaneously (e.g., Goldman Sachs and Wells Fargo), the rates that lenders accept show persistent cross-dealer differences, suggesting imperfect competition.

To identify the factors behind imperfect competition and to quantify the impact of market power on rates, I propose and structurally estimate the first equilibrium model of the Triparty market. The seemingly small rate dispersion observed on Triparty in fact belies a substantial market power held by dealers who are cash-borrowers. Between 2011 and 2017, dealers borrowed at rates that were on average 28 bps lower than their marginal value of funding, claiming 83% of the total surplus. The Triparty dealers' market power stems from Triparty cash-lenders' aversion to portfolio concentration. Monetary policy tools such as the Federal Reserve's Overnight Reverse Repo Facility (RRP) are critical to keeping the Triparty repo rate above policy rate targets. Without the RRP, which constrains dealers' market power by providing an alternative outside option to Triparty cash-lenders, the median Triparty repo rate would have been 16 bps lower between 2014 and 2017, putting it at 11 bps below the lower bound of the policy target. Fifty-six percent (56%) of the counterfactual rate drop is due to dealers' widening market power, giving them 9 bps as profit and lowering the rate that they pass on to the broader financial markets by 7 bps.

I start by documenting three new empirical facts about the Triparty repo market. First, cash-lenders (henceforth, lenders) simultaneously and consistently accept different repo rates against contracts that differ only in the identity of the cash-borrower (henceforth, borrower). Second, borrowers' identities drive repo rate dispersion both in the cross-section and in the time-series; in contrast, different lenders that lend to the same borrower do so at rates that are statistically indistinguishable. Third, the composition of lenders' repo portfolios is size-dependent; in particular, as lenders get larger, they not only lend to more borrowers, but – controlling for the number of borrowers they lend to – also give smaller shares of their portfolios to each borrower.

These patterns provide a new perspective on the working of the Triparty market. First, because Triparty lenders and borrowers repeatedly trade with each other, lending at persistently different rates likely reflects lenders' perception that borrowers are differentiated. I speculate that lenders have a strong preference for stable investment opportunities, and therefore discriminate between borrowers that vary in how consistently they use their scarce balance sheet to take on repo loans. Second, although repo contracts are bilaterally determined, the overwhelming importance of between-borrower variation in explaining repo rate dispersion, hints at a market where borrowers set borrower-specific repo rates for all lenders. Finally, in constructing their portfolios, lenders seem to exhibit a size-dependent aversion to concentration: the larger they are, the more averse they are to lending too much of their portfolio to any one borrower. Such an aversion could stem from lenders' desire to minimize their exposure to headline risks or operational risks.

These empirical insights motivate me to model the Triparty market using a demand-and-supply framework, where the "goods" traded are repo investment opportunities. On the demand side, lenders seek repo investments and allocate their cash portfolios with explicit considerations for portfolio composition. The lender's utility reflects an aversion to concentration and a non-pecuniary preference for stability in lending opportunities. These two forces determine the lender's optimal lending quantity and his sensitivity to repo rate changes. On the supply side, borrowers provide borrowing capacity and engage in monopolistic competition to set repo rates. The borrower's utility is linear in her profit. At her optimum, she offers a repo rate that is her marginal value of funding less a markdown. The ability to build in a markdown is the borrower's market power, and the size of her markdown is a function of the lender's demand elasticity. At a given quantity of repo funding, the less the lender reacts to repo rate changes, the more the borrower can markdown the rate she offers. Thus, the model embeds two forces that could contribute to the presence of imperfect competition: differences in the lender's preference for stability and differences in the lender's aversion to concentration.

The key to separately identifying the forces in my model is to estimate how the lenders respond to rate changes, which directly informs the concentration aversion parameter. Intuitively, when a borrower raises her repo rate to attract more funding, the lender would want to take advantage of the more favorable rate by lending more to this borrower; but if the concentration aversion is high, then the lender's response will be muted because he does not want to have too much repo invested with any one single borrower. I estimate lender's semi-elasticity using Treasury auction offering as an instrumental variable.[1] Over my sample period, a $40 billion (1 standard deviation) increase in the amount offered in non-bill Treasury security auctions is associated with an average increase of $0.65 billion in a borrower's repo borrowing.[2] To raise $0.65b in additional funding (about 4%), a

[1]The U.S. Treasury Department conducts periodic auctions of Treasury securities. The quantity of this auction influences the amount of repo borrowings because dealers buy securities to house before selling to ultimate buyers. At the same time, the amount *offered* – not purchased – at each auction is likely driven by the Treasury department's fiscal concerns and plausibly exogenous to factors that make repo rates fluctuate. My instrument purposely excludes auctions of Treasury bills, as money market funds, the cash-lenders on Triparty, can also purchase Treasury bills.

[2]The total increase in Triparty borrowing is about $11 billion for every $40 billion of auction offer.

borrower needs to raise the repo rate she offers by about 1 bp. This estimate is in-line with the recent funding flow to the RRP following an unexpected rate increase in June 2021.[3] It also signals relative inelasticity in the Triparty market compared to other large markets such as the one for Treasury securities (e.g., Greenwood et al. (2015), Bernanke et al. (2004), Duffee (1996)).[4]

Leveraging moments such as the IV-estimated lender semi-elasticity, I estimate my model parameters using indirect inference and maximum likelihood. My parameter estimates accord with the notion that lenders exhibit size-dependent aversion to concentrated portfolios, thereby purposely spreading out their lending. This aversion leads to a relatively inelastic response in volume to repo rate changes, and grants borrowers market power. The magnitude of borrowers' market power depends on lenders' preference for stable investment opportunities. I calculate that the repo rates offered by borrowers during the sample period reflect a 27.5 bps markdown from their marginal funding value, on average. Compared to the 5.7 bps spread between the repo rate and the lender's outside option, borrowers command 83% of the 33.2 bps total surplus.

With this understanding of the Triparty competitive environment, I ask, what would be the Triparty repo rate relative to the Federal Reserve's policy target if the Overnight Reverse Repo Facility did not exist? First introduced in 2013, the RRP gives the Triparty lenders the ability to place repo with the Federal Reserve (Fed), thus providing the lenders with an alternative to lending to repo borrowers. If in lieu of RRP, lenders placed cash

[3] On June 17, 2021, the repo rate at the RRP increased unexpectedly from 0 to 5 bps. The volume of repo placed at the RRP increased from \$520.9b on June 16, 2021 to \$755.8b on June 17, 2021. The \$225b overnight increase relative to the total size of Triparty Treasury repo, which was \$1628b as of June 9, 2021, implies an elasticity of 2.9% per basis point increase. As the RRP is the lender's alternative to lending to repo borrowers (see section 5.2 for more discussion), the lenders' sensitivity to changes in the RRP rate is also the lenders' sensitivity to changes in the borrowers' repo rates.

[4] As an example, Greenwood et al. (2015) estimates that a 1 percentage point decrease in $\frac{\Delta Treasury}{GDP}$ leads to 38.6 bps decrease in the two-week Treasury yield. The average annual GDP between 2011 and 2017 is \$18.7T. This implies that, over my sample period, 1 bp change in yield is associated with \$4.8b change in Treasury supply. For a comparable 1 bp change, the volume response in the Treasury market is much higher compared to that in the Triparty market (\$0.6b).

not lent to repo borrowers in Treasury bills, then the equilibrium median repo rate – allowing both the Triparty market and the Treasury bills market to adjust – would have been 16 bps lower than the historical rate, and 11 bps below the lower bound of the Federal Reserve's policy target. Critically, much of this rate drop reflects borrower's widening markdown in the absence of the RRP. The passthrough rate from borrowers to the broader financial market would have declined by a more modest 7 bps.

This paper contributes to the existing literature in at least four ways. To start, it offers the first equilibrium characterization of a key funding market. The Triparty market has long drawn the attention of scholars (e.g. Krishnamurthy et al. (2014), Copeland et al. (2014), Hu et al. (2017), Aldasoro et al. (2019), Han and Nikolaou (2016), Weymuller (2013)). This paper not only enriches the understanding of the Triparty market by documenting new empirical facts, but also provides the first joint determination of rate and volume in a structural model that captures these facts. In so doing, this paper departs from the traditional search framework (Duffie et al. (2005), Hendershott et al. (2020)) and pioneers the application of demand models to the over-the-counter (OTC) literature. Moreover, in contrast to the discrete choice model increasingly employed in finance (Koijen and Yogo (2018), Buchak et al. (2018), Benetton (2021)), the lender's model in this paper emphasizes preferences that lead to simultaneous selection of multiple choices at the optimum. My modeling approach takes inspiration from Martin and Yurukoglu (2017), Crawford et al. (2018), and Kim et al. (2002) in the industrial organization literature.

My estimated structural model provides a new method for evaluating monetary policy tools. The Triparty market is one of the few markets in which the Fed directly operates to implement monetary policies. Although there is a long line of work on traditional monetary policy tools such as the Federal Funds Rate, research that focuses on how newer tools such as the RRP operate remains scant. My examination of the RRP's effect through counterfactual analyses is distinct from the approaches taken by the few existing studies of the RRP (Anderson and Kandrac (2017), Chen et al. (2016), Frost et al. (2015)). Importantly, findings of this paper surface and quantify the existence of dealer (borrower) market power.

In demonstrating substantial market power in the large, liquid, and sophisticated Triparty market, this paper adds to a recent literature that documents intermediary market power in other OTC markets. Relative to studies that show imperfect competition in European OTC repo (Eisenschmidt et al. (2021)), Canadian Treasury auctions (Allen and Wittwer (2021)), and the foreign exchange market (Wallen (2020)), this paper does so in a key funding market, which has implication for monetary policy passthrough. Moreover, this paper highlights a different source of market power. The Triparty dealer's market power owes not to quarter-end implementation of regulations that limit dealer participation, but instead to longstanding preferences of the lender.

Finally, this paper furthers the inquiry into how market power impacts the transmission of monetary policy and shows that the interaction between market power and policy transmission happens at the very beginning of the transmission chain. Market power has shown to impede monetary transmission to the deposit market (Drechsler et al. (2017)), the mortgage bonds market (Scharfstein and Sunderam (2017)), the refinancing market (Agarwal et al. (2021)) and the banking sector (Wang et al. (2020)). Taken together, these papers all point to the importance of financial intermediaries in asset pricing and monetary policy transmission (He and Krishnamurthy (2017), Duffie and Krishnamurthy (2016)). Policies and policy tools should therefore be evaluated also by the effect that they have on creating or constraining market power.

In the next section, I provide details on the Triparty market and the data used to study it. In section 3, I present and discuss the salient empirical observations that motivate my modeling choices. Then in section 4, I outline the models for the lender's and the borrower's problem. Estimation of the lender's model and its results are discussed in section 5. I calibrate the borrower's model before conducting two counterfactual analyses in section 6. In section 7, I conclude.

2 Triparty repo market and data

In this section, I highlight the distinct features of the Triparty market, outline the role the Triparty market plays in collateral financing and monetary policy transmission, and describe the data used to study this market.

2.1 The Triparty market and the RRP

Repurchase agreements are contracts between two counterparties to exchange cash against collateral. I refer to the counterparty that provides the cash as the lender, and the counterparty that pledges collateral to get cash as the borrower. The posted collateral, often valued at a haircut, is returned to the borrower when cash is returned – with an interest. The rate used to determine that interest, I refer to as the repo rate. Since repo lending is secured, repo contracts can differ not just in the repo rate specified, but also in the specific collateral used. The Triparty market offers a way to make the OTC repo collateralization more standardized.

The Triparty market derives its name from its institutional set-up. On Triparty, every transaction involves a third agent, who is the clearing bank that handles the logistics of cash and collateral transfers. All Triparty borrowers and the lenders maintain accounts with the same clearing bank.[5] Once a borrower and a lender agree on the terms of a repo, the clearing bank makes collateral allocation behind-the-scene. Triparty repo contracts specify only the class of collateral, e.g., Treasury securities, but not the exact securities used, e.g., CUSIPs of specific five-year on-the-run Treasury securities.[6] This

[5]The sole Triparty clearing bank in the US is Bank of New York Mellon. J.P. Morgan used to also provide Triparty clearing service for about 15% of the market. It discontinued its service in 2017.

[6]In contrast, repos done outside of the Triparty market allows the borrower and lender to maintain

makes Triparty repo contracts standardized within a collateral class, and makes Triparty repo convenient for funding.

Indeed, the Triparty market is a step in the intermediation process that channels cash from outside of the financial system to financial market participants looking to finance their holdings. Cash-rich individuals and corporations place cash in vehicles such as money market funds (MMFs). MMFs keep a stable fraction of their asset under management (AUM) in overnight cash for liquidity. This overnight cash is lent out via Triparty repo to broker-dealers. Dealers, in turn, use their borrowed cash to either finance their own security holdings or pass on to their clients in the broader financial market. Every day, over $2 trillion dollars are injected into the secured market through the Triparty market.

The Federal Reserve (Fed) has long been a keen observer of the Triparty repo market because the Triparty rate affects many other money market rates and security prices. By virtue of being a funding market, conditions on the Triparty market directly affect securities such as Treasury and Agency MBS, which are posted as collateral and thus financed with Triparty lending.[7] Moreover, Triparty repo trades enter the calculation of the Secured Overnight Financing Rate (SOFR), which replaces LIBOR as the new dollar interest rate benchmark, affecting a large swath of dollar-denominated contracts and derivatives.

In September 2013, in anticipation of monetary policy changes, the Fed set up an overnight, fixed-rate, full-allotment reverse repo facility (RRP) on the Triparty market.[8] The RRP gives a wide array of Triparty cash lenders the ability to lend to the Fed in the form of overnight repo at a pre-announced interest rate. The Fed gradually increased the RRP's capacity, and the RRP became a fixture of Triparty in September 2014. When the

accounts at different custodial banks, and even for "general collateral" repo, the borrower needs to stipulate the CUSIPs of all securities used as collateral.

[7]Treasury or Agency MBS account for over 90% of the collateral used in the Triparty market.

[8]`https://www.newyorkfed.org/markets/opolicy/operating_policy_130920.html`

RRP was first set up in September 2013, access to the facility was capped at $500 million per eligible lender. This cap was subsequently raised 6 times, eventually reaching $30 billion per eligible lender by September 2014, at which point the cap no longer seemed binding for any lender. September 2014 was also when the Fed stated in the FOMC's Policy Normalization Principles and Plans that "the Committee intends to use the RRP facility as a tool to help control the federal funds rate during the normalization of the stance of monetary policy", further underscoring the Fed's commitment to the RRP. In effect, by September 2014, Triparty lenders had an attractive alternative to lending to repo borrowers, in the form of the RRP.

2.2 Data

To study the Triparty market, I use monthly SEC filings made by money market funds domiciled in the United States. Money market funds are the largest class of cash lenders on the Triparty market, accounting for 40% to 60% of all repo transactions. Other Triparty lenders include security lenders, pension funds, insurance companies, and various municipalities with temporary excess cash (Copeland et al. (2012)).

MMF are regulated and are required to file monthly N-MFP reports. These filings are snapshots of an MMF's entire portfolio as of the last business day of each month.[9] In particular, for each repo contract that the MMF has, information is available on the counterparty, the amount, the repo rate,[10] the maturity date, and the collateral type and value.

