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Essays on Financial Intermediation and International Finance

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Doctor of Philosophy in Economics

by

Paula Andrea Beltran Saavedra

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ABSTRACT OF THE DISSERTATION

Essays on Financial Intermediation and International Finance

by

Paula Andrea Beltran Saavedra
Doctor of Philosophy in Economics
University of California, Los Angeles, 2022
Professor Pierre-Olivier Weil, Co-Chair
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This dissertation consists of three chapters on financial intermediation and international finance that contribute to our understanding and identification of the transmission of aggregate shocks in imperfect financial markets. The first chapter studies the effect of an aggregate funding supply shock in a lending network in times of distress in a quantitative framework for the money market funds industry in the U.S. The second chapter identifies the effect of cross-border banking flows on macroeconomic and financial outcomes for emerging economies. The third chapter studies the identification of the impact of foreign exchange interventions under a limited risk-bearing capacity of financial intermediaries.

The first chapter studies the implications of network frictions for the allocative efficiency of funding provision of the U.S. Money Markets Funds Industry. I build a tractable model of financial intermediation that features an incomplete network

of counterparties and bilateral bargaining within a network. I use the quantitative model to assess the effect of a large supply shock of funding in the money market funds industry. I provide an identification framework to estimate the model's parameters and discipline the model using portfolio data of the money market funds industry. I assess a counterfactual taking as primitives the drop in assets under management at the onset of the COVID-19 pandemic and show that the model can account for price dispersion and funding allocation observed in the data.

The second chapter assesses the effect of capital flows in emerging countries. We focus on the impact of cross-border banking flows and leverage the size distribution at the bilateral level to construct an instrument for capital inflows. We build a granular instrumental variable to identify the effects on macroeconomic and financial conditions for 22 emerging countries. Cross-border bank credit causes higher domestic activity in EMEs and looser financial conditions. We also show that the effect is heterogeneous across different levels of capital inflow controls.

The third chapter studies the effects of foreign exchange intervention. We estimate the causal effect of foreign exchange intervention. Theoretically, the impact of foreign exchange intervention depends on the imperfect asset substitution that relates to the limited risk-bearing capacity of financial intermediaries. To identify the risk-bearing capacity, we use the variation from information free flows of passive investors around rebalancing dates. These flows are plausibly exogenous with respect to domestic conditions and act as a shock to the risk held by financial intermediaries. We show that information-free flows have effects on UIP and CIP deviations. Our preliminary estimates show that the required foreign exchange intervention to achieve a 10% foreign exchange depreciation in one week is between \$0.02-\$5.06 billion dollars.

The dissertation of Paula Andrea Beltran Saavedra is approved.

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University of California, Los Angeles

2022

Para Juan Sebastian, mi equipo y amor de la vida;

para mi mama y mi hermana.

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CHAPTER 1

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

In this chapter 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.

1.1 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 1.1 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 et al., 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?

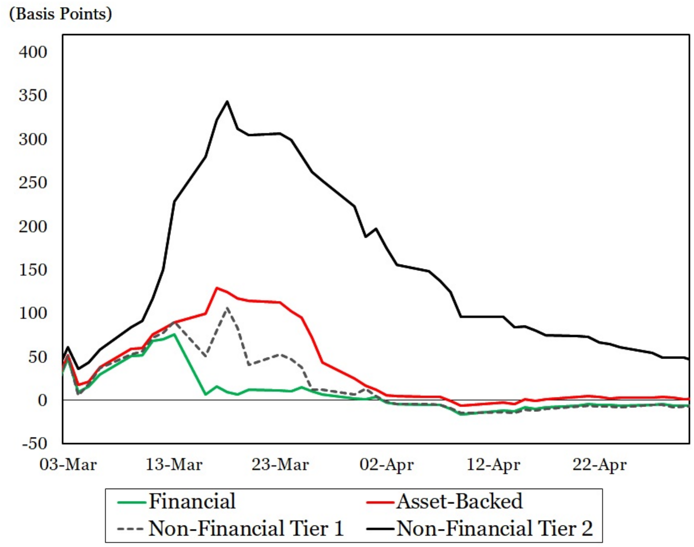
This paper addresses these questions quantitatively in the unsecured funding market, where U.S. Money Market Funds provide a significant source of dollar funding to global banks (FSB, 2020). This $9 trillion industry was under significant stress in March 2020. Prime money market funds were subject to 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 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

Figure 1.1: 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.

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 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

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

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 et al., 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 et al. (2015), both of which feature risk averse agents and limited counterparty risk. Counterparty risk in Atkeson et al. (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 et al. (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 et al., 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 et al. (2019b) 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 et al., 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. (2021b) 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. (2021b) also analyze the impact of the Money Market Mutual Fund Liquidity Facility. Other papers (Haughwout et al., 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 et al. (2021), Correa et al. (2021) and Aldasoro et al. (2019a) 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 1.2 describes the U.S. Money Market Funds industry, section 1.3 presents the static model that rationalizes the motivating facts and describes the key mechanism, section 1.4 presents the identification strategy. Section 1.5 describes the data, section 1.6 presents the empirical results, section 1.7 discusses the counterfactual exercises and the final Section 1.8 concludes the paper.

1.2 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.

1.2.1 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 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]

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[2]The industry structure and its connection to other markets is described in Appendix Figure 1.A.1.

[3]Rule 2a-7 of the Investment Company Act of 1940 limits as well the maturity and credit risk

[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.

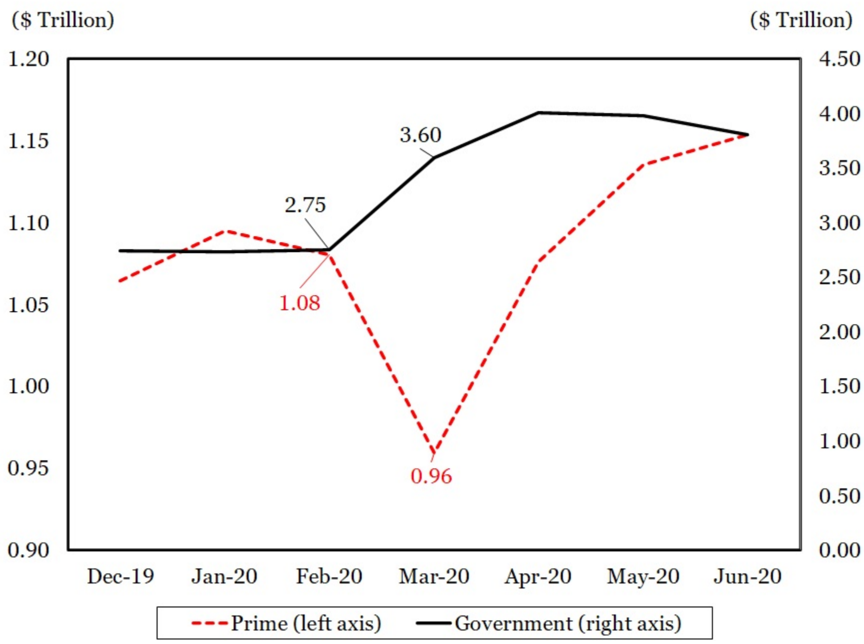
1.2.1.1 The Events of March 2020

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 1.2 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 1.3 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 comparable to the 2008 crisis (Anadu

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

Figure 1.2: 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.

et al., 2021a). [8] [9]

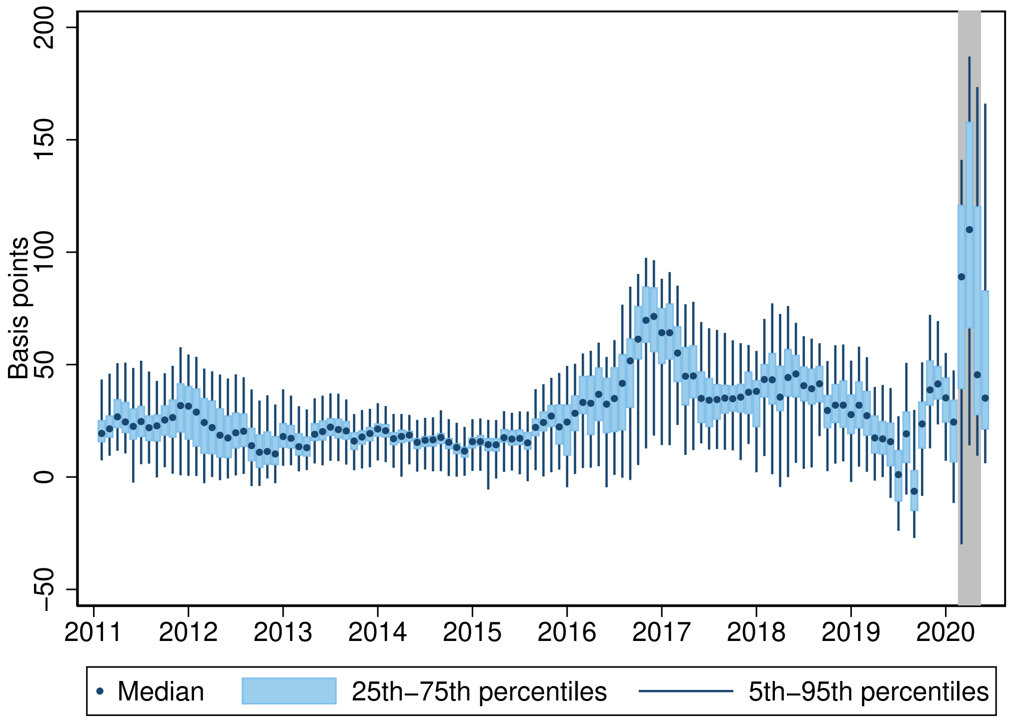
1.2.2 Motivating Evidence

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

[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 1.3: 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.

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 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 1.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 1.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 1.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]

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[10]From conversations with market participants, funds do not revise often their set of counterparties.

Concentration The U.S. Money Market Funds Industry is highly concentrated, as measured by share of the top 15 funds. Figure 1.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 1.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 1.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 accounted for the correlation with the bank and fund's portfolio share of unsecured lending in this industry.

I estimate the following econometric model:

$$r_{b,f,c,t} - r_t^{\star} = \delta_t + \beta_B \frac{Q_b}{S_b} + \beta_F \frac{Q_f}{S_f} + \beta_{BF} \frac{q_{bf}}{S_f} + \gamma' x_{b,f,t} + \epsilon_{b,f,c,t}, \tag{1.1}$$

where $r_{b,f,c,t}$ is the interest rate of contract c, between bank b and fund f at time t,

[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.

$r_t^\star$ 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 1.1 shows the least squares estimates of Equation 1.1.[14] Results in Table 1.1 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 1.1 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.

1.3 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 1.1: 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.

1.3.1 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 1.2.

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.

1.3.1.1 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.

[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.

