A Lending Network under Stress: A Structural Analysis of the Money Market Funds Industry*

Paula Beltran†

February 14, 2022

Click here for the most recent version

Abstract

In this paper, I study the transmission of an aggregate funding supply shock in a lending network and quantitatively assess the implications for the allocative efficiency of funding provision of the US Money Markets Funds Industry. I build a tractable model that features banks and funds that bargain over the terms of trade subject to an incomplete network of existing counterparties and bilateral bargaining. I discipline the model using data on the funds' portfolio. I show how to identify the key parameters of the model by exploiting granular shocks of connected agents. Taking as primitives the observed changes in assets under the management of prime funds at the onset of the COVID-19 crisis, the model accounts for 85% of the drop in total lending and 70% of the increase in price dispersion. I show that the allocation is inefficient. Faced with the same drop in asset under management and taking as given the network of bilateral counterparties, a central planner would reduce lending by 9% instead of 14% in equilibrium. Finally, I use the model to examine the effectiveness of the Overnight Repo Repurchase Facility.

Keywords: Money market funds; banks; networks; funding

JEL Codes: G2; G22; G23; L14; E52

*I thank Pierre-Olivier Weill, Andy Atkeson, and Lee Ohanian for their invaluable guidance, advice, encouragement, and support. I also thank Saki Bigio, Gary Hansen, Bernard Herskovic, and Oleg Itskhoki for useful suggestions and advice. I thank Inaki Aldasoro and Federico Gringberg for many fruitful conversations and their constant support. I thank Gara Afonso, Thomas Eisenbach, and Gabriele La Spada for their mentorship during my Dissertation Internship at the NY Fed. I thank Camilo Acosta, Sadhika Bagga, Christian Bustamante, Wilmar Cabrera, Nicola Cetorelli, Huifeng Chang, Wenxin Du, Andrea Eisfeldt, Andres Fernandez, Connor Foley, Chang He, Ali Haider Ismail, YongKi Hong, David Lindsay, Antoine Martin, Daniel Osorio, Fatih Ozturk, Brian Pustilnik, Juan Rojas, Elham Saeidinezhad, Asani Sarkar, Argia Sbordone, Oscar Valencia, Hernando Vargas, Daniela Vidart, Mengbo Zhang, and Diego Zuniga for their suggestions. I thank seminar and conference participants at UCLA, the NY Fed, the Central Bank of Chile, the Central Bank of Colombia, the Central Bank of Canada, Wisconsin-Madison Department of Finance, ITAM Business School and Universidad de los Andes, for helpful comments. I thank Peter Crane for generously giving me access to CRANE data for this project. All errors and shortcomings are my own.

†UCLA, Department of Economics, paulabeltran@g.ucla.edu

1 Introduction

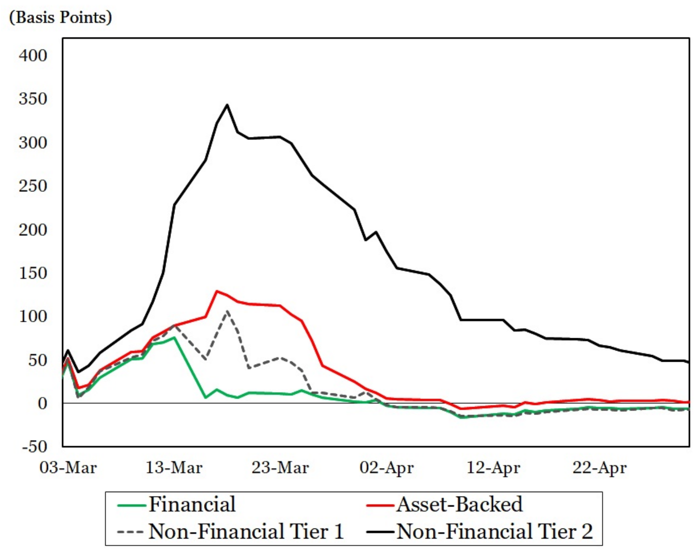
Global funding markets experienced acute distress in March 2020 when the COVID-19 "dash for cash" drained the supply of funding. Severe dislocations in the cost of funding resulted in interest rates spikes in several funding markets. Figure 1 shows the evolution of the overnight funding spreads around this episode. Commercial paper spreads with respect to the T-bill increased by 150 basis points on average around March 15. These dislocations did not subside until unprecedented policy measures were implemented to restore liquidity in key funding markets.

Many of the funding markets that were under significant stress in March 2020 are decentralized, and funding provision in these markets relies on a network of bilateral relationships. The March 2020 events were not isolated. Funding dry-ups occurred in other financial crises; for example, during the 2008 Global Financial Crisis. Many papers highlight the importance of the interconnectedness in financial markets in 2008 (Di Maggio, Kermani, and Song, 2017; Eisfeldt et al., 2019), but leave unanswered two fundamental questions regarding large aggregate funding shocks in a lending network. First, how much of the total funding provision and dispersion in the cost of funding after a large aggregate funding supply shock can be explained by network frictions? Second, how much allocation inefficiency results as a consequence of market power within a lending network under stress?

This paper addresses these questions quantitatively in the unsecured funding market, where U.S. Money Market Funds provide a significant source of dollar funding to global banks (FSB, 2020). This $9 trillion industry was under significant stress in March 2020. Prime money market funds were subject to a liquidity withdrawal comparable to the run experienced by Money Market Funds in September 2008 (Anadu et al., 2021a). This episode provides a suitable setting to study the role of network frictions in the transmission of funding supply shock in the context of a highly concentrated industry.

I build and estimate a model of bilateral unsecured funding within the network of

Figure 1: Spread between Commercial Paper (CP) Rates and the T-Bill Rates



Notes: Data from the Federal Reserve Bank of St Louis, FRED. Author's calculations. The graph shows the spread between the daily overnight commercial paper (CP) rates and the 4-week Treasury bill (T-bill) rates in the secondary market by type (Financial, Asset-Backed, Non-Financial Tiers 1 and 2). The solid green line uses data for the Overnight AA Financial Commercial Paper Interest Rate, the solid red line for the Overnight AA Asset-Backed Commercial Paper Interest Rate, the gray dashed line for the Overnight AA Financial Commercial Paper Interest Rate, and the black solid line for the Overnight A2/P2 Nonfinancial Commercial Paper Interest Rate.

banks and funds, using data from before March 2020. To estimate the main parameters, I use data on the funds' portfolio from 2011 up to January 2020 and rely on granular variation in interest rates and funding provision at the bilateral level. I use the model to produce the counterfactual changes in interest rates and funding supply in this lending network after introducing a large aggregate shock to the funds' assets under management as observed in March 2020.

The model is designed to capture two main features of a lending network composed of funds and banks. First, the model captures limited connectivity between banks and funds. Second, the model features bilateral market power that affects the funds' portfolio choice. Together, limited connectivity and the distribution of market power determine the cost of funding.

Limited connectivity in my model comes from two sources: an exogenous network of possible counterparties and concentration risk. First, I assume an exogenous network as in Eisfeldt et al. (2019). Banks and funds interact through an exogenous network that constrains the agents' set of counterparties. This assumption captures relationship frictions between banks and Money Market Funds. During the COVID-19 crisis, very few new relationships were created: the fraction of trades corresponding to new bilateral relationships was less than 1%. Therefore, an exogenous network is plausible in the short term and implies that the preexisting network of counterparties will shape the outside option of agents and dispersion in terms of trade in the model.

Second, funds face concentration risk, which captures that funds are subject to strict counterparty limits by regulation. Besides aversion to aggregate risk, funds have an additional cost of large bilateral exposures. The costs of bearing aggregate and concentration risk govern the network effects present in the model, since they determine the elasticity of substitution across different counterparties. Moreover, they play different roles in the model. The marginal cost of risk involves all of the marginal units of risky positions. Meanwhile, the marginal cost of concentration risk gives a fund incentives to smooth its exposure across banks within its network of counterparties. Concentration risk prevents equalizing the cost of aggregate risk across counterparties, and its prevalence is larger as the number of counterparties reduces.

Funds can invest in three types of assets. They can lend to banks, hold Treasuries, or hold securities in the Overnight Reverse Repo Repurchase Facility (ON-RRP). I assume that the latter has no risk; meanwhile, Treasuries and unsecured lending are subject to aggregate risk. In the model, funds face a two-stage problem: In the first stage, they determine how many Treasuries to hold. Then, in the second stage, funds and banks meet simultaneously. This setting has an important consequence: Funds internalize the effects of holding Treasuries on the negotiation results with their counterparties. Also, the ON-RRP increases the bargaining power of funds, because it raises the value of the outside option for funds.

I depart from competitive pricing and assume that connected agents negotiate the terms of trade in a bilateral bargaining process characterized by heterogeneous relative bargaining power. Funds and banks meet and decide the terms of the contract in a Nash-in-Nash bargaining process. However, how do they split the surplus depends on their relative bargaining power. Two consequences of this assumption are worth noting. First, this bargaining process distorts prices as a signal of the marginal cost of funding. In this context, prices will be the average of the bank's benefit and the fund's cost of funding with respect to their outside option. Second, market power will affect the funds' portfolio choice: A low market power incentivizes funds to reduce the funds available for negotiation by internalizing the price of aggregate risk-taking.

In estimating the model, I face the challenge that prices and quantities are endogenous. They are determined in equilibrium and, at the same time, funding shocks are correlated with other aggregate shocks, such as uncertainty and liquidity shocks. To estimate the empirical model, I exploit granular shocks from competitors, extending the argument of Gabaix and Koijen (2020). Granular shocks from connected agents are plausibly exogenous with respect to unobserved confounders and determine both prices and quantities. The identification argument relies on the equilibrium network effects, that is, trading motives of competitors will affect terms of trade because they affect the cost of risk.

I identify the ratio of aversion to aggregate risk and aversion to concentration risk and provide an upper and lower bound for the funds' concentration risk. My estimates suggest that the cost of funding provision increases rapidly with the level of concentration risk, so that this risk accounts for 20 to 40 percent of the marginal cost of funding for the average fund. In sum, concentration risk prevents funding from flowing through the network, and especially to banks connected to a small number of counterparties.

I also identify the effect of an increase in total exposure on the bilateral interest rate. With this identified effect, I can deliver an estimate of the bilateral bargaining power.

My estimates predict that on average, the median elasticities of the bilateral interest rate with respect to total exposures are about 6 basis points and are heterogeneous across agents in this market.

To quantify the predicted effects of a funding supply shock from the model's perspective, I take as primitives the observed investors' redemption of shares in prime funds in March 2020. I parameterize the model using the set of estimated parameters and calibrate the remaining to match the initial distribution of bilateral funding and bilateral prices between banks and prime funds as of February 2020. I introduce a negative shock in the size of the funds, which is approximately 11% of the assets under management of the prime segment.[1]

My model predicts an increase in cost of funding, a rise in interest rate dispersion and a drop in funding provision comparable to those observed in the data. Price dispersion, measured by the interquartile range, increases from 22 to 66 basis points in the model. At the same time, the median rate in my model rises 61 basis points. The model predicts a 14% fall in aggregate lending, which is close to that observed in the data of about 16%. A reduction in loanable funds reduces the funds' supply of funding available for banks. I find that the allocative efficiency worsens after the shock. A planner subject to the same preferences and regulatory constraints would allocate 22% more funds to banks than the decentralized solution. The planner would reduce lending by only 9% from February to March 2020.

What can we learn from price dispersion? As the bargaining power of funds increases, prices will place a larger weight on the banks' benefits of funding with respect to their outside option. As the marginal benefit increases with dollar borrowing, a reduction in lending will increase the banks' benefit of the contract. This is consistent with the rise in the median spread. Dispersion in the change of the banks' total exposure will create price dispersion for this reason. Indeed, in partial equilibrium, an increase in market power

[1] Author's calculations using CRANE data on monthly portfolio holdings between February and March

delivers higher and more dispersed prices.

I assess the role of the Overnight Repo Repurchase Program (ON RRP) and show that a reduction in the ON RRP rate can further hurt market outcomes after a supply funding shock. This exercise is of particular interest given the spectacular increase in ON-RRP assets, which peaked in October 2021 and reached a value of $1.6 Trillion. In the model, the ON RRP is the outside option for funds when trading with banks. A decrease in the ON RRP decreases the bargaining power of funds, reducing the incentives to supply funding. Therefore, reducing the ON RRP rate reduces unsecured lending and increases interest rate dispersion. These results show that the ON RRP facility gives funds an appealing outside option.

Related Literature. My main contribution is to empirically assess how network frictions can potentially impact price dispersion and funding provision after a large aggregate funding shock. I show that for the U.S. Money Market Funds industry these frictions have a large impact on price dispersion. Other papers empirically assess the role of relationship lending during turbulent times in the context of other over-the-counter markets (Di Maggio, Kermani, and Song, 2017). I depart from those papers because I provide a structural analysis that distinguishes the value of connections from bilateral bargaining market power. Moreover, I focus on the effect of funding shocks rather than the effects of dealers' risk aversion.

My paper contributes to research on OTC markets. The model is closely related to Eisfeldt et al. (2019) and Atkeson, Eisfeldt, and Weill (2015), both of which feature risk averse agents and limited counterparty risk. Counterparty risk in Atkeson, Eisfeldt, and Weill (2015) is present in the form of bilateral trade limits, while in Eisfeldt et al. (2019) is viewed as concentration risk that creates limited risk bearing capacity. Also, Eisfeldt et al. (2019) studies the role of trading frictions in the context of an incomplete network. Price dispersion arises in their model because of the incompleteness of the network together with concentration risk. I depart from their paper by assuming a bilateral bargaining problem between counterparties within the incomplete network and I allow for heterogeneous market power. Both trading frictions and heterogeneity in bilateral market power can explain price dispersion in my model. In other words, the terms of trade between two equally connected counterparties might differ because of their differences in market power. Moreover, my paper provides an estimation framework for the model's key parameters using microdata. I focus on a different application and quantitatively assess how bilateral relationship frictions affect the transmission of funding shocks.

This paper also contributes to the literature on decentralized markets by testing how terms of trade reflect the incentives for borrowing or lending from a specific counterparty and their outside options. This implication has been emphasized in the literature on search and matching. Ashcraft and Duffie (2007) and Longstaff, Mithal, and Neis (2005) document how the cross-sectional variation in the terms of trade reveal the nature of decentralized markets. The former discusses the implications for the Federal Funds Market, while the later makes this observation for the Credit Default Swap market. This paper tests this hallmark implication for the case of the Money Market Funds Market. I go further by identifying the causal effect of the relative balances of the lender and borrower on the terms of trade.

Furthermore, my identification strategy allows the estimation of the key parameters in the structural model to speak about the role of frictions and market power. Gavazza (2016) also estimates a structural model to quantify the role of search frictions. In contrast, my paper focuses on network frictions that prevent beneficial trades and accounts for heterogeneous intermediaries. In this paper, I use detailed micro-data on the interaction of money market funds and banks, which allows for the identification of rich heterogeneity.

My work also contributes to identifying macro-financial models in the context of linear networks and general equilibrium. Whereas Gabaix and Koijen (2020) provide a framework that allows the identification of aggregate multipliers and social interactions using granular shocks, their framework does not allow for the identification of heterogeneous effects.

I propose a novel identification strategy when bilateral quantities and prices are observed, which allows me to identify the heterogeneity in market power. I depart from the literature on industrial organization that exploits prices from competitors for identification by removing potential confounding variables that move together quantities and prices and correlate across agents. This framework opens new venues of research in the context of decentralized markets where agents are heterogeneous and interact through a network structure.

The broad motivation for this paper draws on the recent literature that highlights the importance of market power for the transmission of aggregate shocks (Drechsler, Savov, and Schnabl, 2017). I focus on market power of banks in the wholesale funding markets, which is often overlooked when thinking about the transmission of aggregate shocks and the role of banks in funding provision. Other papers have explored the monetary policy pass-through of shadow banks (Xiao, 2019; Vandeweyer, 2019) and the implications of the lower bound for shadow banks (Di Maggio and Kacperczyk, 2017). Mine is the first paper that looks at the implications of the ON-RRP facility for shadow banks' intermediation. In contrast to existing papers, I consider bilateral market power and network frictions between shadow and traditional banks.

My paper contributes to the literature on Money Market Funds. Aldasoro, Ehlers, and Eren (2019) shows that there is significant price dispersion that can be accounted by the bargaining positions of funds and banks. Li (2021) also explores the role of relationships between Money Market Funds and banks across different markets. In this paper, I focus on unsecured funding between banks and funds during a funding crisis in a network of counterparties and I provide a structural framework to quantify these mechanisms.

Theoretical papers for the Money Market Funds industry account for liquidity risk (Vandeweyer, 2019; La Spada, 2018; Aldasoro, Huang, and Tarashev, 2021; Parlatore, 2016). These papers abstract from frictional relationships between financial intermediaries. My paper departs from them by considering network frictions between banks and funds. In my model, agents are risk averse and funds are subject to concentration risk, which is an important feature in the U.S. Money Market Funds Industry. Also, I allow for significant heterogeneity across banks and funds. Moreover, I am the first testing the implications of the funds' access to the ON-RRP facility.

Other papers have studied the U.S. Money Market Funds Industry in the context of the COVID-19 pandemic. Anadu et al. (2021a) and Li et al. (2021) explore the role of redemption gates and the Weekly Liquid Assets Ratio in the runs during COVID-19. Cipriani and Spada (2020) and Li et al. (2021) also analyze the impact of the Money Market Mutual Fund Liquidity Facility. Other papers (Haughwout, Hyman, and Shachar, 2021; Bi and Marsh, 2020; Cipriani et al., 2020; Kargar et al., 2021) provide empirical evidence of the impact of policy interventions during COVID-19 in the markets of the municipal bond market and the corporate debt market. My paper also studies the COVID-19 shock in the U.S. Money Market Funds industry, but focuses on the effects of drops in assets under management, taking them as primitives of funding supply shocks in the unsecured funding market. My paper contributes to the literature on COVID-19 and U.S. Money Market Funds by studying the impacts of the COVID-19 funding short-falls of prime Funds on unsecured funding provision to banks and interest rate dispersion in unsecured funding rates between funds and banks.

My paper is related to the literature on the link between global banks and shadow banking. Anderson, Du, and Schlusche (2021), Correa, Sapriza, and Zlate (2021) and Aldasoro et al. (2019) exploit funding dry-ups episodes in the U.S. Money Market Funds Industry to estimate the effects of liquidity short-falls on global banks intermediation. My paper contributes to this literature by identifying the impact of a large aggregate funding shock to the U.S. Money Market Funds Industry on banks' borrowing in unsecured funding. My results show that a funding supply shock in the U.S. Money Market Funds Industry has a heterogeneous impact across banks, which depends heavily on the banks' number of counterparties. I also show that price dispersion increases across banks after a funding shock. These results can explain the heterogeneous responses of global banks after a funding supply shock to unsecured funding markets.