I obtain all N-MFP reports between 2011 and 2017 from the SEC EDGAR data

[9]Although N-MFP filings are done monthly, these reports are likely representative of money market funds' repo activities throughout the month. Anderson et al. (2019) use proprietary data available at the Federal Reserve, and show in Figure 2(b) that repo activities are stable throughout the month, with the exception of window-dressing activities on the last day of the quarter.

[10]Before April 2016, repo rates are not separately reported. I parse the title of each contract to obtain rates where available. To address potential misreporting issues, I winsorize repo rates at 1% and 99%.

base, and collapse the filings by money market fund families.[11] Each money market fund family, e.g. BlackRock, can have a number of different money market funds, e.g. government-security only funds vs. tax-exempt funds. Importantly, money market fund families enter into repo contracts on behalf of all funds in the family and then distribute the investment across funds (Copeland et al. (2014)). To analyze the equilibrium rate and volume determination, it is therefore appropriate to consider all funds in the same fund family as one entity.

Money market funds manage their liquidity by keeping a steady fraction of their AUM in overnight cash. As there are limited options to invest cash overnight, Triparty repo, which is typically overnight, forms an important part of MMFs' overnight portfolio. I explicitly focus on Triparty repo that are overnight in duration.[12]

Triparty repo activities are concentrated in a relatively small set of agents. As Figure 1 illustrates, over 85% of the activities in the N-MFP filing data are done by 18 MMFs and 20 dealers. My analysis thus focuses on these agents. My final data set is a MMF-dealer-month panel of repo transactions from January 2011 through December 2017 on 84 month ends, for a total of 15,469 observations.

I supplement the data from N-MFP filings with the Federal Reserve's releases on repo and RRP activities, TreasuryDirect's reporting of Treasury securities auctions, and CDS pricing from Markit and Bloomberg.

[11] My sample ends in 2017 because I'm interested in the effect of imperfect competition in an abundant reserve regime. The Fed started shrinking its balance sheet in 2018.

[12] As the N-MFP reports the maturity date without reporting the start date, I identify overnight contracts as those that mature on the first business day of the following month. This approach is universal in papers that use N-MFP filing data. See Aldasoro et al. (2019) for discussions of potential shortcomings.

3 Empirical patterns on Triparty

In this section, I present three facts of the Triparty market and discuss possible reasons that give rise to these empirical observations.

Fact 1: MMFs simultaneously and consistently accept different repo rates from different dealers

Against repo contracts that differ only in the identity of the dealer, MMFs simultaneously lend to multiple dealers and do so at consistently different rates.

To compare repo rates across dealers, I focus on a sub-sample of overnight repo contracts that are collateralized only by Treasury securities with a 2% haircut,[13] which retains 73% of all MMF-dealer-month observations.[14] Prior research has documented differences in repo rates between contracts backed by different collateral, even though the haircut on collateral theoretically adjusts for the quality of the underlying (Weymuller (2013)). I therefore compare repo rates only across repos that are backed by the same collateral. This is not restrictive because Triparty repo differentiates collateral not by CUSIP but by asset class. By focusing my analysis of repo rates on Treasury-backed overnight repo contracts that all have 2% of haircut, I retain a sizeable sub-sample where the repo rate is free from impact due to duration, collateral, and haircut, leaving dealer identity the only other factor that differentiates repo.

In this sub-sample of homogeneous repos, MMFs are seen to simultaneously accept different repo rates from different dealers. Figure 2 plots, as an example, the repo rate BlackRock received from lending to Goldman Sachs and Wells Fargo in 2016 and 2017. To remove the effect of general interest rate trends, I re-state the transacted repo rate

[13] I restrict the sample to contracts with collateral to principal ratio of $102\% \pm 0.1\%$.

[14] From the total of 15,469 MMF-dealer-month observations, focusing on transactions that use Treasury as collateral leaves the sample with 13,356 observations, restricting the haircut to 2% leaves the sample with 11,219 observations.

as the deviation to the volume-weighted median on that day. The choice of using the volume-weighted median as the centroid both conforms to the convention in the repo market[15] and minimizes the impact of outliers. We see that although Goldman Sachs and Wells Fargo offered to borrow at consistently different rates, BlackRock nonetheless lent to both borrowers month after month.

This observation is surprising because the difference in repo rates cannot be due to differences in the contractual terms of the repo. Moreover, although creditworthiness of borrowers can often be a source of price dispersion, especially on OTC markets, over 2016 to 2017, the short-term (6M) CDS rates of Goldman Sachs is on average 12 bps above that of Wells Fargo. This observation is all the more surprising in light of the fact that the same three agents transacted every month. It is unlikely that BlackRock was not aware of the systematically different rates offered by Goldman Sachs vs. Wells Fargo. Informational friction cannot explain such persistent difference.

More generally, looking across all MMFs, the difference between the highest and the lowest rate *simultaneously* accepted by MMFs is on average 4 bps. This dispersion is, again, present in the context of repeated interaction. Indeed, the same pairs of MMF and dealer trade with each other over time: the AR(1) persistence of whether a MMF-dealer pair trades is 84% ($R^2 = 0.7$). Between sophisticated financial institutions who repeatedly interact with each other, repos that differ only in the identity of the dealer trade at persistently different rate. Seeing that MMFs simultaneously lend to multiple dealers at different rates, it is natural to wonder, what is the pattern in the Triparty rate dispersion, and what is the pattern in MMFs' lending?

[15] All published repo-based indices are calculated as the volume-weighted median, examples include the Secured Overnight Financing Rate (SOFR), the Triparty repo index, and the DTCC GCF repo index.

Fact 2: Dealer identity drives repo rate dispersion

The dispersion in apparently homogeneous repo contracts is driven by dealer identities. Continue using the overnight Treasury repo sub-sample, I show that, in the cross-section, dealer identities explain the preponderance of the variation in repo rate, while MMF identities have no statistically significant additional explanatory power. While between-dealer variation is important, within a dealer, repo rate variations do not exhibit correlations with MMF and MMF-dealer pair characteristics. In the time series, models with dealer fixed effects account for almost as much variation as that explained by models with MMF-dealer pair fixed effect; in fact, given their parsimony, models that contain only dealer fixed effects are preferred by the Bayesian information criteria (BIC).

In Figure 3, I examine the dispersion of repo rates in the cross-section. I plot in solid red the R^2 from regressing repo rates between MMF-dealer pairs in a particular month on dealer fixed effects.[16] Dealer identities explain about 50% of the variation in the cross-section. Plotted in dotted purple are the R^2 from similar regressions but on MMF fixed effect. MMF identities explain much less of the variation. In fact, even if MMF identities didn't matter for dispersion, we would expect MMF fixed effects to have some explanatory power as long as the sorting of dealer to MMF is not completely symmetric. I thus plot in dashed blue the R^2 from regressing repo rates on both the dealer and the MMF fixed effects. Once dealer identities are controlled for, adding MMF fixed effects does not improve the R^2 by much. I formally test whether the additional MMF fixed effects in the dashed blue regressions are jointly 0, and I cannot reject the null at the 10% significance level in 72 of the 84 months.[17]

To explore further the idea that dealer identities drive repo rate dispersion, in Table 1, I examine if MMF or MMF-dealer pair characteristics matter for within-dealer dispersion.

[16]To avoid fitting fixed effects over 1 or 2 data points, observations where a borrower or a lender has fewer than 3 transactions in a month are excluded, leaving the sample with 10740 observations.

[17]Multiple hypothesis testing is corrected using Holm (1979).

All models in this table look at within-borrower variations by controlling for borrower and month fixed effects. I test the following characteristics: the amount of Treasury-backed overnight repo lending between a MMF-dealer pair (*Pair Treasury repo volume*), the share – or importance – of this pair's lending volume to the MMF's overall Treasury-backed overnight repo lending (*Pair vol as percent of MMF*), the share of this pair's lending volume to the dealer's overall Treasury-backed overnight repo borrowing (*Pair vol as percent of borrower*), the MMF's total Treasury-backed overnight repo lending (*MMF total Treasury repo vol*), and the number of dealers the MMF lends to (*MMF number of counterparty*). None of these characteristics offers a statistically significant explanation to the rate dispersion, judging by either the individual coefficient's statistical significance or the improvement in R^2 from including these regressors (difference between R^2 (proj model) and R^2 (full model)). In other words, while different dealers may systematically pay different rates for repo funding, different MMFs lending to the same dealer do not receive statistically different rates.

Dealer identity is a key driver of repo rate variations in not only the cross-section but also the time series. Given the OTC nature of repo transactions, prior studies such as Han and Nikolaou (2016) focus on the difference among MMF-dealer-pairs to explain rate variations. In Table 2, I compare the goodness of fit between models that include only dealer fixed effects and models that include pair fixed effects. Comparing Models (1) versus (2), it is true that including all the pair fixed effects improves R^2 by about 0.07, yet this is achieved with 252 more regressors. Therefore, the Akaike information criteria (AIC) rank these two models similarly, and the Bayesian information criteria (BIC) prefers the more parsimonious model with only dealer fixed effects. The same pattern holds when comparing Models (3) versus (4), where year fixed effects are also added. In short, dealer identities are of first-order importance in explaining repo rate dispersion.

Fact 3: The larger the MMF, the more distributed the portfolio

MMFs construct their overnight cash portfolio in a systematic and size-dependent way: as MMFs get larger, they lend to more dealers and they lend smaller shares of their portfolio to dealers *holding constant the number of dealers in their portfolio*.

This pattern is illustrated in Figure 4, where the repo lending done in 2016 by the larger BlackRock is drawn next to the portfolio of the smaller Legg Mason. The larger BlackRock not only lent to more dealers but also lent a smaller share of its portfolio to each dealer. Shown more systematically in Table 3, this relationship between the portfolio size and the extensive and the intensive margin of the portfolio holds across MMFs.

To start, in Model (1), we see that the number of dealers MMFs (repeatedly, recall Fact 1) lend to increases by about 3 as the size of MMFs' overnight cash portfolio doubles.

More subtly, as MMFs increase in size, they lend smaller shares of their portfolio to each dealer. In Model (2), we see that as MMFs double in size, the median portfolio share lent to dealers decrease by 6.7% on average. Unlike the mean share of the portfolio, the median share of the portfolio need not change as the number of dealers in the portfolio changes. What this shows is that larger MMFs tend to lend smaller shares of their portfolio to any one dealer. To drive this point home, in Models (3) and (4), I control for the number of dealers in MMFs' portfolios. In Model (3), I control for the number of dealers in a portfolio by including it as a regressor, and it is not statistically significant. In Model (4), I allow for the effect of dealer number to be flexible by including "Number of dealer" fixed effects. Not only is MMF portfolio size still a significant predictor of the median share, but the magnitude of its effect barely changes.

Discussion of empirical patterns

Facing dealers that borrow at different repo rates (Fact 2), MMFs lend to multiple dealers simultaneously (Fact 1), and show a size-dependent tendency in making their portfolios distributed (Fact 3). These facts about the Triparty market suggest at least two economic forces that work in tandem.

First, against repo contracts that differ only in the identity of the dealer, MMFs are willing to accept knowingly different rates from different dealers. This indicates that dealers' identities differentiate repo lending in such a way that rationalizes differences in pecuniary returns. What is different between dealers that is so valued by MMFs? One hypothesis is a dealer's reliability in offering scarce balance sheet to take repo loans from MMFs. Interviews with industry participants reveal that MMFs have a strong preference for stability in repo investment opportunities. However, although dealers are conscientious about creating repo "investment opportunities", some are much more opportunistic because repo borrowing is balance-sheet intensive. It is possible that MMFs favor those dealers who consistently make available ample borrowing capacity.

At the same time, it is noteworthy that MMFs lend to multiple dealers simultaneously. It is as if MMFs have an aversion to concentration and purposely spread out their lending.[18] At first blush, this sounds perplexing, for Triparty repo carries very little credit risk,[19] so why would MMFs be concerned about concentrating their lending in one or a few dealers? MMFs may want to limit their dollar exposure to any one dealer due to headline risks, as their clients may not fully appreciate the collateralized nature of repo. MMFs may also want to diversify their lending to minimize operational risk, in the event, say, all the computers at a given dealer go down.

One manifestation of MMFs' aversion to concentration is that on quarter-ends, when some dealers window dress and cut back on repo borrowing, MMFs do not shift their

[18]There are regulated counterparty caps on certain assets that MMFs own, e.g. commercial paper. However, such caps do not apply to repo as repo is treated as a "look-through" asset so it's as if MMFs are holding the underlying Treasury collateral, which bears no cap.

[19]Triparty repo are largely overnight, over 90% is collateralized by high quality collateral such as Treasury or Agency MBS with haircuts that have been shown to be conservative (Hu et al. (2017)), and these contracts are full recourse. For these reasons, even during the depth of the Great Financial Crisis, there was no run or default on Triaprty (Krishnamurthy et al. (2014)).

lending to the other dealers. As Table 4 shows, on quarter-ends, the 10 dealers governed by regulations in the European Union (EU) and the United Kingdom (UK) cut back on repo borrowing, both in dollar terms (Models (1) and (2)) and in percentage measures (Models (3) and (4)). On average, an EU or UK dealer reduces his repo borrowing by about $7 billion on quarter-ends, even after controlling for his average repo borrowing in a given quarter (Model (2)). Yet the repo borrowing by dealers in CA, JP, and US barely changes on quarter-ends. MMFs' apparent reluctance to shift their lending to CA, JP, or US dealers is not because these dealers offer dramatically lower repo rates on quarter ends (Model (5)). Rather, MMFs' behavior on quarter-ends corroborates with the notion that MMFs are averse to lending too much of the portfolio to any one dealer. The consequence of this aversion, coupled with MMFs' tendency to lend to the same dealers over time, is that MMFs may not nimbly respond to rate changes because shifting volumes may push MMFs against their concentration limits. As differently sized MMFs seem to exhibit different levels of aversion, dealers borrowing from different subsets of MMFs thus face different demand sensitivity to rate change, leading to the dealers' offering potentially different rates.

In short, differences in MMFs' value for dealer stability and in MMF's aversion to concentration could both contribute to the observed empirical pattern. To account for the effect of these forces in the equilibrium requires building and estimating a structural model of the Triparty market. Such a model must be disciplined by patterns in the data. A search model is unlikely to be a candidate, as the dispersion is observed in the context of repeated interactions between the same set of agents. A model that relies purely on linear utility from pecuniary returns is also likely insufficient, as the agent's optimal choice in a linear utility is to concentrate everything in a single best choice, which is at odds with the observed multiplicity of lending. The first-order importance of dealers' identities in explaining rate dispersion, and the striking simultaneity in MMFs' lending, therefore, lead me to develop a model that features lenders with possibly concave utilities responding to posted, borrower-specific pricing.

4 Model

I now develop a model for borrowing and lending overnight cash via repo on the Triparty market. The aim of the model is to capture the key economic forces that generate the striking patterns in the data. The purpose of the model is to describe Triparty's equilibrium so that the impact of monetary policy tools can be assessed through counterfactual analyses.