The balance sheet constraint of the fund is as follows:

$$S_f = Q_f + T_f + M_f. \tag{1.2}$$

Total unsecured instruments is composed by the sum of lending across counterparties, q_{bf}, where b is in the fund's network. That is:

$$Q_f = \sum_{b \in \mathcal{G}_f^{\mathcal{B}}} q_{bf}. \tag{1.3}$$

The fund's preferences are:

$$\begin{aligned} \Pi_f^{\mathcal{F}} = & \overbrace{r^T T_f + r^M M_f + \sum_{b \in \mathcal{G}_f^{\mathcal{B}}} \Big((r_{b,f} + \epsilon_{b,f}) q_{b,f} \Big)}^{\text{Return}} \\ & \underbrace{- \frac{\alpha_F}{2} \frac{1}{S_f} (Q_f + T_f)^2}_{\text{Aggregate Risk}} \underbrace{- \sum_{b \in \mathcal{G}_f^{\mathcal{B}}} \left(\frac{\phi_F}{2} S_f \left(\frac{q_{b,f}}{S_f} \right)^2 \right)}_{\text{Concentration risk}}. \end{aligned} \tag{1.4}$$

The term on the fist line of Equation 1.4 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]

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[16]This assumption also relates to the strong pattern of relationship lending that I observe in

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 1.4.

The various quadratic terms on the second line in Equation 1.4 represent the cost of bearing aggregate and concentration risk. While, I assume linearity in the assets under 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 et al. (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

$$MC_f = \bar{A}_f + \left(\alpha_F + \frac{\phi_F}{K_f}\right)\frac{Q_f}{S_f} + \alpha_F \frac{T_f}{S_f}, \tag{1.5}$$

---

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.

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

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 1.5 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 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

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

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

the remaining available loanable funds. RRP facility becomes the outside option for the funds when trading with banks.

1.3.1.2 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

$$\Pi_b^{\mathcal{B}} = Q_b A_b - \frac{\alpha_B}{2}\frac{1}{S_b}Q_b^2 - \sum_{f \in \mathcal{G}_b^{\mathcal{F}}} (r_{b,f} + \xi_{bf}) q_{bf}, \tag{1.6}$$

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 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.

1.3.2 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 et al. (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:

$$\Delta_{bf}\Pi_f^{\mathcal{F}} = \underbrace{(r_{bf} + \epsilon_{b,f} - r^M)q_{bf}}_{\text{Return}} - \underbrace{\alpha_F\left(T_f + \sum_{b' \in \mathcal{G}^f, b' \neq b}\right)\frac{q_{b'f}}{S_f}}_{\text{Aggregate risk of existing units}} - \underbrace{\frac{1}{2}(\phi_F + \alpha_F)\frac{q_{bf}^2}{S_f}}_{\text{Cost of new units}}. \quad (1.7)$$

The first term in Equation 1.7 is the return of the contract, minus that one of the outside option. The second term in Equation 1.7 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 1.7 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:

$$\Delta_{bf}\Pi_b^{\mathcal{B}} = \underbrace{(A_b - \xi_{bf} - r_{b,f} - r^M)q_{bf}}_{\text{Return}} - \underbrace{\alpha_B\left(\sum_{f'\in\mathcal{G}^b, f'\neq f} \frac{q_{bf'}}{S_b}\right)}_{\text{Aggregate risk of existing units}} - \underbrace{\frac{1}{2}\phi_B \frac{q_{bf}^2}{S_b}}_{\text{Aggregate risk of new units}} . \tag{1.8}$$

The fist term in Equation 1.8 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

$$(r_{bf}, q_{bf}) = \arg\max\left(\Delta_{bf}\Pi_f^{\mathcal{F}}\right)^{\tau_{bf}}\left(\Delta_{bf}\Pi_b^{\mathcal{B}}\right)^{1-\tau_{bf}}, \tag{1.9}$$

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.

1.3.3 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:*

$$\frac{q_{bf}}{S_f} = \frac{A_b + \epsilon_{bf} - \xi_{bf} - r^M}{\phi_F} - \frac{\alpha_B}{\phi_F}\frac{Q_b}{S_b} - \frac{\alpha_F}{\phi_F}\frac{Q_f + T_f}{S_f}, \tag{1.10}$$

$$r_{bf} = \tau_{bf}\left\{A_b - \xi_{bf} - \frac{\alpha_B}{2}\frac{q_{bf}}{S_b} - \alpha_B \sum_{f' \in \mathcal{G}_b, f' \neq f} \frac{q_{bf'}}{S_b}\right\} \tag{1.11}$$

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

Proof See Appendix 1.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:*

$$r_{bf} = (\tau_{bf} + \theta_{bf})(A_b - \xi_{bf}) + (1 - \tau_{bf} + \theta_{bf})(r^M - \epsilon_{bf}) - \theta^B_{bf}\frac{Q_b}{S_b} + \theta^F_{bf}\frac{Q_f + T_f}{S_f}, \quad (1.12)$$

where $\theta_{bf}, \theta^B_{bf}$ and θ^F_{bf} are combinations of parameters. θ^B_{bf} is increasing in the bargaining power of the fund , τ_{bf}; θ^F_{bf} is decreasing in τ_{bf}:

$$\theta^B_{bf} = \alpha_B\left(\frac{1}{2} + \frac{\alpha_B + \alpha_F}{2\phi_F}\right)\tau_{bf} + \frac{\alpha_B}{2}\left(1 - \frac{\alpha_F}{\phi_F}\right), \quad (1.13)$$

$$\theta^F_{bf} = \alpha_F\left(\frac{1}{2} + \frac{\alpha_B + \alpha_F}{2\phi_F}\right)(1 - \tau_{bf}) - \alpha_F\frac{\alpha_B}{2\phi_F}, \quad (1.14)$$

$$\theta_{bf} = \tau_{bf}\frac{1}{2}\left(\frac{\alpha_B + \alpha_F}{\phi_F}\right) + 1 - \frac{1}{2}\frac{\alpha_F}{\phi_F}. \quad (1.15)$$

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 **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]

Proposition 2 *Let* $\mathbf{T}$ *be the column vector that contains the funds' Treasury holdings. The first stage best responses are characterized by Equation 1.12 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:

$$\mathbf{q} = \mathbf{M}\bigg(\mathbf{A} - \frac{\alpha_B}{\phi_F}\mathbf{D}'\mathbf{T}\bigg), \tag{1.16}$$

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 (1.12).

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[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.

Proof See Appendix 1.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.

$$\Lambda_f^F = \frac{\alpha_F}{\frac{\phi_F}{K_f} + \alpha_F} \tag{1.17}$$

$$\Lambda_b^B = \frac{\alpha_B/S_b}{\phi_F/\sum_{f\in\mathcal{G}_b} S_f + \alpha_B/S_b}. \tag{1.18}$$

Where K_f is the number of counterparties of fund f.

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

$$Q_f = \underbrace{\sum_{b=1}^{N_B} \Lambda_f^F \tilde{g}_{bf}^F \omega_{bf}}_{I} \underbrace{- \sum_{b=1}^{N_B}\sum_{s=1}^{N_F} \Lambda_f^F \Lambda_b^B \tilde{g}_{bf}^F \tilde{g}_{bs}^B \omega_{bs} + \sum_{b=1}^{N_B}\sum_{s=1}^{N_F}\sum_{k=1}^{N_B} \Lambda_f^F \Lambda_b^B \Lambda_s^F \tilde{g}_{bf}^F \tilde{g}_{bs}^B \tilde{g}_{sk}^F \omega_{ks} + \ldots}_{II}, \tag{1.19}$$

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 1.19 shows how the multipliers in Equation 1.17 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 1.19, it is clear that the effect of S_f on the funds' funding provision can be decomposed into two parts as noted in Equation 1.19. First, expression I in Equation 1.19 is related to the direct effect of S_f. Second, expression II in Equation 1.19 is related to the effect of S_f through the impact on the fund's counterparties and path-connected agents.

1.3.4 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, $T_{f'}^\star$.

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[21]See Equation 1.5.

The fund's problem in the first stage is:

$$T_f^\star = \arg\max_{T_f+Q_f(T_f,T_{f'}^\star)\le S_f}\Bigg\{(r^T-r^M)T_f+\sum_{b\in G_f^B}\left(r_{b,f}(T_f,T_{f'}^\star)-r^M+\epsilon_{b,f}\right)q_{b,f}(T_f,T_{f'}^\star)$$
$$-\frac{\alpha_F}{2}\frac{1}{S_f}\left(Q_f(T_f,T_{f'}^\star)+T_f\right)^2-\sum_{b\in\mathcal{G}_f}\frac{\phi_F}{2}S_f\left(\frac{q_{b,f}(T_f,T_{f'}^\star)}{S_f}\right)^2\Bigg\}, \tag{1.20}$$

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:*

$$\frac{\partial r_{bf}q_{bf}}{\partial T_f}=\underbrace{\left\{\tau_{bf}\left\{A_b-\xi_{bf}-\alpha_B\frac{q_{bf}}{S_b}\right\}+(1-\tau_{bf})\left\{r^M-\epsilon_{bf}+(\alpha_F+\phi_F)\frac{q_{bf}}{S_f}\right\}\right\}}_{A}\frac{\partial q_{bf}}{\partial T_f}$$
$$+\underbrace{(1-\tau_{bf})\frac{q_{bf}}{S_f}}_{i}-\underbrace{\alpha_B\tau_{bf}\frac{q_{bf}}{S_b}\sum_{f'\in\mathcal{G}_b f'\neq f}\frac{\partial q_{bf'}}{\partial T_f}}_{ii}+\underbrace{\alpha_F(1-\tau_{bf})\frac{q_{bf}}{S_f}\sum_{b'\in\mathcal{G}_f,b'\neq b}\frac{\partial q_{b'f}}{\partial T_f}}_{iii}. \tag{1.21}$$

Lemma 1 presents the marginal change of the contract with respect to Treasuries. Note that expression A in Equation 1.21 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:*

$$r^T - r^M - \alpha_F \frac{T_f + Q_f}{S_f} + \mu_{1,f} + \mu_{2,f} + \mu_{3,f} = 0 \tag{1.22}$$

Where:

$$\mu_{1,f} = \alpha_F \sum_{b \in G_f} (1 - \tau_{bf}) \frac{q^*_{b,f}}{S_f} \tag{1.23}$$

$$\mu_{2,f} = \alpha_F \sum_{b \in G_f} \sum_{b' \in G_f, b' \neq b} (1 - \tau_{bf}) \frac{q^*_{b,f}}{S_f} \frac{\partial q^*_{b',f}}{\partial T_f} \tag{1.24}$$

$$\mu_{3,f} = -\alpha_B \sum_{b \in G_f} \sum_{f' \in G_b, f' \neq f} \tau_{bf} \frac{q^*_{b,f}}{S_b} \frac{\partial q^*_{b,f'}}{\partial T_f}, \tag{1.25}$$

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* $\mu_{3,f} \leq 0$.

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

Proof See Appendix 1.B.2. ■

Proposition 3 characterizes the optimal Treasury holdings. The terms $\mu_{1,f}, \mu_{2,f}$, 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 1.19, it is clear that the bank's network effects are large whenever they are small compared with their counterparties.

1.3.5 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 1.9* $\forall\, b, f$, *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 1.20 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:*

$$\mathbf{T} = \alpha_F^{-1}\left(\mathbf{I} - \frac{1}{\phi_F}(\mathbf{D} - \tilde{\mathbf{D}})\mathbf{M}\right)^{-1}\left(\mathbf{S}(r^T - r^M) - \alpha_F(\mathbf{D} - \tilde{\mathbf{D}})\mathbf{MA}\right), \tag{1.26}$$

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*

$$\Delta Q\% = -1 + \underbrace{\sum_f \sum_{b\in\mathcal{G}_f} \frac{1}{\alpha_F + \frac{\phi_F}{K_f}}(1-\Lambda_b^B)\frac{S_b}{S_f}\frac{y_B}{Q}}_{(a)} \tag{1.27}$$

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 1.27 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.

