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 to this key financial market. I document new empirical facts about this $2 trillion market. These facts lead me to characterize Triparty as cash-lenders allocating their portfolios among differentiated cash-borrowers (dealers) who set repo rates. I show 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 further show through counterfactual analyses that, between 2014 and 2017, the Federal Reserve's Reverse Repo Facility (RRP) aided the passthrough of policy rates: without the RRP, dealers' markdown would widen, leaving the Triparty repo rate 12 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. I show that 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 about 83% of the total surplus. Triparty dealers' market power stems from Triparty cash lenders' aversion to portfolio concentration. Importantly, I find through counterfactual analyses that 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 and 12 bps below the lower bound of the policy target between 2014 and 2017. 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. The Triparty market is where, every day, against collateral, cash-lenders such as money market funds (henceforth, lenders) lend over 2 trillion dollars to broker-dealers who are cash-borrowers (henceforth, borrowers), providing vital funding for the U.S. dollar money market. I note that, first, lenders simultaneously and consistently accept different repo rates against contracts that differ only in the identity of the 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 - they also give smaller shares of their portfolios to each borrower.

These patterns give new perspectives to the working of the Triparty market. First, as Triparty lenders and borrowers repeatedly trade with each other, lending at persistently different rates likely reflects lenders' perceived differences in lending to different borrowers. One source of these differences could be borrowers' varying degrees of reliability in using 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 of portfolio composition. To reflect patterns in the data, the lender's utility deviates from a return-based linear utility in two ways. First, the utility is possibly concave in the amount of lending to a particular borrower, and the degree of this curvature depends on lender's size. This concavity generates the pattern that larger lenders maintain more distributed portfolios, and is meant to capture the lender's apparent aversion to concentration. Second, lenders have non-pecuniary preferences for borrowers. This allows lenders to make different lending decisions against repo contracts that differ only in the identity of the borrower. I speculate the source for this non-pecuniary preference to be lender's strong preference for stable investment opportunities, and I capture this in my model using a reduced-form preference parameter. 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 and is thus proportional to the spread between the use value and the cost of her funding. At her optimum, the repo rate that she offers 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 elasticity that she faces. At a given quantity of repo funding, the less sensitively the lender changes his lending volumes when the 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 identify the forces in my model is to estimate the lender's responsiveness to rate change. The lender's preference for stability and aversion to concentration both affect the amount of lending at a given rate. Yet the concentration aversion parameter is uniquely tied to how the lender responds to rate change. 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 utility curve is concave, the lender's response will be muted because he doesn't want to have too much repo invested with any one single borrower. The lender's elasticity cannot be estimated with OLS, however, due to unobserved preference shocks that can confound the relationship between observed rate and volume. To circumvent this endogeneity, I appeal to Treasury auction offering as an instrumental variable. 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 Treasury department's fiscal concerns and plausibly exogenous to factors that make repo rates fluctuate.[1] Over my sample period, a \$40 billion, or 1 standard deviation, increase in the amount offered in Treasury security auctions is associated with an average increase of \$0.66 billion in repo borrowing per borrower, for a total increase of \$11 billion. To raise that amount of additional funding, borrowers need to raise the rate they offer on repo by on average 1.6 bps. In other words, raising the offered repo rate by 1 bp attracts \$0.6 billion, or about 4% of additional funding. This estimate is in-line with recent funding flow to the Reverse Repo Facility following an unexpected rate increase in June 2021.[2] It also signals substantial inelasticity in Triparty repo compared to other large markets such as the one for Treasury securities (e.g., Greenwood et al. (2015), Bernanke et al. (2004), Duffee (1996)).[3]

[1]My instrument purposely excludes auctions of Treasury bill, as money market funds, the cash-lenders on Triparty, can also purchase Treasury bills.

[2]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 increase relative to the total size of Triparty Treasury repo, which is \$1628b as of June 9, 2021, implies an elasticity of 2.9% per basis point increase. As RRP is lenders' alternative to lending to repo borrowers (see section 5.2 for more discussion), the estimated sensitivity in volume response to RRP rate change also reflects lenders' sensitivity in volume response to borrowers' rate change.

[3]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

Leveraging moments such as the IV-estimated elasticity, I estimate my model parameters using indirect inference and maximum likelihood. Specifically, I choose model parameters such that the data simulated with these parameters would generate predictions that closely match those generated using the actual data. My parameter estimates accord with the notion that lenders exhibit size-dependent aversion to concentrated portfolio, 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 which 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 repo rate and lender's outside option, borrowers command about 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 (RRP) did not exist? RRP is the ability to place repo with the Federal Reserve (Fed), and it was first introduced in 2013 as an alternative investment opportunity for lenders on Triparty. I evaluate the effect of RRP on the incentives of Triparty agents through counterfactual analyses. I find that, if in lieu of RRP, lenders placed cash 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 12 bps below the Federal Reserve's policy target. Critically, much of this rate drop reflects borrower's widening markdown in the absence of 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

2017 is \$18.7T. This implies that \$1b increase in the supply of Treasury increases the yield by 0.21 bps.

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)). This paper not only enriches the understanding of Triparty 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 single discrete choice model increasingly employed in finance (Koijen and Yogo (2018), Buchak et al. (2018)), the lender's model in this paper emphasizes preferences that lead to simultaneous selection of multiple choices in the optimum. My modeling approach takes inspiration from Martin and Yurukoglu (2017) and Kim et al. (2002) in the industrial organization literature.

My estimated structural model provides a new angle to evaluating monetary policy tools. Triparty 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 Federal Funds Rate, research that focuses on how newer tools such as RRP operate remains scant. My examination of RRP's effect through counterfactual exercises is distinct from the empirical approach taken by the few existing studies of RRP (Anderson and Kandrac (2017), 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 auction (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 market power owes not to quarter-end implementation of regulations that limit dealer participation, but instead to longstanding preference on the part 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 to 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 choicec. 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 exercises in section 6. In section 7, I conclude.

2 Triparty repo market and data

In this section, I highlight distinct features of the Triparty market, outline the role it 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 convenient way to make 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.[4] 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., the five-year on-the-run Treasury.[5] This 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 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

[4]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.

[5]In contrast, repos done outside of the Triparty market allows the borrower and lender to maintain accounts at different custodial banks, and even for "general collateral" repo, the borrower needs to stipulate the CUSIPs of all securities used as collateral.

pass on to their clients in the broader financial market. Every day, over $2 trillion dollars are injected into the secured market this way 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 affects securities such as Treasury and Agency MBS, which are posted as collateral on Triparty and thus financed with Triparty lending.[6] 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.[7] 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 RRP's capacity, and RRP became a fixture of Triparty in September 2014. When 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 RRP. In effect, by September 2014, Triparty lenders have an attractive alternative to lending to repo borrowers, in the form of RRP.

[6] Over 90% of Triparty collateral are Treasury or Agency MBS.
[7] https://www.newyorkfed.org/markets/opolicy/operating_policy_130920.html

2.2 Data

To study the Triparty market, I use monthly SEC filings made by money market funds. Money market funds are the largest class of cash lenders on Triparty, accounting for 40% to 60% of all repo transactions on Triparty. 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. In particular, for each repo contract that the MMF has, information is available on the counterparty, the amount, the interest rate,[8] the maturity date, and the collateral type and value.

I obtain all 2011-2017 N-MFP reports from the SEC EDGAR data base, and collapse the filings by money market fund families.[9] 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 asset under management (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'

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

[9]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.

overnight portfolio. I explicitly focus on Triparty repo that are overnight in duration.[10]

Triparty repo activities are concentrated in a relatively small set of agents. As Figure 1 illustrates, over 85% of the activities in the MMF 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 this data set from MMF 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.