The model has two types of agents interacting in the supply and demand of repo investment opportunities. On the demand side, lenders, e.g. MMFs, seek lending opportunities and allocate their overnight cash with possible aversion to portfolio concentration and non-pecuniary preferences for borrowers. On the supply side, borrowers, i.e. dealers, provide borrowing capacities and set repo rates as if they are local monopolies.

4.1 Lender's problem

Let i index lenders and j borrowers. Lender i has a portfolio of investments with one-day maturity, and at each time t, he chooses the share of this overnight portfolio going to each of the J borrowers, x_{ijt}, the share of the portfolio not lent out, x_{izt}, goes to the lender's outside option: safe investments that mature overnight and for which the lender harbors no concentration aversion.[20]

$$U(\mathbf{x_{it}}; \omega, \alpha) = \underset{\mathbf{x_{it}}}{max} \sum_{j=1}^{J} \frac{\omega_{ijt} R_{jt}}{\alpha_{it}} \{\exp(\alpha_{it} x_{ijt}) - 1\} + R_{zt} x_{izt},$$

$$\text{s.t.} \sum_{j=1}^{J} x_{ijt} + x_{izt} = 1, x_1, ..., x_J \geq 0.$$

[20] Examples of the lender's outside option include the RRP and Treasury bills. See section 5.2.

The lender's utility is quasi-linear in his outside option proceeds, which earns a gross return of R_{zt}. His utility from lending to the J borrowers also depends on the gross return of the investment, R_{jt}, which is set by borrowers and taken as given by the lender. However, the utility from repo lending differs from linear utility in two ways. First, his utility from the gross return is scaled by his preference for different borrowers, $\omega_{ijt} \geq 0$. Second, his utility from the shares he lends is possibly concave, with the degree of the curvature controlled by an aversion to concentration parameter, $\alpha_{it} \leq 0$.

From the lender's FOC, the optimal share of portfolio lent to borrower j is:

$$x^*_{ijt} = \frac{\log(R_{jt}) - \log(R_{zt}) + \log(\omega_{ijt})}{-\alpha_{it}}. \tag{1}$$

The optimal share increases in the repo rate borrower j offers and in the non-pecuniary preference j garners. This share decreases in the gross return lender i can earn from the outside option. At a given R_{jt}, R_{zt}, and ω_{ijt}, different lenders will allocate different shares based on their α_{it}. All else equal, the more negative the α_{it}, the smaller the share of portfolio lent to any borrower.

The concentration aversion, α_{it}, controls how distributed lender i's portfolio is and determines i's reaction to repo rate changes. Consider the extreme case of $\alpha_{it} \to 0$: lender i's utility becomes linear in this case and he would concentrate all of his lending into one single best repo investment. As α_{it} becomes more negative, however, the utility becomes more concave, and that compels the lender to spread out his lending, leading to concurrent lending to multiple borrowers and reflecting an aversion to concentration. Intuitively, if the lender is averse to lending too much to any one borrower, then when one of the borrowers raises her rate, the lender will not consolidate his lending to take advantage of this rate increase. The concentration aversion parameter, α_{it}, is thus intimately tied to lender's semi-elasticity. We can see this from the first-order condition of lender's share allocation in Equation 1. Differentiating the optimal share allocation, x^*_{ijt}, with respect to the log of repo rate, the optimal response in share to (percent) rate change is simply $\frac{\partial x^*_{ijt}}{\partial \log(R_{jt})} = -\frac{1}{\alpha_{it}}$. That is, if a borrower doubles the repo rate she offers, the lender who is lending to her would increase his lending by $-\frac{1}{\alpha_{it}}$ of his portfolio.

As documented in Fact 3, there is an empirical relationship between a lender's portfolio size and his aversion to concentration, I therefore parameterize α_{it} as

$$\alpha_{it} = \beta_0 + \beta_1 \cdot \sqrt{y_{it}},$$

where y_{it} is the size of lender's overnight cash portfolio.

The preference, ω_{ijt}, determines to whom i would lend and differentiates by how much i lends to different borrowers. The marginal utility of lending the first dollar to borrower j is $\frac{\partial U}{\partial x_{ijt}}\Big|_{x=0} = \omega_{ijt} R_{jt}$. Given that the lender's cash could otherwise earn a return of R_{zt}, lending to j occurs if and only if $\omega_{ijt} R_{jt} > R_{zt}$. Moreover, since the utility from lending depends on the ω_{ijt}-scaled R_{jt}, differences in ω_{ijt} lead to the same lender lending different shares of his portfolio to different borrowers. I parameterize ω_{ijt} as

$$\begin{aligned} \omega_{ijt} &= \chi_{ijt} \cdot (\nu_{ijt} + \epsilon_{jt}); \qquad (2) \\ \chi_{ijt} &\sim Bernoulli(Logistic(\rho_{ij} + \delta \log(y_{it}))), \\ \nu_{ijt} &\sim 1 + Gamma(shape = k, scale = \psi_j / k), \\ \epsilon_{jt} &\sim LogNormal(\frac{-\sigma^2}{2}, \sigma^2). \end{aligned}$$

χ_{ijt} is a binary random variable that determines whether lender i has a nonzero preference for borrower j. It depends on a borrower-lender pair fixed effect (ρ_{ij}) to reflect that trading is highly persistent. It further depends on the size of the lender's overnight cash portfolio, y_{it}, through δ. This allows for larger lenders to lend to more borrowers, all else equal.[21]

[21] I take the borrower-lender pair effect on the extensive margin as given. The Triparty market has

If the lender has a nonzero preference for a borrower, then his non-pecuniary preference, ν_{ijt}, is drawn from a Gamma distribution[22] whose mean depends on borrower-specific ψ_j. Thus, ψ_j captures the systematic variations in preference ω_{ijt}. This preference parameter, ψ_j, is a reduced form way of capturing the lender's non-pecuniary preferences for a borrower. I speculate that it is driven in part by a preference for reliable borrowing. This interpretation is supported in Table 9, which shows a correlation between the ψ_j parameters I recover and measures of borrower reliability (see section 5.5 for more discussion).

Finally, the model explicitly accounts for possible borrower-time specific shocks to the lender's preference, which are known to market participants but not the econometrician. These "demand shocks", ϵ_{jt}, if present, threaten the OLS identification of the relationship between rate and volume, because these shocks affect the observed lending volume without having observable proxies that one can use to control for their effect.

4.2 Borrower's problem

At each t, borrower j maximizes her profit by choosing the gross repo rate R_{jt} that she offers to all lenders:

$$\max_{R_{jt}} [S_{jt}(Q_{jt}) - R_{jt}] \cdot Q_{jt}(R_{jt}),$$

where $Q_{jt}(R_{jt}) = \sum_i [x_{ijt}(R_{jt}) \cdot y_{it}]$ is the total quantity of funds borrower j obtains at rate R_{jt}, and $S_{jt}(Q_{jt})$ is the average value of funds at Q_{jt}.

Triparty borrowers obtain repo funds because these funds can be used to generate value. For example, the funds could finance a borrower's own security holdings, such as

existed long before my sample began and there is not enough variation to fully micro-found what gives rise to these relationships.

[22] The choice of Gamma ensures positive preferences and gives flexibility in fitting the data. If the *shape* parameter, k is large, the Gamma distribution approximates Normal; if k is small, then the Gamma distribution approximates Exponential.

those obtained during a Treasury security auction. The funds could also be lent out via repo (again) to a borrower's clients, e.g. hedge funds that don't have direct access to the Triparty market. The value that a borrower attaches to her repo funding could depend on the total amount of funds that she obtains. Importantly, the value modeled here reflects the pure economic benefit accruing to the repo funds and is thus *net* of regulatory costs such as balance-sheet cost. Regulatory costs are important in the determination of asset prices, see Du et al. (2020), Duffie and Krishnamurthy (2016). The full cost for a borrower's clients to use repo funds would be the sum of the value of funds, as modeled here, and any applicable regulatory cost.

Differentiating the borrower's problem with respect to repo rate, the first-order condition yields that borrower j's optimal repo rate is:

$$R_{jt}^{*} = \underbrace{S'_{jt} \cdot Q_{jt} + S_{jt}}_{\text{marginal funding value at Q}} - \underbrace{\frac{Q_{jt}}{Q'_{jt}}}_{\text{markdown}} \tag{3}$$

The optimal rate offered by the borrower is a markdown from her marginal value of funds. The magnitude of the markdown is therefore a measure of borrower's market power. This markdown is a direct function of lenders' demand for the borrower's repo borrowing capacity, $Q_{jt}(R_{jt})$. If this demand is elastic, then Q'_{jt} would be large and the markdown would be small. Conversely, the borrower can set a large markdown if the lenders' response to her repo rate changes is inelastic. The ability to set markdown - or the extent of borrower's market power - therefore depends on the lender's concentration aversion (α_{it}) and preference (ψ_j, capturing ω_{ijt}).

5 Estimation

I estimate the lender's problem to separately quantify the two key parameters α_{it} and ψ_j (capturing ω_{ijt}). I first discuss sources of variation, measurement of R_{zt}, and the instrumental variable I employ to achieve identification. I then outline the simulated indirect inference estimation approach that I use. Finally, I present estimated parameters and the implied borrower's markdown.

5.1 Sources of variation

From the lender's FOC (Equation 1), we know that both α_{it} and ω_{ijt} can affect how much lender i lends to borrower j (x_{ijt}) at a given repo rate (R_{jt}). Yet it is possible to separate their effects because α_{it} captures differences across lenders and ω_{ijt} captures differences across borrowers.

Since α_{it} varies by i, comparing lending to the same borrower by different lenders can inform us about the relative magnitude of α_{it}. Similarly, as ψ_j captures the systematic variation in ω_{ijt} and it varies by borrower, comparing lending received by two different borrowers from the same set of lenders can inform us about the relative magnitude of ψ_j.

However, cross-sectional comparisons can only inform about relative magnitude. I pin down the level of these parameters by noting the direct relationship between α_{it} and the demand semi-elasticity. As discussed in section 4.1, the portfolio allocation response of each lender i to borrower j's repo rate change depends on their individual α_{it}. When borrower j is setting her repo rate, the demand function facing her is a function of all the individual α_{it} associated with lenders that lend to her. Estimating the demand semi-elasticity faced by borrowers will therefore inform the average level of α_{it}, and, in turn, the levels of ψ_j.

From estimated α_{it} and ψ_j, we can calculate borrowers' markdown. Borrowers' marginal funding value, according to Equation 3, will be the sum of the estimated markdown and the realized and observed borrower repo rates.

5.2 Measuring R_{zt}, lender's outside option

In lender's FOC (Equation 1), the lending decision directly depends on the comparison between a borrower's offered repo rate (R_{jt}) and the return on lender's outside option (R_{zt}). I will use the higher of the RRP rate or the 1-day Treasury bill yield as R_{zt}.

The lender's outside option is a safe, overnight investment, for which the lender harbors no concentration aversion. Placing repo with the Federal Reserve through the RRP fulfills these functions, making $R_{RRP,t}$ a credible alternative to lending to repo borrowers. Another possible outside option is the 1-day Treasury bill yield. MMFs can invest in Treasury securities that have a maturity of less than one year. Buying Treasury securities is also investing with the U.S. government and thus bears similar attributes to lending to the RRP. However, there is no reported overnight Treasury yield. I thus impute a 1-day Treasury yield by adjusting for the term-structure using the 1-day and the 1-month OIS.

I generate the time series of R_{zt} as 1-day Treasury bill yield before September 2013, and the RRP rate thereafter, as the RRP rate is always higher than the 1-day Treasury bill yield in my sample. In the data, the correlation between the 1-day Treasury bill yield and the median Triparty repo rate is 0.77 before the introduction of the RRP and 0.12 thereafter, supporting my choice of R_{zt}.

The introduction of the RRP cuts the sample that I use in the estimation into two subperiods. The Pre period covers January 2011 through August 2013, and the Post period goes from October 2014 through November 2017. I purposely leave out the September 2013 to September 2014 period, as the RRP was in testing and had a constraining counterparty cap, making it difficult to ascertain the true marginal outside option for lenders. In my estimation, I also exclude all quarter-end months because many regulations are enforced only on quarter-ends. Numerous studies have focused on quarter-ends to study the distortion regulations have on markets (Du et al. (2018), Wallen (2020)). My study aims to reveal the extent of imperfect competition even outside of quarter-ends. The final estimation sample therefore consists of 48 month ends from 2011 through 2017.

5.3 Instrumental variable

Finding the demand semi-elasticity is key to estimating my model parameters. However, the OLS relationship between rate and volume may be biased due to preference shocks that are unobserved by the econometrician (ϵ_{jt} in Equation 2). For example, if there are negative preference shocks, a borrower will be observed to offer a high repo rate but attracting only a modest amount of funds, biasing the true relationship to 0.

I estimate the Triparty market demand semi-elasticity using an instrumental variable that shocks the borrowers' borrowing capacity. The U.S. Treasury department periodically auctions marketable debt securities of various maturities. The amount of securities *offered* to be auctioned likely reflects the Treasury department's fiscal concerns and is plausibly exogenous to borrower-specific preference shocks. At the same time, dealers bid, make markets, and take speculative positions around Treasury auctions (Fleming and Rosenberg (2008)), and they typically finance their Treasury holding with repo, making the amount of Treasury auction correlate with how much borrowers want to borrow. Using Treasury auction offer as an instrument for borrowers' borrowing need, I can find by how much borrowers need to raise their repo rates to attract the desired funding volume.

I collect Treasury auction information from TreasuryDirect, and calculate the amount of *non-bill* Treasury securities *offered* to be auctioned such that they *settle* on the same days as money market fund reporting dates. On these dates, titles transfer and dealers must finance their acquisitions. Repo volumes on settlement days are therefore mostly directly impacted by Treasury auctions. To avoid potential endogeneity between repo rates and how much dealers decide to purchase, I focus on the amount of Treasury securities offered for sale. Finally, I include only auctions of Treasury securities with maturities of 1 year or more, as securities with shorter maturities can also be bought be money market funds and are typically not financed via repo.

Table 5 summarizes the instrument-induced inverse semi-elasticity. All regressions in the table are run at the borrower-time level, as borrowers set borrower-time specific repo rates. Because the instrument shock impacts all borrowers at each point in time, all standard errors are clustered by time (month).

Models (1) and (2) show the first-stage impact of Treasury auction offers on repo volume: $Vol_{jt} = \beta_{1st} TreasuryOffer + BorrowerFE + YearFE + e_{1st,jt}$. Model (1) shows that in the estimation sample period of January 2011-August 2013 and October 2014-November 2017, there is a strong correlation between the amount of Treasury securities offered in auctions and the amount of Triparty repo funding obtained by borrowers. To avoid possible macroeconomic shocks that affect both the Treasury department's decision to raise funding and the Triparty repo market, I add year fixed effects in Model (2). In so doing, my instrument relies on auction variations within the calendar year, which typically reflects tax revenue fluctuations in the fiscal year.[23] The magnitude of the volume response reduces from 46.8 to 16.3, but are still significant at the 5% level. As I measure Treasury auction offers in trillions of dollars, the estimated coefficient imply that a $40 billion, or 1 standard deviation, increase in the amount offered in Treasury auction is associated with an average increase of $0.65 billion in repo borrowing per borrower.