1.4 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.

1.4.1 Quantities

Equation 1.10 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 1.10 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 (1.4.1.1). 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

$$Z_{b,f} = \frac{\sum_{f \in \mathcal{G}_b, f \neq f'} S_{f'} A_{bf}}{S_b}. \tag{1.28}$$

The following moment condition could be used for identification:

$$\mathbf{E}\left\{ Z_{bf} \left(\frac{q_{bf}}{S_f} - \theta \frac{Q_b}{S_b} \right) \right\} = 0. \tag{1.29}$$

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]

[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

In this example, a valid IV is

$$Z_{b,f}^{GIV} \equiv \frac{\sum_{f' \in \mathcal{G}_b, f \neq f'} S_{f'} \left(\tilde{q}_{bf'} - \rho_{b,f} \right)}{S_b} \tag{1.30}$$

$$Z_{b,f}^{GIV} = \frac{\sum_{f' \in \mathcal{G}_b, f \neq f'} S_{f'} \left(A_{bf'} - \bar{A}_{b,f} \right)}{S_b}, \tag{1.31}$$

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.

1.4.1.1 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]

[25] An alternative procedure involves using factor analysis.

I assume the following assumption:

$$\mathbf{E}\left\{ v_{b'f't} A_{bft} \right\} = 0 \; \forall \, b'f' \neq bf. \tag{1.32}$$

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

From Equation 1.16, 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.

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

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

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

1.4.2 Bilateral interest rates

Similarly, the model predicts the relationship between bilateral interest rates and total bank and fund's funding as described in Equation 1.12. I am interested in the estimation of θ_{bf}^B, which is the elasticity of bilateral interest rate with respect to the bank's total funding. Note that θ_{bf}^B 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 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_{bf}^B.

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}*

$$\mathbf{E}\left\{ Z_{bf}\left(r_{bf} - \beta_{bf}\frac{Q_b}{S_b}\right)\middle| \frac{Q_{f'} + T_{f'}}{S_{f'}}, v_{bf} \right\} = 0. \tag{1.33}$$

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

$$\phi_F \leq \frac{\min_{(bf)\in\mathcal{G}} \theta^B_{bf}}{\frac{\alpha_B}{2\phi_F}\left(1 - \frac{\alpha_F}{\phi_F}\right)}, \tag{1.34}$$

$$\phi_F \geq \frac{\max_{(bf)\in\mathcal{G}} \theta^B_{bf}}{\frac{\alpha_B}{\phi_F}\left(1 + \frac{\alpha_B}{2\phi_F}\right)}. \tag{1.35}$$

Moreover, for a given ϕ_F, Equation 1.33 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.

1.5 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.

1.6 Estimates

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

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

1.6.1 Quantities

Table 1.2 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

$$\frac{q_{bft}}{S_{ft}} = -\frac{\alpha_B}{\phi_F}\frac{Q_{bt}}{S_{bt}} - \frac{\alpha_F}{\phi_F}\frac{Q_{ft}}{S_{ft}} + \varepsilon_{bft}, \qquad (1.36)$$

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 1.2 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 1.2, 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 1.2 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.

Table 1.2: 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' cost to concentration risk	α_F/ϕ_F	-0.017***	0.094***	-6.110***
		(0.001)	(0.027)	(1.161)
Ratio of banks' cost to concentration risk	α_B/ϕ_F	-0.242***	0.571***	0.192***
		(0.016)	(0.093)	(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.

1.6.2 Bilateral interest rates

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

$$r_{b,f,fam,t} = \theta_{1,b,fam}\frac{Q_{bt}}{S_{bt}} + \theta_{2,b,fam}\frac{Q_{ft}}{S_{f,t}} + \nu_{bft} \tag{1.37}$$

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 1.4, 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 1.13 and 1.14. 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.

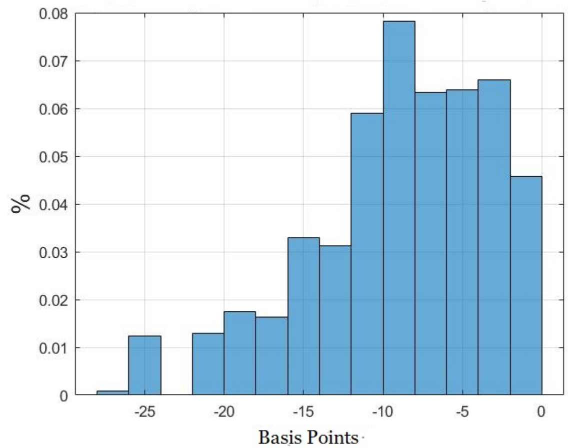
Figure 1.4, panel A, shows the elasticity of bilateral interest rates with respect to the bank's funding, which ranges between 0 to -25 basis points. The median elasticity is -8 basis points. Similarly, panel B shows the elasticity of bilateral interest rates with respect to the fund's funding. This 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.

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.

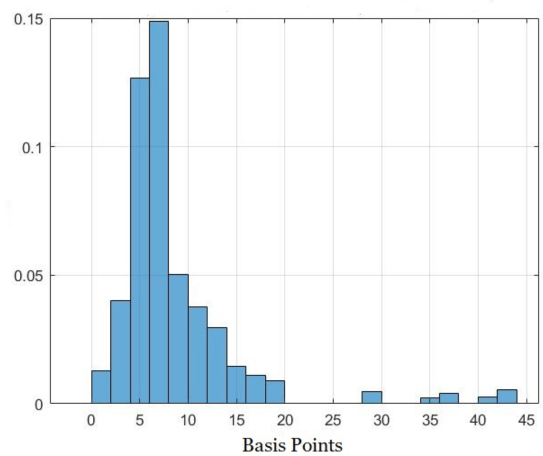
Table 1.3 shows that the bilateral bargaining power correlates with size. It is decreasing in the bank's size, suggesting that large banks tend to have better terms of trade. The fund's number of counterparties also correlates with the relative bargaining power. A fund with more investment opportunities have more beneficial contracts. Figure 1.5 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 1.4: Semi-elasticity of the Bilateral Interest Rate to Changes to

Panel A: Banks' Total Funding



Panel B: Funds' Total Funding



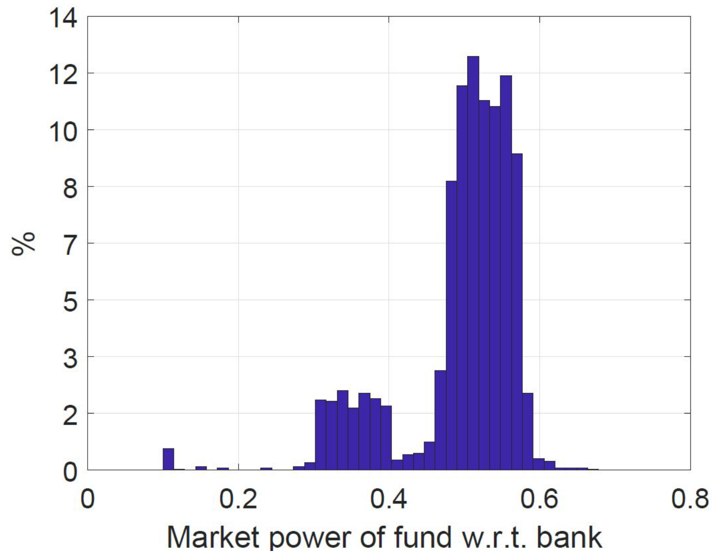
Notes: Author's calculation. The median rate in the the initial distribution (as of February 2020) is 26. Panel A shows the distribution of the response of the bilateral interest rate to a 1% increase in the total borrowing from banks. Panel B shows the distribution of the response of the bilateral interest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

Table 1.3: 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.

Figure 1.5: 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.

1.7 Conterfactual Exercises

1.7.1 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 1.A.6 shows the distribution of flows in the prime segment. Appendix Figure 1.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.

1.7.2 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

[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.

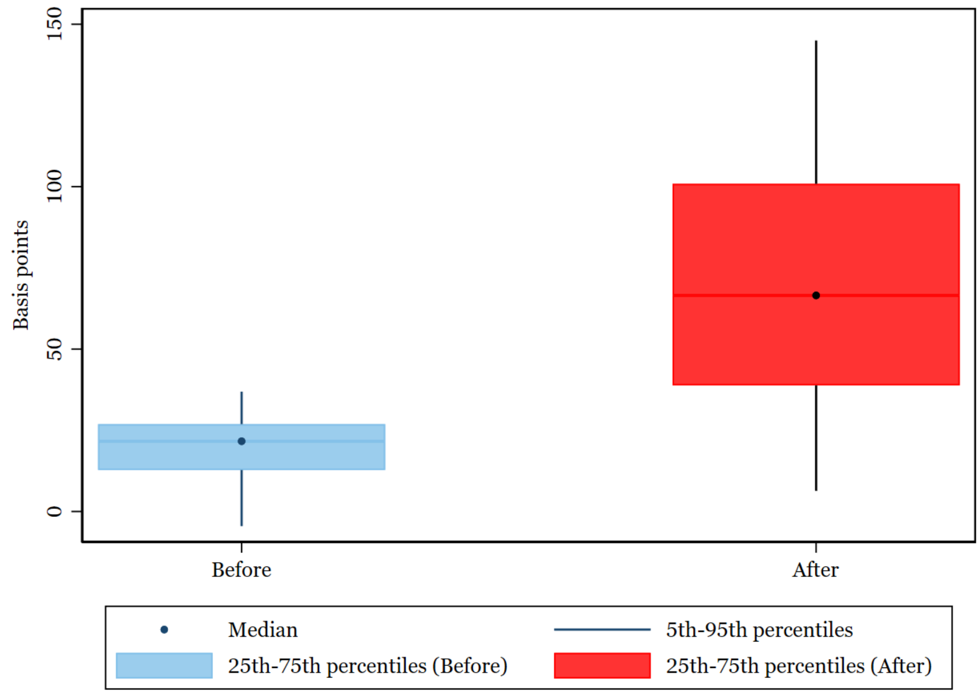
S_f consistent to what was observed in March 2020 and produce the counterfactual bilateral funding and bilateral interest rates after the shock.

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 1.6 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 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 1.7, Panels A and B, show the initial and final distribution across banks and funds. Appendix Figure 1.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.

Figure 1.6: 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.

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 1.8 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 1.8 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 1.A.8 shows the wedges as defined in Equation 1.23 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.

1.7.3 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 away from funding provision.

Figure 1.9 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 1.9 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.

1.8 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.