Outline. The paper is as follows. Section 2 describes the U.S. Money Market Funds industry, section 3 presents the static model that rationalizes the motivating facts and describes the key mechanism, section 4 presents the identification strategy. Section 5 describes the data, section 6 presents the empirical results, section 7 discusses the counterfactual exercises and the final Section 8 concludes the paper.

2 The U.S. Money Market Funds Industry

In this section, I provide the institutional background of the U.S. Money Market Funds industry. First, I discuss the institutional context and the consequences of the Covid-19 dash-for-cash episode in this industry. I then provide some motivating evidence for the key frictions in my model.

2.1 Institutional Context

U.S. Money Market Funds are open-ended mutual funds that invest in short-term money market instruments. This industry supplies about 35% of U.S. dollar short-term lending and it is sizable as measured by size in assets under management about $5 trillion. U.S. Money Market Funds can be either government or prime funds. Government funds' portfolio is limited to U.S government securities and repurchase agreements. Prime funds are allowed to invest in unsecured lending instruments and are an important source of funding for global banks.[2]

The Securities and Exchange Commission (SEC) regulates the domestic Money Market Funds, and limits, under Rule 2a-7 of the Investment Company Act of 1940, the risks associated to their portfolios including concentration risk and liquidity risk.[3] Importantly, a fund cannot invest more than 5% of its total assets in one issuer and no more than 10% in

[2]The industry structure and its connection to other markets is described in Appendix Figure A.1.
[3]Rule 2a-7 of the Investment Company Act of 1940 limits as well the maturity and credit risk

securities issued by or subject to guarantees or demand feature from any one institution.[4] Also, Money Market Funds are required to file Form N-MFP, which includes detailed monthly information on their portfolio holdings.[5] [6]

2.1.1 The Events of March 2020

In the context of the Covid-19 *dash-for-cash*, investors redeemed massively their shares in the prime segment. Between March 6 and March 26, the outflows totalled 19% of the industry's assets in December 2019, comparable to those in 2008 (Cipriani and Spada, 2020) Figure 2 shows the monthly change in assets under management by segment. Prime funds experienced a large fall in assets under management that totaled 11% between February and March. On the other hand, government funds received inflows of about 30% of their assets under management. Outflows from prime funds improved after the Money Market Liquidity Facility (MMLF) was in place.[7]

Following the massive redemptions from prime money market funds, distress in unsecured lending markets reflected in large interest increases and interest rate dispersion in contract rates between banks and funds. Figure 3 shows the distribution of the spread between interest rates of Commercial Paper (CP) and Certificates of Deposits (CD) with respect to the risk free rate measured by Interest on Excess Reserves Rate (IOER). The median spread increased by around 85 basis points. At the same time, price dispersion increased substantially, registering a record of 160 basis points in the difference between the 95th and 5th percentiles. Price dislocations in the March 2020 episode were larger and only

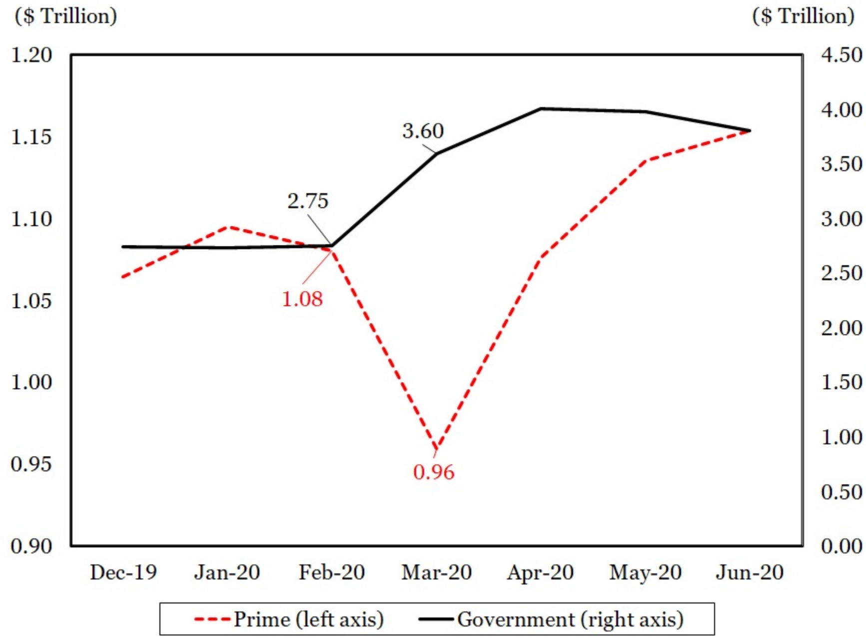
[4] Furthermore, the SEC provides special provisions for second-tier securities.

[5] Funds also provide other useful information for evaluating risk, including the NAV per share and liquidity levels and shareholder flows

[6] To reduce investor risks, the SEC adopted the 2016 reform, which includes a floating net asset value and the introduction of redemption gates.

[7] Anadu et al. (2021a) and Li et al. (2021) assess the effects of the MMLF on the money market fund industry.

Figure 2: Assets Under Management by Type of Money Market Fund



Notes: Data from Crane. Author's calculations. The black solid line shows the assets under management for prime funds in trillion US dollars.The red dashed line shows the assets under management for government funds in trillion US dollars.

comparable to the 2008 crisis (Anadu et al., 2021a). [8] [9]

2.2 Motivating Evidence

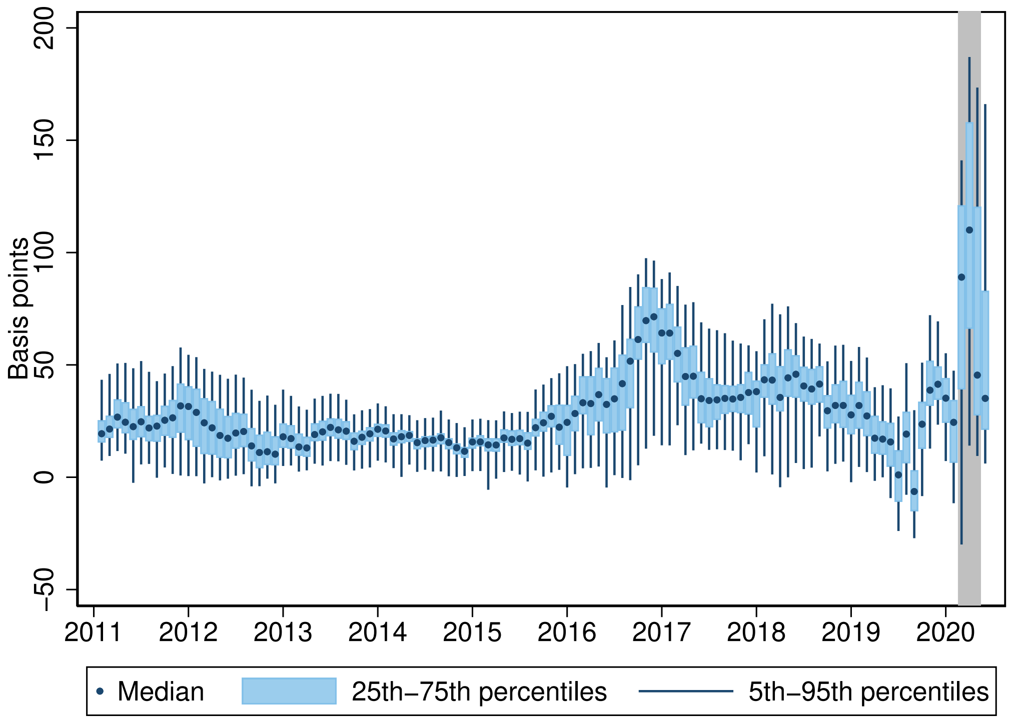
In this section, I provide evidence on prime segment characteristics and their interaction with banks.

Network of counterparties Prime funds provide funding in secured and unsecured market to banks and other financial and non-financial institutions. The number of prime funds functioning as of December 2019 is 65, and the number of banks is 81. The network of counterparties is incomplete, but large entities, measured by size of their assets, have more connections than smaller entities. The average number of a bank's counterparties is 22, but

[8]There is no data before 2011 to evaluate the impacts of the liquidity withdrawals in the global financial crisis. The European crisis is also an episode of distress in this market, but relates to the risk profile of European banks. The 2016 reform also created price dispersion. However, the effects were of longer duration and had been anticipated since 2014.

[9]The Covid-19 run responded to a flight to safety by investors, rather than concerns about the risk profile of the funds' counterparties

Figure 3: Percentiles for the Spread between the Rates for Certificates of Deposit and Commercial Paper and the Secured Overnight Funding Rate (SOFR)



Notes: Data from CRANE. Author's calculations. The rates are monthly and show the quantity-weighted average of the transaction between a fund and a specific counterpart in the trade of certificates of deposit (CD) and commercial paper (CP). The blue dot shows the median spread between CD and CP rates and the secured overnight repo rate. The light blue area shows the interquartile range (25th-75th percentiles) and the solid blue line the 5th-95th percentiles). The shaded gray area corresponds to March and April, 2020, which correspond to the Covid-19 dash-for-cash episode.

the number of counterparties varies from 1 to 50. Similarly, the average number of a fund's counterparties is 27, ranging from 1 to 47.

Appendix Figure A.2 represents the network of counterparties by December 2019 in the prime segment. The figure highlights that there is substantial heterogeneity in the number and intensity of bilateral relationships as measured by value of the bilateral funding. Appendix Figure A.2 also shows that large funds and large banks typically have more bilateral relationships. Because of regulatory constraints, U.S. Money Market funds have counterparty limits, which results in large entities having more connections.

Sticky relationships Relationship frictions are important between funds and banks, as the length in months of bilateral relationships between banks and funds is long. Appendix Figure A.3 shows the cumulative density of the number of months of a existing bilateral relationship in March 2020. First, the median number of months of a bilateral relationship is about 2 years. Second, the probability of trading without a preexisting relationship is lower than 1 %

This aspect of the Money Market Funds Industry and its relationship with banks suggests limited connectivity and banks' difficulties substituing lenders during a funding crisis. Limited substitution implies that banks rely on their existing counterparties, which limits the outside options for banks. These observations can be explained by thorough evaluation of the risk profiles of the funds' counterparties.[10]

Concentration The U.S. Money Market Funds Industry is highly concentrated, as measured by share of the top 15 funds. Figure A.4 presents the evolution in time of the market share of the top 15 funds in unsecured instruments held by U.S. Money Market Funds Industry. The market share of the 15 funds has increased over time, and it accounts for around 60% in unsecured lending.[11] [12]

Bilateral funding relationships in unsecured instruments between banks and funds are also highly concentrated. Figure A.5 shows the distribution of the share of the bank's top lender in unsecured lending. Typically, the top lender has a very large share of lending: the median share of the bank's top lender is around 30%. Figure A.5 also shows that approximately 25% of banks satisfy half of their funding needs with only one counterparty.

Cross-sectional interest rate dispersion How does interest rate dispersion depend on the agents' exposures to unsecured funding? I assess this question by estimating how much of the cross-sectional variation in bilateral interest rates in unsecured instruments can be

[10]From conversations with market participants, funds do not revise often their set of counterparties.
[11]The share of the top 15 families is about 80%, showing larger concentration at the family level
[12]Top 15 prime funds accounted for a 40% share of unsecured instruments as of March 2020.

accounted for the correlation with the bank and fund's portfolio share of unsecured lending in this industry.

I estimate the following econometric model:

$$r_{b,f,c,t} - r_t^\star = \delta_t + \beta_B \frac{Q_b}{S_b} + \beta_F \frac{Q_f}{S_f} + \beta_{BF} \frac{q_{bf}}{S_f} + \gamma' x_{b,f,t} + \epsilon_{b,f,c,t}, \tag{1}$$

where $r_{b,f,c,t}$ is the interest rate of contract c, between bank b and fund f at time t, $r_t^\star$ denotes the Secured Overnight Funding Rate (SOFR),[13] δ_t is a time-fixed effect, $\frac{Q_b}{S_b}$ and $\frac{Q_f}{S_f}$ are the share of unsecured funding with respect to total assets of bank b and fund f respectively, $\frac{q_{bf}}{S_f}$ is the bilateral portfolio share and x_t includes other control variables.

I provide evidence of terms of trade being correlated to the banks and funds' portfolio exposure in unsecured funding. Table 1 shows the least squares estimates of Equation (1).[14] Results in Table 1 show that the bilateral interest correlates with the agents' portfolio shares. This correlation suggests that the terms of trade depend on the bilateral bargaining positions of banks and funds. Table 1 shows a negative correlation between the bank's total unsecured funding and the bilateral interest rate of the contract. I find a positive correlation between the fund's total unsecured funding and the bilateral interest rate of the contract.

3 Model

In this section I build a partial equilibrium model of unsecured funding between Money Market Funds and banks. This framework allows me to quantify the impact of network frictions on the transmission of a large drop in funds' assets under management as that observed in March 2020.

[13] I subtract the SOFR to control for the effects of the monetary policy stance in the regressions.

[14] Note that all the 4 estimates include a time-fixed effect, and therefore I can interpret the effects as the effects on cross-sectional dispersion

Table 1: The Effect of the Bank and Fund's Exposures on the Spread of Prime Contract Rates and the and the Secured Overnight Funding Rate (SOFR)

	Prime contract rates spread			
	(1)	(2)	(3)	(4)
Banks' exposure	-0.122***	-0.0780**	-0.107***	-0.0632*
	(0.0382)	(0.0368)	(0.0351)	(0.0340)
Funds' exposure	6.235**	5.094**	5.848**	4.599*
	(2.593)	(2.472)	(2.811)	(2.694)
Bilateral lending	-8.500***	-7.807***	-8.393***	-7.731***
	(1.048)	(0.930)	(1.032)	(0.922)
Family portfolio share			2.319	2.442
			(3.690)	(3.381)
Observations	402,523	402,513	445,471	445,460
R-squared	0.947	0.950	0.946	0.948
Time FE	YES	YES	YES	YES
Country and Time FE	NO	YES	NO	YES
Fund FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES

Notes: ***p<0.01, **p<0.05, *p<0.1. Data from CRANE. The observation level is contract-bank-fund-month. Clustered standard errors at the bank-family-month level in parentheses. The dependent variable is the spread of the prime fund rates relative to the Secured Overnight Funding Rate (SOFR) and is measured in basis points. The covariates are the ratio of bank's total borrowing in CP and CD instruments with respect to total assets, the fund's total portfolio share in CP and CD instruments, and the value of the contract as a share of the fund's assets under management. All estimations include the prime segment only. Controls include the change in assets, bank's return on assets and equity prices. The standard deviation of the funds' portfolio share is 11.2 percentage points. The standard deviation of the banks' exposure is 1.5 percentage points. Column 2 includes country and time fixed effects. Column 3 includes as a covariate the value of the contract as a share of the fund family's assets under management, and excludes country and time fixed effects. Column 4 includes the fund family portfolio share and country-time fixed effects.

3.1 Agents

The market is composed of finitely many agents, who come in two types: banks and funds. Banks, indexed by $b \in \mathcal{B}$, borrow from money market funds and receive an heterogeneous return on assets. Funds, indexed by $f \in \mathcal{F}$, provide funding to banks.

Banks and funds are connected through a network. The network of trade connections can be incomplete and specifies which agents can bilaterally trade together. The network is represented by $\mathcal{G} \subseteq \{0,1\}^{|\mathcal{B}|\times|\mathcal{F}|}$, where I denote by $bf \in \mathcal{G}$ that bank b and fund f can trade bilaterally. I denote $\mathcal{G}_f^{\mathcal{B}}$ and $\mathcal{G}_b^{\mathcal{B}}$ the fund f's and bank b's set of counterparties respectively.

I assume that the network is exogenous. This exogenous trade structure is a plausible assumption given that links tend to be sticky, as discussed in Section 2.

A contract between bank b and fund f specifies that bank b promises to pay r_{bf} to fund f for each unit of debt, which I denote by q_{bf}. The terms of the contract (r_{bf}, q_{bf}) will be determined in a bilateral bargaining between bank b and fund f.

3.1.1 The Fund's Problem

Each fund is endowed with assets under management S_f. The fund invests in unsecured instruments issued by banks, treasuries or overnight reverse repurchase instruments (RRP).[15] I denote Q_f, T_f and M_f as the funds' holdings of unsecured instruments, treasuries and RRP respectively.

The balance sheet constraint of the fund is as follows:

$$S_f = Q_f + T_f + M_f. \tag{2}$$

Total unsecured instruments is composed by the sum of lending across counterpar-

[15]Treasuries in the model are other instruments besides unsecured lending that have aggregate risk. In practice, it could represent any other risky or illiquid asset.

ties, q_{bf}, where b is in the fund's network. That is:

$$Q_f = \sum_{b \in \mathcal{G}_f^{\mathcal{B}}} q_{bf}. \tag{3}$$

The fund's preferences are:

$$\begin{aligned}\Pi_f^{\mathcal{F}} =& \overbrace{r^T T_f + r^M M_f + \sum_{b \in \mathcal{G}_f^{\mathcal{B}}} \Big((r_{b,f} + \epsilon_{b,f}) q_{b,f} \Big)}^{\text{Return}} \\ & \underbrace{- \frac{\alpha_F}{2} \frac{1}{S_f} (Q_f + T_f)^2}_{\text{Aggregate Risk}} \underbrace{- \sum_{b \in \mathcal{G}_f^{\mathcal{B}}} \left(\frac{\phi_F}{2} S_f \left(\frac{q_{b,f}}{S_f} \right)^2 \right)}_{\text{Concentration risk}}.\end{aligned} \tag{4}$$

The term on the fist line of Equation 4 is the return on assets, where r^T, r^M and $r_{b,f}$ denote the return of Treasuries, RRP and bilateral lending respectively.

The term $\epsilon_{b,f}$ is an idiosyncratic speculative trading motive, which is a supply shifter that reflect preferential trading with bank b. In other words, $\epsilon_{b,f}$ in the model allows for heterogeneity in the value that funds assign to a specific bilateral relationship. It gives the funds an additional incentive to hold debt from a specific bank. [16]

The presence and the importance of bilateral shocks to lending will be key for the identification strategy. The argument is as follows: supply shocks of competitors will explain the variation of bilateral quantities in equilibrium through network effects. At the same time, given that I can estimate them from the observed bilateral quantities and prices after removing potential confounding unobserved variables, these shocks are arguably exogenous. I will elaborate on this in Section 4.