Model (3) shows the repo rate response to instrumented volume change: $\log(R_{jt}) -$

[23]The year fixed effects are, specifically, indicator variables for each of 2011, 2012, 2015, 2016, 2017, and one indicator variable for the first 6 non-QE months in 2013 and the last 2 non-QE months in 2014. The two calendar months included in 2014 are the two calendar months missing in 2013, which completes the fiscal year. Robustness checks using separate fixed effect for 2013 and 2014 show similar results that are more noisely estimated.

$\log(R_{zt}) = \beta^{IV}\widehat{Vol_{jt}} + BorrowerFE + YearFE + e_{IV,jt}$.[24] The estimated coefficient shows that to raise \$1 billion more in repo funding, a borrower needs to raise her repo rate by 1.6 bps. In other words, a 1 bp increase in repo rate is associated with a \$0.62 billion increase in funding per borrower. For the average borrower, this is about 3.5% of her funding. This estimate compares to recent events in the Triparty market. When the Fed unexpectedly raised the RRP rate by 5 bps on June 17, 2021, the RRP saw an overnight inflow of \$225 billion from a base of \$1628 billion Treasury-backed Triparty repo,[25] implying an elasticity of 2.9%. At the same time, this estimate is higher than demand estimates for the Treasury bill market in Greenwood et al. (2015),[26] Duffee (1996),[27] and Bernanke et al. (2004),[28] suggesting that the demand on Triparty is more inelastic.

The first-stage specification in Model (2) features a market-wide instrument, $TsyOffer_t$, which applies to all Triparty borrowers. The IV estimate in Model 3 is therefore the average rate response to the average induced volume. Borrowers may have heterogeneous volume response to Treasury auction offers. If I knew the borrower-specific participation rate in Treasury auctions, I could refine my instrument to be individual shocks that are the product of Treasury auction offer and individual auction participation. This data is not publicly available. In Models (4) and (5), I run a version of this heterogeneous-response IV by using borrowers' average repo share as a proxy for their auction participation.

[24] I obtain borrower-time specific repo rates (R_{jt}) by volume-weighting the observed borrower-lender pair repo rates for Treasury-backed repo with 2% haircut.

[25] The closest public release of the size of the Triparty market is as of June 9, 2021: `https://www.newyorkfed.org/data-and-statistics/data-visualization/tri-party-repo`.

[26] Greenwood et al. (2015) estimates, using instrumental variable on sample from 1983 to 2007, that a 1 percentage point decrease in $\frac{\Delta Treasury}{GDP}$ leads to 38.6 bps decrease in the two-week Treasury yield. The average annual GDP between 2011 and 2017 is \$18.7T. This implies that \$1b increase in the supply of Treasury increases the yield by 0.21 bps.

[27] Duffee (1996) estimates, using data on each January from 1983 to 1994, that 1% increase in 1-month Treasury bill outstanding increases yield by 1.012 bps. The average Treasury bill outstanding over the sample period is \$1.6 trillion, of which roughly 30% is due within a month. This implies that, again, a \$1b increase in 1-month Treasury bill outstanding increases the yield by 0.21 bps.

[28] Bernanke et al. (2004) estimates using Japanese purchase of Treasury securities that a \$1b reduction in Treasury outstanding decreases the yield on 3-month Treasury by 0.18 bps and on 2-year Treasury by 0.55 bps.

Specifically, I calculate each borrower's share in the overall Triparty repo volume at each point in time, and take the time series average to arrive at a time-invariant borrower share. The assumption behind using the product of Treasury auction offer and borrower repo share as an instrument is two-fold. First, borrowers that are more active in repo would also respond more in Treasury auction. Second, since this share is time-invariant, it is not correlated with errors in the IV regression. The estimated inverse semi-elasticity from Model (5) is very similar in magnitude to the estimate in Model (3).

The precision of the instrumental variable estimation depends on the strength of the instrument. The cluster-robust effective F-stat of the instrument in Model (2) is 5.8, below the rule-of-the-thumb threshold of 10. To better understand the implication of using a weak instrument on the IV inference in Model (3), I compute the Anderson-Rubin confidence interval. The Anderson-Rubin confidence interval has the correct coverage regardless of the strength of the instrument and is efficient in just-identified models with a single instrument (Andrews et al. (2019)), as is the case here. When an instrument is too weak for identification, the Anderson-Rubin confidence interval is unbounded. As shown in Model (3) and Figure 5, the 95% Anderson-Rubin confidence interval for this estimation is (0.6, 9.1). This interval is bounded away from the imprecise and near-zero OLS estimate in Model (6), suggesting that the instrument is useful. At the same time, this interval is very wide in the other direction. In other words, there is reasonable confidence that the instrumented semi-elasticity is not zero, however, I am much less certain that the true value is not larger. A larger estimate would mean that borrowers need to raise their rates even more in order to induce additional volume, implying an even more inelastic demand.

5.4 Estimation approach

I estimate the parameters of the lender's model using a mixture of indirect inference (Gourieroux et al. (1993)) and maximum likelihood.

Applying indirect inference, I choose parameters that make up ω_{ijt} and α_{it} such that the data simulated by these parameters would generate moments matching those generated using the original data. The moments that I include summarize the distinct data patterns discussed so far. To inform parameters β_0 and β_1 in α_{it}, I include the IV coefficient on $\widehat{Vol_{jt}}$ (Model (3) of Table 5). This coefficient is a direct function of α_{it}: $\beta_{IV} = \frac{1}{T}\frac{1}{J}\sum_{t\in T}\sum_{j\in J}\left(\sum_{i\in x_{ijt}>0}\frac{y_{it}}{\alpha_{it}}\right)^{-1}$. The parameter β_1 governs the dependence of α_{it} on lender's portfolio size. I therefore include as a moment the regression coefficient on $\log(y_{it})$ in predicting lender's median portfolio share (Model (2) of Table 3). To inform parameters ψ_j in ω_{ijt}, I include the average lender share that each borrower receives conditional on borrowing and the average unconditional fraction of lenders each borrower borrows from.[29] These moments are useful because ψ_j reflect borrower-specific influences on portfolio allocation. Finally, as σ^2 and k ($shape$) determine the variance of ϵ_{jt} and ν_{ijt}, respectively, they determine how much variation in the observed data can be explained by the included model parameters. I use the R^2 from regressing portfolio shares on lender portfolio size and borrower fixed effects,[30] and on lender portoflio size and borrower-time fixed effects[31] to learn about these two parameters.

The χ_{ijt} in ω_{ijt} controls whether a borrower receives funds. I recover the parameters of χ_{ijt} by maximizing the proportion of correctly predicted lending occurrence between

[29]Unconditional probabilities are necessary to inform ψ because there are observations where borrower's repo rate (R_{jt}) is less than the return on the outside option (R_{zt}). To rationalize these observations, not only would χ_{ijt} need to take on the value of 1 (as opposed to 0) but ψ_j also needs to be sufficiently large.

[30]$x_{ijt} = b_{1,\sigma}\log(y_{it}) + BorrowerFE + e_{\sigma,ijt}$, where $\log(y_{it})$ absorbs the effect from α_{it} and $BorrowerFE$ absorbs the effect from ψ_j

[31]$x_{ijt} = b_{1,k}\log(y_{it}) + BorrowerMonthFE + e_{k,ijt}$, where $\log(y_{it})$ absorbs the effect from α_{it} and $BorrowerMonthFE$ absorbs the effect from ψ_j and ϵ_{jt}

each pair at each time. Given the logistic transformation of underlying parameters, the inclusion of pair-specific fixed effect poses a potential incidental parameter problem. I apply the analytical bias correction as suggested by Hahn and Newey (2004) to specifically address this concern. The difference between the bias corrected estimates and the simple maximum likelihood estimates are small because the sample period is moderately large ($T = 48$ for most pairs).

The parameters of the model are over-identified. I weigh the moments using the inverse of the variance-covariance matrix for moment conditions calculated in bootstrapped samples. The bootstrapped samples are bootstrapped in blocks of time (month) clusters, in accordance with the IV regression. Throughout, a key assumption is that the size of lender's portfolio, y_{it} is exogenous. This is plausible as overnight cash portfolios serve money market fund's liquidity needs and tend to be a stable fraction of the fund's overall AUM.

5.5 Results and discussions

The model parameters estimated using indirect inference are summarized in Table 6, along with their time-clustered block-bootstrapped confidence intervals. The maximum likelihood estimate of δ is separately reported in Table 7.[32]

The two moments that inform β_0 and β_1 are well matched, see Figure 6. The estimated β_0 and β_1 show an α_{it} with a mean of -0.045 and an interquartile range of (-0.033, -0.056). The estimated α_{it} is less than 0, indicating that lenders do exhibit aversion to portfolio concentration. Since $\frac{\partial x^*_{ijt}}{\partial \log(R_{jt})} = -\frac{1}{\alpha_{it}}$, on average, a 1 bp increase in the repo rate attracts an additional 0.2% of a lender's portfolio. Consider that the average lender portfolio size is about \$29b, and that borrowers have, on average, 10 links, this estimate suggests that 1 bp increase leads to \$0.64b increase in borrower funding, which closely tracks

[32] Pair-specific fixed effects ρ_{ij} are omitted for brevity and are available upon request.

the IV estimate. Relative to the IV estimate, which is a market-level semi-elasticity, it is now possible to examine the elasticity facing individual borrowers. Table 8 shows that if borrowers were to raise the price offered by 1 basis point, they would increase their funding between 1.3% and 6.3%. Of note: Goldman Sachs and the Royal Bank of Canada, who offer among the lowest rates, both face among the highest elasticity. This suggests that the aggressive pricing borrowers deploy comes with the trade-off of being on the more elastic portion of the demand curve. The estimated ψ_j has a median of 16 bps and a mean of 20 bps, with an interquartile range of (10 bps, 20 bps), and a range of 55 bps. Using the median as the representative centroid, we see that lenders in the model typically perceive a 16 bps increase to their utility on the *first* dollar lent to borrowers.[33] As a thought experiment, if a new borrower appears on the market and receives no lender preference, then she would need to offer 16 bps more than the typical, existing borrower.

One possible explanation for lender's preferences for specific borrowers is reliability. I find that my estimated parameters do indeed correlate with borrower's reliability in repo activities. In Figure 7, I show the correlation between the estimated ψ_j (the mean of ω_{ijt}) and a measure of borrower's reliability. I proxy a borrower's reliability with her average coefficient of variation in volume vis-à-vis lenders: $\overline{CoefVar}_j = mean_j(\frac{SD_{ij}(vol_{ijt})}{mean_{ij}(vol_{ijt})})$. The lower the coefficient of variation, the more reliable a borrower is in using her balance sheet to provide consistent repo investment opportunities. The estimated ψ_j shows a strong and negative correlation with borrower's average coefficient of variation. In Table 9, I explore the correlation between estimated ψ_j with both the average and the median of borrower's coefficient of variation, as well as with creditworthiness as measured in CDS rates. The conventional CDS contract varies by jurisdiction,[34] yet even after controlling

[33]In the model, ω_{ijt} (whose conditional mean is ψ_j) enters the lender's utility as a multiplier to gross repo rates. Here, I suggest an additive increase heuristically because gross repo rates are close to 1 and the first order condition is in based on the logs of R_{jt} and ω_{ijt}.

[34]The most common CDS terms are no restructuring (XR) in the U.S., modified restructuring (MM) in the EU, and full-restructuring (CR) in Japan.

for jurisdictions, that is, comparing estimated ψ_j with CDS rates among borrowers within the same jurisdiction, CDS rates still do not appear to be a significant predictor of ψ_j. In contrast, measures of borrower's reliability are strongly correlated with estimated ψ_j.

Having estimated α_{it} and ω_{ijt} in the lender's problem, we can now calculate borrower's markdown based on Equation 3. In the cross-section, the time-series average of each borrower's markdown has an interquartile range of (24 bps, 41 bps) and a range of 61 bps; see Table 8. Compared to the cross-section of borrowers' time-series average repo rates,[35] which has a range of 9 bps, we see that the observed dispersion in repo rate belies a much larger dispersion in borrowers' markdown. The large variation in borrowers' markdown is reminiscent of the spread in lenders' preference for borrowers (ψ_j of ω_{ijt}). Indeed, lenders' aversion to concentration gives rise to borrowers' market power, and the extent of this market power depends on distinct borrower characteristics (i.e. reliability). In deriving borrower's markdown from Equation 3, we moreover see a possible reason behind borrowers' divergent reliability. Because borrowers' value of funding, S_{jt}, is net of regulatory cost, for borrowers whose scarce balance sheets can be used for more lucrative intermediation, repo comes at a high opportunity cost.

It is instructive to also look at the time series of borrowers' markdown. In Figure 8, I plot the time series of the median borrower's markdown through the estimation period. The average of the median markdown over the sample period is 27.5 bps. Compared to the 5.6 bps average spread between the median Triparty repo rate and lender's outside option, borrowers extract 83% of the (27.5 + 5.6 =) 33.1 bps total surplus in the Triparty market.

Several recent studies have estimated, in various markets, the difference between the rate that large financial intermediaries pay on funding and the implied rate when that funding is used (e.g., van Binsbergen et al. (2021), Song and Zhu (2019)). One paper,

[35] Net of R_{zt} (i.e. 1-day Treasury bill yield before 2014 and the RRP rate after) to be comparable across interest rate environments.

Fleckenstein and Longstaff (2020), is particularly relevant. The authors calculate the basis between the rate in the Treasury cash market and the rate implied in the Treasury futures market. As the Treasury cash rate is also a repo rate,[36] and the Treasury cash-futures trade is nearly riskless, this Treasury cash-futures basis closely relates to the markdown I calculate. For every dollar of funding that a borrower wants to obtain on Triparty, he could use the same balance sheet space to engage in a (nearly) riskless Treasury cash-futures trade. The borrower who comes on Triparty must therefore earn a markdown that is at least as large as what he can arbitrage through Treasury cash-futures, net of regulatory cost. Over my sample period, the Treasury cash-futures basis is about 47.6 bps. Viewed through the lens of my model, this basis estimate and my markdown estimate jointly imply a balance-sheet cost (regulatory cost) of about 20 bps. They further imply that over half of the near-arbitrage basis exists because of dealers' market power.

In the time-series, there is noticeable a 11 bps drop in the level of the markdown before vs. after the introduction of the RRP. The magnitude of the markdown not only reflects borrowers' market power, but also directly affects the funding cost of other securities that rely on the Triparty market. How much of this reduction in markdown owes to the Fed's action through the RRP? I answer this question by comparing my estimated markdown with the markdown in a counterfactual world where the RRP did not exist.

6 Counterfactual

In this section, I first calibrate a version of the borrower's problem. Then combining estimates from the lender's and the borrower's problem, I consider two policy questions through counterfactual analyses. First, what would be the equilibrium Triparty repo

[36]The Treasury repo rates used in Fleckenstein and Longstaff (2020) are obtained from the dealer-to-dealer bilateral market, where collateral posting requires specifying the CUSIPs of the Treasury securities used.

rate relative to the Fed's policy target if the RRP were not established? Second, how would the importance of the RRP change if the 2016 Money Market Fund Reform did not happen?