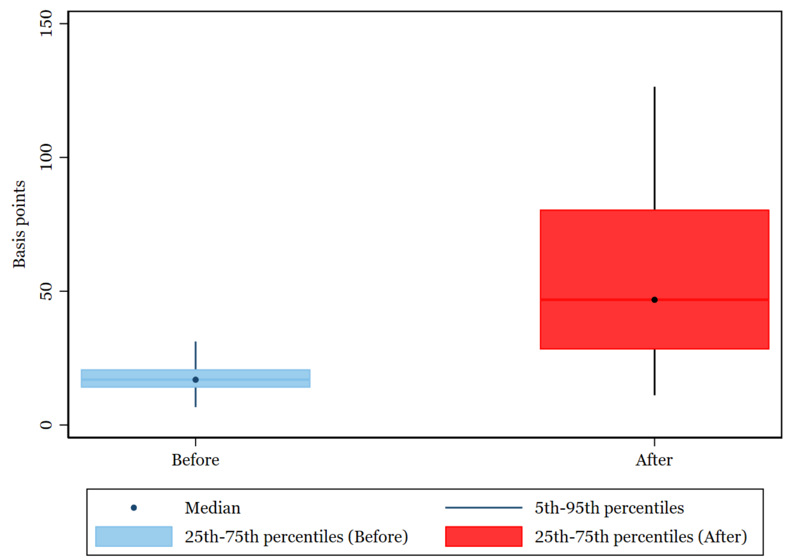
This paper highlights the importance of the access to the ON-RRP facility for

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

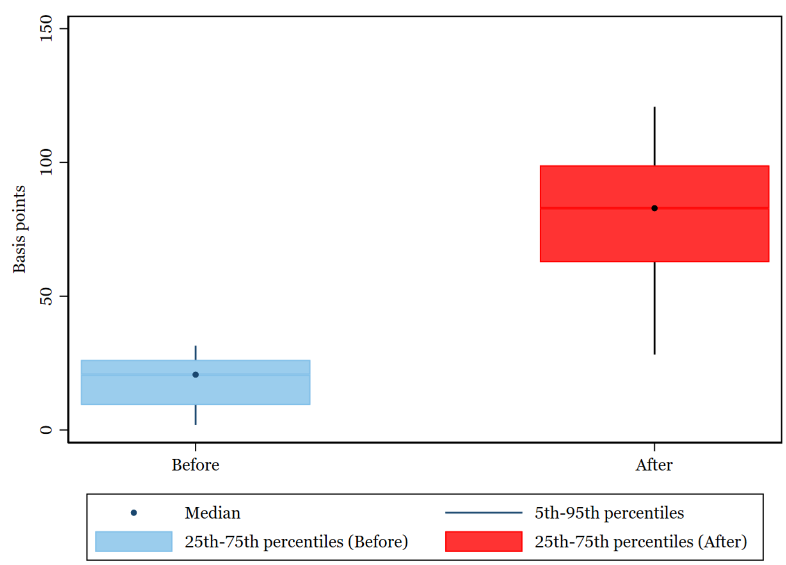
non-bank intermediaries. The ON-RRP facility gives an outside option for Money Market Funds. The assets in this facility have increased substantially after March 2020 following a large inflow of deposits in government funds. My paper offers a framework to study the impact of monetary policy through the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

Figure 1.7: Model Predicted Price Distribution

Panel A. Across Banks

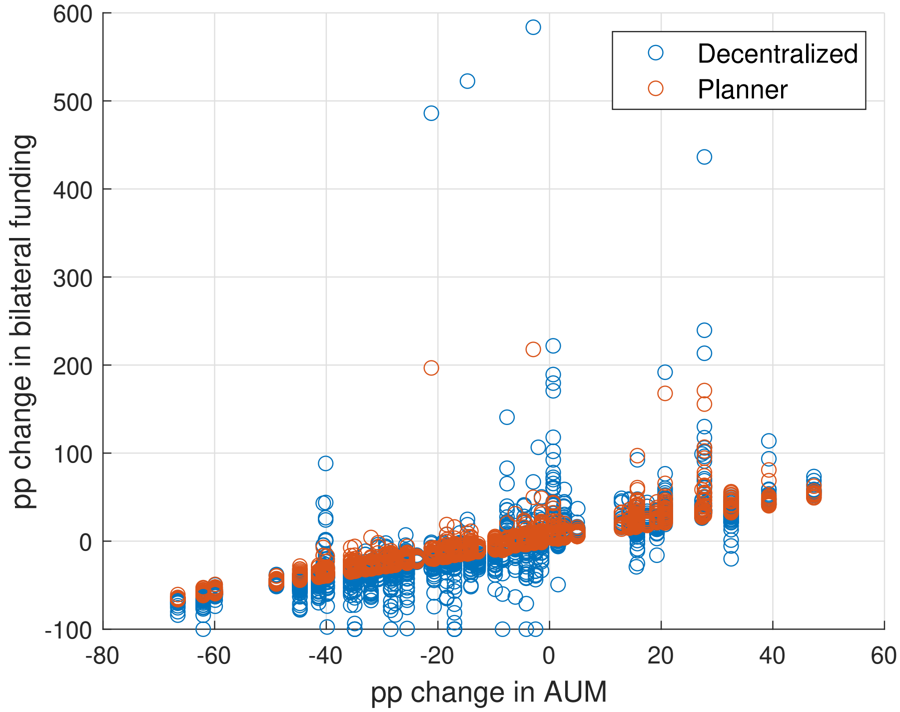


Panel B. Across Funds



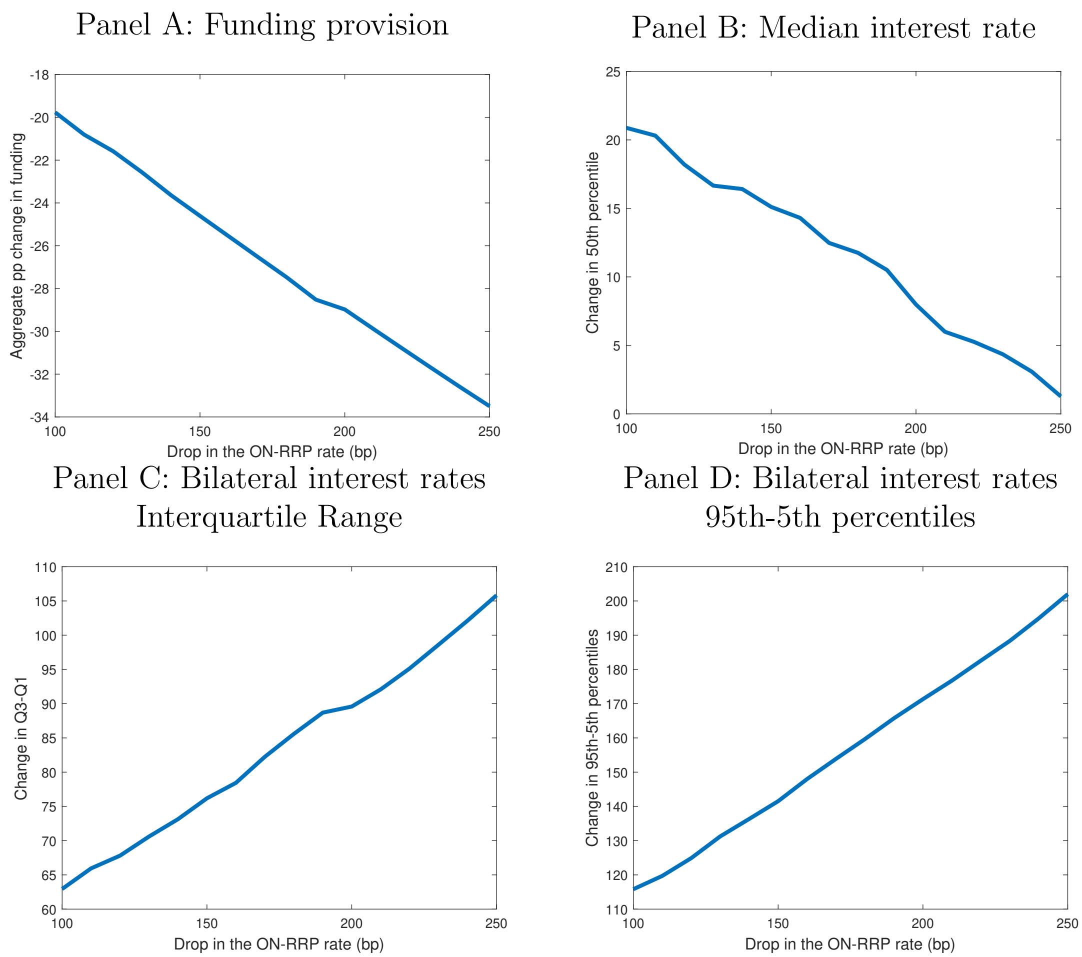
Notes: Data from Crane. Author's calculations. Distribution of the size-weighted interest rate with respect to the Secured Overnight Financing Rate (SOFR) at the bank level (Panel A) and the fund level (Panel B). I assume the SOFR is fixed in the counterfactual. The initial bilateral distribution of 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 1.8: 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

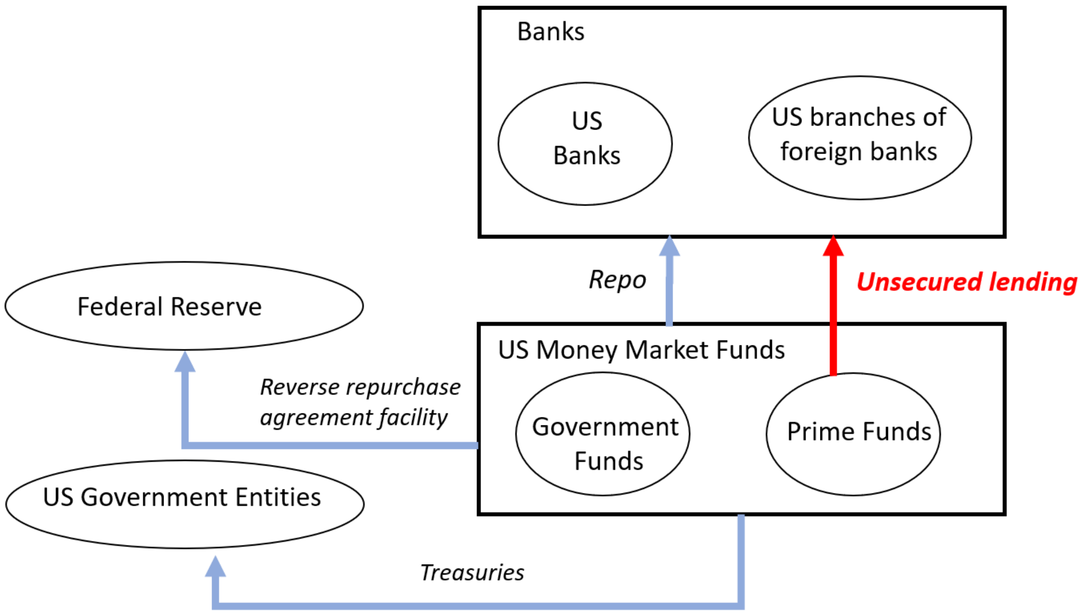
Figure 1.9: Effects of a drop in the ON-RRP rate



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.