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,[11] which retains 73% of all MMF-dealer-month observations.[12] Prior research has documented difference in repo rates between contracts backed by different collateral, even though the haircut

[10] As N-MFP reports maturity date without reporting start date, overnight contracts are classified as those contracts that have a maturity that is the first business day of the following month. See Aldasoro et al. (2019) for discussions of potential shortcomings with this approach.

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

[12] 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.

on collateral theoretically adjusts for the quality of the underlying (Weymuller (2013)). I thus consider repos that are backed by the same collateral. This is not restrictive because Triparty repo differentiates collateral only by the 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 as the deviation to the volume-weighted median on that day. The choice of using the volume-weighted median as the centroid is to both conform to the convention in the repo market[13] and minimize 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. Creditworthiness of borrowers can often be a source of price dispersion, especially on OTC markets, but 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 even 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

[13] 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.

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 MMFs and dealer trade over time: the AR(1) persistence of whether a MMF-dealer pair traded 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 Triparty rate dispersion, and what is the pattern in MMFs lending?

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, price variations do not exhibit correlation 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 borrower identities are preferred by the Bayesian information criteria (BIC).

In Figure 4, I examine repo rate dispersion in the cross-section. I plot in red the R^2 from regressing deviations from median on dealer fixed effects.[14] Dealer identities alone explain about 50% of the variation in the cross-section. Plotted in dash 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

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

to MMF is not completely symmetric. I thus plot in blue the R^2 from regressing the rate deviations 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 blue regressions are jointly 0, and I cannot reject the null at the 10% significance level in 72 of the 84 months.[15]

To explore further the idea that dealer identities drive repo rate dispersion, in Table 2, I examine if MMF or MMF-dealer pair characteristics drive within-dealer dispersion. 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 - or importance - of the pair 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 price dispersion, judging by both the individual coefficient's statistical significance and 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 over-the-counter nature of repo transactions, prior studies such as Han and Nikolaou (2016) focus on the difference between MMF-dealer-pairs to explain price variations. In Table 1, I compare the goodness of fit between models that

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

use only dealer FE and models that use all pair FE. Looking at Columns (1) and (2), it is true that including all pair FE improves R^2 by about 0.07, yet this is achieved with 252 more regressors. Therefore, the Akaike information criteria rank these two models similarly, and the Bayesian information criteria prefers the more parsimonious model with only dealer FE. 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 3, where the repo lending done in 2016 by the larger BlackRock is drawn next to the portfolio of the smaller Legg Mason. The two portfolios differ in both the number of lending and the share going to each lending. The relationship between portfolio size and the extensive and the intensive margin of the portfolio holds across MMFs, as shown in Table 3. We know from Fact 1 that MMFs repeatedly lend to the same dealers. In Column (1), we see that the number of dealers MMFs (repeatedly) 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 Column (3), 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 Column (3) and (4), I control for the number of dealers in MMFs' portfolios. In Column (3), I control for the effect of number of dealers by including it as a regressor, and it is not statistically significant: at a given size of portfolio, the number of lending in the portfolio doesn't affect the median share. In Column (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 predicator of 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 they in fact exhibit a size-dependent tendency to make their portfolios more distributed (Fact 3). These facts about the Triparty market are the result of at least three 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 suggests that dealer identity differentiates repo lending in such a way that rationalizes difference in pecuniary returns. What is different between dealers that is so valued by MMFs? One hypothesis is 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.

Yet seeing a dealer "getting away" with a low repo rate does not necessarily mean that the dealer is more preferred by MMFs, because dealers could also have different value for repo funding. Dealers borrow via repo for security financing of their own assets or intermediation to clients. These uses yield benefits to the dealer. If the marginal value of the repo funds is low, then a dealer won't be offering a high repo rate regardless of how much MMFs like or dislike the dealer. Differences in dealer's marginal value for funding could therefore be another reason why Triparty repo rates are dispersed.

Finally, it is noteworthy that MMFs simultaneously lend to multiple dealers. It is as if MMFs have an aversion to concentration.[16] At first blush, this sounds perplexing, for Triparty repo carries very little credit risk,[17] 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 - because their clients may not fully appreciate the collateralized nature of repo - or operational risk - in the event, say, all the computers at a given dealer go down. One stark 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 lending to other dealers. As Table 4 shows, on quarter-ends, 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)). However, the lending to dealers in other jurisdictions do not increase commensurately. The consequence of MMF's aversion to concentration, 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 could face different responsiveness to rate changes and dealers may thus choose to offer different rates.

In short, differences in MMFs' value for dealer stability, dealers' marginal value of

[16]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.

[17]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)).

funding, and MMF's aversion to concentration could all contribute to the observed empirical pattern. To separately identify these forces 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 interaction between the same set of agents. A model that relies purely on linear utility from pecuniary returns is also likely insufficient, as 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 Triparty. The purpose of the model is two-fold: first, the model allows for counterfactual predictions, so that we can examine the effect of monetary policy tools and regulatory reforms by considering how the Triparty market would be if these tools or reforms did not exist. Second, the model nests the three candidate explanations for the observed rate dispersion and lending concurrence, and separately quantifies each force.

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 their distinct market-wide repo rate 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}, remains in lender's outside option: other safe, overnight investments, for which the lender harbors no concentration aversion.

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

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

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

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

This optimal share intuitively 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 simply earn on cash. 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 reflects 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, making volume response to rate change sluggish. The concentration aversion parameter, α_{it}, is thus intimately tied to lender's 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 repo rate, the optimal response in share to rate change is simply $\frac{\partial x^*_{ijt}}{\partial \log(R_{jt})} = -\frac{1}{\alpha_{it}}$. That is, if a borrower raises the repo rate she offers by 1, 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 how much is lent by i to different borrowers. The marginal utility of lending the first dollar to borrower j is $\left.\frac{\partial U}{\partial x_{ijt}}\right|_{x=0} = \omega_{ijt} R_{jt}$. 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 to different borrowers different shares of his portfolio. I therefore parameterize

ω_{ijt} as

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

χ 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.[18]

If the lender has a nonzero preference for a borrower, then his non-pecuniary preference, ν_{ijt}, is drawn from a Gamma distribution[19] whose mean depends on borrower-specific fixed effects 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 a measure 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 shocks, ϵ_{jt}, if present, threaten the OLS identification of the relationship between

[18] I take the borrower-lender pair effect on extensive margin as given, because Triparty market has existed long before my sample and there is not enough variation to fully micro-found what gives rise to these relationships.

[19] 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.

rate and quantity, because these shocks move quantities yet there are no observable proxies for them.

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:

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

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 then be used and generate value. For example, the funds could finance a borrower's own security holdings, such as 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, who don't have direct access to Triparty. The marginal value of repo funds could depend on the total amount of funds a borrower 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 borrower's clients to use repo funds should therefore be the sum of the value of funds, 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 lenders' response to her repo rate changes is inelastic. The ability to set markdown - or the extent of borrower's market power - depends on the concentration aversion (α_{it}) and the preference (ψ_j, capturing ω_{ijt}) of the lenders that lend to the borrower.

In borrower's optimal rate setting, the forces that generate rate dispersion come together. Differences in rates could come either from differences in borrowers' marginal funding value or from differences in borrowers' ability to set markdown.

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 elasticity facing borrowers. 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 elasticity facing her is a function of all the individual α_{it} associated with lenders that lend to her. Estimating the demand 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 rate.

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

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

R_{zt} represents the return on lender's outside option: 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 RRP. However, there is no reported overnight Treasury yield. I thus impute a 1-day Treasury yield by adjusting for the term-structure using 1-day and 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 1-day Treasury bill yield and the median Triparty repo rate is 0.77 before the introduction of RRP and 0.12 thereafter, supporting my choice of R_{zt}.