6.1 Calibrating borrower's problem

The relationship between borrower's optimal rate, her marginal value, and her markdown, as shown in Equation 3, remains valid irrespective of the parameterization of borrower's funding value. I now specify the dependence of borrower funding value on quantity as: $S_{jt} = \hat{S}_{jt} - \zeta \cdot \log(Q_{jt})$. This functional form reflects possible diminishing marginal returns in the quantity of funding. The first-order condition of the borrower's problem now becomes

$$\max_{R_{jt}}(S_{jt}(Q_{jt}) \cdot Q_{ijt}(R_{jt}) - R_{jt} \cdot Q_{ijt}(R_{jt}))$$
$$R^*_{jt} = \underbrace{\hat{S}_{jt} - \zeta - \zeta \log(Q_{jt})}_{\text{marginal funding value at Q}} - \frac{Q_{jt}}{Q'_{jt}}.$$

I calibrate ζ using the 2016 Money Market Fund Reform. In 2016, the money market fund industry underwent a major reform aimed at addressing practices that made the MMF industry vulnerable during the financial crisis of 2007-2008. One of the biggest changes is the mandate for prime funds to keep a floating instead of fixed NAV. This caused an outflow of AUM from prime funds, which mostly invest in unsecured securities such as commercial paper, to government funds, which mostly invest in Treasury securities and could keep using a fixed NAV. As Figure 10 illustrates, the share of government funds increased to about 75% from 25%. This happened against a backdrop of almost constant total AUM in MMF. Government funds typically keep a larger fraction of their AUM in overnight cash.[37] Consequently, the amount of overnight cash in the industry as a whole

[37] Government funds can only invest in a limited number of securities. To improve their yield, government funds invest heavily into longer maturity government securities. To comply with regulations on

increased from about 10% in 2015 to almost 20% in 2017.

The MMF reform introduced an increase in the amount of cash seeking repo investment opportunities. As this increase is plausibly exogenous to variations in borrowers' marginal value of funding, if borrowers drop the repo rates they offer, that decrease likely reflects a deterioration in funding value. I therefore use the MMF reform as an instrument for increases in funding that borrowers have to absorb, and estimate the corresponding repo rate change. Specifically, I construct an indicator of MMF reform that takes the value 1 on or post October 2016, when the MMF reform was fully implemented, and take the value 0 before, and I estimate $\log(R_{jt}) - \log(R_{zt}) = b_1 \widehat{vol}_{jt} + BorrowerFE + e_{1,jt}$, where $\widehat{vol}_{jt} = b_0 \mathbf{1}_{t \geq 201610} + BorrowerFE + e_{0,jt}$. I estimate using observations in the one year before and after October 2016. Results of the estimation are summarized in Table 10. On average, a borrower had to absorb \$2.1b more because of MMF reform, and each additional billion of funding lowered the repo rate she offered by about 0.6 bps.

This estimate of $\frac{d \log R}{dQ}$ can be used to inform ζ, as $\zeta = -2QR \cdot \frac{d \log R}{dQ}$. Based on the average value of Q, R in the estimation period, I derive a ζ of 1.86×10^{-3}. In Appendix section A, I discuss the sensitivity of counterfactual results to different values of ζ.

6.2 Triparty without RRP

The Fed instituted the Reverse Repo Facility in anticipation of increasing its policy interest rate. The RRP is thought to have put a floor on repo rates, which allowed the Fed to successfully raise the interest rate 4 times between 2015 and 2017, even as the Fed's usual tool – reserve supply adjustment – was made obsolete by the abundance of reserves during this period. If the RRP were not available, would the Triparty repo rate still have conformed to the Fed's policy target?

To answer this question, I first conduct a counterfactual where I assume that, in the

the fund's average maturity, they keep a larger overnight cash portfolio. Industry participants refer to this as the "barbell strategy".

absence of the RRP, the Triparty lenders would have as their outside option the realized historical 1-day Treasury yield. As Panel A of Figure 9 illustrates, this new outside option is on average 12 bps lower than the RRP between 2014 and 2017. Given this change, repo borrowers would lower the rates they offer. Panel B of Figure 9 illustrates the median counterfactual repo rate. On average from October 2014 to November 2017, the counterfactual median Triparty repo rate is down 8 basis points from historical, which puts the median Triparty rate at 3 bps below the lower bound of the Federal Reserve's policy target. A drop in the repo rates notwithstanding, because borrowers would still offer rates that are higher than the outside option, the total volume to repo borrowers actually increases by on average $40b per month, as illustrated in Panel C of Figure 9.

Although the total volume to Triparty borrowers increases, this increase is not enough to offset the amount of cash the lenders used to place at the RRP. In fact, in this scenario (#1), about $109b/month would be redirected from the RRP to the new outside option, the Treasury bills. This represents a sizeable additional demand for Treasury securities, and likely would have changed the equilibrium Treasury yield.

I therefore consider a second scenario where, as in scenario #1, lenders put the cash not lent to repo borrowers in Treasury bills instead of the RRP. However, the yield that lenders get from investing in Treasury bills is no longer the historical 1-day yield. Instead, I allow the Treasury market to respond to the inflow of cash, even as I allow the Triparty agents to re-optimize concurrently. Using the Treasury elasticity estimate from Greenwood et al. (2015), where 1 percentage point decrease in $\frac{\Delta Treasury}{GDP}$ leads to 38.6 bps decrease in Treasury yield, I search for the new Triparty equilibrium, letting both the Triparty market and the Treasury market adjust.[38] Table 11 reports this new equilibrium relative to historical. The counterfactual median Triparty rate is lower in this second scenario than in the first, because the Treasury yield declines in response to

[38]See Appendix section A for the sensitivity of counterfactual results to different values of Treasury yield sensitivity.

inflows of cash displaced from the RRP. Indeed, the new median Triparty rate is 16 bps below historical. This puts the counterfactual median Triparty repo rate at 11 basis point below the lower bound of the Fed's policy target. Importantly, borrower's market power expands by 9 bps, leaving the passthrough rate to the broader financial market lower by a more modest 7 bps.

The counterfactual estimates show that the RRP buoyed up the Triparty repo rate by as much as 64% of a typical 25-bps rate hike. More than half of the RRP's impact comes from constraining the borrower's market power through giving the lenders a better outside option.

6.3 Absence of MMF Reform

The 2016 MMF Reform discussed in section 6.1 represented a major change to the money market fund industry. What would have happened to the Triparty market if the reform didn't happen? More specifically, what would have been the Triparty equilibrium if the share of government funds didn't increase so that the amount of overnight cash lenders have remained at their 2015 level?

I consider this experiment in two steps, and summarize the results in Table 11. First, I assume that while the MMF Reform did not happen, the RRP was still available. In this third counterfactual scenario, the lenders' overnight cash portfolios in 2016 and 2017 are assumed to be the same percent of AUM as in 2015, effectively reducing the portfolios' size. As lenders become smaller, they lend less to repo borrowers, pushing up borrowers' marginal funding values, and the counterfactual median Triparty rate in this third scenario is in fact higher than historical.

Next, I bring the policy discussions together in one scenario by assuming that the MMF reform didn't happen *and* the RRP were not available *and* the lenders had as their outside option a Treasury market that adjusted to inflows. In this fourth scenario, the impact of removing RRP is much smaller. The median counterfactual repo rate in scenario #4 is 10 bps below historical, compared to 16 bps in scenario #2. This difference owes to a more rate-sensitive lender community. As lenders' portfolios become smaller, they are less averse to concentrated portfolios and are more nimble to respond to rate changes. Consequently, borrowers cannot extract as large a markdown, even as their marginal funding value increases due to smaller funding quantity.

In summary, the difference between the counterfactual results in scenario #3 and scenario #4 highlights the Triparty lenders' reliance on the RRP to constrain borrower market power. Moreover, contrasting the counterfactual results in scenario #4 with those in scenario #2, we see that the lenders' reliance on the RRP grows only stronger as the lenders themselves have more cash to deploy.

7 Conclusion

Leveraging the institutional and empirical features of the Triparty repo market, I describe Triparty's equilibrium using a system of demand and supply. I identify substantial market power enjoyed by the Triparty cash-borrowers (dealers). My estimated model allows me to assess the effect of the Reverse Repo Facility through counterfactual analyses. By constraining borrowers' market power, the RRP meaningfully buoyed up the equilibrium Triparty repo rate and moderately lifted the rate passed on from the Triparty market to the broader economy.

The competitive environment facing financial intermediaries directly affects asset prices and the transmission of monetary policy. An understanding of the impact on intermediaries' competitive environment is thus requisite of any effective policy design.

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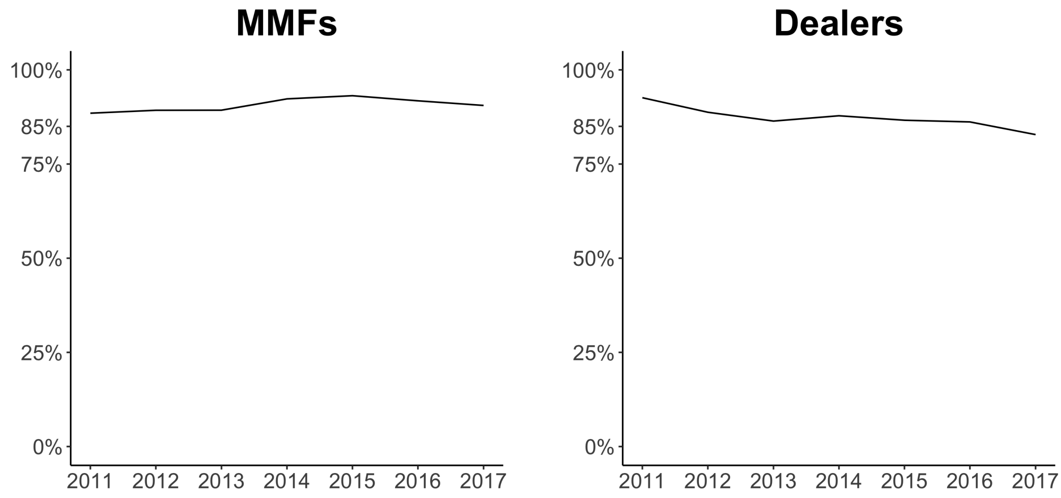
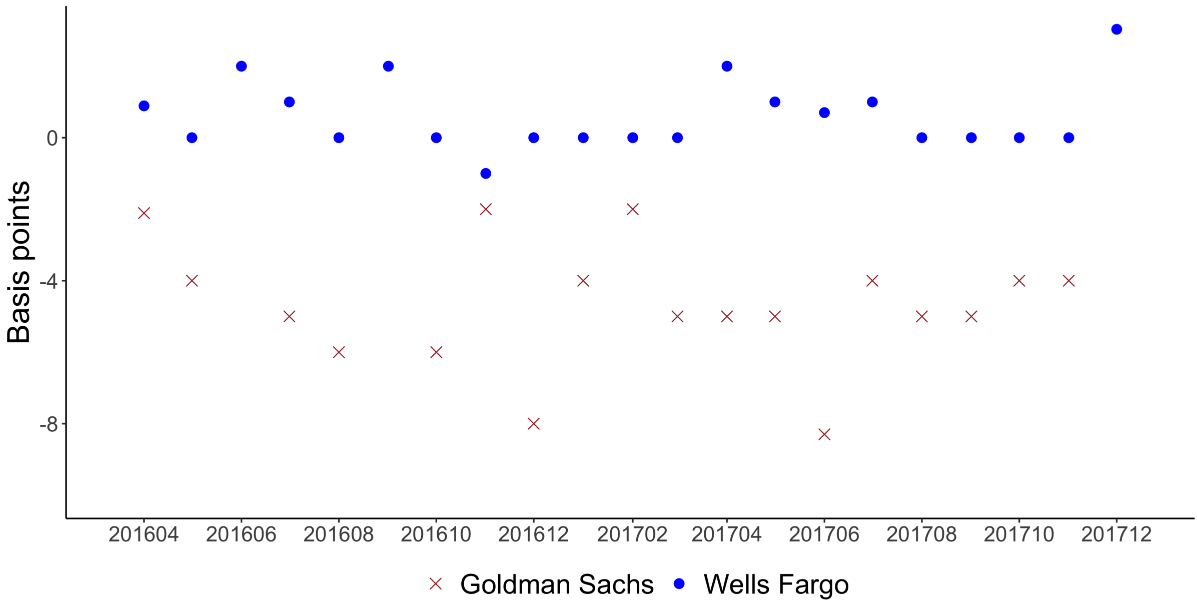
Tables and Figures

Figure 1: **Percentage of overnight repo market represented by top 18 MMFs and top 20 dealers in the sample**



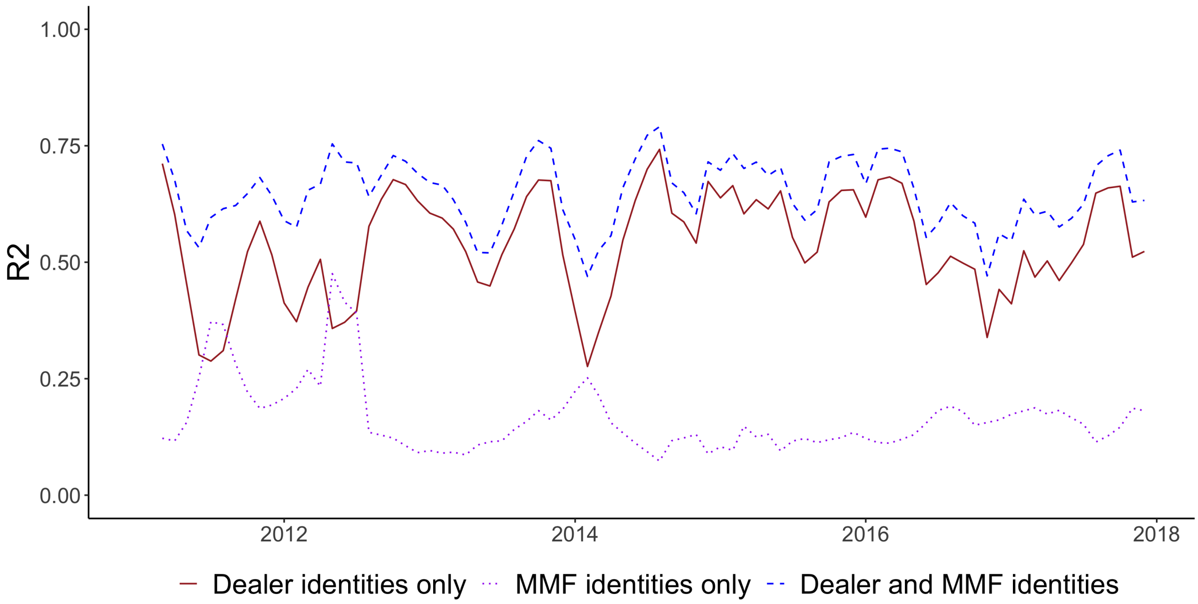
Notes: This figure plots, on the left, the share of overnight repo done by the top 18 money market fund families relative to all overnight repo done by money market funds that filed N-MFP reports between January 2011 through December 2017. Plotted on the right is the share of overnight repo done by the top 20 dealers relative to all dealers based on money market funds' N-MFP reports from January 2011 through December 2017.