1.A Appendix: Additional Figures

Figure 1.A.1: Market Structure

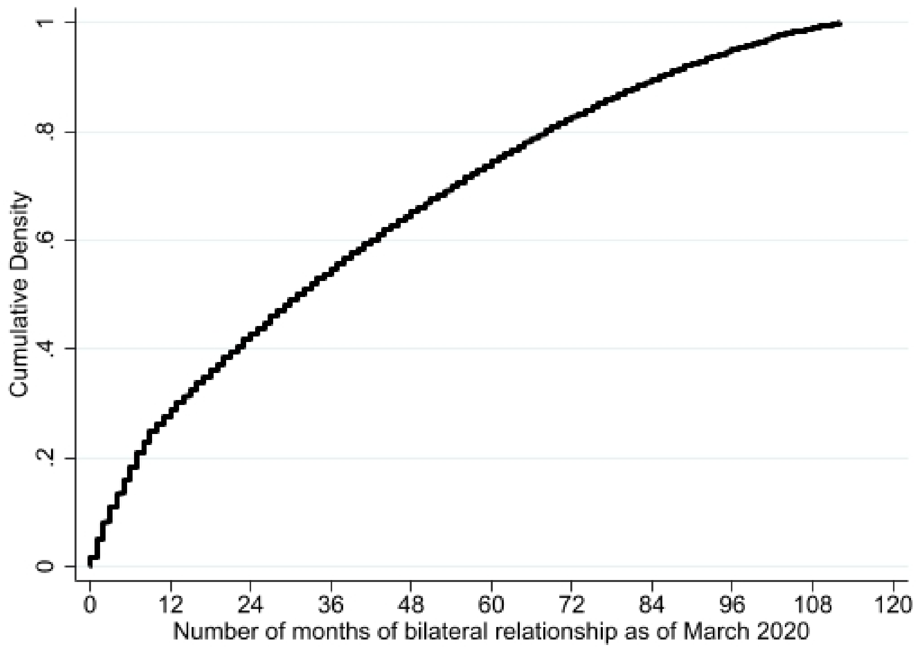


Notes: US money market funds have three main outlets for their assets under management. Prime money market funds can provide liquidity to US banks or to US branches of foreign banks through unsecured lending (mostly commercial paper, certificates of deposit, or asset-backed commercial paper) or repurchase 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 1.A.2: Network Structure

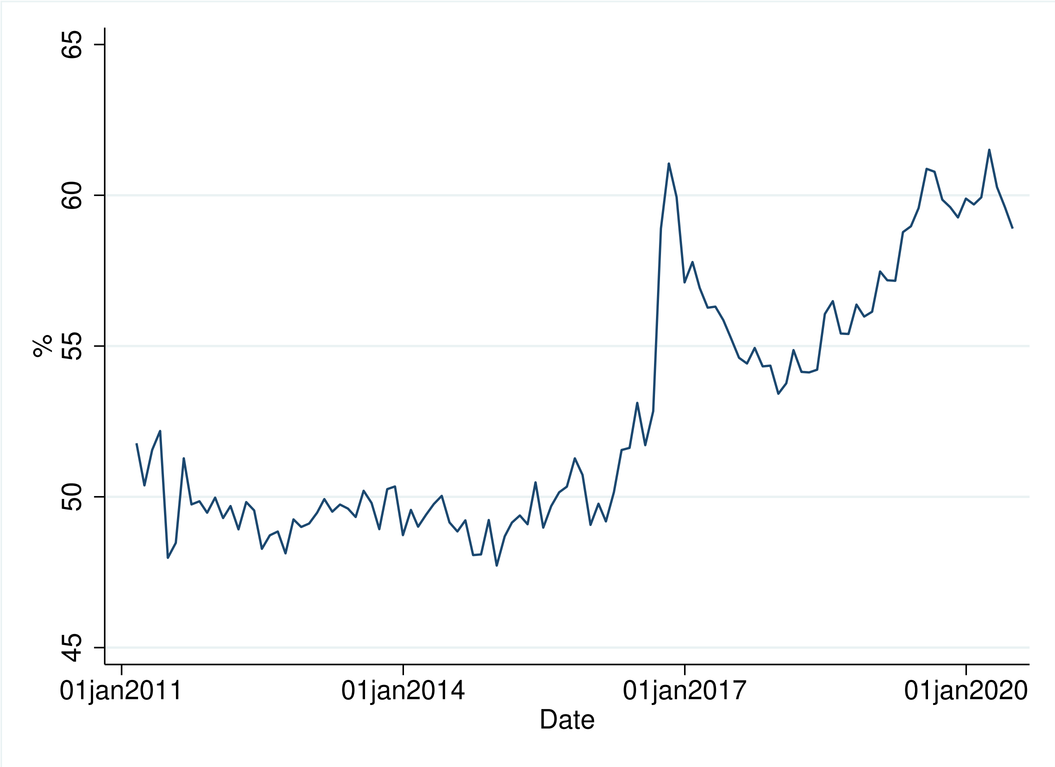
Notes: Data from Crane. Author's calculations. A blue node represents a money markey funds, a gold node is a bank, and grey arrows represent a bilateral contract. The size of the fund's nodes represents the total size of the assests under management and the size of the bank's nodes represents total assets.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

Figure 1.A.3: Cumulative Distribution of Duration of Bilateral Relationship



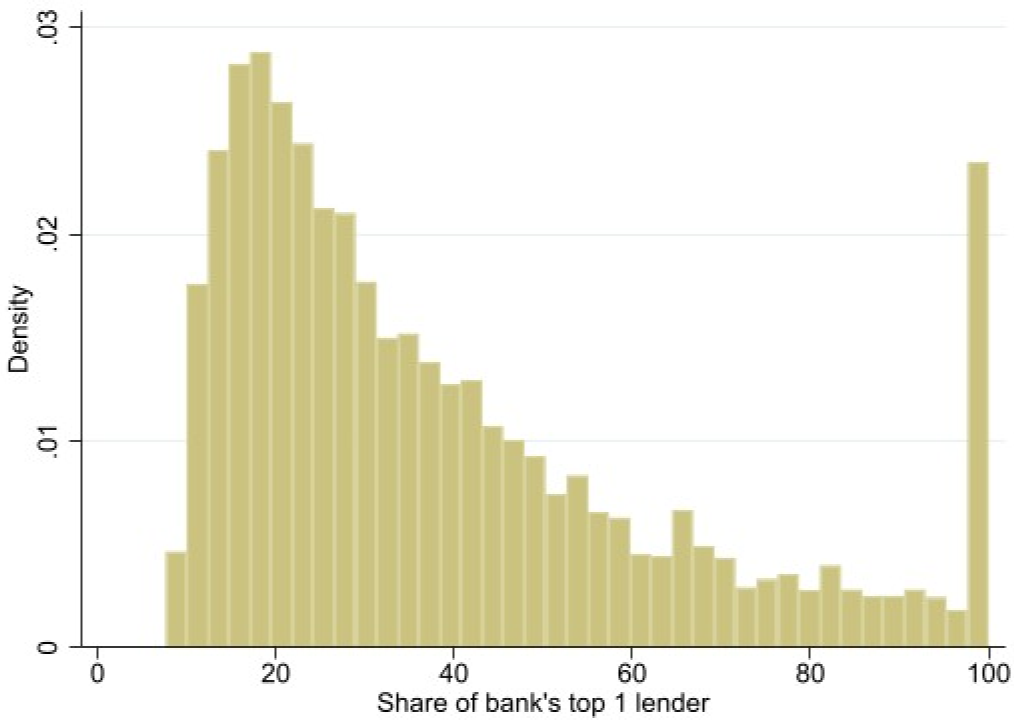
Notes: Data from Crane. Author's calculations. The measure of the duration of the bilateral relationship takes as reference all existing contracts between banks and funds on March 2020. The duration of the bilateral relationship is measured as the time elapsed in months between the first time a bank-fund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

Figure 1.A.4: Market Share of the 5 Largest Money Market Funds, CR_5



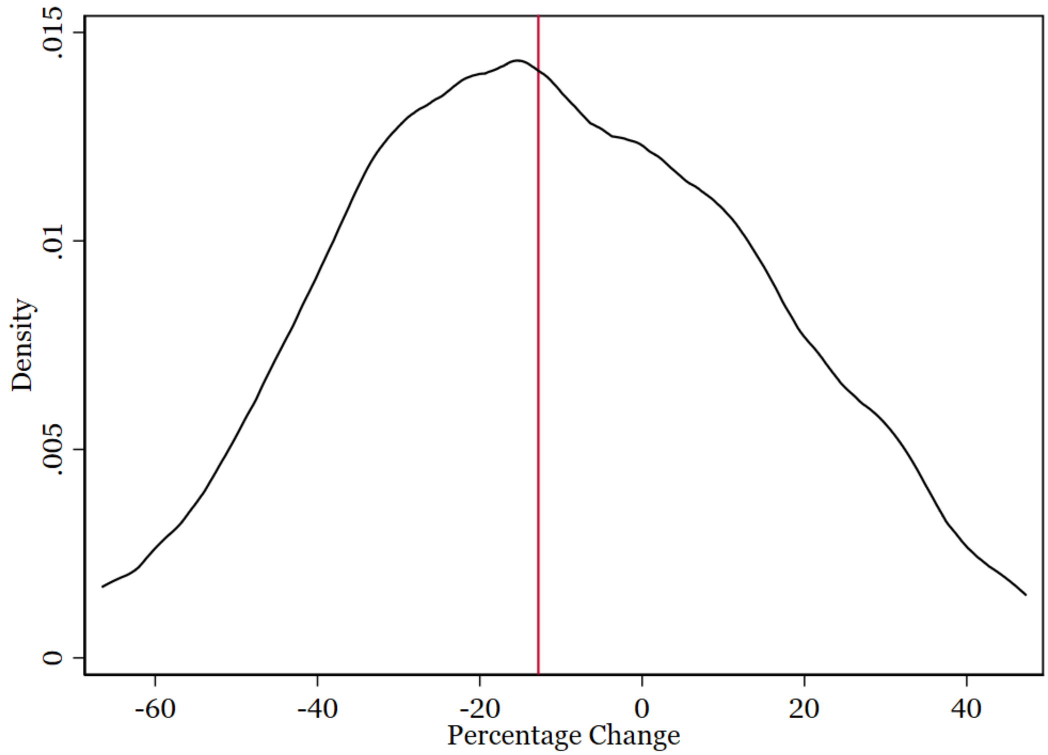
Notes: Data from Crane. Author's calculations. The graph shows the monthly 5-firm concentration ratio, which is the sum of the percentage market share of the five largest money market funds in a given month.

Figure 1.A.5: Distribution of the Share of a Bank's Funding by its Largest Counterparty



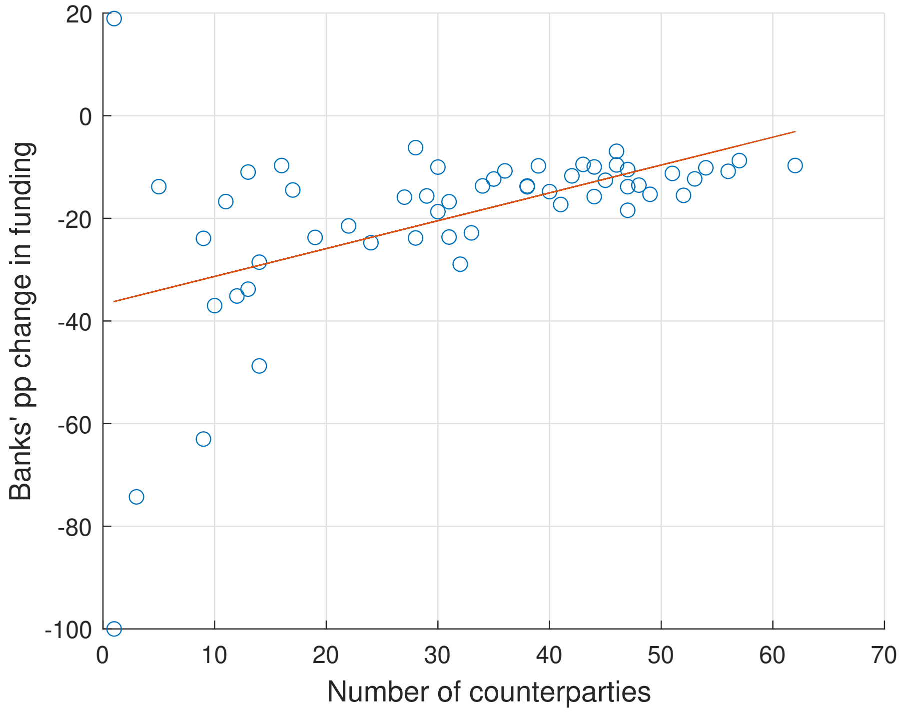
Notes: Data from Crane. Author's calculations. Data as of December 2019 and at the bank-level. This measure of concentration corresponds to the share of a bank's funding in money markets that is provided by its largest counterparty.