Because of the introduction of RRP, the sample that I use in estimation consists of two sub-periods. 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 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 market-level demand 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 thus estimate the Triparty market demand elasticity using an instrumental variable that shocks the borrower's 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 Treasury department's fiscal concerns and is plausibly exogenous to Triparty 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 borrower's borrowing need, I can find by how much borrowers need to raise the repo rates they offer to attract the desired funding volume.

I collect Treasury auction information from TreasuryDirect, and calculate the amount of *non-bill* Treasury securities that are *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 those with shorter maturities can also be bought be money market funds and are typically not financed via repo.

Table 5 summarizes the instrument-induced lender inverse repo-rate 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 at the (monthly) time level.

Columns 1 and 2 show the first-stage impact of Treasury auction offers on repo volume: $Vol_{jt} = \beta_{1st} TreasuryOffer + BorrowerFE + YearFE + e_{1st,jt}$. Column 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 structural macro economic shocks that affect both the Treasury department's decision to raise funding and the Triparty repo market, I add year fixed effects in Column (2). In so doing, my instrument relies on auction variations within the calendar year, which typically reflects tax revenue fluctuations in the fiscal year.[20] The magnitude of the volume response reduces from 46.8 to 16.3, but are still significant at the 5% level. Since I measure Treasury auction offer 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 \$0.66 billion in repo borrowing per borrower.

Column 3 shows the repo rate response to instrumented volume change in $R_{jt} - R_{zt} = \beta^{IV} \widehat{Vol_{jt}} + BorrowerFE + YearFE + e_{IV,jt}$.[21] The estimated coefficient shows that to raise \$1 billion more in repo funding, borrowers need to raise repo rates by 1.6 bps. In other words, a 1 bp increase in repo rate is associated with a \$0.66 billion increase in

[20] 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. Note that 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.

[21] 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, so that the repo rates reflect differences in borrower-identity.

funding per borrower. For the average borrower, this is about 3.7% of their 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, RRP saw an overnight inflow of $230 billion from a base of $1628 billion Treasury-backed Triparty repo, implying an elasticity of 2.9%. At the same time, this estimate is higher than comparable estimates for the Treasury bill market in Greenwood et al. (2015),[22], Duffee (1996),[23] and Bernanke et al. (2004),[24] suggesting that the demand on Triparty is more inelastic.

The first-stage specification in Column 2 features a market-wide instrument, $TsyOffer_t$, that applies to all Triparty borrowers. The IV estimate in Column 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 Columns 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. 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 this Treasury auction offer and borrower repo share product 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

[22] Greenwood et al. (2015) estimates, using instrumental variable on sample from 1983 to 2009, 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.

[23] 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.

[24] 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.

correlated with errors in the IV regression. The estimated inverse elasticity from Column 5 is very similar in magnitude to the estimate in Column 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 Column 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 Column 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 Column 3 and Figure 5, the 95% Anderson-Rubin confidence interval for this estimation is (0.6, 9.1). Note that this interval is still bounded away from the imprecise and near-zero OLS estimate in Column 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 elasticity is not zero, however, we are much less certain that the true value is not larger. A larger estimate would mean that borrowers need to raise their rate even higher in order to induce more 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 $\widehat{Vol_{jt}}$ (Column 3 of Table 5), as it 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 (Column 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.[25] 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 therefore use the R^2 from regressing portfolio shares on lender portfolio size and borrower fixed effects[26] and on lender portoflio size and borrower-time fixed effects[27] to learn about these two parameters.

The primitive 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 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 the possible bias. 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

[25]Unconditional probabilities are necessary to inform ψ because there are observations where borrower's repo rate (R_{jt}) is less than the cash rate (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.

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

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

samples. The bootstrapped samples are bootstrapped in blocks by 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.[28]

The two moments that inform β_0 and β_1 are well matched, see Figure **??**. 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). α 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 borrowers have, on average, 10 links, this estimate suggests that 1 bp increase leads to \$0.64b increase in borrower funding, which closely tracks the IV estimate. Relative to the IV estimate, which is a market-level 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 RBC, who offer among the lowest rates, both face among the highest elasticity. This suggests that the aggressive pricing borrowers deploy comes at a trade-off of being on the more elastic portion of the demand curve.

The estimated ψ_j ranges from 7 bps to 62 bps, with an interquartile range of (10 bps, 20 bps), a median of 16 bps and a mean of 20 bps. Using the median as the representative

[28]Pair-specific fixed effects $\rho_i j$ are omitted for brevity and are available upon request.

centroid, we see that lenders in the model typically perceive a 16 bps increase to their utility on the *first* dollar lent to borrowers.[29] 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 estimate 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: $CoefVar_j = mean_j(\frac{SD_{ij}(vol_{ijt})}{mean_{ij}(vol_{ijt})})$. The lower the coefficient of variation, the more reliable a borrower is in using his 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,[30] yet even after controlling 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 ranges from 15 bps to 76 bps, with an interquartile range of (24 bps, 41 bps); see Table 8. Compare to the cross-section of borrower's time-series average repo rates,[31] which has a range of 9 bps, we see that the observed dispersion in repo rate belies

[29] 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}.

[30] 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

[31] Net of R_{zt} to compare across interest rate environments.

a much larger dispersion in borrowers' markdown. As each borrower's marginal value is the sum of her observed (optimal) repo rate and her markdown, we can deduce borrowers' marginal value of funding, also reported in Table 8. In fact, the observed rate dispersion in Triparty repo is the result of large variations in the cross-section of borrowers' marginal value of funding and almost equally large variations in the borrowers' markdown. It may be surprising to see such large variations in borrowers' marginal value of funds. Yet considering that the value of funds is net of any regulatory cost, the differences in values of funds may reflect the fact that certain borrowers have much higher opportunity costs to using their balance sheets. This explanation would be consistent with a view that differences in borrowers' broader investment opportunities lead to differences in borrowers' marginal values of repo funds, which would then cause borrowers to borrow via repo with varying degrees of reliability, generating differences in lenders' preferences for borrowers.

It is also instructive to look at the time series of borrower markdown. In Figure 8, I plot the time series of the median borrower 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 median Triparty repo rates and lender's outside option, borrowers extract about 83% of the (27.5 + 5.6 =) 32.1 bps total surplus in the Triparty market.

Several recent studies have estimated, in different 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, 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 a rate that broker-dealers pay for funding,[32],

[32]In fact, Fleckenstein and Longstaff (2020) also uses a repo rate as the rate for financing Treasury purchases via cash. The authors use the Treasury repo rates in the dealer-to-dealer bilateral market,

and the implied Treasury futures rate is a rate that dealers' clients would pay to make Treasury purchases via futures, this Treasury cash-futures basis closely relates to the markdown I calculate. Specifically, as the markdown represents the difference between what Triparty borrowers (dealers) pay and their marginal funding value, *net of regulatory cost*, the Triparty markdown plus regulatory cost should be comparable to the Treasury cash-futures basis. Over my sample period, the Treasury cash-futures basis is about 47.6 bps. My estimates imply that over half of the empirical near-arbitrage basis owes to intermediaries' market power.

In the time-series, there is also a 11 bps drop in the level of the markdown before vs. after the introduction of RRP. The magnitude of 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 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. What would be the equilibrium Triparty repo rate and volume if RRP were not established? If the 2016 Money Market Fund Reform did not happen?

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where collateral posting requires specifying the CUSIPs of the Treasury securities used. Important differences in institutional features notwithstanding, the bilateral market rate can be seen as comparable to Triparty repo rate.