Figure 2: **Select repo rates (relative to median) of BlackRock's lending**



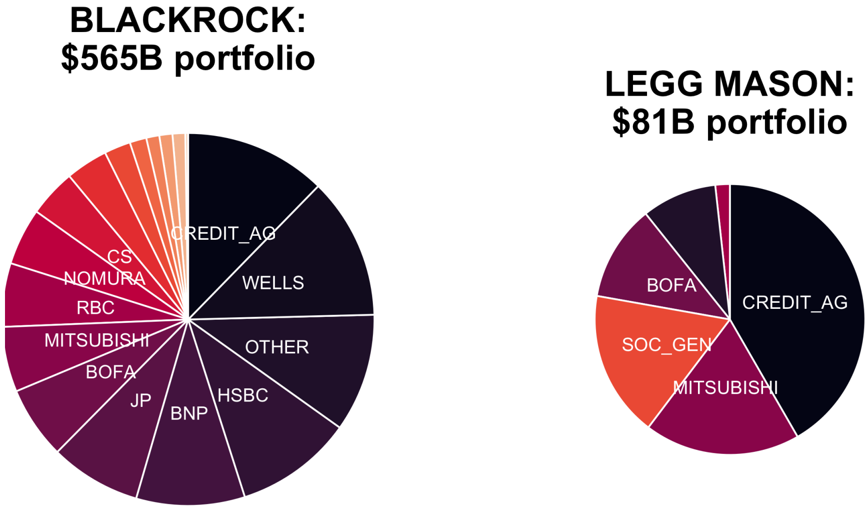
Notes: This figure plots the repo rates accepted by BlackRock for lending to Goldman Sachs and Wells Fargo via overnight repo collateralized by Treasury securities with 2% haircut. The repo rates are reported as gross rates less the daily median repo rate and are stated in basis points. Two outliers are omitted: the repo rate by Goldman Sachs was 20 bps below median on September 2016, and 12 bps below median on December 2017.

Figure 3: **Decomposition of cross-sectional variation in rate dispersion**



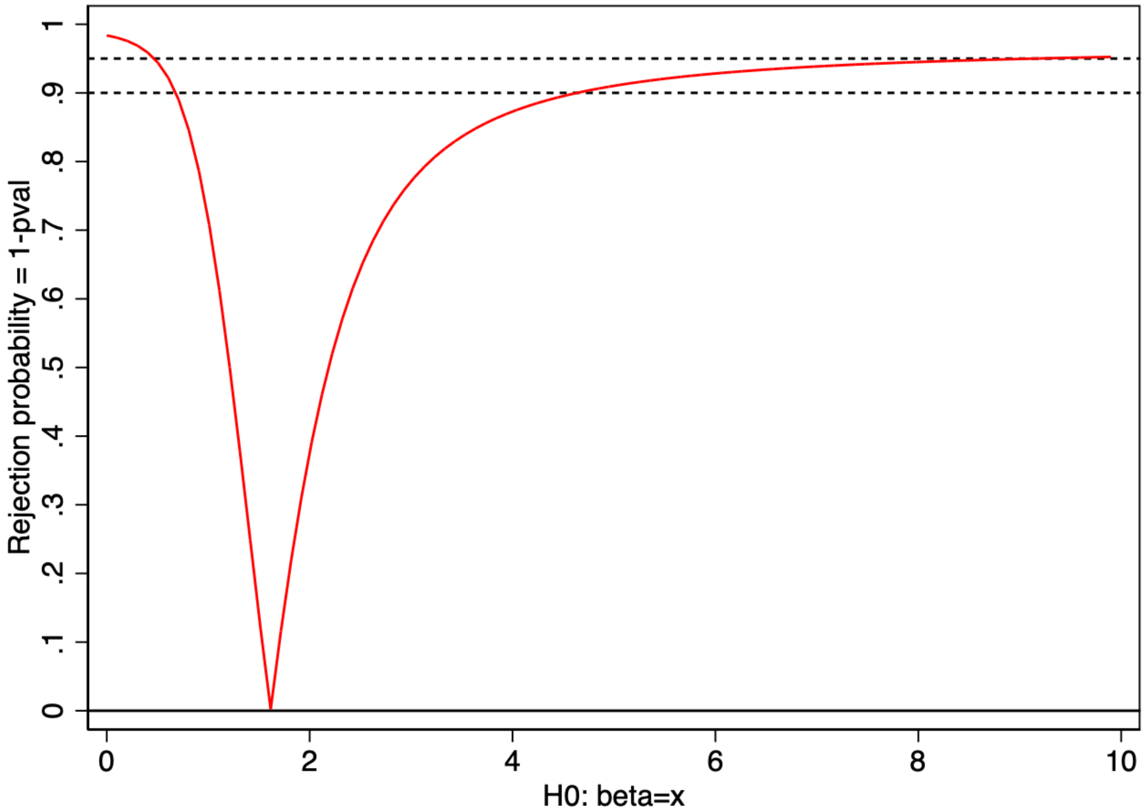
Notes: This figure plots the three-month rolling average of the R^2 from monthly cross-sectional regressions of repo rates on MMF and dealer fixed effects. Repo rates are measured as gross repo rates less the daily median repo rate, and are for overnight repo collateralized by Treasury securities with 2% haircut. The solid red line is the R^2 from regressing repo rates on dealer fixed effects, the dotted purple line is the R^2 from regressing repo rates on MMF fixed effects, and the dashed blue line is the R^2 from regressing repo rates on dealer fixed effects and MMF fixed effects. The sample period is from January 2011 through December 2017.

Figure 4: **Select MMF repo portfolios in 2016**



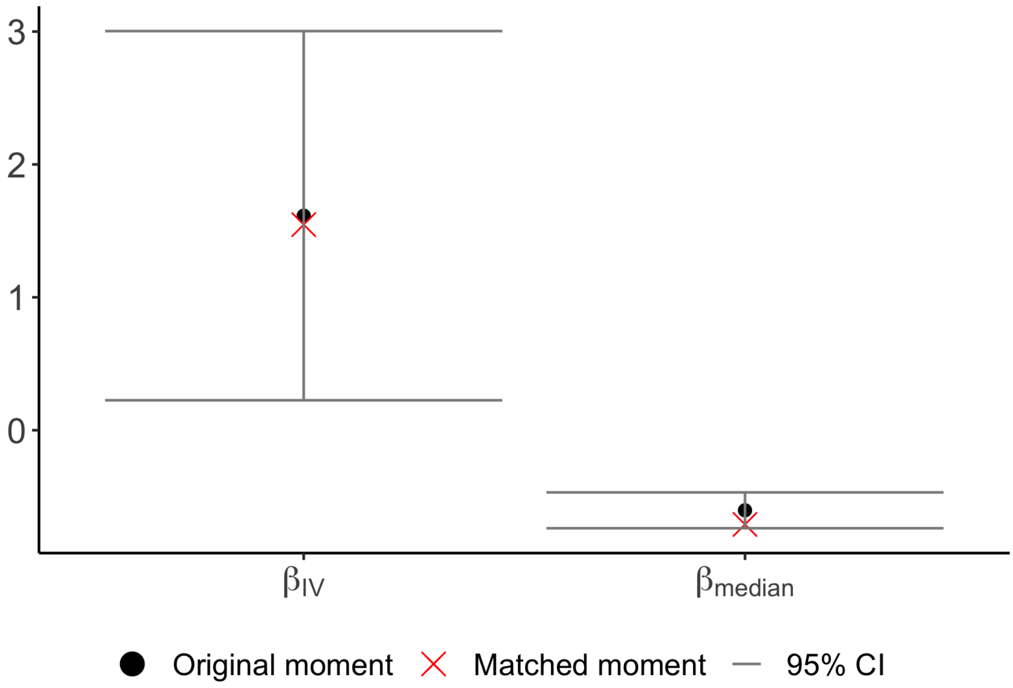
Notes: This figure plots the repo lending to dealers by BlackRock and Legg Mason in 2016. The size of the pie corresponds to BlackRock and Legg Mason's annual overnight repo lending volume, as labeled. The size of each slice represents the share of the portfolio lent to different dealers.

Figure 5: **Anderson-Rubin test of instrumental variable estimate**



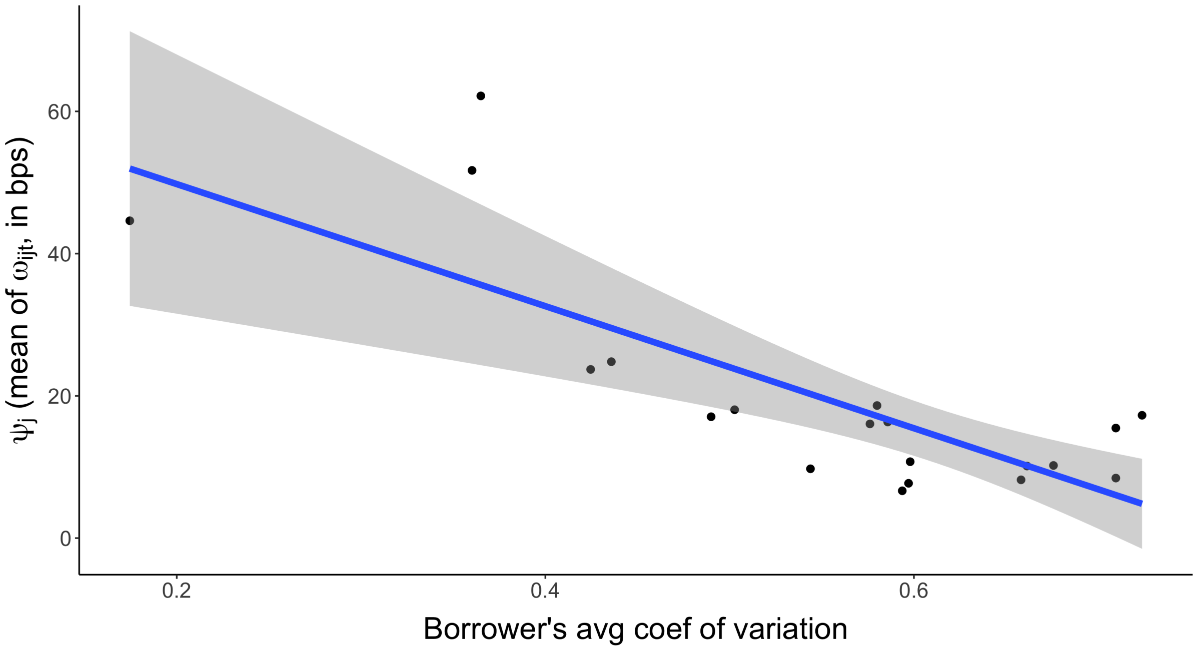
Notes: This figure plots the Anderson-Rubin rejection probability for the null hypothesis that the true β_{IV} equals to a given value on the x-axis. β_{IV} is estimated from $\log(R_{jt}) - \log(R_{zt}) = \beta_{IV}\widehat{vol}_{jt} + BorrowerFE + YearFE + e_{IV,jt}$ in the model estimation period of January 2011 to December 2017, excluding September 2013 through September 2014 when RRP was first introduced and was in testing, and excluding months that fall on quarter ends. The horizontal dashed lines are at y = 0.9 and y = 0.95. The points where the solid red line crosses the dashed lines represent, respectively, the end points of the Anderson-Rubin 90% confidence interval and 95% confidence interval for the null hypothesis.

Figure 6: **Moment comparison between data and simulation**



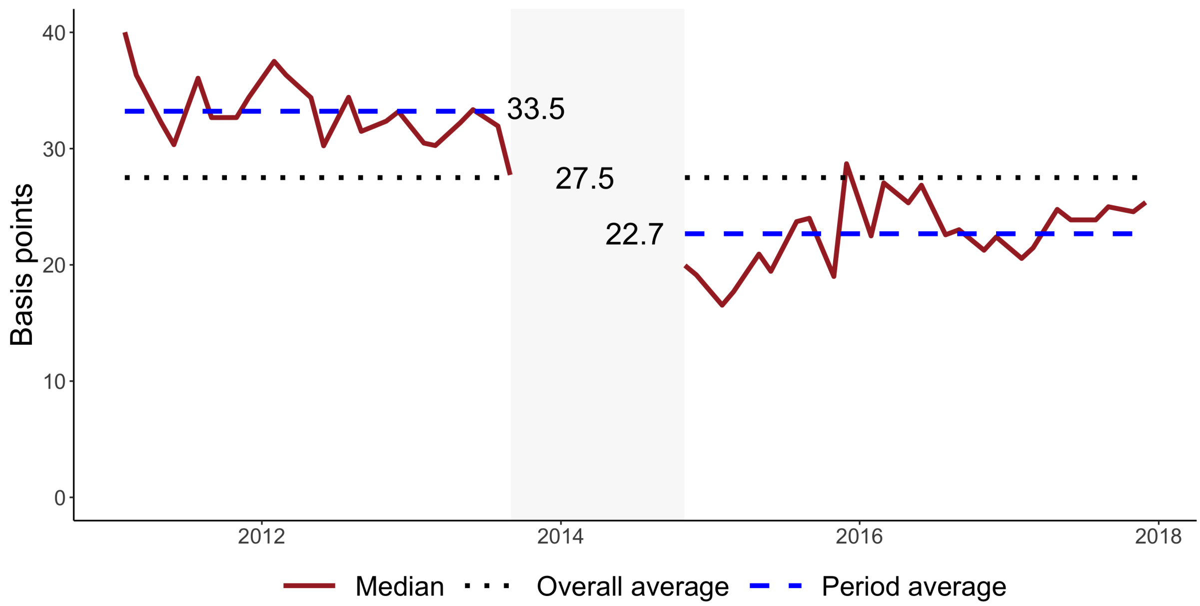
Notes: This figure plots two moments evaluated in the original sample data ("Original moment") and in model-simulated data ("Matched moment"). The two moments are the regression coefficients from the IV-estimated inverse elasticity (β_{IV}, Model (3) of Table 5) and from the relationship between median portfolio share and portfolio size (β_{median}, Model (2) of Table 3). The matched moment is calculated as the average moment value in 50 sets of data simulated using the estimated parameters. The estimates of β_{median} are scaled by a factor of 10 for presentation. The grey bars signal the bounds of 95% confidence interval, clustered by time (month). The model estimation period is January 2011 to December 2017, excluding September 2013 through September 2014 when RRP was first introduced and was in testing, and excluding months that fall on quarter ends.