Figure 1.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%).

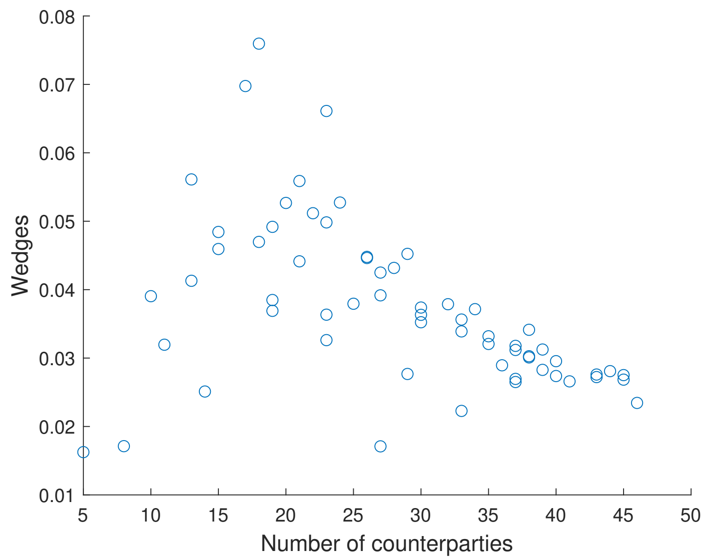
Figure 1.A.7: Number of Counterparties



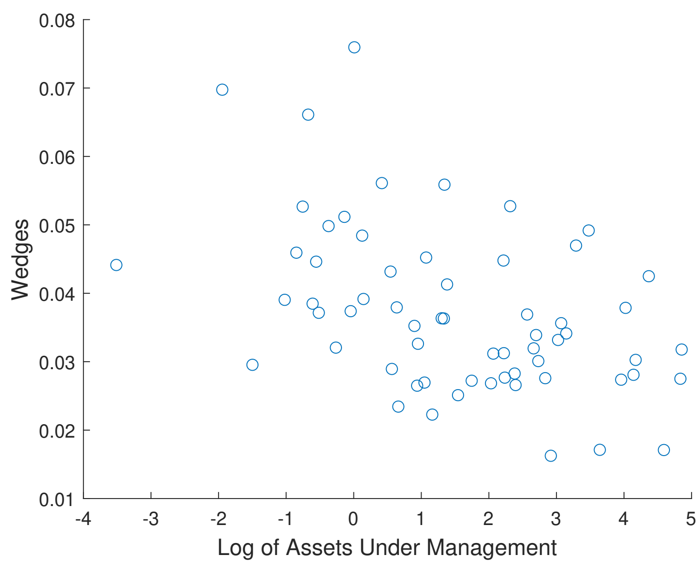
Notes: Data from Crane. Author's calculations. Distribution of the bilateral interest rate. I present the spread with respect to the Secured Overnight Financing Rate (SOFR). I assume the SOFR is fixed in the counterfactual. The observation level is bank-fund. The initial distribution is calibrated to 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 1.A.8: Wedges and Fund's Characteristics

Panel A. Across Banks

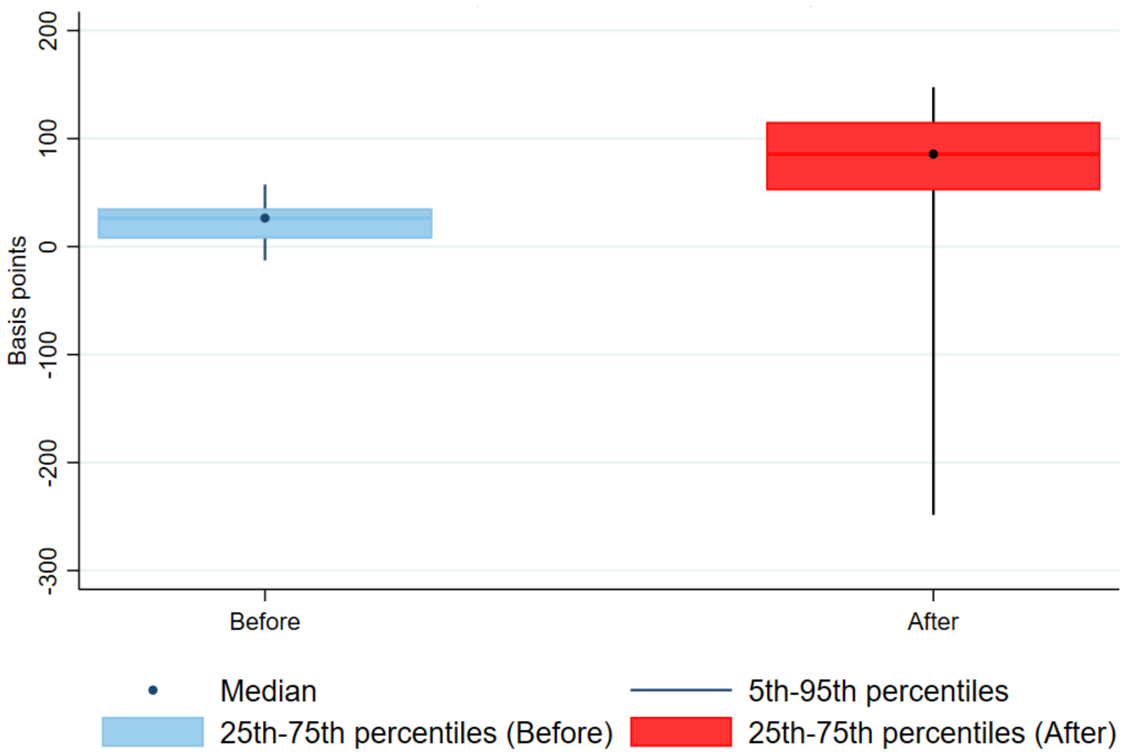


Panel B. Across Funds



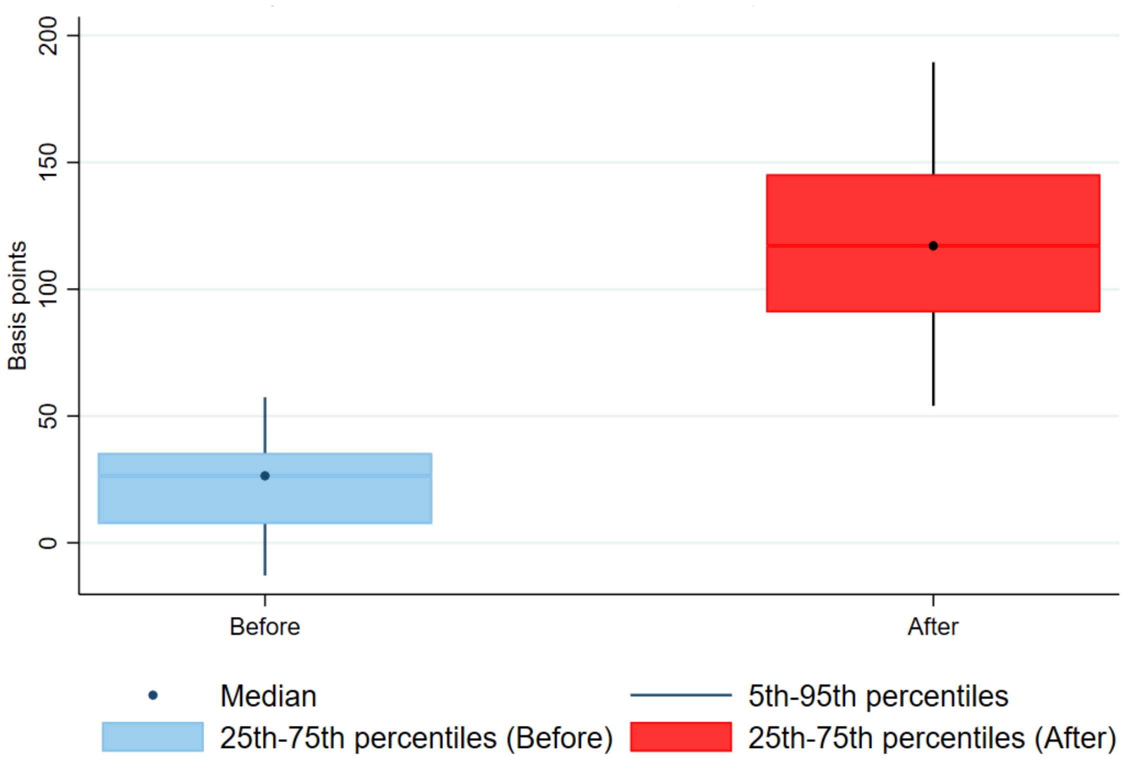
Notes: Author's calculations. Figures present the sum of wedges, defined as in 1.23, after the shock in assets under management.

Figure 1.A.9: Model Predicted Price Distribution



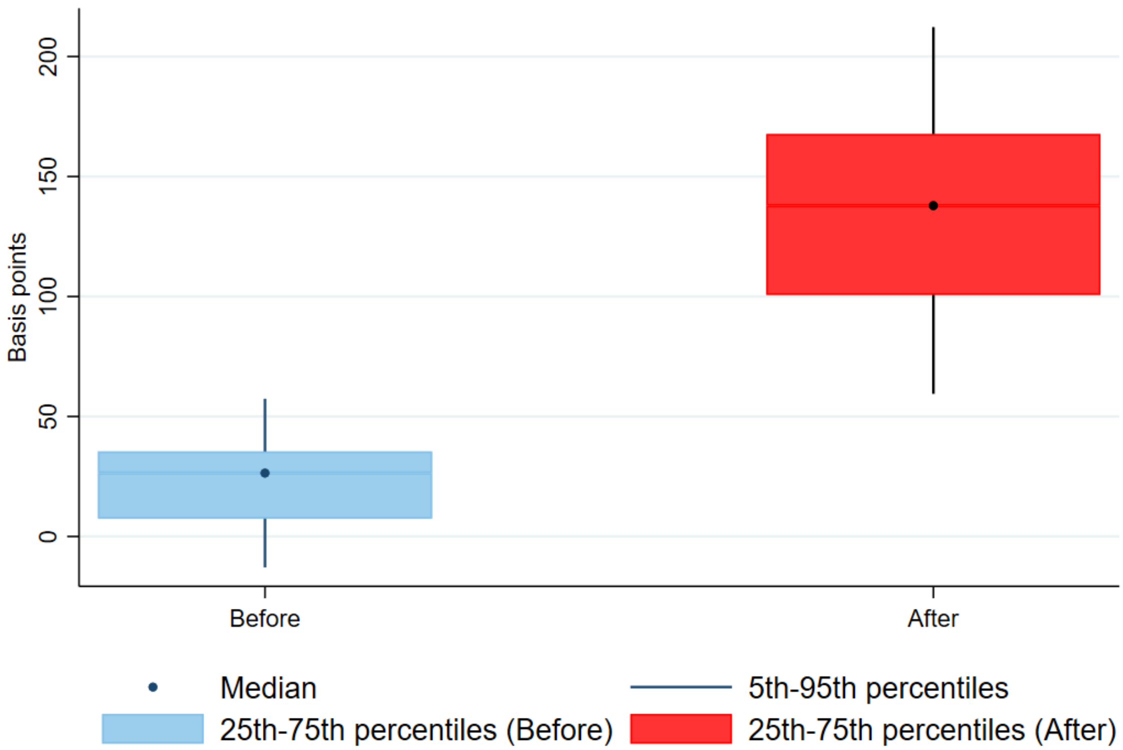
Notes: Data from Crane. Author's calculations. Distribution of the bilateral interest rate. I present the spread with respect to the Secured Overnight Financing Rate (SOFR). I assume the SOFR is fixed in the counterfactual. The observation level is bank-fund. The initial distribution is calibrated to 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 1.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 1.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.