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

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

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 invests in unsecured securities such as commercial paper, to government funds, which mostly invests 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.[33] Consequently, the amount of overnight cash in the industry as a whole 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 borrow-

[33] This is because government funds can only invest in a limited number of securities and so to achieve better return, they invest heavily into longer maturity government securities and need to have more overnight cash to bring down the fund's average maturity

ers' marginal value of funding, if borrowers drop the repo rates they offer, it is likely that the decrease reflects deterioration in funding value. I therefore use the MMF reform as an instrument for increases in funding volumes that borrowers have to absorb to find the corresponding repo rate change. Specifically, I construct an indicator of MMF reform that takes on the value 1 on or post October 2016, when the MMF reform was fully implemented, and take on the value 0 before, and I estimate $R_{jt} - R_{zt} = b_1 \widehat{vol}_{jt} + BorrowerFE + e_1$, where $\widehat{vol}_{jt} = b_0 \mathbf{1}_{t \geq 201610} + BorrowerFE + e_0$. I estimate using observations in the one year before and after October 2016. Results of the estimation are summarized in Table 10. On average, borrowers had to absorb \$2.1b more because of MMF reform, and each additional billion of funding lowered the repo rate they offer 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 $1.88 \cdot 1e - 3$.

6.2 Triparty without RRP

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

To answer this question, I first conduct a counterfactual where I assume that, in the absence of RRP, Triparty lenders would have as their outside option the realized historical 1D Treasury yield. This new outside option for lenders is about 12 bps lower than RRP, on average. Given this change, the new Triparty equilibrium rates and volume is illustrated in Figure 9. On average over the October 2014 through November 2017 estimation window, the counterfactual median Triparty repo rate is down 7 basis points, which puts the reported median Triparty rate 3 bps below the lower bound of the Federal Reserve's policy target. Despite this rate drop, because the repo rate is still more favorable compared to the outside option of 1D Treasury, volume to repo borrowers actually increase by $36b per month.

Although lending to Triparty borrowers increases, the increase is not enough to offset the amount of cash lenders used to place at RRP. In fact, in this scenario, about $113.5b/month would be redirected from RRP to Treasury bills. This is an enormous amount of demand for Treasury, and certainly would have caused yield responses.

Using the Treasury elasticity estimate from Greenwood et al. (2015), where 1 pp increase 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. Table 11 summarizes the new equilibrium relative to historical. The counterfactual median Triparty rate now drops even more because the Treasury yield declines due to inflow. The new Triparty rate is 12 basis point below the lower bound of the Fed's policy target. Importantly, borrower's market power expands by 10 bps, leaving the passthrough rate to the broader financial market lower by a more modest 6 bps.

6.3 Absence of MMF Reform

The 2016 MMF Reform represented a major change to the money market fund industry. What would have happened to Triparty 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 the results are summarized in Table 11. First, I assume that RRP is still available so that the only change in the market is that lender's overnight cash portfolios became smaller in 2016 and 2017. In this scenario, the counterfactual median Triparty rate would in fact have been higher than historical because lenders are more elastic (their portfolios are smaller and they are therefore less averse to concentration) and because lenders lend less in general, pushing borrower's marginal funding value higher. Next, I consider a scenario where the MMF reform didn't happen *and* RRP was not available. In this scenario, the counterfactual median Triparty repo rate would have been lower than historical, though not as low as in the counterfactual where MMF reform took place. The contrast between these two counterfactual scenario without RRP underscores lenders' reliance on RRP to constrain borrower market power; this reliance grows only stronger the larger the lenders become.

7 Conclusion

Observing institutional and empirical features of the Triparty market, I describe its equilibrium through a system of demand and supply. This framework allows me to identify substantial market power enjoyed by borrowers on the Triparty market. The estimated model enables counterfactual exercises that assess the effect of the Reverse Repo Facility on Triparty. Increasing evidence points to the central role financial intermediaries play in asset pricing. It is therefore also increasingly important to understand the competitive environment in which intermediaries play and the implication of that environment on policy designs.

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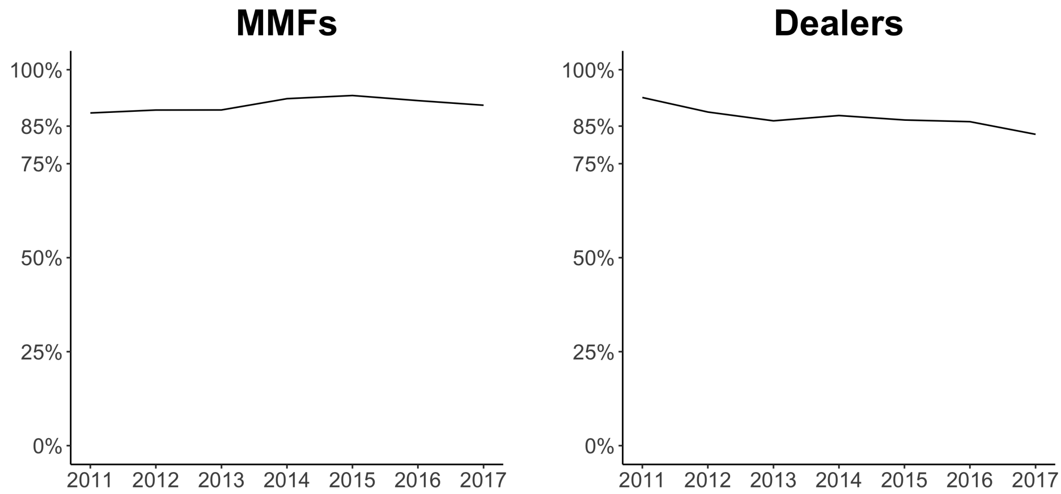
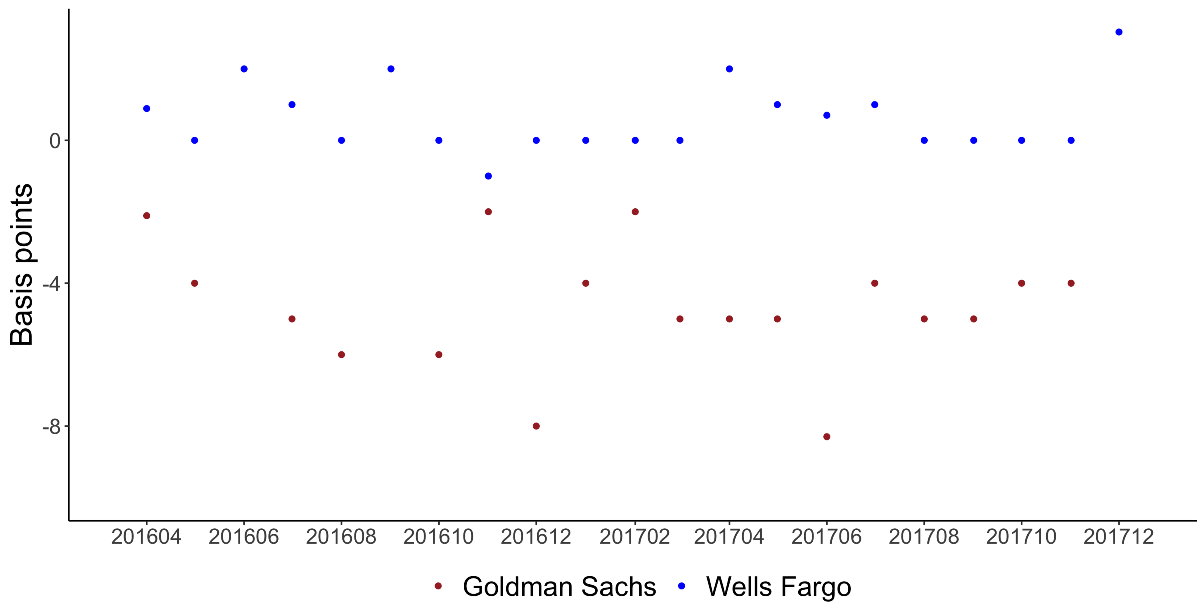
Tables and Figures