The various quadratic terms on the second line in Equation 4 represent the cost of bearing aggregate and concentration risk. While, I assume linearity in the assets under

[16] This assumption also relates to the strong pattern of relationship lending that I observe in the data. See appendix 2. Bilateral relationships explain around half of the observed variation in quantities, after controlling for bank and fund characteristics over time. This is also very persistent over time.

management, the problem can be thought as a portfolio problem of the fund. Two parameters are key: α_F and ϕ_F. The former governs liquidity risk, and the latter governs concentration risk.

The parameter ϕ_F captures aversion to bilateral concentration, which is in line with institutional and regulatory constraints that restrict concentration in bilateral positions as in Atkeson, Eisfeldt, and Weill (2015) and Eisfeldt et al. (2019). Indeed, Money Market Funds have strict counterparty limits and are required to hold no more than 5 percent of they portfolio in one issuer.[17]

Concentration risk and aggregate risk increase the marginal cost of funding, yet they have two different effects. The marginal cost of funding provision can be written as follows

$$MC_f = \bar{A}_f + \left(\alpha_F + \frac{\phi_F}{K_f}\right)\frac{Q_f}{S_f} + \alpha_F \frac{T_f}{S_f}, \tag{5}$$

where K_f is the number of banks in the funds' network and $\bar{A}_f = r^M - \frac{1}{K_f}\sum_b \epsilon_{b,f}$.

Importantly, the cost of concentration risk decreases with the number of counterparties. Intuitively, given a total funding supply, having a large set of counterparties makes it easier to diversify across banks.

Equation 5 also shows the effect of size on the marginal cost of funding. A drop in assets under management increases the marginal cost of funding by reducing the elasticity of the supply of funding.[18] Later in my counterfactual exercises, I will introduce a shock in S_f, assets under management, consistent with what I observe in monthly portfolio data at the fund level.

The relationship between concentration risk and aggregate risk aversion will be key in the importance of network effects in our model. Their ratio will govern the substitution across banks. A large ϕ_F makes substitution hard, meanwhile a low value of ϕ_F makes

[17] I focus on concentration risks of the funds, but it is possible to introduce such risk for the banks.

[18] Note, however, that the problem is linear in size. Therefore, I can write the solution as a portfolio problem.

unsecured lending perfect substitutes.

The three type of assets vary in return and risk. I assume that RRP have no aggregate risk. Meanwhile, Treasuries and unsecured lending incur in aggregate risk. This aspect of the model is in line with liquidity management risk faced by money market funds, as well as other shadow banks.[19] Moreover, the choice of Treasuries impacts the marginal cost of funding, as increasing the portfolio position in Treasuries reduces the funds' risk capacity.

Fund's portfolio choice In the first stage of the game, funds decide their exposures to Treasuries. In the second stage, funds bargain with their counterparties on the remaining available loanable funds. RRP facility becomes the outside option for the funds when trading with banks.

3.1.2 The Bank's Problem

Each bank is endowed with capacity S_b, which is exogenous in this model. The banks raise funding Q_b, and invests the funds in other assets.

The bank's preferences are

$$\Pi_b^{\mathcal{B}} = Q_b A_b - \frac{\alpha_B}{2}\frac{1}{S_b}Q_b^2 - \sum_{f\in\mathcal{G}_b^{\mathcal{F}}}(r_{b,f} + \xi_{bf})q_{bf}, \tag{6}$$

where $q_{b,f}$ is the bilateral lending from fund f to bank b , $r_{b,f}$ is bilateral interest rate from fund f to bank b and Q_b is total dollar borrowing of bank b, i.e $Q_b = \sum_{f\in\mathcal{G}_b^{\mathcal{M}}} q_{b,f}$.

The parameter A_b captures the returns on assets of bank b and I allow it to vary across banks, which captures heterogeneous investment opportunities at the bank level. As in the funds' problem, I assume idiosyncratic motives for trading ξ_{bf}, which will be used in the empirical strategy.

As presented here, banks are subject to a quadratic cost of debt holdings, which is

[19] See Vandeweyer (2019) for a micro-fundation

governed by the parameter α_B. This parameter captures a quadratic cost of investment, risk aversion and aversion to large exposures in the Money Market. The latter can be justified by the Liquidity Coverage Ratio imposed by regulation.

For simplicity, I assume that banks do not have concentration risk. I assume concentration risk is one the funds' side as I focus on institutional aspects of the Money Market Funds Industry that limits the flow of loanable funds through the network. In practice, global banks have counterparty limits. Yet, these limits are between 15 to 25 percent of total assets, which one could argue are not binding conditional on the existing funds' counterparty limits.

3.2 Bilateral Bargaining

I assume that for each link bf there exists a pair of traders that negotiate bilaterally taking as given the equilibrium bargaining results from other negotiation as in Collard-Wexler, Gowrisankaran, and Lee (2019). Specifically, the contract (r_{bf}, q_{bf}) maximizes the Nash product of bank b and fund f given all other negotiated prices $r_{b',f'}$ and quantities $q_{b',f'}$ for any pair $(b', f') \neq (b, f)$.

The gains-from-trade from an agreement are defined as the difference between the profits under the contract (r_{bf}, q_{bf}) and profits when (b, f) do not negotiate, which is equivalent to the case of not having this counterparty in the network. I define the gains from trade of bank b and fund f as $\Delta_{bf}\Pi_f^{\mathcal{F}}$ and $\Delta_{bf}\Pi_b^{\mathcal{B}}$ respectively.

The fund's outside option is the ON-RRP facility. Therefore, the fund's gains from trade are:

$$\Delta_{bf}\Pi_f^{\mathcal{F}} = \underbrace{(r_{bf} + \epsilon_{b,f} - r^M)q_{bf}}_{\text{Return}} - \underbrace{\alpha_F\left(T_f + \sum_{b'\in\mathcal{G}^f, b'\neq b}\right)\frac{q_{b'f}}{S_f}}_{\text{Aggregate risk of existing units}} - \underbrace{\frac{1}{2}(\phi_F + \alpha_F)\frac{q_{bf}^2}{S_f}}_{\text{Cost of new units}}. \tag{7}$$

The first term in Equation 7 is the return of the contract, minus that one of the outside option. The second term in Equation 7 is the reduction in the fund's profits coming from the increase in the marginal cost of aggregate risk of the fund's existing risky assets. The last term in Equation 7 is the cost of additional units, and it includes the aggregate and concentration risks of the new funding units.

On the other hand, the bank's outside option is leaving the negotiation without funding from fund f. The bank's gains from trade are:

$$\Delta_{bf}\Pi_b^{\mathcal{B}} = \underbrace{(A_b - \xi_{bf} - r_{b,f} - r^M)q_{bf}}_{\text{Return}} - \underbrace{\alpha_B\Bigg(\sum_{f'\in\mathcal{G}^b, f'\neq f}\frac{q_{bf'}}{S_b}\Bigg)}_{\text{Aggregate risk of existing units}} - \underbrace{\frac{1}{2}\phi_B\frac{q_{bf}^2}{S_b}}_{\text{Aggregate risk of new units}} \quad . \tag{8}$$

The fist term in Equation 8 is the return on assets minus the cost of funding. The expression also includes the cost of aggregate risk of existing and new units.

The bundle (r_{bf}, q_{bf}) is determined in a bilateral Nash bargaining that maximizes

$$(r_{bf}, q_{bf}) = \arg\max\Big(\Delta_{bf}\Pi_f^{\mathcal{F}}\Big)^{\tau_{bf}}\Big(\Delta_{bf}\Pi_b^{\mathcal{B}}\Big)^{1-\tau_{bf}}, \tag{9}$$

subject to the participation constraints:

$$\Delta_{bf}\Pi_f^{\mathcal{F}} \geq 0$$
$$\Delta_{bf}\Pi_b^{\mathcal{B}} \geq 0.$$

The Nash bargaining parameter is represented by $\tau_{bf} \in [0,1]$. I allow this parameter to vary across banks and funds.

3.3 Terms of Trade

This section provides the solution of the bargaining problem, given T_f.

Proposition 1: *Given T_f and terms of trade in other bilateral units, the optimal q_{bf} and r_{bf} satisfy:*

$$\frac{q_{bf}}{S_f} = \frac{A_b + \epsilon_{bf} - \xi_{bf} - r^M}{\phi_F} - \frac{\alpha_B}{\phi_F}\frac{Q_b}{S_b} - \frac{\alpha_F}{\phi_F}\frac{Q_f + T_f}{S_f}, \tag{10}$$

$$r_{bf} = \tau_{bf}\left\{A_b - \xi_{bf} - \frac{\alpha_B}{2}\frac{q_{bf}}{S_b} - \alpha_B \sum_{f' \in \mathcal{G}_b, f' \neq f} \frac{q_{bf'}}{S_b}\right\} \tag{11}$$

$$+ (1 - \tau_{bf})\left\{r^M - \epsilon_{bf} + \frac{\alpha_F + \phi_F}{2}\frac{q_{bf}}{S_f} + \alpha_F \frac{T_f}{S_f} + \alpha_F \sum_{b' \in \mathcal{G}_f, b' \neq b} \frac{q_{b'f}}{S_f}\right\}.$$

Proof See Appendix B.2. ■

The first implication of Nash bargaining is that the quantities maximize the pair's gains from trade, given an exogenous T. The first equation shows that, in partial equilibrium, bilateral funding decreases with the fund's and bank's portfolio share in unsecured funding. These effects arise from the cost of bearing aggregate risk and create substitution effects from other counterparties. The substitution depends on the cost of aggregate risk relative to that one of concentration risk. In absence of concentration risk, there is perfect substitution.

The second implication of Nash bargaining is that bank b and fund f will split the value of the contract consistently with their relative market power. The equation that characterizes the interest rate of the contract weights the costs and benefits accordingly. When the funds possess relatively large market power, prices tend to respond more to variation in banks' investment opportunities.

Corollary 1 *Bilateral interest rates can be expressed as a function of the bank's and fund's total portfolio holdings as follows:*

$$r_{bf} = (\tau_{bf} + \theta_{bf})(A_b - \xi_{bf}) + (1 - \tau_{bf} + \theta_{bf})(r^M - \epsilon_{bf}) - \theta^B_{bf}\frac{Q_b}{S_b} + \theta^F_{bf}\frac{Q_f + T_f}{S_f}, \tag{12}$$

where $\theta_{bf}, \theta_{bf}^B$ and θ_{bf}^F are combinations of parameters. θ_{bf}^B is increasing in the bargaining power of the fund , τ_{bf}; θ_{bf}^F is decreasing in τ_{bf}:

$$\theta_{bf}^B = \alpha_B\left(\frac{1}{2} + \frac{\alpha_B + \alpha_F}{2\phi_F}\right)\tau_{bf} + \frac{\alpha_B}{2}\left(1 - \frac{\alpha_F}{\phi_F}\right), \tag{13}$$

$$\theta_{bf}^F = \alpha_F\left(\frac{1}{2} + \frac{\alpha_B + \alpha_F}{2\phi_F}\right)(1 - \tau_{bf}) - \alpha_F\frac{\alpha_B}{2\phi_F}, \tag{14}$$

$$\theta_{bf} = \tau_{bf}\frac{1}{2}\left(\frac{\alpha_B + \alpha_F}{\phi_F}\right) + 1 - \frac{1}{2}\frac{\alpha_F}{\phi_F}. \tag{15}$$

The system of equations presented here show how some main parameters in the model can be identified in the data. That is, the ratio of concentration risk to aversion to aggregate risk can be identified from the partial elasticity of bilateral funding with respect to the bank and fund's portfolio shares in unsecured funding. Moreover, given the partial elasticity of bilateral interest rates with respect to the banks' exposure, we can identify τ_{bf} given a level of ϕ_F. I will use this set of equilibrium conditions for the empirical strategy.

Proposition 1 solves for bilateral funding given aggregate portfolio holdings. To solve for bilateral funding, I solve a fixed point problem. Due to the linearity of the terms-of-trade equation, this problem has a sufficiently simple structure that it can be represented as a system of linear equations.

Define $\mathbf{q}$ as the column vector that contains bilateral funding of connected agents, where $\mathbf{q}_n = q_{b(n)f(n)}$. Define $\mathbf{G}^F$ and $\mathbf{G}^B$ as follows:

$$\mathbf{G}^F_{n,n'} = \begin{cases} 1 & \text{if } f(n\prime) \in \mathcal{G}_{b(n)} \\ 0 & \text{otherwise} \end{cases}, \quad \mathbf{G}^B_{n,n'} = \begin{cases} S_{f(n)}/S_{b(n)} & \text{if } b(n\prime) \in \mathcal{G}_{f(n)} \\ 0 & \text{otherwise} \end{cases}$$

The following proposition characterizes the solution for bilateral funding.[20]

[20] The solution can be generalized for the case of heterogeneous costs and to include concentration risk in the other side of the market. For those cases, one would need to adjust $\mathbf{G}^B$ and $\mathbf{G}^B$ accordingly.

Proposition 2: *Let* $\mathbf{T}$ *be the column vector that contains the funds' Treasury holdings. The first stage best responses are characterized by Equation 12 and the following equation system:*

$$\mathbf{q} = \mathbf{A} - \frac{\alpha_B}{\phi_F}\mathbf{G}^F\mathbf{q} - \frac{\alpha_B}{\phi_F}\mathbf{D}'\mathbf{T} - \frac{\alpha_B}{\phi_F}\mathbf{G}^B\mathbf{q},$$

where

$$\mathbf{A}_n = \frac{S_{f(n)}}{\phi_F}\bigg(A_{b(n)} + \epsilon_{b(n)f(n)} - \xi_{b(n)f(n)} - r^M\bigg),$$

and $\mathbf{D}_{b,n} = 1$ *if* $f(n) = f$ *and zero otherwise.*

Furthermore, the solution to this system of equations is:

$$\mathbf{q} = \mathbf{M}\bigg(\mathbf{A} - \frac{\alpha_B}{\phi_F}\mathbf{D}'\mathbf{T}\bigg), \tag{16}$$

where $\mathbf{M} = \bigg(\mathbf{I} + \frac{\alpha_F}{\phi_F}\mathbf{G}^F + \frac{\alpha_B}{\phi_F}\mathbf{G}^B\bigg)^{-1}$,

and bilateral interest rates satisfy Equation (12).

Proof See Appendix B.2. ■

Note that the previous solution for bilateral funding implies that returns on assets and, more importantly, Treasury holdings affect agents even if they are not directly connected. To characterize network effects intuitively, I define the following multipliers that govern the influence of other agents' exposures through the network.

$$\Lambda_f^F = \frac{\alpha_F}{\frac{\phi_F}{K_f} + \alpha_F} \tag{17}$$

$$\Lambda_b^B = \frac{\alpha_B/S_b}{\phi_F/\sum_{f\in\mathcal{G}_b} S_f + \alpha_B/S_b}. \tag{18}$$

Where K_f is the number of counterparties of fund f.

Denote $\omega_{bf} = \frac{S_f}{\alpha_F}\bigg(A_b + \epsilon_{bf} - \xi_{bf} - r^M - \alpha_F K_f T_f\bigg)$. We can write the fund's supply of funding as follows:

$$Q_f = \underbrace{\sum_{b=1}^{N_B} \Lambda_f^F \tilde{g}_{bf}^F \omega_{bf}}_{I} \underbrace{- \sum_{b=1}^{N_B} \sum_{s=1}^{N_F} \Lambda_f^F \Lambda_b^B \tilde{g}_{bf}^F \tilde{g}_{bs}^B \omega_{bs} + \sum_{b=1}^{N_B} \sum_{s=1}^{N_F} \sum_{k=1}^{N_B} \Lambda_f^F \Lambda_b^B \Lambda_s^F \tilde{g}_{bf}^F \tilde{g}_{bs}^B \tilde{g}_{sk}^F \omega_{ks} + \ldots,}_{II} \tag{19}$$

where $\tilde{g}_{bf}^B = \frac{1}{\sum_{f \in \mathcal{G}_b} S_f}$ if $f \in \mathcal{G}_b$, and zero otherwise; and $\tilde{g}_{bf}^F = \frac{1}{K_f}$ if $b \in \mathcal{G}_f$, and zero otherwise.

Equation 19 shows how the multipliers in Equation 17 affect the transmission of funding shocks across the network on the fund's funding provision. It is worth highlighting three determinants of these multipliers: (1) the ratio of aversion to aggregate risk to concentration risk; (2) the number of counterparties; and (3) the relative size.

The fund's multiplier is the ratio of the cost of aggregate risk to the total cost of funding.[21] As I described before, the cost of concentration risk becomes zero if either ϕ_F becomes small or if the fund has a large number of counterparties. When any of these conditions is satisfied, the multiplier becomes 1, and the relevant cost is aggregate risk aversion. Whenever concentration risk is large, the fund's becomes less responsive to funding shocks.

The bank's multiplier takes a similar form to that one of the fund's. The numerator is the bank's cost of aggregate risk. The denominator includes the bank's cost of aggregate risk and the cost of concentration risk for its counterparties. Note that, when the bank is small compared with its counterparties, the multiplier converges to 1. In this case, the relevant cost is the bank's aversion to aggregate risk. Meanwhile, a large bank becomes less responsive to funding shocks as the relevant cost becomes that one of concentration risk for its counterparties.

From Equation 19, it is clear that the effect of S_f on the funds' funding provision can be decomposed into two parts as noted in Equation 19. First, expression I in Equation

[21]See Equation 5.

19 is related to the direct effect of S_f. Second, expression II in Equation 19 is related to the effect of S_f through the impact on the fund's counterparties and path-connected agents.

3.4 Fund's Portfolio Choice

In the first stage of the game, funds' choose simultaneously their Treasury holdings, $T_f^\star$, considering the effects on bilateral funding $\mathbf{q}(\mathbf{T})$ and taking as given the best response function of other funds, $T_{f'}^\star$.

The fund's problem in the first stage is:

$$\begin{aligned} T_f^\star = \arg\max_{T_f + Q_f(T_f, T_{f'}^\star)\leq S_f} \Bigg\{ & (r^T - r^M)T_f + \sum_{b\in G_f^B} \left(r_{b,f}(T_f, T_{f'}^\star) - r^M + \epsilon_{b,f}\right) q_{b,f}(T_f, T_{f'}^\star) \\ & - \frac{\alpha_F}{2}\frac{1}{S_f}\left(Q_f(T_f, T_{f'}^\star) + T_f\right)^2 - \sum_{b\in\mathcal{G}_f} \frac{\phi_F}{2} S_f \left(\frac{q_{b,f}(T_f, T_{f'}^\star)}{S_f}\right)^2 \Bigg\}, \end{aligned} \tag{20}$$

where $\mathbf{q}(\mathbf{T})$ and $\mathbf{r}(\mathbf{T})$ are defined in Proposition 2.

Proposition 2 characterizes the best responses from the second stage of the game, taking as given T. In what follows, I solve for the quantities optimal decision in first stage, where funds choose T_f to maximize the gains from the whole game, considering the subsequent outcomes from the first stage. The ex-ante decision impacts the bargaining set, as the funds have incentives to decrease the marginal value to obtain better terms of trade in second stage.