1.B Appendix: Additional Exercises

1.B.1 Other counterfactuals

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

1.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 1.B.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,

Table 1.B.1: Counterfactual Effects on Rates and Lending

	Data March 2020 (1)	Baseline (2)	Network Frictions (3)	Fixed cost (4)	Increase in Market Power (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
Med. int. rate	85.10	94.30	26.42	85.59	75.37
Change in lend.	-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.

as presented in Table 1.B.1, Column 4 and Appendix Figure 1.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.

1.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 1.B.1, Column 5 and Appendix Figure 1.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.

1.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 1.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.

1.B.2 Gains from Trade

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

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

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

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

Similarly,

$$\Delta_{bf}\Pi_f^{\mathcal{M}} = (R_{bf} - r^\star)\gamma_{b,f} - \frac{\alpha_F}{2}(2z_f - \gamma_{bf})\gamma_{b,f} - \frac{\phi}{2}\gamma_{bf}^2 \tag{1.B.2}$$

The total surplus of the negotiation is

$$\Delta_{bf}\Pi_b^{\mathcal{B}}+\Delta_{bf}\Pi_f^{\mathcal{M}} = (A_b-r^\star)\gamma_{b,f}-\frac{\alpha_B}{2}(2z_b-\gamma_{bf})\gamma_{b,f}-\frac{\alpha_F}{2}(2z_f-\gamma_{bf})\gamma_{b,f}-\frac{\phi}{2}\gamma_{bf}^2 \tag{1.B.3}$$

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

$$(A_b - r^\star) - \alpha_B(z_b - \gamma_{bf} - \alpha_F(z_f - \gamma_{bf}) - \phi\gamma_{bf} = 0 \tag{1.B.4}$$

We can rearrange as follows:

$$\gamma_{bf} = \frac{A_b - r^\star - \alpha_B z_b - \alpha_F z_f}{\phi} \tag{1.B.5}$$

CHAPTER 2

The Macro-financial Effects of International Bank Lending on Emerging Markets

This chapter provides novel empirical evidence on the effects of cross-border bank lending on emerging market economies' (EMEs) macro-financial conditions. We identify causal effects by leveraging the heterogeneity in the size distribution of bilateral cross-border bank lending to construct granular instrumental variables for aggregate cross-border bank lending to 22 EMEs. We find that cross-border bank credit causes higher domestic activity in EMEs, and looser financial conditions. Financial condition indices ease, nominal and real effective exchange rates appreciate, sovereign and corporate spreads narrow, domestic interest rates fall, and housing prices increase. Similarly, real domestic credit grows, real GDP expands, and imports rise. Effects are weaker for countries with relatively higher levels of capital inflow controls, supporting the view that these policy measures can be effective in dampening the vulnerabilities associated with external funding shocks.

2.1 Introduction

What are the effects of capital inflows on the macro-financial conditions of emerging market economies (EMEs)? The question is of particular importance to policy-makers, who tend to see capital inflows as expansionary as they ease domestic financial conditions and boost credit and domestic demand (Blanchard et al., 2016).[1] Higher asset valuations and stretched balance sheets could increase an economy's vulnerability to boom-bust cycles as capital flows to EMEs ebb (Reinhart et al., 2016).[2] That is the worry of policy-makers as they consider capital flow management measures and macroprudential policies to potentially smooth capital inflows. While the decision to resort to these measures must be rooted in convincing estimates, a clearly identified causal effect of capital inflows on domestic macro-financial conditions has been notoriously difficult to pin down.

Identifying this effect is challenging. First, capital flows are endogenous to the current and future prospects of recipient countries. Improved domestic economic prospects will induce foreign lending, which in turn will affect domestic economic conditions (such as exchange rates, housing prices, corporate spreads, and credit and real GDP growth). Second, other confounding factors associated with global developments may influence both capital flows to EMEs, and these countries' economies through independent channels. Capital flows are sensitive to risk perceptions that are in turn affected by global financial cycles and US monetary policy (Kalemli-Özcan, 2020). For example, a global increase in risk appetite could increase demand for

[1]Models with imperfect asset substitution (Greenwood and Vayanos, 2010; Gromb and Vayanos, 2010) predict that an increase in the supply of international lending appreciates domestic assets and the real exchange rate. The effect of an appreciation is ambiguous. Standard Mundell-Fleming models highlight the contractionary effects of expenditure switching away from exports. Models with financial frictions can help reconcile theory with policy-makers' views as they argue an appreciation can be expansionary by improving the net worth of borrowing firms with foreign currency debt, and lenders to these firms (Jeanne and Korinek, 2010; Mendoza, 2010; Bianchi, 2011).

[2]This idea is well established in the international finance literature. Early discussions emphasized the role of "push" versus "pull" factors in driving cross-border capital flows (Calvo et al., 1993, 1996), followed by the literature on "sudden stops" (Calvo and Reinhart, 2000).

EMEs' exports, growth expectations, and appreciate the real exchange rate.[3]

This paper draws on a novel technique – that of granular instrumental variables (GIVs) in the spirit of Gabaix and Koijen (2019) – to deal with endogeneity in estimating the causal effect of capital flows on macro-financial variables in EMEs. Intuitively, the GIV approach requires a large cross-sectional dataset of country-level lending to any given EME, where some lending countries play a larger role than others. The idiosyncratic shocks to those countries' lending – over an above average fluctuations common to all lenders – serve as exogenous and excludable instruments.

We focus on the effects of international bank lending on key financial and real variables for a sample of 22 EMEs over the 1990Q1 to 2018Q4 period. We draw on a confidential dataset of bilateral country-level international bank lending data from the Bank for International Settlements' (BIS) locational banking statistics.[4] The size distribution of international bilateral bank claims is heterogeneous and concentrated (Aldasoro and Ehlers, 2019). Accordingly, some international lenders have large shares in aggregate international lending to any given EME and idiosyncratic shocks to such lenders should thus drive the volatility in total cross-border bank lending to that EME. Thus, not only does this dataset have properties that allow us to extract granular instruments as outlined above, but international bank lending is also a theoretically appropriate variable to capture capital flows in at least two respects. First, it accounts for a significant share of capital flows, as emphasized by the growing literature on the role of global banks in transmitting financial conditions

[3]Work using matched firm-bank data (di Giovanni et al., 2018, 2019) or event studies (Williams, 2018; Pandolfi and Williams, 2019a) provide clean identification in specific circumstances and for particular countries. The issue of the general applicability of such results, however, remains open.

[4]The bilateral data used capture lending from banks resident in BIS reporting countries to bank and non-bank borrowers resident in 22 EMEs.

across borders.[5] Second, international bank lending tends to be the marginal source of funding during credit booms, growing faster than domestic credit (Borio et al., 2011; Cesa-Bianchi et al., 2019).[6]

Our empirical strategy relies on constructing instrumental variables for *aggregate* international bank lending using *bilateral* lending data. We start by recovering idiosyncratic shocks to bilateral lending relationships. We do so by removing common factors among all bilateral claims to a given EME.[7] We use these shocks weighted by the heterogeneous bilateral lending shares to construct a valid and optimal instrument for aggregate lending. After obtaining the GIVs, the methodology boils down to a standard two-stage least squares approach. We use the instruments to assess the dynamic causal effect of shocks to aggregate international bank lending on EMEs' domestic macro-financial variables, using local projections with instrumental variables (Jordà, 2005).

The exclusion restriction on which our identification strategy relies is that idiosyncratic shocks to bilateral bank lending affect economies only through international bank lending. We argue that the common component of bilateral bank lending captures both the recipient EME's macro economic conditions, and international conditions related to a global financial cycle. As a result, the remaining idiosyncratic shocks to each of the bilateral lending relationships to a particular EME are exogenous to the EME's macroeconomic outcomes. Moreover, the shocks are likely

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[5] See for instance Rey (2015), Miranda-Agrippino and Rey (2015) and Bruno and Shin (2015a,b).

[6] Evidence pointing to the procyclicality of capital inflows includes Aguiar (2005); Baskaya et al. (2017b); Bruno and Shin (2015a); Gabaix and Maggiori (2015a); Miranda-Agrippino and Rey (2015).

[7] We do this by means of factor analysis. Results are robust to alternative methods to extract factors.

to affect the EME's conditions exclusively through bank lending, and not through other confounding factors.

Instead, variables related to global financial conditions will yield biased estimates of the causal effect of international bank lending. When used as instruments, these variables may be exogenous to a recipient EME's macroeconomic conditions but they are likely to affect the EME through other channels. For instance, measures of the global financial cycle will affect the availability and cost of capital flows, but they will also affect the recipient EME's terms of trade and global demand for exports.[8] Thus, common components of international bank lending that are driven by global financial conditions would not be valid instruments.

The GIVs we construct are orthogonal to indicators of the global financial cycle.[9] The fit of regressions of our GIVs on these indicators is virtually indistinguishable from zero and the point estimate for each global financial cycle indicator is very small and not statistically significant. We document that international bank lending is linked with measures of the global financial cycle but, in line with the literature (see Cerutti et al. (2017)), it explains a small share of its variation.

We find that international bank lending boosts EMEs' domestic activity and loosens financial conditions. This is in line with the literature emphasizing the financial channel of exchange rate appreciation through firms' balance sheet constraints

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[8]So while it could be sound to regress EMEs' outcomes on measures of the global financial cycle, the estimated coefficients should be interpreted carefully as they will capture the full effect of the shock including, for example, the effects on present and future global growth.

[9]We proxy the global financial cycle by the three most commonly used measures: the common factor in global risky asset prices (Rey, 2015; Miranda-Agrippino and Rey, 2015), the first principal component of capital flows (Cerutti et al., 2019b) and the VIX (di Giovanni et al., 2019). See Arregui et al. (2018) and Acalin and Rebucci (2020) for recent contributions to global financial cycle measurement.

(Bruno and Shin, 2015a,b), that tends to be more pronounced for EMEs (Banerjee et al., 2020). A positive shock to international bank inflows causes EMEs' financial condition indices to ease, nominal and real effective exchange rates to appreciate, sovereign and corporate spreads to narrow, domestic interest rates to fall, and housing prices to increase. On the real side, the shock has a positive causal effect on real domestic credit growth, and on real gross domestic product, mostly through investment. Our baseline results are robust to extensive checks regarding the role of crises, the sample of lending countries, and the method used to construct the GIVs.