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



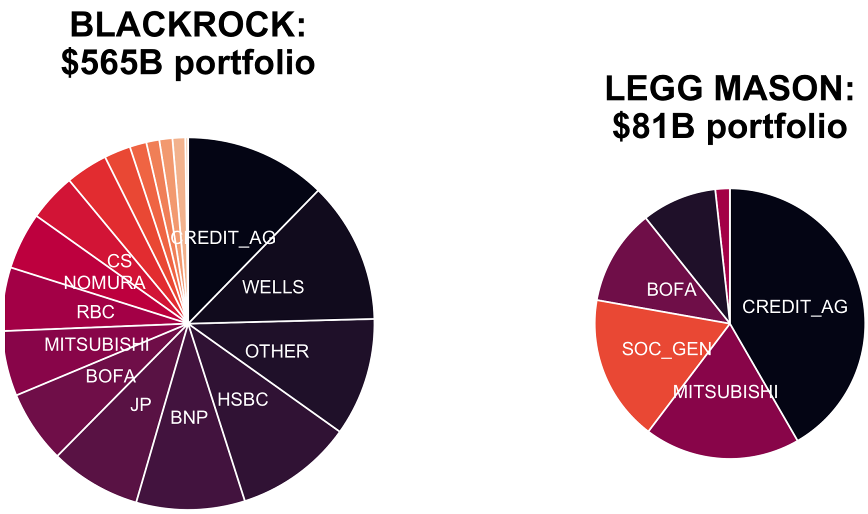
Notes: This figure plots, on the left, the share of overnight repo done by the top 18 money market fund families relative to all overnight repo done by money market funds that filed N-MFP reports between January 2011 through December 2017. Plotted on the right is the share of overnight repo done by the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



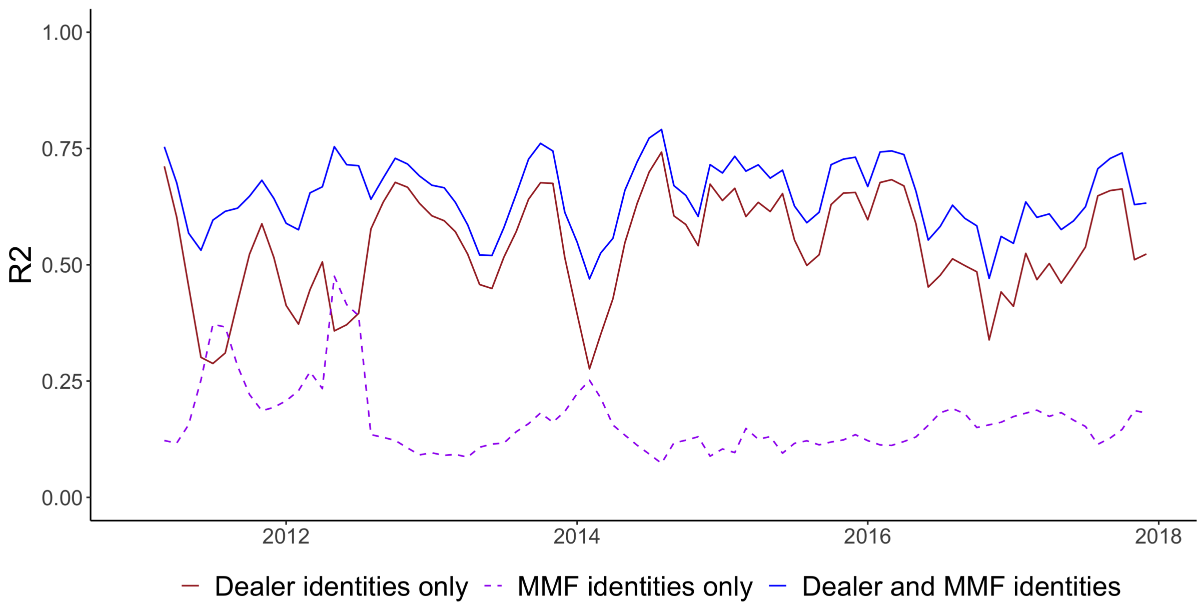
Notes: This figure plots the repo rates accepted by BlackRock for lending to Goldman Sachs and Wells Fargo via overnight repo collateralized by Treasury securities with 2% haircut. The repo rates are reported as gross rates less the daily median repo rate and are stated in basis points. Two outliers 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: **Select MMF repo portfolios in 2016**



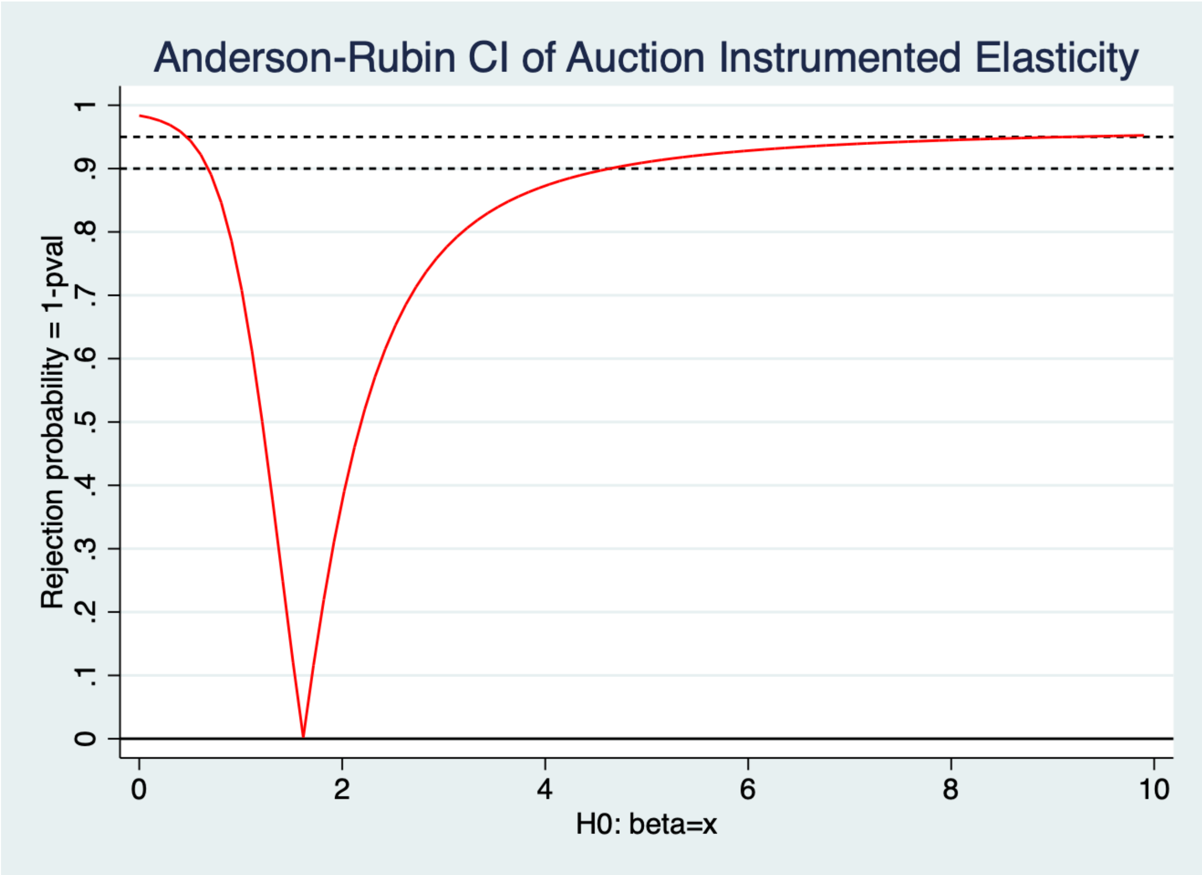
Notes: This figure plots the repo lending to dealers by BlackRock and Legg Mason in 2016. The size of the pie corresponds to BlackRock and Legg Mason's annual overnight repo lending volume, as labeled. The size of each slice represents the share of lending going to different dealers.