Lemma 1 *The value of the contract satisfies:*

$$\begin{aligned} \frac{\partial r_{bf} q_{bf}}{\partial T_f} = & \underbrace{\left\{ \tau_{bf}\left\{A_b - \xi_{bf} - \alpha_B \frac{q_{bf}}{S_b}\right\} + (1-\tau_{bf})\left\{r^M - \epsilon_{bf} + (\alpha_F + \phi_F)\frac{q_{bf}}{S_f}\right\}\right\}}_{A} \frac{\partial q_{bf}}{\partial T_f} \\ & + \underbrace{(1-\tau_{bf})\frac{q_{bf}}{S_f}}_{i} - \underbrace{\alpha_B \tau_{bf} \frac{q_{bf}}{S_b} \sum_{f'\in\mathcal{G}_b f'\neq f} \frac{\partial q_{bf'}}{\partial T_f}}_{ii} + \underbrace{\alpha_F(1-\tau_{bf})\frac{q_{bf}}{S_f} \sum_{b'\in\mathcal{G}_f, b'\neq b} \frac{\partial q_{b'f}}{\partial T_f}}_{iii} \quad . \end{aligned} \tag{21}$$

Lemma 1 presents the marginal change of the contract with respect to Treasuries.

Note that expression A in Equation 21 is equal to the fund's marginal cost of bilateral funding.[22] Expression i shows the change in the value of the contract through the direct effect in the cost of aggregate risk. In absence of this mechanism, the fund would have taken as given the additional risk bearing in the price of funding. Expressions ii and iii are the increase in the value of the contract through the indirect effects of other negotiation processes.

Lemma 1 shows the incentives of the fund to increase or decrease Treasury holdings to improve the terms-of-trade when negotiating with its counterparties. Proposition 3 shows the fund's optimal portfolio choice that follows Lemma 1.

Proposition 3: *The equilibrium portfolio holdings satisfy:*

$$r^T - r^M - \alpha_F \frac{T_f + Q_f}{S_f} + \mu_{1,f} + \mu_{2,f} + \mu_{3,f} = 0 \tag{22}$$

Where:

$$\mu_{1,f} = \alpha_F \sum_{b \in G_f} (1 - \tau_{bf}) \frac{q^*_{b,f}}{S_f} \tag{23}$$

$$\mu_{2,f} = \alpha_F \sum_{b \in G_f} \sum_{b' \in G_f, b' \neq b} (1 - \tau_{bf}) \frac{q^*_{b,f}}{S_f} \frac{\partial q^*_{b',f}}{\partial T_f} \tag{24}$$

$$\mu_{3,f} = -\alpha_B \sum_{b \in G_f} \sum_{f' \in G_b, f' \neq f} \tau_{bf} \frac{q^*_{b,f}}{S_b} \frac{\partial q^*_{b,f'}}{\partial T_f}, \tag{25}$$

Where

$$\frac{\partial \mathbf{q}^\star}{\partial \mathbf{T}} = -\frac{\alpha_F}{\phi_F} \mathbf{M}$$

Moreover, $\mu_{1,f} \geq 0, \mu_{2,f} \leq 0,$ *and* $\mu_{3,f} \leq 0.$

Proof See Appendix B.2. ■

Proposition 3 characterizes the optimal Treasury holdings. The terms $\mu_{1,f}, \mu_{2,f}$,

[22] Bilateral funding satisfies Hosios Theorem in this setting.

and $\mu_{3,f}$ are effects linked to monopolistic competition, since funds internalize that the price of the contract includes the price of aggregate risk of the new additional funding units. Funds with low market power will hold more risky units, which increases Treasury holdings. Note that from the planners' perspective, the marginal cost of aggregate risk should be equal to the relative return on Treasuries with respect to money holdings. Instead, under imperfect competition, the model will deliver meaningful network effects that relate to the distribution of market power and connectivity across agents.

Proposition 3 predicts that distributional effects across funds and across banks will arise as a consequence of differences in bilateral bargaining power, connectivity and size. These characteristics create opposing forces that drive Treasury holdings: Low bargaining power generally creates incentives to increase risk-taking; agents' connectivity reduces this effect, especially when funds are large compared with banks.

First, $\mu_{1,f}$ reflects the incentives of funds to bear larger aggregate risk to receive better terms of trade in the subsequent negotiations.To see how $\mu_{1,f}$ induces a larger position in Treasuries, consider a fund with zero market power. For simplicity, consider the case in which banks connected to f are not connected to other funds. In this case,

$$T_f = \frac{S_f(r^T - r^M)}{\alpha_F} > \frac{S_f(r^T - r^M)}{\alpha_F} - Q_f.$$

In this case, the fund provides less funding than optimal and holds a larger portfolio's share in Treasuries.

The wedges $\mu_{2,f}$ and $\mu_{3,f}$ appear from network effects. First, when the fund is connected to a large number of banks, increasing Treasuries reduces the price of risk indirectly through the reduction in risk bearing in other negotiations. When the fund has relatively low market power, it is compensated by the cost of the contract. Therefore, the fund has incentives to reduce the portfolio share of risky assets.

The last effect, $\mu_{3,f}$, is negative when the fund's counterparties are connected to a large number of funds and the fund has relatively large market power. Banks are able to substitute away from fund f when fund f increases the cost of funding. This reduces the value of the contract for fund f, because increasing Treasuries reduces the marginal benefit of the bank. Funds internalize this effect by decreasing the portfolio share of risky assets when they have large market power and many connections. This effect is larger if banks are small compared with their counterparties. From Equation 19, it is clear that the bank's network effects are large whenever they are small compared with their counterparties.

3.5 Equilibrium

Definition 1 *A subgame perfect equilibrium is a set of strategies $\mathbf{T}^\star$, M $q(\mathbf{T})$ and $r(\mathbf{T})$ such that:*

- $q^*_{bf}(\mathbf{T})$ *and* $r^*_{bf}(\mathbf{T})$ *that solve the bilateral bargaining problem in Equation 9* $\forall\, b, f$*, given* $T_f\ \forall\, b, f$*, and* $q^*_{b'f'}(\mathbf{T})$ *and* $r^*_{b'f'}(\mathbf{T})\ \forall\, b', f'$
- T^*_f *solves the fund's problem in Equation 20 considering* $q^*_{bf}(\mathbf{T}^*)\ \forall\, b, f.$
- $M_f = S_f - T^\star_f - \sum_{b\in\mathcal{G}_f} q^\star_{bf}(T^*)$

Propositions 1 and 3 fully characterize the equilibrium as a system of linear equations. We can solve for Treasury holdings as follows.

Corollary 2 *Equilibrium Treasury holdings satisfy:*

$$\mathbf{T} = \alpha_F^{-1}\left(\mathbf{I} - \frac{1}{\phi_F}(\mathbf{D}-\tilde{\mathbf{D}})\mathbf{M}\right)^{-1}\left(\mathbf{S}(r^T - r^M) - \alpha_F(\mathbf{D}-\tilde{\mathbf{D}})\mathbf{M}\mathbf{A}\right), \tag{26}$$

where $\mathbf{S}$ *is the column vector of sizes,* $\mathbf{A}$ *and* $\mathbf{D}$ *are defined in Proposition 2, and*

$$\tilde{\mathbf{D}}_n = \frac{1}{\alpha_F}\mathbf{D}_n\left\{\alpha_F(1-\tau_{b(n)f(n)})\left\{1+\sum_{b'\in G_{f(n)},b'\neq b(n)}\frac{\partial q^*_{b',f(n)}}{\partial T_{f(n)}}\right\}-\alpha_B\tau_{b(n)f(n)}\sum_{f'\in G_{b(n)},f'\neq f(n)}\frac{\partial q^*_{b(n),f'}}{\partial T_{f(n)}}\right\}$$

Corollary 2 shows the effects of the bargaining frictions on Treasury holdings through the network. Bargaining frictions affect the level and the elasticity of Treasury holdings with respect to size and relative returns. The effects of the distortions will propagate to connected competitors through the cost of aggregate risk.

The effects of an aggregate funding shock I take as primitives the size in assets under management and produce counterfactual estimates of the effects of a drop in the funds' assets under management. The following proposition characterizes the response of the planner after a shock in S_f.

Proposition 4: *Consider a 1 percent drop in S_f for all f. The planners' drop in aggregate funding, Q is*

$$\Delta Q\% = -1 + \underbrace{\sum_f \sum_{b \in \mathcal{G}_f} \frac{1}{\alpha_F + \frac{\phi_F}{K_f}} (1 - \Lambda_b^B) \frac{S_b}{S_f} \frac{y_B}{Q}}_{(a)} \tag{27}$$

Also, allocative efficiency deteriorates when the market's funding provision starts below the planner's.

Proposition 4 shows the planners' response as consequence of a 1 percent drop in assets under management. The planners' elasticity of aggregate funding with respect to assets under management is lower than 1, because the marginal benefit of funding does not fall as much as does the marginal cost. The aggregate elasticity depends on the set of banks' multipliers, the banks' initial share of funding and the funds' cost of funding. Note that Λ_b^B weights the bank's aggregate risk aversion and the cost of concentration risk faced by its counterparties. When concentration risk dominates, $\Lambda_b^B = 1$ and the planner's funding drops 1 percent. When concentration risk is relatively small, the importance of the effects in *(a)* in Equation 27 depends on the funds' cost, as can be noted in the denominator.

Proposition 4 also states that allocative efficiency worsens after a drop in assets under management if the economy's funding provision starts below the planner's allocation.

I will assess empirically the allocative efficiency after a drop in assets under management.

4 Empirical Design

Proposition 1 provides a system of equations for quantities and prices. In this section, I will discuss how to identify the key parameters of the model.

4.1 Quantities

Equation 10 relates bilateral funding from fund f to bank b, q_{bf} to the bank and fund's total funding Q_b and Q_f, respectively. As noted in the previous section, the key parameters in this equation are α_B, α_F and ϕ_F. These parameters govern the transmission of funding shocks. Equation 10 shows that the relative cost of aggregate risk and concentration risk can be estimated from the empirical elasticity of bilateral funding to the bank's and fund's total funding.

In this setting, the bank and fund's total funding are mechanically related to the bilateral funding. By definition,

$$Q_b = q_{bf} + \sum_{f' \in \mathcal{G}_b} q_{b'f}.$$

Hence, an increase in q_{bf} increases Q_b, which is a classic reflection problem.

Estimating α_B/ϕ_F requires exogenous variation that moves q_{bf} only through Q_b. Ideal candidates for exogenous shifters come from the variation in the supply of other funds. I will use granular variation from connected agents to identify the effects of Q_b and Q_f on q_{bf}.

To fix ideas, I will assume $\alpha_F = 0$ to explain the intuition of the identification strategy. I will show the estimation recipe for the general case in Section (4.1.1). When $\alpha_F = 0$,

$$\frac{q_{bf}}{S_f} = \underbrace{\frac{A_b + \epsilon_{bf} - \xi_{bf} - r^M}{\phi_F}}_{A_{b,f}} - \frac{\alpha_B}{\phi_F}\frac{Q_b}{S_b}$$
$$\frac{q_{bf}}{S_f} = A_{b,f} - \frac{\alpha_B}{\phi_F}\frac{Q_b}{S_b}.$$

In equilibrium,

$$\frac{Q_b}{S_b} = \Lambda_b \sum_{f \in \mathcal{G}_b} \frac{S_f A_{bf}}{S_b}.$$

Suppose we were to observe A_{bf} and that are not correlated across funds.[23] Define

$$Z_{b,f} = \frac{\sum_{f \in \mathcal{G}_b, f \neq f'} S_{f'} A_{bf}}{S_b}. \tag{28}$$

The following moment condition could be used for identification:

$$\mathbf{E}\left\{ Z_{bf} \left(\frac{q_{bf}}{S_f} - \theta \frac{Q_b}{S_b} \right) \right\} = 0. \tag{29}$$

Of course, we don't observe A_{bf}. Gabaix and Koijen (2020) propose a setting that leverage size distribution to identify the causal effects using the variation across agents with respect to the media. Extending Gabaix and Koijen (2020), I define $\rho_{b,f} \equiv \frac{1}{K_b - 1} \sum_{f \in \mathcal{G}_b, f \neq f'} \tilde{q}_{bf'}$. This would be the the predicted funding for bank b assuming all funds $f' \neq f$ have the same portfolio share in b. This captures the average appetite for b of competitors. [24]

In this example, a valid IV is

$$Z^{GIV}_{b,f} \equiv \frac{\sum_{f' \in \mathcal{G}_b, f \neq f'} S_{f'} \left(\tilde{q}_{bf'} - \rho_{b,f} \right)}{S_b} \tag{30}$$

[23] This is not a necessary condition, but one that simplifies the setting at this point. Indeed, I will remove commonality across banks and funds.

[24] In Gabaix and Koijen (2020), the average is taken across all entities. Note that doing so in this setting implies a bias as the average would be correlated to A_{bf} by construction

$$Z_{b,f}^{GIV} = \frac{\sum_{f' \in \mathcal{G}_b, f \neq f'} S_{f'} \left(A_{bf'} - \bar{A}_{b,f} \right)}{S_b}, \tag{31}$$

where $\bar{A}_{b,f}$ is the average return across competitors.

As in Gabaix and Koijen (2020), the variation in the proposed instrument comes from variation in size. I allow for network effects in an incomplete network, which gives me variation not only in size but also variation in the network multipliers coming from the number of counterparties. Then, even in absence of a size distribution, I can build an instrument that exploits the network effects in the model.

4.1.1 Estimation procedure

My observation level is bank-fund-time. I index time using t. I assume A_{bft} has the following structure:

$$A_{bft} = A_{bt} + A_{ft} + v_{bft},$$

This assumption is consistent with the model, as I assume heterogeneity at the bank level and idiosyncratic shocks that enter in v_{bft}. I also let A_{ft} to be correlated to aggregate conditions.[25]

I assume the following assumption:

$$\mathbf{E}\left\{ v_{b'f't} A_{bft} \right\} = 0 \ \forall \, b'f' \neq bf. \tag{32}$$

This assumption means that bilateral shocks, after removing commonalities, are exogenous with respect to aggregate conditions.

From Equation 16, given $v_{b,t}$, I can build an instrument using a guess for α_B/ϕ_F and α_F/ϕ_F. I also use information on the funds' assets under management, the banks' total assets, and the network of connections.

[25] An alternative procedure involves using factor analysis.

I summarize here the estimation procedure:

1. I use a initial guess $\beta_0^B = (\alpha_B/\phi_F)_0$ and $\beta_0^F = (\alpha_F/\phi_F)_0$

2. Using this guess, I calculate

$$\tilde{A}^0_{bf} = q_{bf} - \beta_0^B Q_b - \beta_0^F (Q_f + T_f)$$

3. Remove commonalities across $\tilde{A}^0_{bf}$:[26]

$$A^0_{bf} = A_{bft} = A_{bt} + A_{ft} + v_{bft}$$

4. Compute instrument using v_{bf} according to the multipliers from the model:

   - $Z_b = f(\hat{v}_{b'f'}, (b'f') \neq bf)$; $Z_f = f(\hat{v}_{b'f'}, (b'f') \neq bf)$;

5. Use moment condition:

$$\mathbf{E}\{Z_b(q_{bf} - \beta_1^B Q_b - \delta_f)\} = 0$$

$$\mathbf{E}\{Z_f(q_{bf} - \beta_1^B Q_b - \beta_1^F (Q_f + T_f))|T_f\} = 0$$

6. Iterate until convergence

4.2 Bilateral interest rates

Similarly, the model predicts the relationship between bilateral interest rates and total bank and fund's funding as described in Equation 12. I am interested in the estimation of θ^B_{bf}, which is the elasticity of bilateral interest rate with respect to the bank's total funding. Note that θ^B_{bf} can be identified from the variation in interest rates and quantities.

However, the unobserved variation that affects bilateral interest rates also correlates with the bank's total funding demand. For instance, a shock in the bank's return on assets

[26] I do this for each pair b, f

increases the bank's demand for funding and, at the same time, increases the bilateral interest rate.

As before, I can use the variation from connected neighbors that moves bilateral interest rates only through the effects of the bank's demand for funding. In what follows, I show that my instruments that use granular shocks can be used for identification of θ^B_{bf}.

Proposition 5: *Controlling for the effect of the effect of the vector of the funds' portfolio holdings on r_{bf} and v_{bf}, the following moment condition identifies θ^B_{bf}*

$$\mathbf{E}\left\{ Z_{bf}\left(r_{bf} - \beta_{bf}\frac{Q_b}{S_b}\right)\middle| \frac{Q_{f'}+T_{f'}}{S_{f'}}, v_{bf}\right\} = 0. \tag{33}$$

Furthermore, given α_B/ϕ_F and α_F/ϕ_F, I can identify bounds for ϕ_F as follows:

$$\phi_F \leq \frac{\min_{(bf)\in\mathcal{G}} \theta^B_{bf}}{\frac{\alpha_B}{2\phi_F}\left(1-\frac{\alpha_F}{\phi_F}\right)}, \tag{34}$$

$$\phi_F \geq \frac{\max_{(bf)\in\mathcal{G}} \theta^B_{bf}}{\frac{\alpha_B}{\phi_F}\left(1+\frac{\alpha_B}{2\phi_F}\right)}. \tag{35}$$

Moreover, for a given ϕ_F, Equation 33 identifies τ_{bf}.

I identify $\beta = -\theta^B_{bf}$. As θ^B_{bf} is strictly increasing in $\tau_{b,f}$, I identify $\tau_{b,f}$ from β given the estimates of the remaining parameters of the model.

An appealing feature of the model is that it provides convenient expressions for the equilibrium quantities and prices. The model implies a linear equation that maps the bilateral funding to the total exposures of the bank and the fund. Hence, this equation characterizes the substitution effects through the network. Similarly, bilateral interest rates depend linearly on total funding exposures at the bank and fund level. The elasticity of bilateral interest rates with respect to the total funding depends on the bargaining power of the agents. The larger the bargaining power of the bank, the more important is the cost of funding in determining the bilateral interest rate. This convenient set of equations provides an empirical setting suitable for identification.

5 Data

This section describes the data sources.

Money Market Funds Data Crane data collects the month-ends portfolio holdings of MMFs as reported in their regulatory filings to the SEC (SEC N-MFP forms) from 2011 to 2020. This dataset contains detailed information on the portfolio, including transaction amounts, prices, and maturity. More importantly, I can identify the issuer of the instrument.

I focus on the prime segment. I restrict the sample to Commercial Paper and Certificate Deposits, that account for more than 90% of unsecured funding instruments through which banks borrow from MMFs.[27].

Bank data I use quarterly balance sheet data from Fitch. I complement this information from equity prices and CDS from Markit.