Figure 7: **Correlation between estimated borrower preference and coefficient of variation in volume**



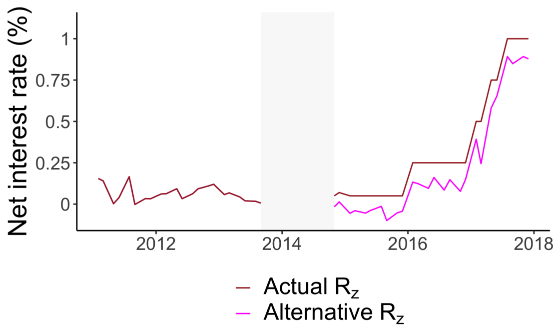
Notes: This figure plots estimated ψ_j against borrower's average coefficient of variation. The blue line represents the fitted value from regressing ψ_j on borrower's average coefficient of variation and the shaded regions is the 95% heteroskedasticity-robust confidence bands. Borrower's average coefficient of variation is as defined in section 5.5, and is the by-borrower average of borrower-lender coefficient of variation in repo volume throughout the model estimation period. The model estimation period is January 2011 to December 2017, excluding September 2013 through September 2014 when RRP was first introduced and was in testing, and excluding months that fall on quarter ends.

Figure 8: **Triparty borrower markdown**

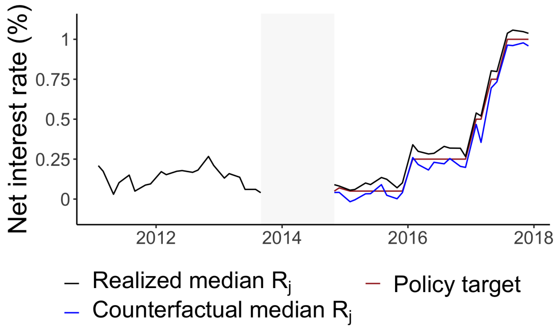


Notes: This figure plots, in solid red, the time series variation in the median borrower markdown over the model estimation period. The dotted black line indicates the average of this value over the whole sample. The dashed blue lines indicate the average of this value in the pre- and post-RRP periods. The shaded area correspond to September 2013 through September 2014 when RRP was in testing. The model estimation period is January 2011 to December 2017, excluding September 2013 through September 2014 and months that fall on quarter ends.

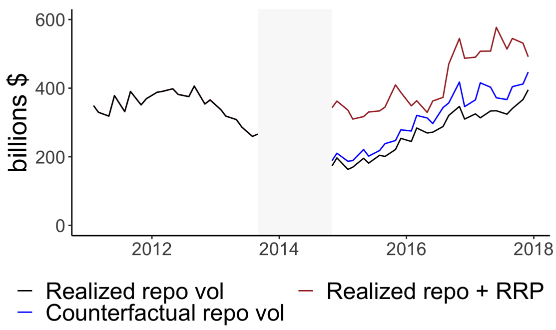
Figure 9: **Scenario: no RRP, lenders access historical Treasury yield**



(a) **Counterfactual** R_{zt}



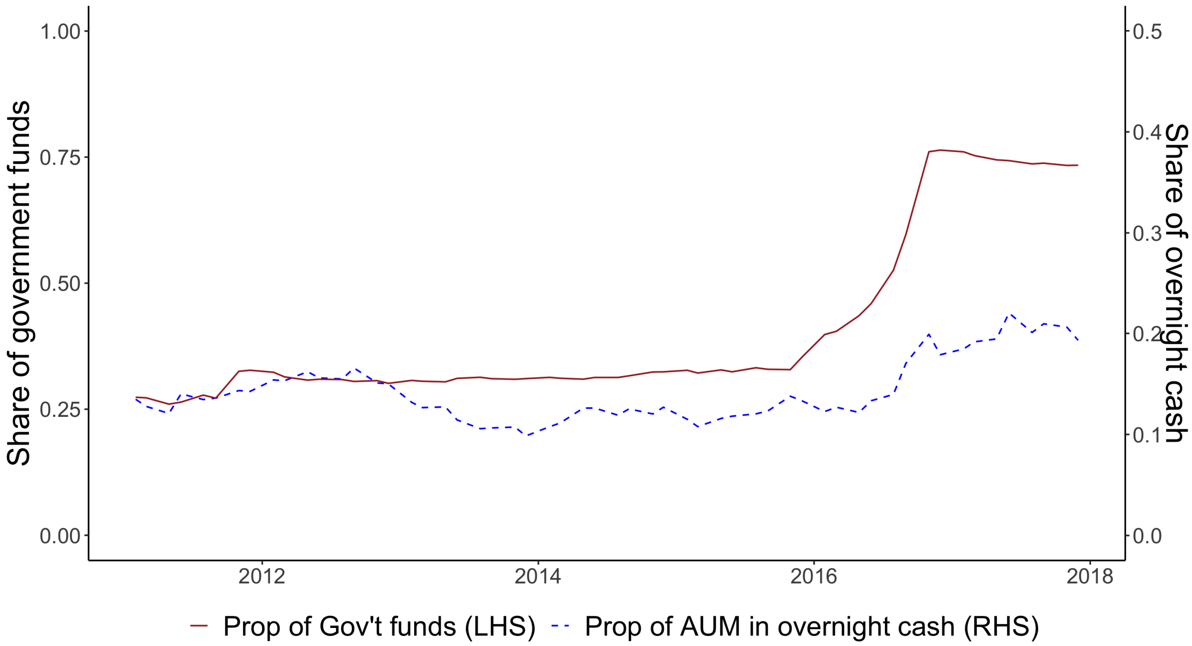
(b) **Counterfactual rate**



(c) **Counterfactual volume**

Notes: This figure plots the counterfactual median Triparty repo rate and the total Triparty repo volume in scenario #1: the RRP were not available in 2014 through 2017 and lenders considered the historical 1-day Treasury yield as the outside option to lending to borrowers. Panel A shows the actual R_{zt} in red, which is the 1-day Treasury yield before 2014 and the RRP rate after 2014; and it shows the alternative R_{zt} in pink, which is the 1-day Treasury yield throughout. Panel B shows the counterfactual median Triparty repo rate in blue, against the realized (historical) median Triparty repo rate in black, and the lower bound of the Fed's policy target in red. Panel C shows the counterfactual total repo lending to Triparty dealers in blue, the historical total repo lending to Triparty dealers in black, and the historical total lending to dealers and the RRP in red. The shaded area correspond to September 2013 through September 2014 when the RRP was in testing. The model estimation period is January 2011 to December 2017, excluding September 2013 through September 2014 and months that fall on quarter ends. This figure is best viewed in color.

Figure 10: **Share of MMF AUM in Government Funds and in Repo**



Notes: This figure plots in solid red and against the y-axis on the left, the proportion of MMF AUM in government funds. This figure plots in dashed blue and against the y-axis on the right, the share of total AUM that is overnight cash, measured as lending via overnight repo to dealers and to the RRP.

Table 1: **Within dealer characteristics and rate dispersion**

	Deviation of Treasury repo rate from median					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Pair Treasury repo volume	0.012					0.050
	(0.022)					(0.040)
Pair vol as percent of MMF		0.038				-0.590
		(0.356)				(0.403)
Pair vol as percent of dealer			0.250			0.442
			(0.238)			(0.342)
MMF total Treasury repo vol				-0.007		-0.013
				(0.007)		(0.013)
MMF number of counterparty					-0.011	-0.008
					(0.011)	(0.017)
Dealer + Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	10740	10740	10740	10740	10740	10740
R^2 (full model)	0.228	0.228	0.228	0.228	0.228	0.229
R^2 (proj model)	0.000	0.000	0.000	0.000	0.000	0.001

Standard errors in parentheses.

Notes: In this table, repo rates are regressed on MMF characteristics and MMF-dealer pair characteristics, as well as dealer fixed effects and month (time) fixed effects. Repo rates are for lending between MMF-dealer pairs via overnight repo collateralized by Treasury securities with 2% haircut, and they are measured as deviation from the daily median. "Pair Treasury repo volume" is the amount of overnight repo lending collateralized by Treasury securities with 2% haircut on the day of the observation between a pair of MMF-dealer. "Pair vol as percent of MMF" is the pair's volume as a percentage of the MMF's total lending via overnight repo collateralized by Treasury securities with 2% haircut. "Pair vol as percent of dealer" is the same ratio against the total borrowing of the dealer. "MMF total Treasury repo vol" is the MMF's total amount of lending via overnight repo collateralized by Treasury securities with 2% haircut, on the day of the observation. "MMF number of counterparty" is the number of dealers that MMF lends to via overnight repo collateralized by Treasury securities with 2% haircut on the day of observation. The sample period is from January 2011 through December 2017. Standard errors are clustered by dealer. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table 2: **Model fit with dealer vs. MMF-dealer pair fixed effects**

	Deviation of Treasury repo rate from median			
	Model 1	Model 2	Model 3	Model 4
Dealer FE	Yes	No	Yes	No
MMF-Dealer Pair FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes
Num. obs.	10740	10740	10740	10740
Num of FE	20	272	26	278
R^2	0.18	0.25	0.19	0.26
AIC (in 1000s)	42.67	42.22	42.52	42.07
BIC (in 1000s)	42.82	44.21	42.72	44.10

Notes: This table reports the goodness of fit for regressions of repo rates on dealer fixed effects or MMF-dealer pair fixed effects. Repo rates are for lending between MMF-dealer pairs via overnight repo collateralized by Treasury securities with 2% haircut, and they are measured as deviation from the daily median. Goodness of fit measures are R^2, Akaike information criterion (AIC), and Bayesian information criterion (BIC). The estimation sample is January 2011 through December 2017.

Table 3: **MMF size and portfolio composition**

	Number of dealers	Median portfolio share		
	Model 1	Model 2	Model 3	Model 4
Constant	1.332	0.267***	0.267***	
	(1.040)	(0.037)	(0.034)	
Log(MMF portfolio size)	3.063***	-0.067***	-0.066***	-0.053**
	(0.303)	(0.013)	(0.019)	(0.019)
Number of dealers			-0.000	
			(0.003)	
Num. of dealer FE	No	No	No	Yes
Num. obs.	1467	1467	1467	1467
R^2 (full model)	0.560	0.525	0.525	0.611
R^2 (proj model)	0.560	0.525	0.525	0.236

Standard errors in parentheses.

Notes: This table reports regressions of the extensive and intensive margins of MMFs' portfolio on MMFs' overnight portfolio size and a constant. Model (1) uses the number of dealers that a MMF lends to. Models (2) through (4) use the median share of MMF's portfolio lent to dealers. The number of dealers a MMF lends to is included as a regressor in Model (3) and as fixed effects in Model (4). The sample period is from January 2011 through December 2017. Standard errors are clustered by MMF. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table 4: **Dealer repo activities on quarter-ends**

	Dealer repo volume (vol_{jt})		Log(dealer repo volume)		Dear rate
	Model 1	Model 2	Model 3	Model 4	Model 5
QE	0.844	0.717	0.086	0.078	-0.048
	(0.733)	(0.872)	(0.087)	(0.082)	(0.299)
QE * Dealer EU	-7.758***	-7.712***	-0.498***	-0.494***	-0.045
	(1.203)	(1.225)	(0.120)	(0.111)	(0.349)
QE * Dealer JP	-0.617	-0.598	-0.080	-0.082	0.253
	(2.704)	(2.532)	(0.233)	(0.204)	(0.612)
QE * Dealer UK	-4.531***	-4.428***	-0.346**	-0.338***	0.108
	(1.656)	(1.473)	(0.151)	(0.130)	(0.345)
QE * Dealer US	-1.655	-1.546	-0.156	-0.149	0.138
	(1.395)	(1.424)	(0.112)	(0.106)	(0.385)
Avg change: EU, UK	-6.989	-6.787			
Avg change: CA, JP, US	-1.039	-0.954			
Dealer HQ FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	No	Yes	No	Yes	Yes
Num. obs.	1419	1419	1419	1419	1419
R^2 (full model)	0.098	0.251	0.080	0.260	0.110
R^2 (proj model)	0.098	0.108	0.080	0.089	0.075

Standard errors in parentheses.

Notes: This table reports regressions of dealer's overnight repo volume and rate on indicators of quarter-ends and the dealer's headquarter jurisdiction. The dependent variable is dealer's repo volume in Models (1) and (2), the log of dealer's overnight repo volume in Models (3) and (4), and the dealer repo rate in Model (5). Headquarter jurisdictions are Canada (CA), the European Union (EU), Japan (JP), the United Kingdom (UK), and the United States (US). "Avg change: EU, UK" is calculated as $(QE * DealerEU + QE * DealerUK - QE * 2)/2$. "Avg change: CA, JP, US" is calculated as $(QE * DealerJP + QE * DealerUS - QE)/3$. Dealer's repo rate is defined as the volume-weighted average of repo rates between a dealer and all lenders in overnight repo collateralized by Treasury securities with 2% haircut. It is reported as the gross rate less the daily median, in basis points. The sample period is from January 2011 through December 2017. Standard errors are robust to heteroskedasticity. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table 5: **Inverse semi-elasticity using Treasury auction IV**

	1st stage: vol_{jt}		IV: R_{jt}-R_{zt}	Alt. 1st	Alt. IV	OLS
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Non-bill Treasury offer amount	46.79***	16.29**				
	(14.66)	(6.76)				
Treasury offer * borrower share				241.64**		
				(97.20)		
Vol_jt (fit)			1.61**		1.61**	
			(0.69)		(0.64)	
Vol_jt						0.01
						(0.01)
Dealer FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Cluster-robust F-stat		5.81		6.18		
Anderson-Rubin 95% CI			(0.6, 9.1)		(0.6, 8.3)	
Num. obs.	821	821	821	821	821	821

Standard errors in parentheses.

Notes: This table reports the instrumental variable estimations of the inverse semi-elasticity facing borrowers. Models (1) and (2) are first-stage regressions of borrower's overnight repo volume on the amount of non-bill Treasury securities offered to be auctioned and settled on the same day as MMF N-MFP reporting dates. Model (3) regresses the difference between borrower's repo rate and the outside option, on borrower's overnight repo volume, as instrumented using model (2). Models (4) and (5) are similar to models (2) and (3) but uses as the instrument: the product of Treasury auction offer (as defined above) and each borrower's average share of the total Triparty overnight repo volume. Model (6) regresses borrower's repo rates on volume, without using an instrument. Borrower's repo rate is defined as the volume-weighted average of repo rates between a borrower and all lenders in overnight repo collateralized by Treasury securities with 2% haircut. The outside option is defined as the imputed 1-day Treasury bill yield before September 2013 and the rate on RRP after September 2014. The estimation period is January 2011 to December 2017, excluding September 2013 through September 2014 when RRP was in testing, and excluding months that fall on quarter ends. Standard errors are clustered by month (frequency of observation). *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table 6: **Model parameter estimates via indirect inference**

Parameter	Estimate	95% CI	Parameter	Estimate	95% CI
$\beta_0 \cdot 1e3$	2.98	(1.97, 6.01)	ψ_j		
$\beta_1 \cdot 1e3$	-10.53	(-19.34, -7.44)	Bank of America	10.21	(6.46, 21.64)
σ^2	0.26	(0.06, 3.21)	Barclays	17.27	(11.77, 33.52)
$k(shape)$	133.65	(102.57, 138.29)	BNP Paribas	6.65	(3.4, 14.43)
			Citi	17.06	(10.31, 35.68)
			Crédit Agricole	23.72	(16.03, 46.17)
			Credit Suisse	15.48	(9.45, 34.02)
			Deutsche Bank	16.06	(10.21, 33.3)
			Goldman Sachs	10.13	(6.48, 19.84)
			HSBC	7.71	(4.45, 16.8)
			JP Morgan	8.19	(4.15, 18.53)
			Mitsubishi	18.05	(11.73, 35.51)
			Natixis	44.62	(30.15, 87.28)
			Nomura	62.18	(41.78, 116.32)
			Nova Scotia	9.75	(5.11, 22.17)
			Royal Bank of Canada	10.74	(6.46, 23.41)
			Royal Bank of Scotland	16.33	(10.09, 35.58)
			Société Générale	18.64	(12.01, 38.72)
			Sumitomo	51.70	(34.09, 99.57)
			UBS	8.44	(3.35, 22.91)
			Wells Fargo	24.81	(16.1, 51.18)

95% confidence interval in parentheses.