Figure 4: **Decomposition of cross-sectional variation in rate dispersion**



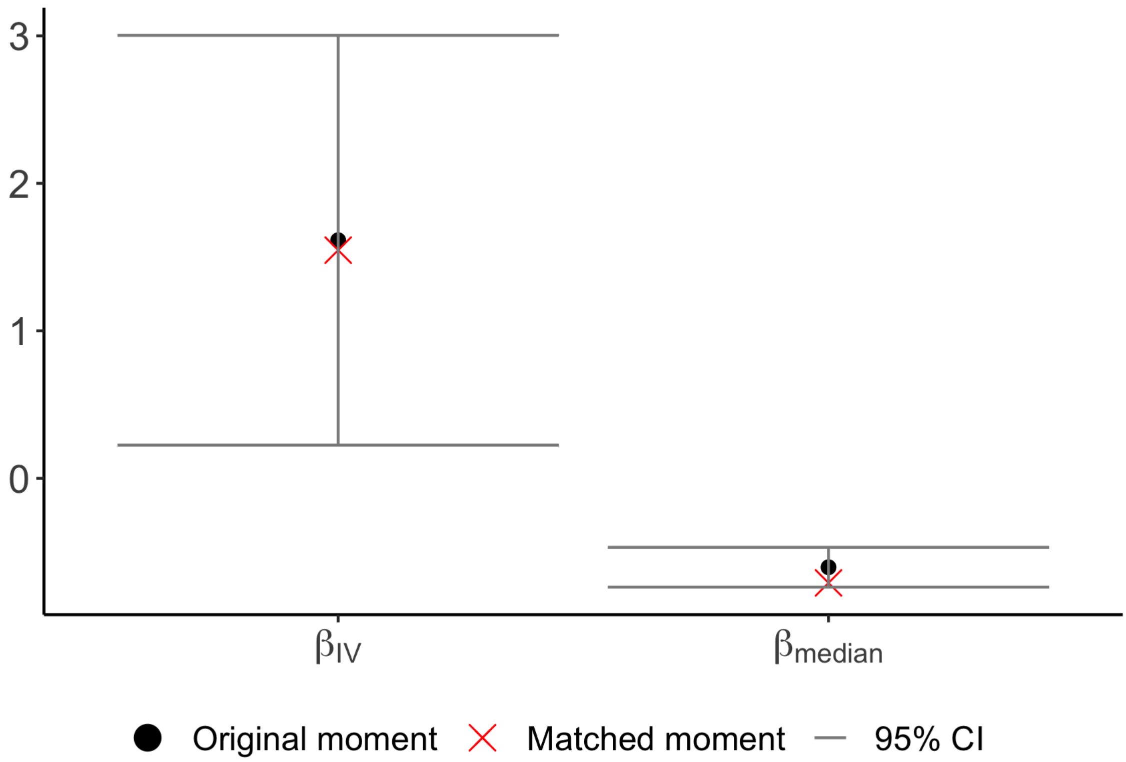
Notes: This figure plots the three-month rolling average of the R^2 from monthly cross-sectional regressions of repo rates on MMF and dealer fixed effects. Repo rates are measured as gross repo rates less the daily median repo rate, and are for overnight repo collateralized by Treasury securities with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

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



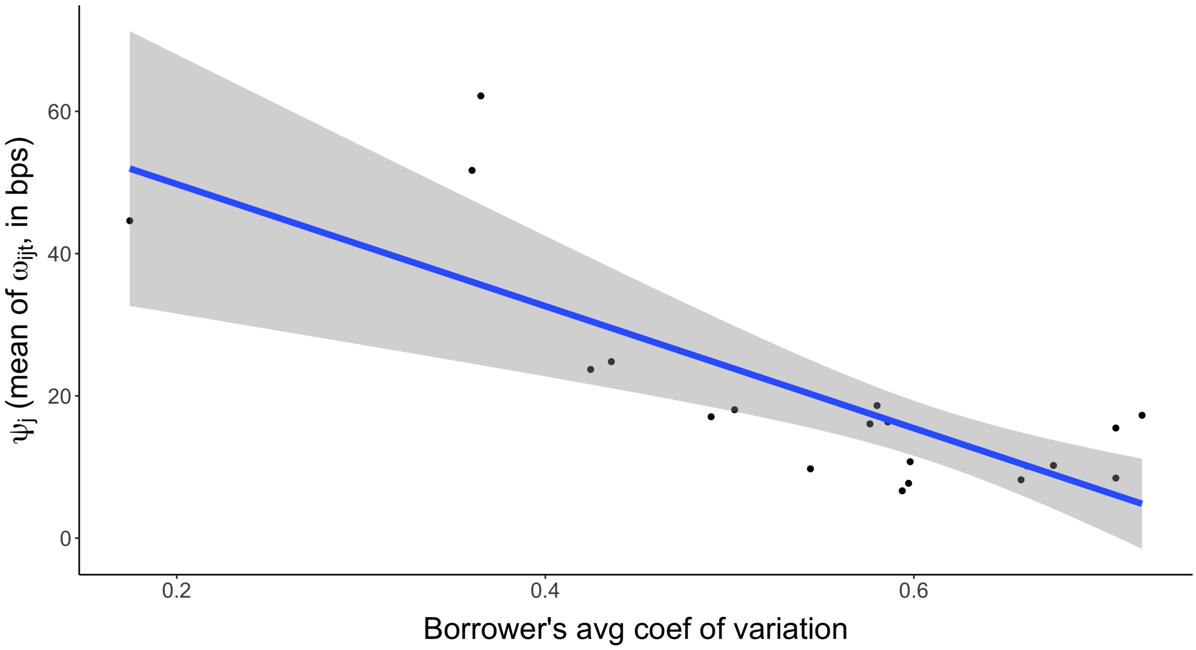
Notes: This figure plots the Anderson-Rubin rejection probability for the null hypothesis that the true β_{IV} equals to a given value on the x-axis. β_{IV} is estimated from $\log(R_{jt}) - \log(R_{zt}) = \beta_{IV}\widehat{vol}_{jt} + BorrowerFE + YearFE + e_{IV,jt}$ in the model estimation period of January 2011 to December 2017, excluding September 2013 through September 2014 and quarter-end months. The horizontal dashed lines are at y = 0.9 and y = 0.95. The points where the 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**