6 Estimates

This section presents the empirical results and discusses the implications of the point estimates.

6.1 Quantities

Table 2 presents the estimates of the parameters that govern banks' and funds' preferences. As explained in the previous section, I use the variation in bilateral quantities to produce an optimal instrument for the bank and fund's portfolio shares. The empirical econometric model is

[27]I restrict the attention to unsecured lending because government segments, which can invest in Repo, were experiencing a large inflow of deposits

$$\frac{q_{bft}}{S_{ft}} = -\frac{\alpha_B}{\phi_F}\frac{Q_{bt}}{S_{bt}} - \frac{\alpha_F}{\phi_F}\frac{Q_{ft}}{S_{ft}} + \varepsilon_{bft}, \tag{36}$$

where $\frac{q_{bf}}{S_f}$ is the porftolio share of fund f in b,and $\frac{Q_b}{S_b}$ and $\frac{Q_f}{S_f}$ are the bank and fund's total funding, respectively. ε_{bf} is an unobserved confounder. I use z_b and z_f as noted in the previous section as a shifter of the bank and fund total exposure. I identify α_B/ϕ and α_F/ϕ, which refer to the relative importance of the quadratic costs of lending with respect to concentration risk.

Table 2 presents the estimates from OLS and those of instrumental variables. I control for bank and fund fixed effects, as well as other controls at the bank level. The OLS estimates are large and negative (Table 2, Column 1), which is consistent with a positive and mechanical correlation between total funding and bilateral funding. This is also consistent with the fact that bilateral funding is correlated with size. Column 3 in Table 2 presents the first stage coefficient for the instruments and the significance of the instrument.

The interpretation of the IV estimates are as follows. My estimates show that the cost of aggregate risk relative to concentration risk is significant: one standard deviation increase in unsecured funding portfolio share implies a reduction of 1 standard deviation of bilateral lending. This suggest that there are large substitution effects across banks.

The marginal benefit of banks is decreasing, as bilateral funding decreases with the bank's total funding. One standard deviation in total borrowing causes a reduction in 0.4 standard deviations of bilateral funding for the median bank. These estimates suggest that the cost of aggregate risk is large and is an important driver in this market.

6.2 Bilateral interest rates

In this section I present the results of the estimation of the bilateral bargaining power. The empirical econometric model is

Table 2: Estimates for the Ratios of the Fund and Bank Managing Costs to the Concentration Risk

	Estimator	OLS (1)	IV (2)	First Stage (3)
Ratio of funds' liquidity managing cost to concentration risk	α_F/ϕ_F	-0.017*** (0.001)	0.094*** (0.027)	-6.110*** (1.161)
Ratio of banks' managing cost to concentration risk	α_B/ϕ_F	-0.242*** (0.016)	0.571*** (0.093)	0.192*** (0.009)
Observations		140,289	140,289	140,289
Funds		226	226	226
Banks		57	57	57
Controls		YES	YES	YES

Notes: ***p<0.01, **p<0.05, *p<0.1. Data from CRANE. Author's calculations. Data is at the bank-fund-month level. OLS (Column 1) refers to a regression predicting the bilateral funding. IV (Column 2) corresponds to the estimation using granular shocks. The estimation of α_F/ϕ_F controls for equity, the change in assets, size-weighted maturity, bank and fund fixed effects and a time-fund fixed effect. The estimation of α_B/ϕ_F controls for a time-bank fixed effect, Treasury holdings and size-weighted maturity. Standard errors in parenthesis are clustered at the fund-bank level.

$$r_{b,f,fam,t} = \theta_{1,b,fam}\frac{Q_{bt}}{S_{bt}} + \theta_{2,b,fam}\frac{Q_{ft}}{S_{f,t}} + \nu_{bft} \tag{37}$$

where $r_{b,f,fam}$ is the interest rate of the bank b, fund f and fund family fam. I assume that the bilateral bargaining power is constant for pairs of bank and family. That is, $\tau_{b,f} = \tau_{b,f'}$ for f' in the same family. The variation I exploit comes from variation in bilateral funding and bilateral interest rates across funds within the same family and the same bank. Note that the variation in my instrument comes from differences in the fund's position in the network within the same family.

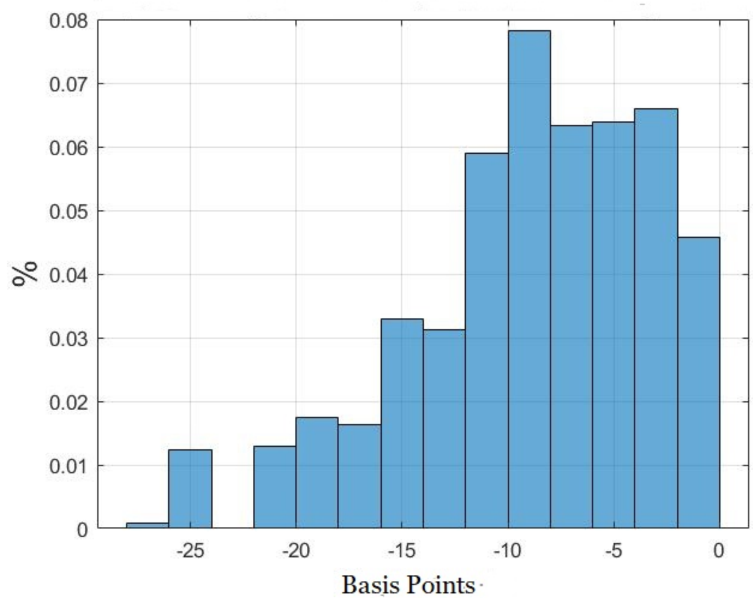
I can identify $\theta_{1,b,fam}$ from the variation in the proposed instrument as explained in the previous section. From $\theta_{1,b,fam}$, which captures the elasticity of the interest rate with respect to the bank's total funding from funds, I can identify a combination of ϕ_F and $\tau_{b,fam}$.

Figure 4, Panels A and B, presents the distribution of the elasticity of bilateral interest rates with respect to the bank and fund's exposures. The formulas for the elasticities are in Equations 13 and 14. Note that the magnitude of the elasticity with respect to the bank's total funding increases with the fund's market power. This is intuitive, as the bank's benefit becomes more relevant in the determination of bilateral interest rates. Similarly,the magnitude of the elasticity with respect to the fund's total funding decreases with the fund's market power.

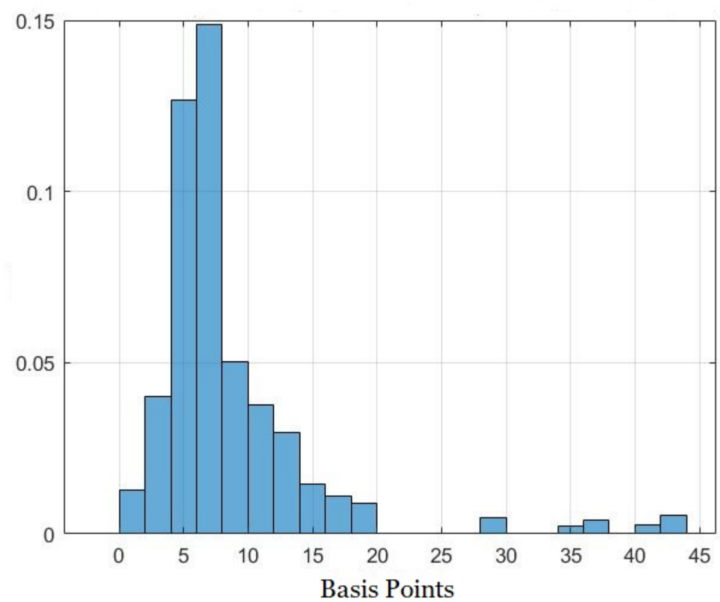
Figure 4, panel A, shows the elasticity of bilateral interest rates with respect to the bank's funding, which ranges between 0 to -25 basis points. The median elasticity is -8 basis points. Similarly, panel B shows the elasticity of bilateral interest rates with respect to the fund's funding. This elasticity ranges between 0 and 45 basis points. The median elasticity for the fund's funding is about 5.5 basis points. Altogether, this evidence suggests large dispersion in bilateral bargaining market power across banks and funds.

Figure 4: Semi-elasticity of the Bilateral Interest Rate to Changes to

Panel A: Banks' Total Funding



Panel B: Funds' Total Funding



Notes: Author's calculation. The median rate in the the initial distribution (as of February 2020) is 26. Panel A shows the distribution of the response of the bilateral interest rate to a 1% increase in the total borrowing from banks. Panel B shows the distribution of the response of the bilateral interest rate to a 1% increase in the total lending from funds.

Table 3: Fund's Bargaining Power Correlation with Agents' Characteristics

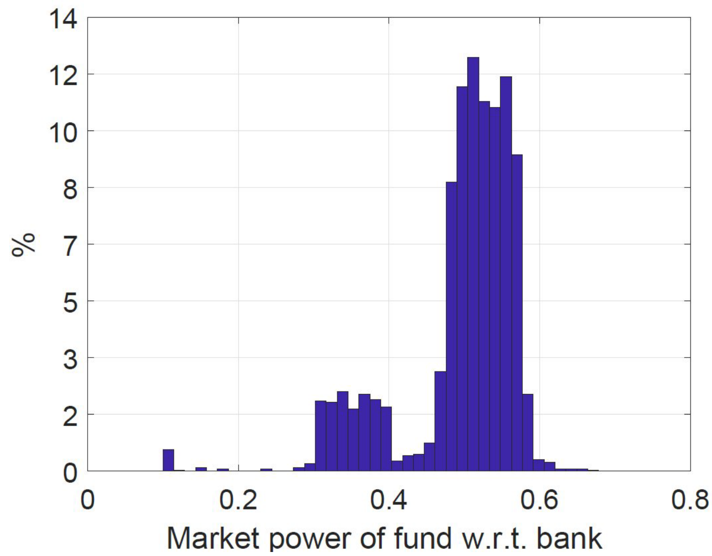
Variables	Fund's Market Power (1)	(2)
Log Assets Under Management	-0.00149	-0.00116
	(0.00109)	(0.00123)
Log Bank's Assets	-0.01310***	-0.01390***
	(0.00299)	(0.00299)
Number of bank's counterparties		-0.00003
		(0.00029)
Number of funds' counterparties		0.00108***
		(0.00038)
Observations	759	759
R-squared	0.027	0.037

Notes: ***p<0.01, **p<0.05, *p<0.1. Data from Crane. Author's calculations. The observation level is bank-fund family. Standard errors in parenthesis. Column 1 shows the regression that uses the fund's market power as the dependent variable and the logarithm of the assets under management and bank's assets as covariates. Column 2 adds the number of bank's and fund's counterparties as covariates.

Moreover, I can identify bounds for ϕ_F given the estimated parameters in the previous section. From my estimates, $\phi_F \in (4.4, 9.5)$. I use the middle point between the upper and lower bounds for the main exercises and do robustness checks on changes to this parameter. Using ϕ_F, I can deliver an estimate of the bilateral bargaining power.

Table 3 shows that the bilateral bargaining power correlates with size. It is decreasing in the bank's size, suggesting that large banks tend to have better terms of trade. The fund's number of counterparties also correlates with the relative bargaining power. A fund with more investment opportunities have more beneficial contracts. Figure 5 shows the distribution of bilateral bargaining power under the initial calibration. This figure shows that the distribution is concentrated in values lower than 0.6 for funds.

Figure 5: Distribution of Funds' Bargaining Power



Notes: Data from Crane. Author's calculations. Data is at the family fund- bank level. The graph shows the histogram of the estimated family funds' market power for the bargaining problem with banks.

7 Conterfactual Exercises

7.1 Calibration and Counterfactual

My model assumes that assets under management are exogenous from the perspective of funds. I model a drop in assets under management for prime funds as observed in the data between February 2020 and March 2020. To do so, I produce a comparative static using S_f to match the assets under management before and after the COVID-19 episode.

Appendix Figure A.6 shows the distribution of flows in the prime segment. Appendix Figure A.6 shows that there is substantial heterogeneity across funds in the change in assets under management. The median fund experienced a drop in assets under management of 12.79% from February to March 2020.

I calibrate the network using funds that were active as of December 2019. I consider links active between 2018 and 2019 to calibrate the network of counterparties. The number of banks is 57, which is limited because of data availability on the banks' assets. The number of active prime funds is 62.

I calibrate the initial quantities and prices at the bilateral level. Note that to match exactly each bilateral price and funding, I require 2 degrees of freedom per link in my model. I use the idiosyncratic trading motives ξ_{bf} and ϵ_{bf} to match q_{bf} and r_{bf} as observed in the data. I use bilateral quantities and prices as of February 2020 if available. Otherwise, I take the closest observation available in the data.[28] I calibrate R_T to match the initial Treasury holdings by this industry.

Finally, I calibrate ϕ_F to be equal to 6.7, which is the middle point between the upper and lower bounds for ϕ_F identified in the previous section. Note that in doing so, I preserve the estimated partial elasticities with respect to the total funding estimated in the previous section.

7.2 Effects of the COVID-19 shocks in assets under management

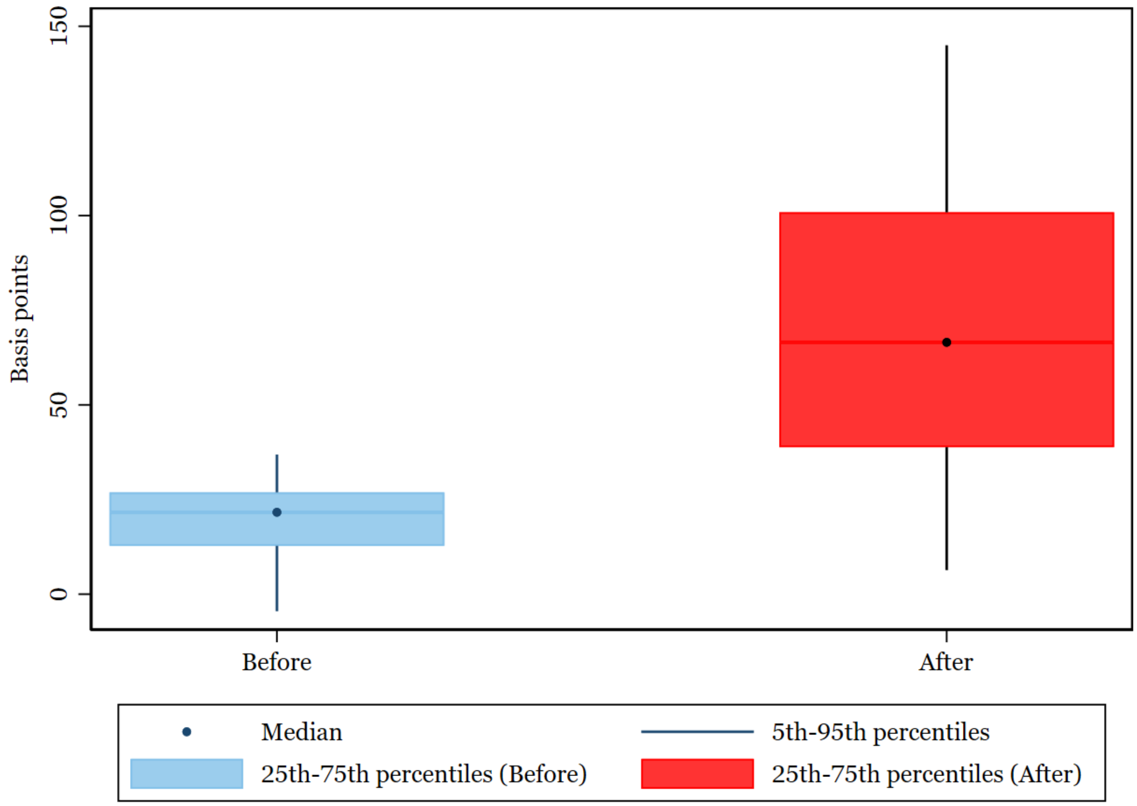
In this section, I summarize the main results of the counterfactual exercise. The shock in assets under management is equivalent to 11% of the assets under management in February 2020, as described in the previous section. I introduce a shock in S_f consistent to what was observed in March 2020 and produce the counterfactual bilateral funding and bilateral interest rates after the shock.

I find that funding drops and price dispersion increases as a consequence of the shock in assets under management. First, total funding reduces by 14%, which is sizable compared to 16% observed in the data. This reduction is consistent with a predicted reduction in 2 percentage points in the industry's portfolio share in funding in the model. Meanwhile, aggregate Treasury holdings and ON-RRP holdings increase.

Figure 6 shows the counterfactual price dispersion predicted by the model. The median spread increases by 46 basis points, which is 76% of the increase in the median

[28] The percentage of links active in February is approximately equal to 60%. For those that were not active, the average closest observation is about 3 months. The initial distribution resembles that one of the full dataset.

Figure 6: Model Predicted Price Distribution



Notes: Data from Crane. Author's calculations. Distribution of the bilateral interest rate spread with respect to the Secured Overnight Financing Rate (SOFR). I assume the SOFR is fixed at the observed level in the counterfactual. The observation level is bank-fund. The initial distribution is calibrated to that one of the observed data. The final distribution presents the price dispersion after a drop in assets under management as observed from Feb. 2020 to March 2020. The initial median spread is 22 basis points.

spread in unsecured funding during the COVID-19 crisis. Moreover,the measures of price dispersion increase in the model and can account for around 70% of the observed effects in March 2020. The interquartile range increases 48 basis points in the model, which is comparable to the increase in the data of 42 basis points. Similarly, the difference between the 95th percentile and the 25th percentile increases by 100 basis points, out of 120 in the data.

I also show that price dispersion is larger across banks than across funds, highlighting initial dispersion in market power as well as dispersion in the investment opportunities. Figure 7, Panels A and B, show the initial and final distribution across banks and funds.

Appendix Figure A.7 shows that indeed, the decrease in funding is very dispersed across banks and the magnitude of the fall is negatively correlated to the number of counterparties of the bank. Banks can smooth better when connected to a large number of funds.

Planner's solution In this section I compare the planner's and decentralized funding provision. The planner's solution predicts a drop in funding of 9%, which is smaller compared to the drop predicted in the decentralized solution. That is, bargaining frictions explain a larger drop in funding.

Misallocation coming from bargaining frictions increases after the shock. In the baseline scenario, the initial allocation is 16% below that one of the planner's. After the shock, the final allocation is 22% below the planner's allocation.

Figure 8 shows the percentage change in bilateral funding and the percentage change in assets under management for both the planner's solution and the decentralized solution. Figure 8 shows a positive correlation between the percentage change in assets under management. Yet, there are large differences between the planner's percentage change in bilateral funding and the decentralized solution.