Notes: This table reports the estimates of the parameters in the lender's problem using indirect inference, as discussed in section 5. β_0, β_1 are parameters of α_{it}: $\alpha_{it} = \beta_0 + \beta_1 \cdot \sqrt{y_{it}}$. ψ_j, k are parameters of ν_{ijt}: $\nu_{ijt} \sim 1 + Gamma(shape = k, scale = \psi_j/k)$; the random variable defined by $Gamma$ is scaled by 1×10^{-4}. σ^2 is the parameter of ϵ_{jt}: $\epsilon_{jt} \sim LogNormal(\frac{-\sigma^2}{2}, \sigma^2)$; where ϵ_{jt} is scaled by 5×10^{-5}. Reported in parentheses are the bootstrapped 95% confidence interval. Bootstraps are done by time (month) blocks (clusters). The model estimation period is January 2011 to December 2017, excluding September 2013 through September 2014 when RRP was in testing, and excluding months that fall on quarter ends.

Table 7: **Model parameter estimates via MLE**

	Indicator for lending	
	No adjustment	Incidental parameter bias corrected
Log(lender portfolio size) [δ]	0.653^{***}	0.637^{***}
	(0.063)	(0.063)
Pair FE included	210	210
Log Likelihood	-4381.097	-4381.128
Deviance	8762.194	8762.257
Num. obs.	8888	8888

Standard errors in parentheses.

Notes: This table reports the estimates of the parameters in the lender's problem using maximum likelihood, as discussed in section 5. Both specifications include indicators for borrower-lender pair, and the model in column 2 corrects for potential incidental parameter bias from including fixed effects in a non-linear model. The model estimation period is January 2011 to December 2017, excluding September 2013 through September 2014 when RRP was in testing, and excluding months that fall on quarter ends. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table 8: **Borrowers' demand elasticity and markdown**

Borrower	Elasticity (%)	Average markdown (bps)
Bank of America	2.4	37.5
Barclays	2.5	34.8
BNP Paribas	2.4	40.8
Citi	3.9	25.3
Crédit Agricole	2.2	44.9
Credit Suisse	3.3	26.9
Deutsche Bank	2.4	33.8
Goldman Sachs	6.3	15.5
HSBC	3.8	25.4
JP Morgan	3.8	24.0
Mitsubishi	4.3	24.9
Natixis	1.8	57.9
Nomura	1.3	75.9
Nova Scotia	4.9	24.3
Royal Bank of Canada	5.6	17.6
Royal Bank of Scotland	3.4	24.0
Société Générale	2.9	35.3
Sumitomo	2.0	54.0
UBS	4.5	19.3
Wells Fargo	2.1	43.0

Notes: This table reports two calculated borrower-specific values as discussed in section 5.5. "Elasticity" shows the percentage volume a borrower would attract if she raises her repo rate by 1 bp. "Average markdown" shows in basis points the time-series average of a borrower's markdown. Based on parameters estimated in the model estimation period of January 2011 to December 2017, excluding September 2013 through September 2014 when RRP was in testing, and excluding months that fall on quarter ends.

Table 9: **Estimated ψ_j vs. borrowing reliability and CDS**

	Estimated ψ_j				
	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	66.942***	60.802***	22.248**		
	(12.074)	(8.230)	(9.941)		
Average coef of variation	-85.824***				
	(19.598)				
Median coef of variation		-77.813***			
		(13.451)			
Average CDS: last 3 days of month			-0.030	0.297	
			(0.206)	(0.245)	
Average CDS					0.279
					(0.237)
Dealer HQ FE	No	No	No	Yes	Yes
Num. obs.	20	20	18	18	18
R^2 (full model)	0.618	0.623	0.001	0.537	0.533
R^2 (proj model)	0.618	0.623	0.001	0.128	0.120

Standard errors in parentheses.

Notes: This table reports the regression of the estimated preference parameter, ψ_j (capturing ω_{ijt}), on measures of borrower's borrowing reliability and creditworthiness. "Average coef of variation" is the average of a borrower's coefficients of variation in volume vis-à-vis all lenders. "Median coef of variation" is the median of a borrower's coefficients of variation. "Average CDS on last 3 days of month" is the average a borrower's credit default swap rate on the last 3 business days of each month in the model estimation period. "Average CDS" is the average of a borrower's CDS rate over the model estimation period. CDS rates are for 6M debt for all borrowers except for Mitsubishi and Royal Bank of Scotland, who only has 5Y CDS. CDS rates are moreover for contracts in local currency, and follow the most common CDS convention, which is no restructuring (XR) in the U.S., modified restructuring (MM) in the EU, and full-restructuring (CR) in Japan. Canadian banks, Nova Scotia and Royal Bank of Canada do not have CDS traded. The model estimation period is January 2011 to December 2017, excluding September 2013 through September 2014 when RRP was in testing, and excluding months that fall on quarter ends. Standard errors are robust to heteroskedasticity. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table 10: **Borrower sensitivity to value of funds**

	1st stage: vol_{jt}	IV: R_{jt}-R_{zt}	OLS: R_{jt}-R_{zt}
Indicator: post 2016 Oct	2.130***		
	(0.637)		
Vol_jt (fit)		-0.575***	
		(0.218)	
Vol_jt			0.005
			(0.030)
Borrower FE	Yes	Yes	Yes
Effective F-stat	11.187		
Num. obs.	293	293	293

Standard errors in parentheses.

Notes: This table reports the instrumental variable estimate of borrower's sensitivity to value of funds. In the first-stage regression, borrower's total overnight repo volume is regressed on the indicator for post-2016 October. In the IV regression, the difference between borrower's repo rate and the outside optione is regressed on borrower's overnight repo volume, as instrumented using first-stage. The OLS regression regresses borrower's repo rates on volume, without using an instrument. Borrower's repo rate is defined as the volume-weighted average of repo rates between a borrower and all lenders in overnight repo collateralized by Treasury securities with 2% haircut. The outside option is defined as the RRP rate. The estimation period is from October 2015 to October 2017, the one year before and after October 2016, excluding months that fall on quarter ends. Standard errors are robust to heteroskedasticity. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table 11: **Summary of results from counterfactual analyses**

Scenario	Market	Rate change	Markdown change	Volume change
1. No RRP, historical Treasury yield	Triparty repo	↓ 8 bps (3 bps below target)	↑ 4 bps	↑ \$40b
2. No RRP, Treasury yield adjusts	Triparty repo	↓ 16 bps (11 bps below target)	↑ 9 bps	↑ \$86b
	Treasury	↓ 13 bps	-	↑ \$63b
3. No MMF reform, keep RRP	Triparty repo	↑ 1 bp	↑ 1 bps	↓ \$81b
4. No MMF reform, no RRP, Treasury yield adjusts	Triparty repo	↓ 10 bps (5 bps below target)	↑ 9 bps	↓ \$27b
	Treasury	↓ 6 bps	-	↑ \$28b

Notes: This table summarizes the results from different counterfactual scenarios. "1. No RRP, historical Treasury yield" is the scenario where, between 2014 and 2017, lenders see the realized 1-day Treasury yield instead of the RRP rate as the outside option to lending to borrowers via overnight repo. "2. No RRP, Treasury yield adjusts" is the scenario where, between 2014 and 2017, lenders see the 1-day Treasury yield instead of the RRP rate as the outside option to lending to borrowers via overnight repo, but the Treasury yield also responds to changes in demand. "3. No MMF reform, keep RRP" is the scenario where, between October 2016 and 2017, lenders' overnight cash portfolios are kept at the same fraction of AUM as they were in 2015. "4. No MMF reform, no RRP, Treasury yield adjusts" is the scenario where, between October 2016 and 2017, lenders' overnight cash portfolios are kept at the same fraction of AUM as they were in 2015; moreover, lenders see the realized 1-day Treasury yield as the outside option to lending to borrowers via overnight repo, and the Treasury yield also responds to changes in demand. The measure of "below target" is relative to the lower bound of the Fed's policy target band. "Rate change" and "Markdown change" refer to the time series average of the difference between the historical and the median counterfactual repo rate and markdown, respectively. "Volume change" refers to the time series average of the difference between the historical and the counterfactual total volume of overnight repo lent to borrowers in the sample. Based on parameters estimated in the model estimation period of January 2011 to December 2017, excluding September 2013 through September 2014 when RRP was in testing, and excluding months that fall on quarter ends.

Appendix

A Counterfactual sensitivity to calibrated parameters

The main policy experiment, which is scenario #2 in Table 11, considers a world where the RRP were not available, and the Triparty lenders viewed the 1-day Treasury bill yield as the return on their outside option. To conduct the counterfactual analyses, I need estimates of the parameters in the lender's problem (Tables 6, 7), as well as a calibrated sensitivity of borrower's marginal value of funding to funding quantity, and an assumption of how the 1-day Treasury yield changes to inflows of cash. In this section, I discuss how the counterfactual results change when the calibrated and assumed parameters change.

In section 6.1, I parameterize the borrower's optimal rate setting in Equation 3 by specifying the dependence of borrower funding value on quantity: $S_{jt} = \hat{S}_{jt} - \zeta \cdot \log(Q_{jt})$. The first-order condition of the borrower's problem becomes $R^*_{jt} = \hat{S}_{jt} - \zeta - \zeta \log(Q_{jt}) - \frac{Q_{jt}}{Q'_{jt}}$. I use the 2016 MMF Reform as an instrumental variable and estimate that the Triparty borrowers lower their repo rate by about 0.575 bps for each additional billion of funding they have to absorb (Table 10). From this, I calibrate ζ to be 1.86×10^{-3}. There are estimation errors associated with the borrower's rate response: the standard error on the point estimate of 0.575 bps is 0.218 bps. I explore the implication of this estimation error and re-calculate the counterfactual equilibrium in scenario #2 by using a borrower's rate response that's 1 standard error above the point estimate and a borrower's rate response that's 1 standard error below the point estimate. Table A1 summarizes the results.

When borrowers' marginal value of funding decreases more rapidly with funding volume (variation 1, ζ of 2.57×10^{-3}, *more* sensitive), the equilibrium Triparty rate would be lower than in the original counterfactual (variation 0). This is because borrowers are more reluctant to take on additional repo funding, pushing more cash into Treasury bills, and suppressing the lender's outside option further. Borrowers' reluctance also lowers their markdown relative to the original. When borrowers' marginal value of funding decreases less rapidly with funding volume (variation 2, ζ of 1.16×10^{-3}), the opposite happens. The equilibrium Triparty repo rate in variation 2 is higher than in the original because borrowers take on more funding and the Treasury yield is not as impacted. At the same time, borrower's markdown expands slightly. Importantly, all of these changes are quite small, suggesting that the counterfactual results are not driven primarily by the calibration of ζ.

In scenario #2, the 1-day Treasury yield adjusts to cash inflows. Taking into account a possible yield response in the Treasury market is not only more realistic but also meaningfully changes the counterfactual results. In Table 11, when the Treasury yield was held fixed at its historical values (scenario #1), the counterfactual median Triparty repo rate is on average 8 bps below historical. This impact is only half of that in scenario #2 (16 bps), where the Treasury yield is allowed to adjust to cash inflows. In scenario #2, the sensitivity of Treasury bill's yield to changes in demand is taken from Greenwood et al. (2015). Authors in Greenwood et al. (2015) arrive at their estimate exploiting the seasonal variation in Treasury supply driven by the Federal tax calendar, and their estimate has a standard error of 10.35 bps.

In variations 3 and 4 of Table A1, I re-calculate the counterfactual equilibrium in scenario #2 using Treasury yield sensitivities that are 1 standard error away from the point estimate in Greenwood et al. (2015). The Treasury yield sensitivity in variation 3 is 48.97 bps for 1 percentage point change in $\frac{\Delta Treasury}{GDP}$. The corresponding counterfactual median Triparty repo rate is on average lower than in the original (variation 0). As Treasury yield is lower in this variation due to higher sensitivity to demand, the borrowers expand their market power. Conversely, when the Treasury yield is less sensitive: at 28.27 bps in variation 4, the median Triparty repo rate is higher because borrowers cannot extract as large a markdown. Although the standard error around the Treasury yield sensitivity is large (10.35 bps), changing this sensitivity does not materially change the counterfactual results.

B Additional Figures and Tables

Table A1: **Counterfactual sensitivity for scenario 2 (no RRP, Treasury yield adjusts)**

Variation	Triparty repo rate change	Mardown change	Treasury yield change
0. Original	$\downarrow$ 15.8	$\uparrow$ 9.0	$\downarrow$ 13.1
1. Borrower marginal value *more* sensitive to volume ($\uparrow \zeta$)	$\downarrow$ 17.0	$\uparrow$ 8.7	$\downarrow$ 13.9
2. Borrower marginal value *less* sensitive to volume ($\downarrow \zeta$)	$\downarrow$ 13.8	$\uparrow$ 9.9	$\downarrow$ 11.9
3. Treasury yield *more* sensitive to volume	$\downarrow$ 17.0	$\uparrow$ 9.7	$\downarrow$ 15.0
4. Treasury yield *less* sensitive to volume	$\downarrow$ 14.4	$\uparrow$ 8.1	$\downarrow$ 10.8

Notes: This table reports the counterfactual estimates under different assumptions for the scenario "2. No RRP, historical Treasury yield". In this scenario, between 2014 and 2017, lenders see realized 1-day Treasury yield instead of the RRP rate as the outside option to lending to borrowers via overnight repo. Variation 0, "Original", is as reported in Table 11; specifically, the sensitivity of borrower's marginal value to volume, ζ, is 1.86×10^{-3}, and the sensitivity of Treasury yield to volume is 38.62 bps per p.p. change in $\frac{\Delta Treasury}{GDP}$. Variations 1 and 2 consider $\zeta \pm$ 1 standard error, at 2.57×10^{-3} and 1.16×10^{-3}, respectively. Variations 3 and 4 consider Treasury yield's sensitivity $\pm$ 1 standard error, at 48.97 bps and 28.27 bps, respectively. "Triparty repo rate change", "Markdown change", and "Treasury yield change" refer to the time series average of the difference between the historical and the median counterfactual repo rate, borrower's markdown, and the 1-day Treasury yield, respectively. All numbers are in basis points. Based on parameters estimated in the model estimation period of January 2011 to December 2017, excluding September 2013 through September 2014 when RRP was in testing, and excluding months that fall on quarter ends.