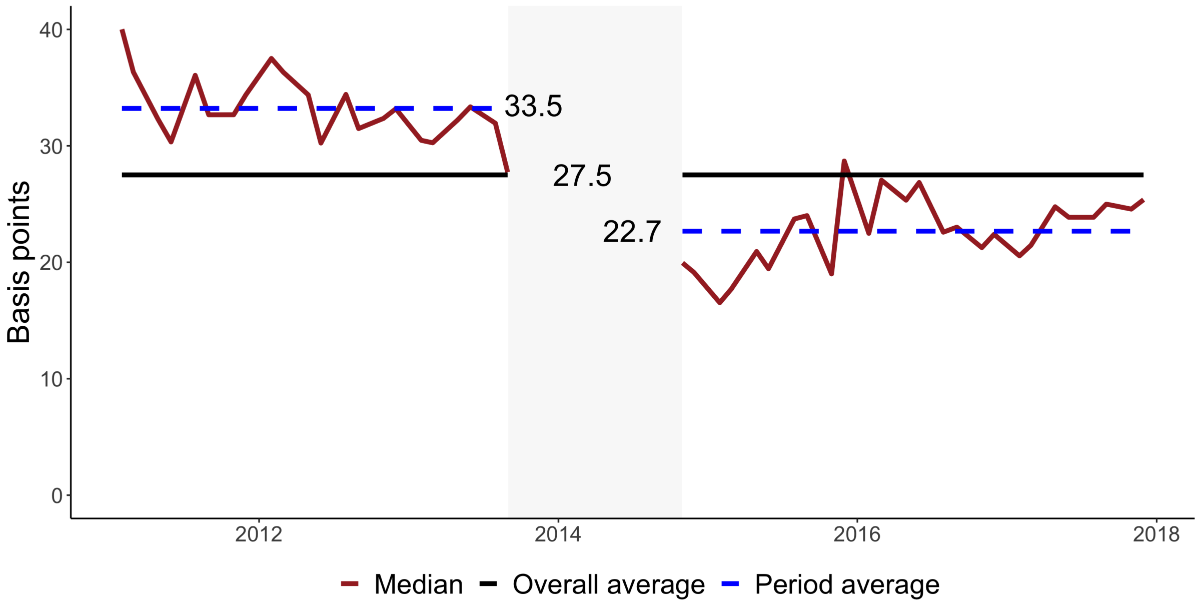
Notes: This figure plots two estimation moments evaluated in the sample data ("Original moment") and in model-simulated data ("Matched moment"). The two moments are the regression coefficients from the IV-estimated inverse elasticity (β_{IV}, Column 3 of Table 5) and from the relationship between median portfolio share and portfolio size (β_{median}, Column 2 of Table 3). The matched moment is calculated as the average over 50 sets of data simulated using the estimated parameters. The estimates of β_{median} are all 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 and quarter-end months.

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



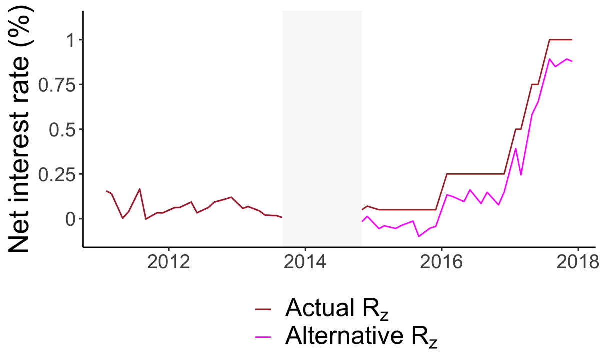
Notes: This figure plots estimated ψ_j against borrower's average coefficient of variation. The blue line represents the fitted value from regressing ψ_j on borrower's average coefficient of variation and the shaded regions is the 95% heteroskedasticity-robust confidence bands. Borrower's average coefficient 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 and quarter-end months.

Figure 8: **Triparty borrower markdown**

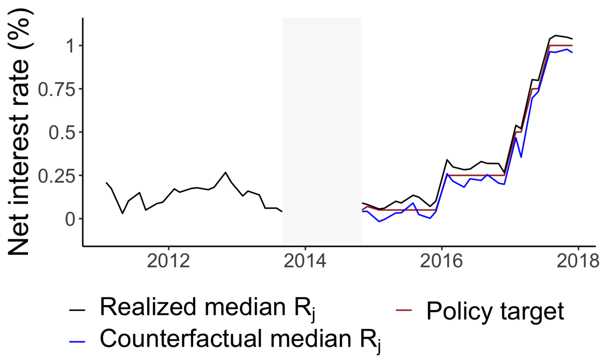


Notes: This figure plots, in solid red, the time series variation in the median borrower markdown over the model estimation period. The solid black line indicates the average of this value over the whole sample. The dashed blue lines indicate the average of this value in the pre- and post-RRP periods. 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 when RRP was first introduced and was in testing, and excluding months that fall on quarter ends.

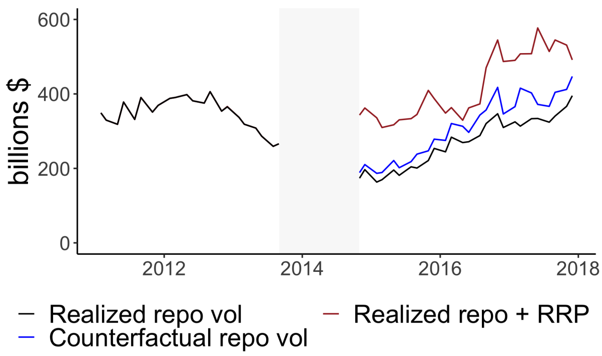
Figure 9: **Scenario: no RRP, lenders access historical Treasury yield**



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



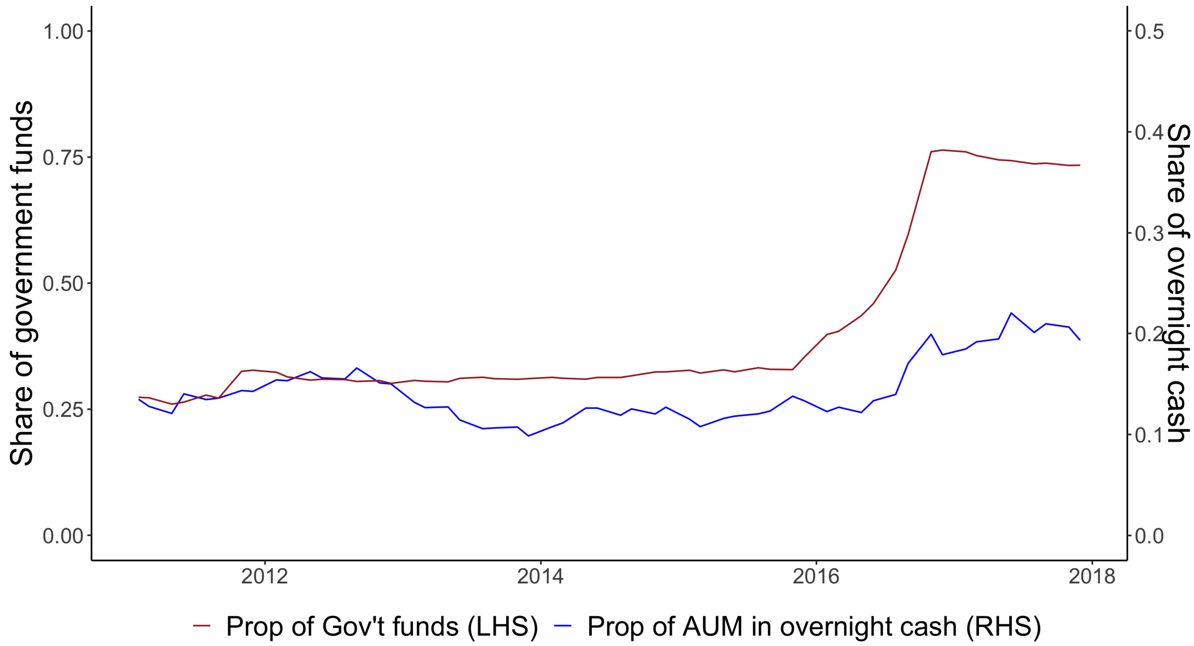
(b) **Counterfactual rate**



(c) **Counterfactual volume**

Notes: This figure plots the counterfactual Triparty median rate and total volume in the scenario that 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 $_{zt}$ 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 Triparty repo lending to dealers in blue, the historical Triparty repo lending to dealers in black, and the total lending to dealers and RRP in red. 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 quarter-end months.