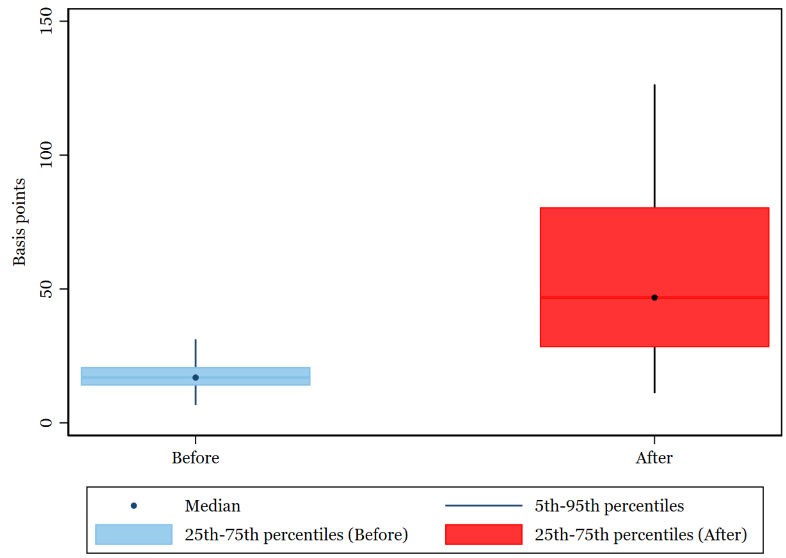
Appendix Figure A.8 shows the wedges as defined in Equation 23 and the correlation with funds' characteristics. The wedge with respect to the planner solution decreases with the fund's size and the number of counterparties, suggesting that misallocation comes from small entities that face large concentration risk.

7.3 The ON-RRP facility

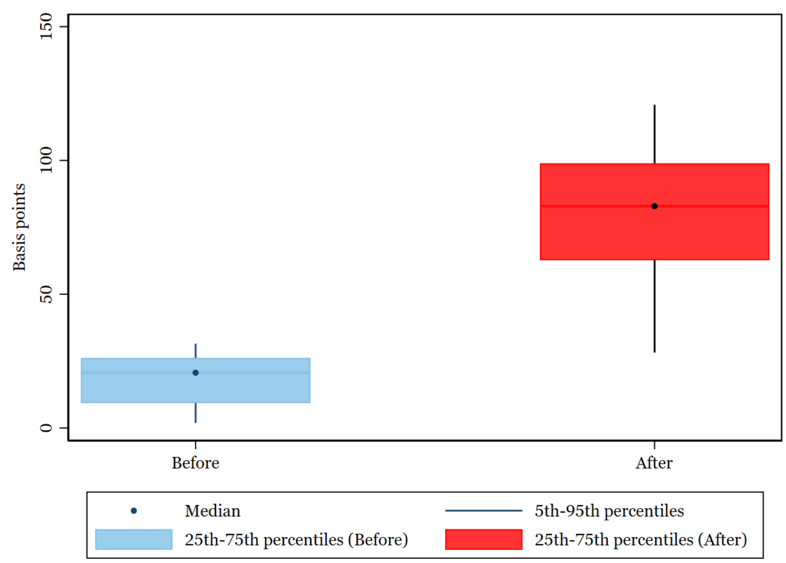
In this section I explore the effect of a reduction in the ON-RRP rate. The ON-RRP facility is the outside option of funds when negotiating with banks, and therefore it increases the bargaining power of funds. A decrease in the ON-RRP rate reduces the funds' incentives to provide funding. Moreover, a large drop in the ON-RRP rate creates incentives to hold more Treasuries, which increases the fund's risky positions and creates a larger substitution

Figure 7: Model Predicted Price Distribution

Panel A. Across Banks

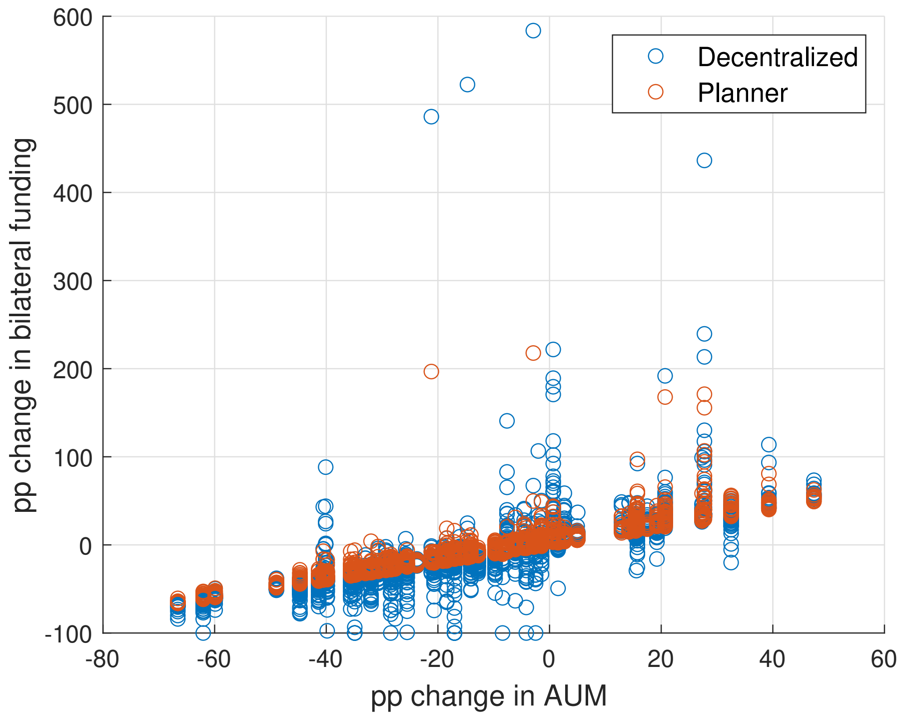


Panel B. Across Funds



Notes: Data from Crane. Author's calculations. Distribution of the size-weighted interest rate with respect to the Secured Overnight Financing Rate (SOFR) at the bank level (Panel A) and the fund level (Panel B). I assume the SOFR is fixed in the counterfactual. The initial bilateral distribution of prices and quantities is calibrated to that one of the observed data. The final distribution presents the price dispersion after a drop in assets under management as observed from Feb. 2020 to March 2020. The number of banks is 57 (Panel A) and of funds is 62 (Panel B). Funds include the prime (retail and institutional) funds that were active as of December 2019.

Figure 8: Decentralized and Planner's funding provision



Notes: Data from Crane. Author's calculations. This figure presents the percentage change in bilateral funding after a shock in assets under management as described in the baseline scenario. The planner is subject to the same regulatory constraints and preferences

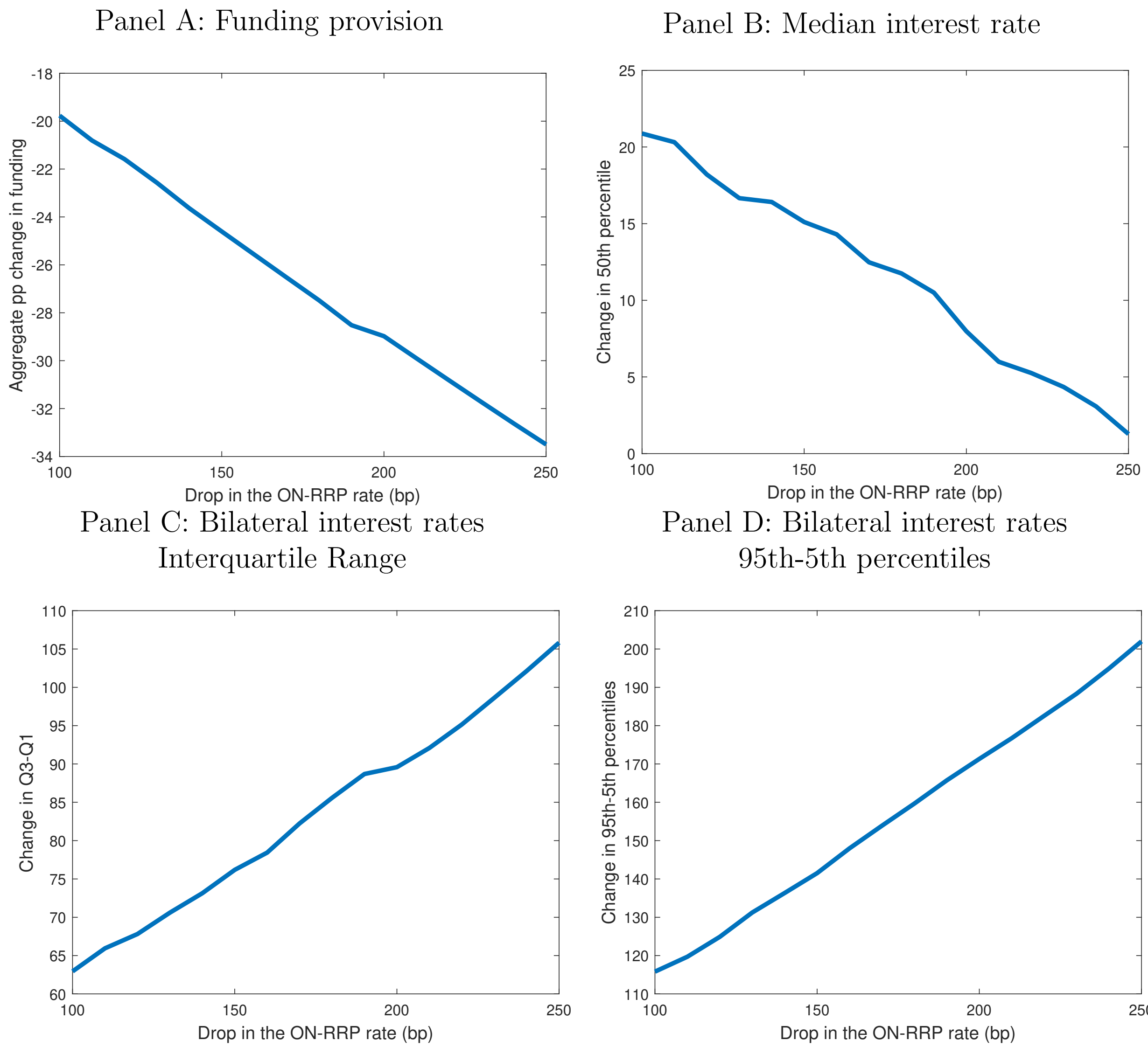
away from funding provision.

Figure 9 presents the effects of a reduction in the ON-RRP rate that ranges between 100 and 250 basis points.[29] Panel A shows the drop in funding provision after the shock. Funding provision decreases with the reduction of the ON-RRP rate. A drop in 100 basis points implies a drop in funding of 20%, which is 6% larger than the baseline scenario.

Panel B in Figure 9 shows the effects of a reduction in the ON-RRP rate on the median bilateral interest rate. A drop in the ON-RRP rate reduces the median cost of funding with respect to the baseline scenario. However, price dispersion increases, as Panel C and D show.

[29]For reference, the level of the ON-RRP rate in February 2020 was 150 basis points and reached zero during COVID-19.

Figure 9: Effects of a drop in the ON-RRP rate



Notes: Data from Crane. Interest rates are reported in basis points. This figure presents the counterfactual changes in funding provision and the distribution of the bilateral interest rates after the shock in assets under management as in the baseline scenario and a drop in the ON-RRP.

8 Conclusion

In this paper, I propose a new framework for the identification of network effects in a lending network with bilateral market power using microdata at the bilateral level. The model and identification strategy allows for substantial heterogeneity across agents. Therefore, this setting can be used to explore other markets and the effects of other aggregate shocks in a network.

I provide a structural analysis of the U.S. Money Market Funds Industry. I show that network frictions in unsecured funding between funds and banks explain a sizable fraction of observed market outcomes during the March 2020 turmoil. I also show that the allocation of funds is inefficient. Inefficiency comes from monopolistic behaviour of funds.

This paper highlights the importance of the access to the ON-RRP facility for non-bank intermediaries. The ON-RRP facility gives an outside option for Money Market Funds. The assets in this facility have increased substantially after March 2020 following a large inflow of deposits in government funds. My paper offers a framework to study the impact of monetary policy through the ON-RRP rate on the portfolio choice of funds.

References

Aldasoro, Iñaki, Florian Balke, Andreas Barth, and Egemen Eren. 2019. "Spillovers of funding dry ups." BIS Working Papers 810, Bank for International Settlements. URL https://ideas.repec.org/p/bis/biswps/810.html.

Aldasoro, Iñaki, Torsten Ehlers, and Egemen Eren. 2019. "Global Banks, Dollar Funding, and Regulation." *SSRN Electronic Journal* .

Aldasoro, Iñaki, Wenqian Huang, and Nikola Tarashev. 2021. "Asset managers, market liquidity and bank regulation." BIS Working Papers 933, Bank for International Settlements. URL https://ideas.repec.org/p/bis/biswps/933.html.

Anadu, Kenechukwu E., Marco Cipriani, Ryan M. Craver, and Gabriele La Spada. 2021a. "COVID Response: The Money Market Mutual Fund Facility." Staff Reports 980, Federal Reserve Bank of New York. URL https://ideas.repec.org/p/fip/fednsr/93071.html.

———. 2021b. "COVID Response: The Money Market Mutual Fund Facility." Staff Reports 980, Federal Reserve Bank of New York. URL https://ideas.repec.org/p/fip/fednsr/93071.html.

Anderson, Alyssa G., Wenxin Du, and Bernd Schlusche. 2021. "Arbitrage Capital of Global Banks." Finance and Economics Discussion Series 2021-032, Board of Governors of the Federal Reserve System (U.S.). URL https://ideas.repec.org/p/fip/fedgfe/2021-32.html.

Ashcraft, Adam B. and Darrell Duffie. 2007. "Systemic Illiquidity in the Federal Funds Market." *American Economic Review* 97 (2):221–225. URL https://www.aeaweb.org/

articles?id=10.1257/aer.97.2.221.

Atkeson, Andrew G., Andrea L. Eisfeldt, and Pierre-Olivier Weill. 2015. "Entry and Exit in OTC Derivatives Markets." *Econometrica* 83 (6):2231–2292. URL http://www.jstor.org/stable/43866413.

Bi, Huixin and W. Blake Marsh. 2020. "Flight to Liquidity or Safety? Recent Evidence from the Municipal Bond Market." Research Working Paper RWP 20-19, Federal Reserve Bank of Kansas City. URL https://ideas.repec.org/p/fip/fedkrw/89531.html.

Cipriani, Marco, Andrew F. Haughwout, Benjamin Hyman, Anna Kovner, Gabriele La Spada, Matthew Lieber, and Shawn Nee. 2020. "Municipal Debt Markets and the COVID-19 Pandemic." Liberty Street Economics 20200629, Federal Reserve Bank of New York. URL https://ideas.repec.org/p/fip/fednls/88240.html.

Cipriani, Marco and Gabriele La Spada. 2021. "Investors' appetite for money-like assets: The MMF industry after the 2014 regulatory reform." *Journal of Financial Economics* 140 (1):250–269. URL https://www.sciencedirect.com/science/article/pii/S0304405X20303111.

Cipriani, Marco and Gabriele La Spada. 2017. "Investors' appetite for money-like assets: the money market fund industry after the 2014 regulatory reform." Staff Reports 816, Federal Reserve Bank of New York. URL https://ideas.repec.org/p/fip/fednsr/816.html.

———. 2020. "Sophisticated and Unsophisticated Runs." Staff Reports 956, Federal Reserve Bank of New York. URL https://ideas.repec.org/p/fip/fednsr/89274.html.

———. 2021. "Sophisticated and Unsophisticated Runs." Liberty Street Economics 20210602, Federal Reserve Bank of New York. URL https://ideas.repec.org/p/fip/fednls/92279.html.

Collard-Wexler, Allan, Gautam Gowrisankaran, and Robin S. Lee. 2019. ""Nash-in-Nash" Bargaining: A Microfoundation for Applied Work." *Journal of Political Economy* 127 (1):163–195. URL https://ideas.repec.org/a/ucp/jpolec/doi10.1086-700729.html.

Correa, Ricardo, Horacio Sapriza, and Andrei Zlate. 2021. "Wholesale funding runs, global banks' supply of liquidity insurance, and corporate investment." *Journal of International Economics* 133:103519. URL https://www.sciencedirect.com/science/article/pii/S0022199621000994.

Di Maggio, Marco and Marcin Kacperczyk. 2017. "The unintended consequences of the zero lower bound policy." *Journal of Financial Economics* 123 (1):59–80. URL https://ideas.repec.org/a/eee/jfinec/v123y2017i1p59-80.html.

Di Maggio, Marco, Amir Kermani, and Zhaogang Song. 2017. "The value of trading relations in turbulent times." *Journal of Financial Economics* 124 (2):266–284. URL https://EconPapers.repec.org/RePEc:eee:jfinec:v:124:y:2017:i:2:p:266-284.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2017. "The Deposits Channel of Monetary Policy*." *The Quarterly Journal of Economics* 132 (4):1819–1876. URL https://doi.org/10.1093/qje/qjx019.

Eisfeldt, Andrea, Bernard Herskovic, Emil Siriwardane, and Sriram Rajan. 2019. "OTC Intermediaries." 2019 Meeting Papers 204, Society for Economic Dynamics. URL https://ideas.repec.org/p/red/sed019/204.html.

FSB. 2020. "Holistic Review of the March Market Turmoil." Staff reports, Financial Stability Board. URL https://www.fsb.org/wp-content/uploads/P171120-2.pdf.

Gabaix, Xavier and Ralph S. J Koijen. 2020. "Granular Instrumental Variables." Working Paper 28204, National Bureau of Economic Research. URL http://www.nber.org/papers/w28204.

Gavazza, Alessandro. 2016. "An Empirical Equilibrium Model of a Decentralized Asset Market." *Econometrica* 84 (5):1755–1798. URL http://www.jstor.org/stable/44155346.

Haughwout, Andrew F., Benjamin Hyman, and Or Shachar. 2021. "The Option Value of Municipal Liquidity: Evidence from Federal Lending Cutoffs during COVID-19." Staff Reports 988, Federal Reserve Bank of New York. URL https://ideas.repec.org/p/fip/fednsr/93156.html.

Kargar, Mahyar, Benjamin Lester, David Lindsay, Shuo Liu, Pierre-Olivier Weill, and Diego Zúñiga. 2021. "Corporate Bond Liquidity during the COVID-19 Crisis." *The Review of Financial Studies* 34 (11):5352–5401. URL https://doi.org/10.1093/rfs/hhab063.

La Spada, Gabriele. 2018. "Competition, reach for yield, and money market funds." *Journal of Financial Economics* 129 (1):87–110. URL https://www.sciencedirect.com/science/article/pii/S0304405X18301004.

Li, Lei, Yi Li, Marco Macchiavelli, and Xing (Alex) Zhou. 2021. "Liquidity Restrictions, Runs, and Central Bank Interventions: Evidence from Money Market Funds." *The Review of Financial Studies* 34 (11):5402–5437. URL https://doi.org/10.1093/rfs/hhab065.

Li, Yi. 2021. "Reciprocal lending relationships in shadow banking." *Journal of Financial Economics* 141 (2):600–619. URL https://ideas.repec.org/a/eee/jfinec/v141y2021i2p600-619.html.

Longstaff, Francis A., Sanjay Mithal, and Eric Neis. 2005. "Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market." *The Journal of Finance* 60 (5):2213–2253. URL https://onlinelibrary.wiley.com/doi/abs/10.

1111/j.1540-6261.2005.00797.x.

Parlatore, Cecilia. 2016. "Fragility in money market funds: Sponsor support and regulation." *Journal of Financial Economics* 121 (3):595–623. URL https://ideas.repec.org/a/eee/jfinec/v121y2016i3p595-623.html.

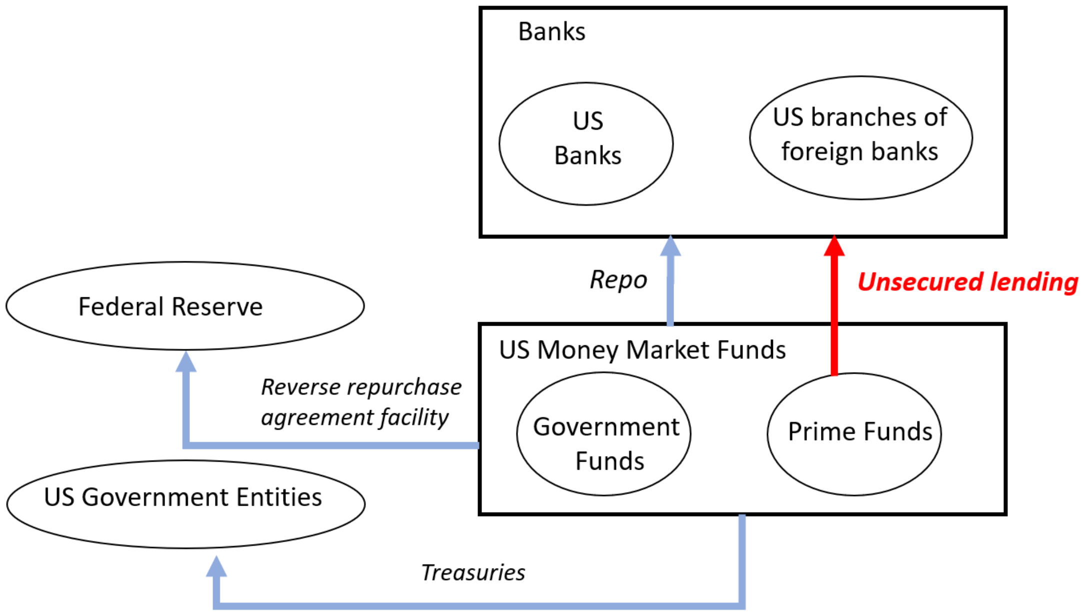
Vandeweyer, Quentin. 2019. "Treasury Debt and the Pricing of Short-Term Assets." URL https://faculty.chicagobooth.edu/quentin-vandeweyer/research.

Xiao, Kairong. 2019. "Monetary Transmission through Shadow Banks." *The Review of Financial Studies* 33 (6):2379–2420. URL https://doi.org/10.1093/rfs/hhz112.

Appendix

A Additional Figures

Figure A.1: Market Structure

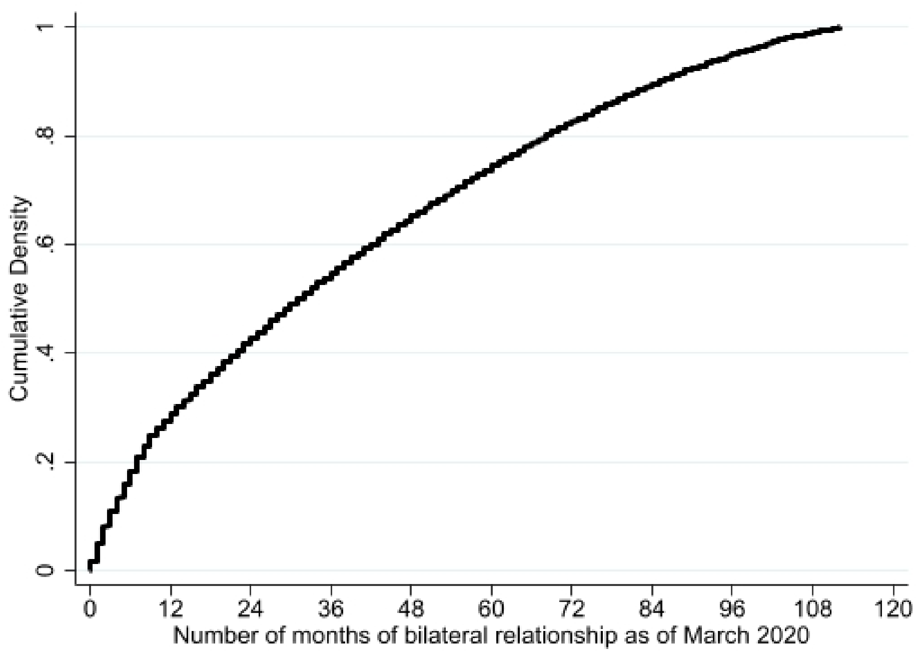


Notes: US money market funds have three main outlets for their assets under management. Prime money market funds can provide liquidity to US banks or to US branches of foreign banks through unsecured lending (mostly commercial paper, certificates of deposit, or asset-backed commercial paper) or repurchase agreements (repo). Government funds are limited to repos. Both type of funds can also buy treasuries and other titles backed by the federal, state, or local governments. Finally, funds can also access the Overnight Reverse Repo Facility (ON RRP) of the Federal Reserve.

Figure A.2: Network Structure

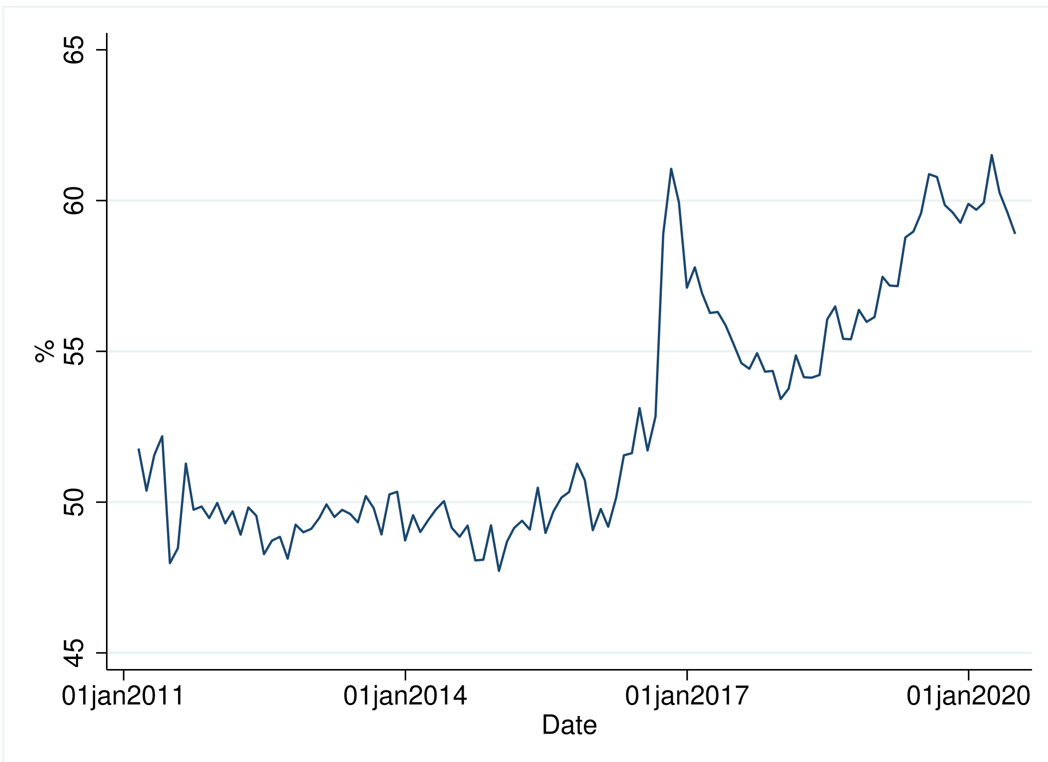
Notes: Data from Crane. Author's calculations. A blue node represents a money markey funds, a gold node is a bank, and grey arrows represent a bilateral contract. The size of the fund's nodes represents the total size of the assests under management and the size of the bank's nodes represents total assets. The thickness of the grey line represents the value of the bilateral contract. All data is as of December 2019.

Figure A.3: Cumulative Distribution of Duration of Bilateral Relationship



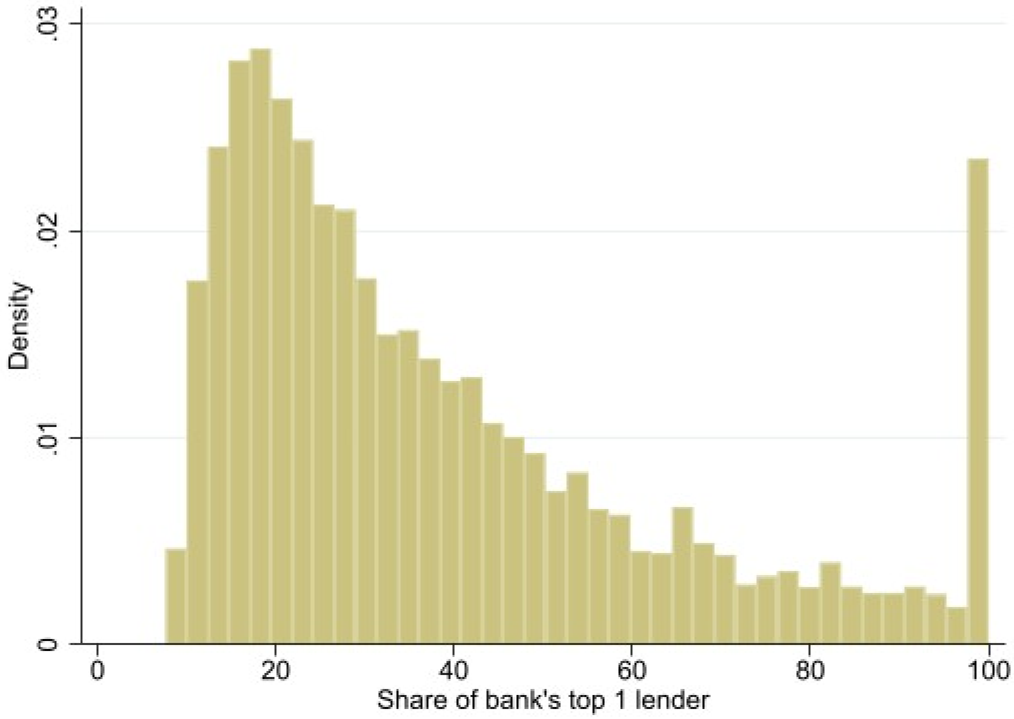
Notes: Data from Crane. Author's calculations. The measure of the duration of the bilateral relationship takes as reference all existing contracts between banks and funds on March 2020. The duration of the bilateral relationship is measured as the time elapsed in months between the first time a bank-fund contract is observed (with starting date on March 2011) and March 2020.

Figure A.4: Market Share of the 5 Largest Money Market Funds, CR_5



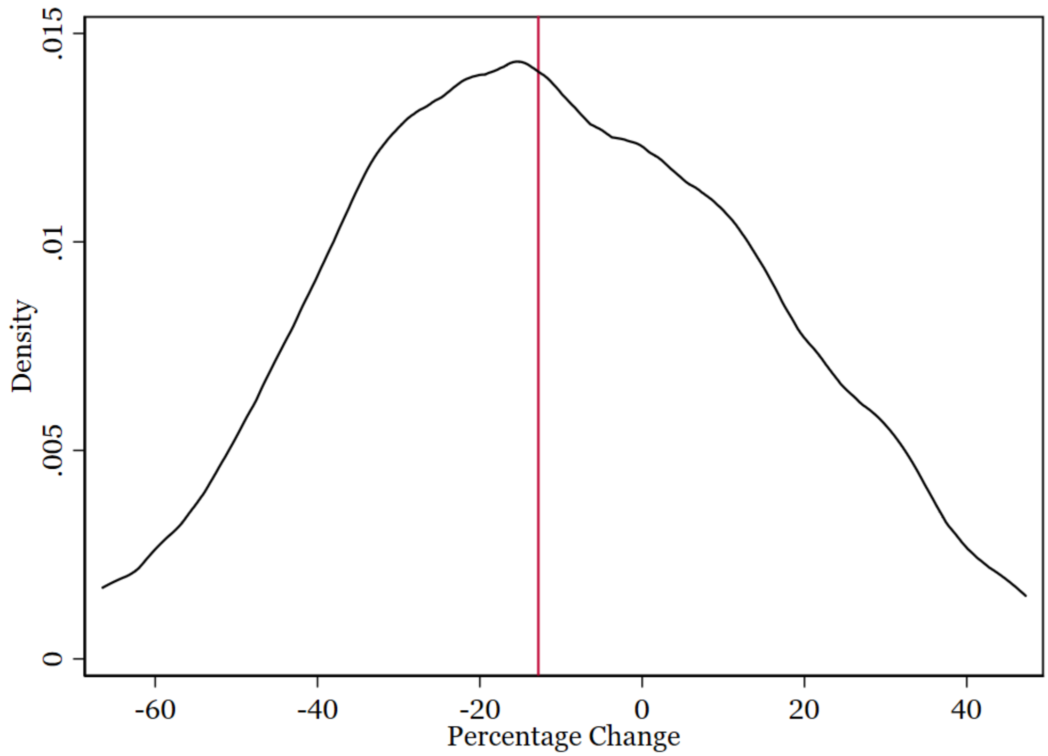
Notes: Data from Crane. Author's calculations. The graph shows the monthly 5-firm concentration ratio, which is the sum of the percentage market share of the five largest money market funds in a given month.

Figure A.5: Distribution of the Share of a Bank's Funding by its Largest Counterparty



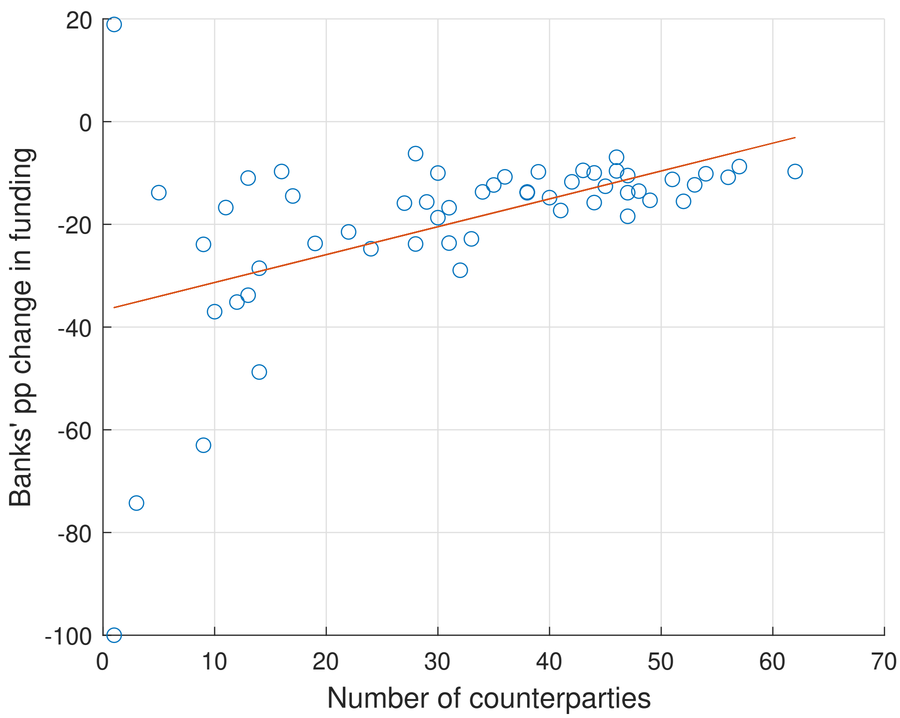
Notes: Data from Crane. Author's calculations. Data as of December 2019 and at the bank-level. This measure of concentration corresponds to the share of a bank's funding in money markets that is provided by its largest counterparty.

Figure A.6: Distribution of the Percentage Change in the Value of Prime Funds' Assets Under Management between February and March 2020



Notes: Data from Crane. Author's calculations. Data is at the fund level. The figure shows the distribution of the change in the value of a prime fund's asset under management during Covid's *dash-for-cash* in March 2020, using February 2020 as reference. The red line is the median change (12.8%).