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



Notes: This figure plots in red and against the y-axis on the left, the proportion of MMF AUM in government funds. This figure plots in 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 RRP.

Table 1: 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 MMF-dealer repo rates on dealer fixed effects or MMF-dealer pair fixed effects. Repo rates are measured as deviation from the daily median. Goodness of fit measures are R^2, Akaike information criterion, and Bayesian information criterion. The estimation sample is January 2011 through December 2017.

Table 2: 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 MMF-dealer pair rates of lending 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 that 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 all volume 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 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 given 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)	
	Model 1	Model 2	Model 3	Model 4
QE	0.844	0.717	0.086	0.078
	(0.733)	(0.872)	(0.087)	(0.082)
QE * Dealer EU	-7.758***	-7.712***	-0.498***	-0.494***
	(1.203)	(1.225)	(0.120)	(0.111)
QE * Dealer JP	-0.617	-0.598	-0.080	-0.082
	(2.704)	(2.532)	(0.233)	(0.204)
QE * Dealer UK	-4.531***	-4.428***	-0.346**	-0.338***
	(1.656)	(1.473)	(0.151)	(0.130)
QE * Dealer US	-1.655	-1.546	-0.156	-0.149
	(1.395)	(1.424)	(0.112)	(0.106)
Total vol: EU + UK	-13.978	-13.574		
Total vol: CA + JP + US	-3.117	-2.861		
Dealer HQ FE	Yes	Yes	Yes	Yes
Quarter FE	No	Yes	No	Yes
Num. obs.	1419	1419	1419	1419
R^2 (full model)	0.098	0.251	0.080	0.260
R^2 (proj model)	0.098	0.108	0.080	0.089

Standard errors in parentheses.

Notes: This table reports regressions of dealer's overnight repo volume on indicators of quarter-ends and the dealer's headquarter jurisdiction. The dependent variable is dealer's repo volume in models (1) and (2), and the log of dealer's repo volume in models (3) and (4). Headquarter jurisdictions are Canada (CA), the European Union (EU), Japan (JP), the United Kingdom (UK), and the United States (US). The sum of the average volume change for dealers in EU and UK, and dealers in CA, JP, and US are summarized. 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 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 repo rate 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 cash rate 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 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. Cash rate 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 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 **NEED UPDATE**

Parameter	Estimate	95% CI	Parameter	Estimate	95% CI
$\beta_0 \cdot 1e3$	0.16	(-9.68, 2.38)	ψ_j		
$\beta_1 \cdot 1e3$	-11.60	(-13.95, -9.77)	BARCLAYS	44.19	(31.11, 64.96)
σ	3.55	(2.06, 3.99)	BNP	41.07	(20.78, 65.9)
$k(shape)$	1.26	(0.38, 2.86)	BOFA	36.14	(11.6, 54.28)
			CITI	22.06	(7.01, 34.67)
			CREDIT AG	51.61	(31.79, 82.89)
			CS	21.85	(5.03, 35.58)
			DEUTSCHE	47.14	(29.26, 71.51)
			GS	17.40	(5.61, 24.68)
			HSBC	24.63	(7.9, 36.45)
			JP	16.81	(7.89, 31.45)
			MITSUBISHI	28.12	(19.57, 40.67)
			NATIXIS	60.77	(46.28, 89.25)
			NATWEST	35.85	(19.72, 52.66)
			NOMURA	86.47	(61.58, 108.56)
			NOVA SCOTIA	23.35	(8.33, 37.5)
			RBC	19.22	(5.74, 27.14)
			SOC GEN	38.46	(15.66, 55.02)
			SUMITOMO	60.26	(42.74, 77.59)
			UBS	18.02	(10.26, 26.97)
			WELLS	45.32	(23.26, 61.88)

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. Reported in parentheses are the bootstrapped 95% confidence interval. Bootstraps are done with time (monthly) clusters. The model estimation period is January 2011 to December 2017, excluding September 2013 through September 2014 when RRP was in testing, and 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 months that fall on quarter ends. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table 8: Borrowers' demand elasticity, markdown, and marginal value

Borrower	Elasticity (%)	Average markdown (bps)	Avg marginal value (bps, less R_{zt})
BARCLAYS	2.5	34.8	40.6
BNP	2.4	40.8	46.8
BOFA	2.4	37.5	42.9
CITI	3.9	25.3	31.0
CREDIT_AG	2.2	44.9	50.6
CS	3.3	26.9	32.6
DEUTSCHE	2.4	33.8	40.4
GS	6.3	15.5	17.2
HSBC	3.8	25.4	30.0
JP	3.8	24.0	29.6
MITSUBISHI	4.3	24.9	28.5
NATIXIS	1.8	57.9	63.6
NATWEST	3.4	24.0	30.0
NOMURA	1.3	75.9	82.4
NOVA_SCOTIA	4.9	24.3	30.5
RBC	5.6	17.6	21.7
SOC_GEN	2.9	35.3	41.9
SUMITOMO	2.0	54.0	61.7
UBS	4.5	19.3	26.5
WELLS	2.1	43.0	49.1

Notes: This table reports three 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. "Average marginal value" shows in basis points the time-series average of a borrower's marginal value of funding, net of R_{zt}. Results are 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 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: In this table, I regress 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 sample. "Average CDS" is the average of a borrower's CDS rate over the model estimation sample. CDS rates are for 6M debt (except for Mitsubishi and Royal Bank of Scotland, who only has 5Y CDS), in local currency, and following 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 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 Price Setting Sensitivity

	1st stage: vol_{jt}	IV: R_{jt}-R_{zt}	OLS: R_{jt}-R_{zt}
Indicator: post 2016 Oct	2.130***		
	(0.605)		
Vol_jt (fit)		-0.575***	
		(0.215)	
Vol_jt			0.005
			(0.028)
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 price setting sensitivity. 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 cash rate 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. Cash rate is defined as the rate on RRP. The estimation period is from October 2015 to October 2017, the one year before and after October 2016, and months that fall on quarter ends are excluded. Standard errors are robust to heteroskedasticity. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table 11: Summary of counterfactual exercises

Scenario	Market	Rate change	Markdown change	Volume change
No RRP, historical Treasury yield	Triparty repo	↓ 8 bps (3 bps below target)	↑ 4 bps	↑ \$39b
No RRP, Treasury yield adjusts	Triparty repo	↓ 16 bps (12 bps below target)	↑ 9 bps	↑ \$85b
	Treasury	↓ 13 bps	-	↑ \$64b
No MMF reform, keep RRP	Triparty repo	↑ 1 bp	↑ 1 bps	↓ \$82b
No MMF reform, no RRP, Treasury yield adjusts	Triparty repo	↓ 11 bps (6 bps below target)	↑ 9 bps	↓ \$28b
	Treasury	↓ 6 bps	-	↑ \$28b

Notes: This table summarizes results from different counterfactual scenarios. "No RRP, historical Treasury yield" is the scenario where, between 2014 and 2017, lenders see realized 1-day Treasury yield instead of the RRP as the outside option to lending to borrowers via overnight repo. "No RRP, Treasury yield adjusts" is the scenario where, between 2014 and 2017, lenders see 1-day Treasury yield instead of the RRP as the outside option to lending to borrowers via overnight repo, but Treasury yield also responds to changes in demand. "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. "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 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.