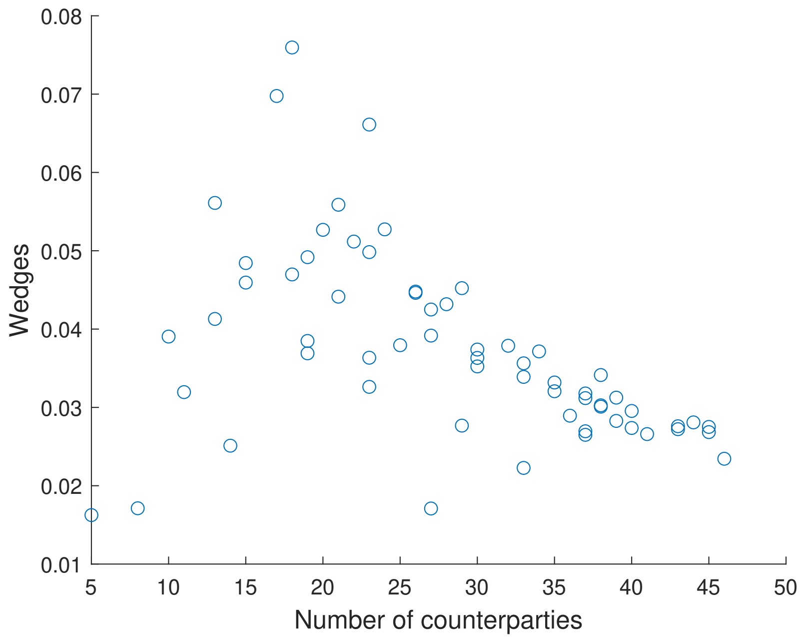
Figure A.7: Number of Counterparties



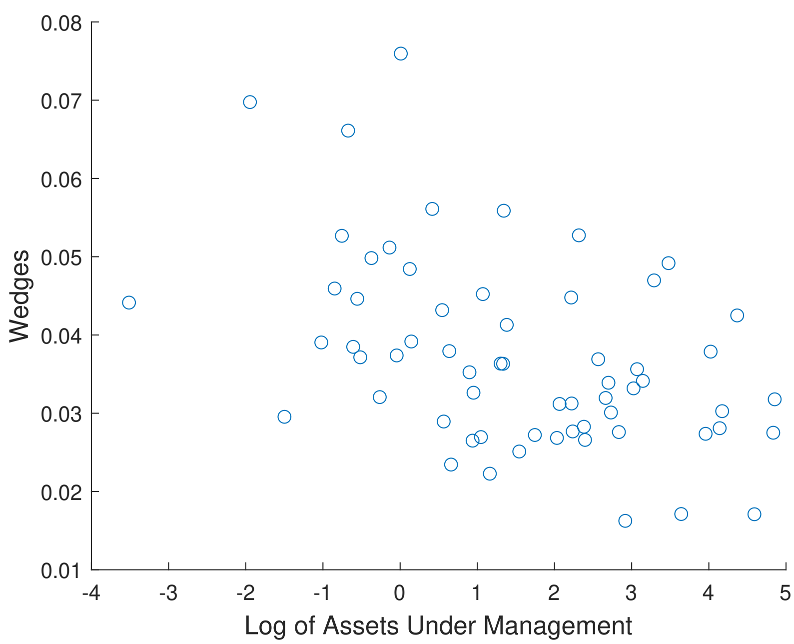
Notes: Data from Crane. Author's calculations. Distribution of the bilateral interest rate. I present the spread with respect to the Secured Overnight Financing Rate (SOFR). I assume the SOFR is fixed in the counterfactual. The observation level is bank-fund. The initial distribution is calibrated to that one of the original data from Crane. The final distribution presents the price dispersion after a drop in assets under management as observed from Feb. 2020 to March 2020. This simulation assumes an homogeneous drop in assets across funds The initial median spread is 26 basis points.

Figure A.8: Wedges and Fund's Characteristics

Panel A. Across Banks

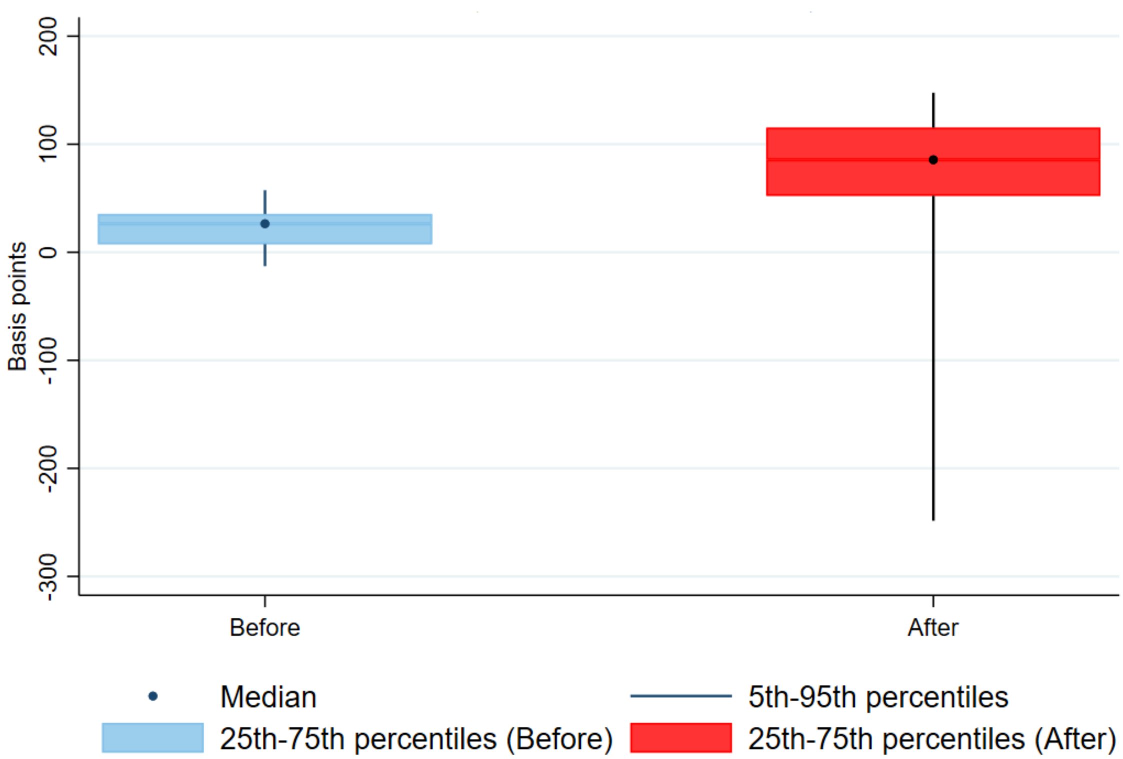


Panel B. Across Funds



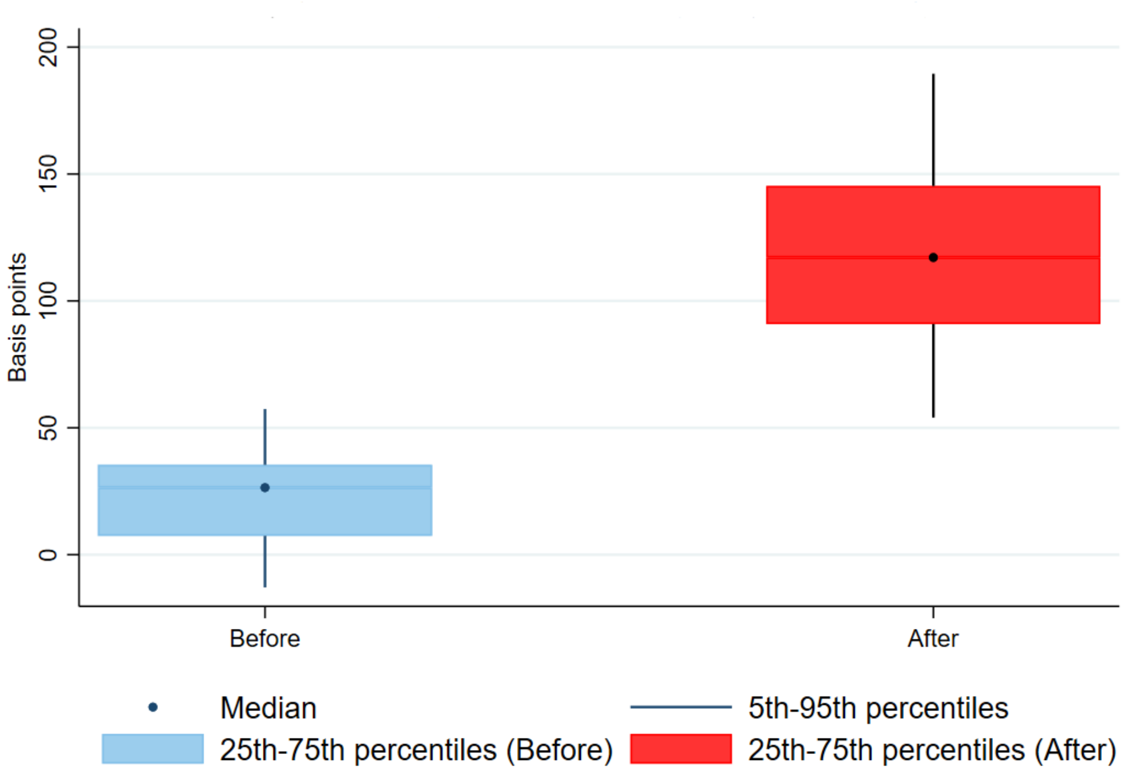
Notes: Author's calculations. Figures present the sum of wedges, defined as in 23, after the shock in assets under management.

Figure A.9: Model Predicted Price Distribution



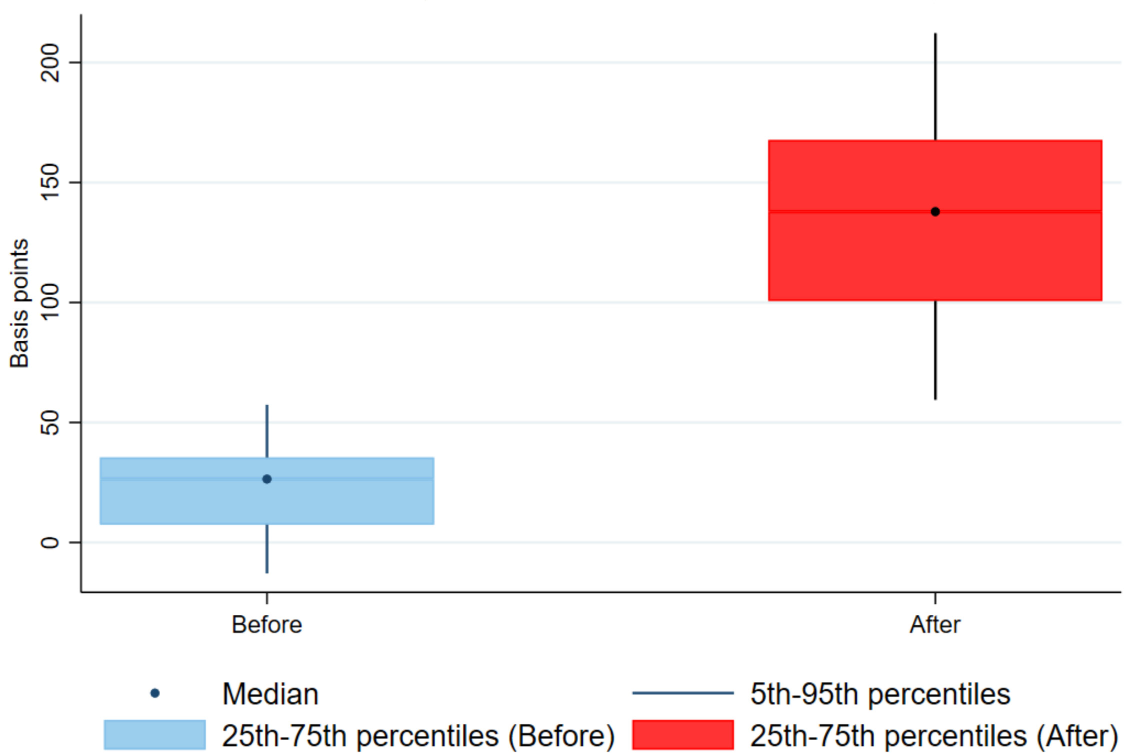
Notes: Data from Crane. Author's calculations. Distribution of the bilateral interest rate. I present the spread with respect to the Secured Overnight Financing Rate (SOFR). I assume the SOFR is fixed in the counterfactual. The observation level is bank-fund. The initial distribution is calibrated to that one of the original data from Crane. The final distribution presents the price dispersion after a drop in assets under management as observed from Feb. 2020 to March 2020. I assume a fixed cost equivalent to the fifth percentile of the bilateral gains from trade in the initial equilibrium. The initial median spread is 26 basis points.

Figure A.10: The Effect of Market Power in Partial Equilibrium



Notes: Data from Crane. Author's calculations. Distribution of the bilateral interest rate. I present the spread with respect to the Secured Overnight Financing Rate (SOFR). I assume the SOFR is fixed in the counterfactual. The observation level is bank-fund. The initial distribution is calibrated to that one of the original data from Crane. The final distribution presents the price dispersion after a drop in assets under management as observed from Feb. 2020 to March 2020 and a 5% increase in the bargaining power of funds in partial equilibrium. The initial median spread is 26 basis points.

Figure A.11: Model Predicted Price Distribution after an Homogeneous Aggregate Funding Liquidity Shock



Notes: Data from Crane. Author's calculations. Distribution of the bilateral interest rate. I present the spread with respect to the Secured Overnight Financing Rate (SOFR). I assume the SOFR is fixed in the counterfactual. The observation level is bank-fund. The initial distribution is calibrated to that one of the original data from Crane. The final distribution presents the price dispersion after a drop in assets under management as observed from Feb. 2020 to March 2020. This simulation assumes an homogeneous drop in assets across funds The initial median spread is 26 basis points.

Table A.1: Counterfactual Effects on Rates and Lending

	Data March 2020	Baseline	Network Frictions	Fixed cost	Increase in Market Power
	(1)	(2)	(3)	(4)	(5)
Price					
5th-95th	163.10	109.12	18.12	393.53	142.16
25th-75th	64.30	50.12	28.00	63.00	54.34
Median interest rate	85.10	94.30	26.42	85.59	75.37
Change in lending	-15.20	-11.23	-6.11	-11.48	-11.23

Notes: Data from Crane. Author's calculations. The table presents the counterfactual effects of different scenarios on the spread of bilateral rates with respect to the Secured Overnight Financing Rate (SOFR) in basis points and on lending. Column 1 presents the statistics of the bilateral interest rates by the end of March 2020, as observed using Crane Data. The initial median spread is 26 basis points. Column 2 presents the baseline results of the model. Column 3 presents the contribution of network frictions in the absence of market power. Column 4 presents the results of the model with a small fixed cost of bargaining. Column 5 presents the results of a partial equilibrium effect of a 5% increase in funds' market power, taking quantities as given.

B Appendix

B.1 Other counterfactuals

I produce other counterfactual exercises, with the interest of learning about the key mechanisms of the model. Table A.1 presents a summary of the main effects.

B.1.1 Network Effects

First, to account for the effects of network frictions, I compute the counterfactual changes using my main calibration of the model assuming markets are competitive. Then, I compute the change in price dispersion and liquidity. Table A.1, Column 3 shows that this counterfactual explains about 15% of the total effects in price dispersion measures. The key message from this exercise is that market power creates misallocation of liquidity in the presence of a dispersed network.

An ideal exercise would be changing the network structure that maximizes welfare. This exercise, however, requires an estimate on the bilateral market power and bilateral idiosyncratic motives that can not be identified in the data. I take a different path and ask what is the effect of dropping connections in the initial network. I do this by assuming a fixed cost of negotiation shared by the two involved parties. I assume a fixed cost of the size of the 5th percentile of the gains from trade before the shock.

The results of dropping connections from the network have little effects in aggregate liquidity because of the size distribution of the gains from trade that follow the distribution of bilateral funding. However, there is a large impact in price dispersion, as presented in Table A.1, Column 4 and Appendix Figure A.9. This counterfactual increases the interquartile range to 63 basis points, which is comparable in magnitude to the effects in the data.

From this exercise we learn that price dispersion in this model arises because substitution effects are large, as estimated in the data, and because banks vary in the number and type of connections in the network. Banks' average market power is more dispersed.

B.1.2 Effect of Market Power

In a third exercise, I compute the partial equilibrium effect of increasing market power by 5%. This brings the model closer to the data, increasing price dispersion as presented in Table A.1, Column 5 and Appendix Figure A.10: the difference between the top 95% and the bottom 5% increases 33 basis points with respect to the baseline, and the interquartile range increases 4 basis points. As the average market power of banks is low, the increase in dispersion comes from large dispersion of the banks' investment opportunities.

B.1.3 Homogeneous Aggregate Shock

In the baseline exercise, I use the observed drop in assets under management to predict liquidity in this market. The outflows were very heterogeneous across funds, yet in the data most funds decreased their liquidity provision. I ask what would be the effect of an aggregate and homogeneous shock in liquidity of the same aggregate magnitude.

I introduce a shock in assets under management of 20%. The model predicts a drop in 17 percent in unsecured lending and a larger price dispersion. Appendix Figure A.11 shows the impacts in the price distribution. The effects are closer to the data for two reasons: First, this can be explained by larger risk aversion that I don't account in the model for. Instead, my exercise is predicting the pure liquidity effect and is a lower bound of the potential destabilizing effects of a liquidity withdrawal that goes accompanied by increases in risk aversion.

B.2 Gains from Trade

Proof for Proposition 1: From the definition of the bank's profits we have:

$$\begin{aligned}
\Delta_{bf}\Pi_b^{\mathcal{B}} &= A_b \sum_{f' \in \mathcal{G}_b^{\mathcal{M}}} R_{b,f'}\gamma_{b,f'} - \tfrac{\alpha_B}{2}\left(\sum_{f' \in \mathcal{G}_b^{\mathcal{M}}} \gamma_{b,f'}\right)^2 - \sum_{f' \in \mathcal{G}_b^{\mathcal{M}}} R_{b,f'}\gamma_{b,f'} \\
&\quad - A_b \sum_{f' \in \mathcal{G}_b^{\mathcal{M}}, f' \neq f} R_{b,f'}\gamma_{b,f'} + \tfrac{\alpha_B}{2}\left(\sum_{f' \in \mathcal{G}_b^{\mathcal{M}}, f' \neq f} \gamma_{b,f'}\right)^2 \\
&\quad + \sum_{f' \in \mathcal{G}_b^{\mathcal{M}}, f' \neq f} R_{b,f'}\gamma_{b,f'}
\end{aligned}$$

$$\Delta_{bf}\Pi_b^{\mathcal{B}} = (A_b - R_{bf})\gamma_{b,f'} - \tfrac{\alpha_B}{2} z_b^2 + \tfrac{\alpha_B}{2}(z_b - \gamma_{b,f})^2$$ We can write the gains from trade as follows:

$$\Delta_{bf}\Pi_b^{\mathcal{B}} = (A_b - R_{bf})\gamma_{b,f} - \frac{\alpha_B}{2}(2z_b - \gamma_{bf})\gamma_{b,f} \tag{A.1}$$

Similarly,

$$\Delta_{bf}\Pi_f^{\mathcal{M}} = (R_{bf} - r^\star)\gamma_{b,f} - \frac{\alpha_F}{2}(2z_f - \gamma_{bf})\gamma_{b,f} - \frac{\phi}{2}\gamma_{bf}^2 \tag{A.2}$$

The total surplus of the negotiation is

$$\Delta_{bf}\Pi_b^{\mathcal{B}} + \Delta_{bf}\Pi_f^{\mathcal{M}} = (A_b - r^\star)\gamma_{b,f} - \frac{\alpha_B}{2}(2z_b - \gamma_{bf})\gamma_{b,f} - \frac{\alpha_F}{2}(2z_f - \gamma_{bf})\gamma_{b,f} - \frac{\phi}{2}\gamma_{bf}^2 \tag{A.3}$$

The first order condition with respect to $\gamma_{b,f}$ is

$$(A_b - r^\star) - \alpha_B(z_b - \gamma_{bf} - \alpha_F(z_f - \gamma_{bf}) - \phi\gamma_{bf} = 0 \tag{A.4}$$

We can rearrange as follows:

$$\gamma_{bf} = \frac{A_b - r^\star - \alpha_B z_b - \alpha_F z_f}{\phi} \tag{A.5}$$