We also find that higher levels of capital controls can be effective in moderating the financial easing and macroeconomic expansion caused by higher international bank lending inflows. The flexibility of our framework allows to introduce non-linear effects based on different states. We construct a measure of the relative level of capital flow controls using the capital control index of Fernández et al. (2016) and interact this measure with our GIVs to estimate how the effect of higher capital controls may change the total effect of international bank lending. We find that the causal effects of international bank lending on domestic EME outcomes are weaker for countries that have higher degrees of capital inflow controls (e.g. moderate a boom in financial conditions, or limit the growth of credit), consistent with Forbes et al. (2015), Zeev (2017), Pasricha (2017) and Nier et al. (2020).[10]

Our GIVs improve upon other instruments used in the literature. We show that, when used to instrument international banking claims, these alternative instruments:

[10] In principle, our methodology could be used to assess the role of other regimes or states as well. We have explored the role of different exchange rate regimes, as in Zeev (2019) and Kalemli-Özcan (2020). The findings are broadly consistent with theirs showing a stronger effect for more rigid exchange rate regimes, but the unbalanced nature of the exchange rate regime data generates results that are likely driven by only few observations/countries.

(i) are either not relevant as their first stage statistics are poor; or (ii) very likely reflect the global financial cycle and thus are not excludable. In particular, we apply to our cross-border banking data the excess bond premium measure of Gilchrist and Zakrajšek (2012) as used by Zeev (2019), the leverage of the US broker-dealer sector as in Cesa-Bianchi et al. (2018), a Bartik-type instrument inspired by the measure used in Blanchard et al. (2016), and the "host" and "common" components of aggregate cross-border lending growth as identified in Avdjiev et al. (2020) based on the methodology of Amiti and Weinstein (2018).[11] The only instruments that are relevant in the first stage regressions are the common component of Avdjiev et al. (2020), the leverage of the US broker-dealer sector, and the instrument based on Blanchard et al. (2016). However, they are strongly correlated with different measures of the global financial cycle, making them non-excludable. We show that these instruments can generate large biases in the estimation of the causal effect of international banking lending on domestic EME macro-financial conditions. We argue that such biases are consistent with the global demand shocks that these instruments cannot fully purge themselves from.

Related literature. Our paper contributes to the literature along several dimensions. First, we directly estimate a macro-causal effect of capital (banking) flows on EMEs. Previous studies (Calvo and Reinhart, 2000; Calvo et al., 1996; Reinhart and Reinhart, 2009) have shown that capital flows correlate with boom-bust cycles. This paper contributes to this literature by providing an identification strategy for the causal macroeconomic impact of international bank flows.

[11]In an appendix we extensively compare our GIVs with the bank lending growth decomposition in Avdjiev et al. (2020). Our GIVs are uncorrelated with the components of this decomposition, whereas the endogenous factors we explicitly exclude from the construction of our GIVs are.

Second, to the best of our knowledge, this paper is the first application of the GIV approach to international bank lending and capital flows. International banking data such as the locational banking statistics of the BIS are a natural candidate for the GIV approach. Recent applications of the method include Galaasen et al. (2019), which estimates the effect of firm level shocks on the banks that lend to these firms, or Camanho et al. (2019), which estimates the elasticity of supply of foreign exchange and quantifies the effect of portfolio rebalancing on the exchange rate. di Giovanni et al. (2018) uses detailed firm-level data for French firms to document that large firms are the key channel through which foreign shocks are transmitted domestically.

Third, we extend the GIV method to a non-linear panel setting and adapt the local projection approach to estimate the dynamic effects of bank lending shocks on EME macroeconomic and financial outcomes. Gabaix and Koijen (2019), which introduces this methodology, only shows how to achieve identification using the procedure in static frameworks. We develop a dynamic framework for the evolution of cross-border bank flows and domestic macroeconomic variables and show how to use GIV in this setting.

A number of recent studies leverage bilateral international banking data. Related to our paper, Amiti et al. (2019) and Avdjiev et al. (2020) provide a decomposition of aggregate growth rates of international bank claims using the BIS consolidated and locational banking statistics respectively. We focus on the country/geographical perimeter and use the BIS locational banking statistics, which align with national accounting and balance-of-payments accounting conventions and therefore are a better fit to assess the impact of cross border lending on EMEs' domestic macro-financial variables. We compare our GIVs with the decomposition in Avdjiev et al. (2020) and use it to further validate our identification strategy.

Several related papers study the transmission of international credit supply shocks and show they have expansionary effects in EMEs. Cesa-Bianchi et al. (2018) and Zeev (2019) use US credit supply shocks (US broker dealer leverage and the excess bond premium of Gilchrist and Zakrajšek (2012), respectively) to identify the effects on several macroeconomic variables. Obstfeld et al. (2019) and Baskaya et al. (2017a) use the variation of global risk to study the transmission of global financial conditions to domestic financial markets. Our approach differs from these papers by extracting not only the potential domestic confounding factors, but also foreign shocks that might be related to domestic variables through, for example, global growth expectations. Other studies focus on either a single country or at a single point in time. di Giovanni et al. (2019) use corporate loan transactions matched to banks' balance sheets for Turkey to study in detail how changes in global financial conditions transmit to domestic financial conditions, using the VIX as a proxy for the global financial cycle. Finally, Williams (2018) and Pandolfi and Williams (2019a) exploit episodes of large sovereign debt inflows to EMEs to identify the effects of these inflows on credit and firm returns.

A final strand of related literature studies the role of capital controls in the transmission of international shocks.[12] A key difference of our paper in addition to our identification of shocks, is the ability to condition on different levels of capital controls in our non-linear model. The work by Bergant et al. (2020) is closest to our analysis. They study the effectiveness of the level of macroprudential measures on the transmission of external financial shocks proxied by the VIX and a Bartik-type measure of exposure to push factors as in Blanchard et al. (2016).

[12] See Forbes et al. (2015), Edwards and Rigobon (2009), Pasricha et al. (2018), Pasricha (2017).

Roadmap. The rest of the paper is structured as follows. Section 2.2 briefly motivates the importance of looking at international bank claims. Section 2.3 presents the intuition behind the granular instrumental variable approach in a simple and generic context, in order to highlight the source of identification. It then presents the extended model and the estimation approach. Section 2.4 describe the data, with an emphasis on that used for construction of the GIVs. Section 2.5 presents and discuss the results, as well as the validity of our GIVs. Section 2.6 shows several robustness checks on the construction of our GIVs. Section 2.7 compares the GIVs with other instruments from the literature. Finally, Section 2.8 concludes.

2.2 Cross-border Bank Lending in Perspective

Cross-border bank credit is an important component of gross liabilities of countries, more so after excluding foreign direct investment (FDI).[13] This credit is for the most part composed of direct cross-border bank loans and bank holdings of debt securities[14] and according to the balance of payments (BoP), it is registered under two international claims' categories.[15] Bank loans fall within (and take the lion's share of) the "other investment" category under BoP definitions. Bank holdings of debt securities, in turn, are reflected in the BoP under "portfolio debt". To give

[13]The most comprehensive and complete source of cross-border banking data comes from the BIS locational banking statistics, which are collected following principles consistent with balance of payments statistics. We provide more details on the data in Section 2.4.

[14]About two thirds of cross-border bank credit is accounted for by bank loans, around 20% by debt securities, and the residual is made of other instruments and positions unallocated by instrument type.

[15]According to the BoP accounting framework, total liabilities in the international investment position (IIP) of a country can be decomposed into four broad types of gross liabilities: FDI (both debt and equity), portfolio debt and equity investment, financial derivatives, and other investments.

a sense of the importance of cross-border bank claims, we compute their ratio to (i) total international liabilities, and (ii) total international liabilities excluding FDI liabilities, which we call "non-FDI" liabilities. Figure 2.1 shows that, for the median EME in our sample of 22 countries (see Table 2.1), bank claims represent around 18 percent of total IIP liabilities, and 28 percent if FDI is excluded. As shown in Figure 2.1 the median ratio of banking claims to non-FDI liabilities has been stable over the last two decades.[16]

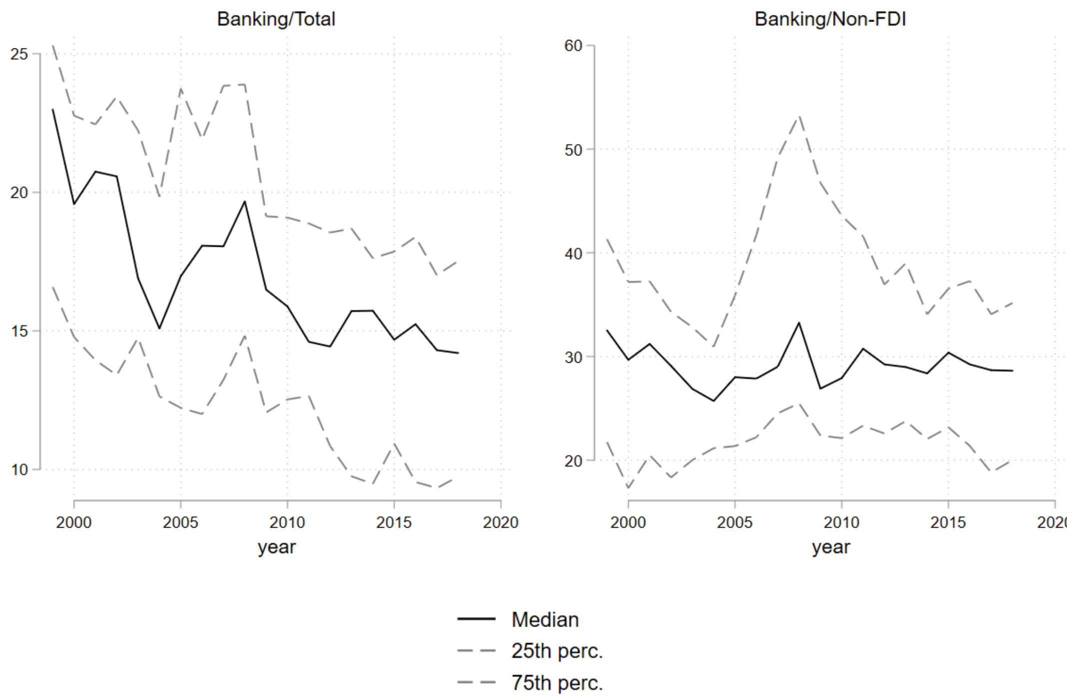
Table 2.1: Country sample list

Argentina	Hungary	Poland
Brazil	India	Russia
Bulgaria	Indonesia	South Africa
Chile	Israel	Thailand
China	Malaysia	Turkey
Colombia	Mexico	Ukraine
Czech Republic	Peru	
Egypt	Philippines	

Notes: This table shows the list of 22 countries covered in our sample.

[16]These ratios should be taken as illustrative of the magnitudes. While both IIP and the banking statistics are measured in US dollars (USD), the BIS locational banking statistics correct for exchange rate movements whereas the IIP does not. So any movement in the exchange rate will result in changes in IIP positions for liabilities issued in currencies other than the USD.

Figure 2.1: Importance of cross-border bank claims over time



Notes: This figure shows the median, 25th, and 75th percentiles of the ratios of international bank claims ("Banking") to total gross international liabilities ("Total") from the IIP, and Total excluding Foreign Direct Investment liabilities ("Non-FDI") over time. The sample comprises 22 EMEs, as presented in Table 2.1.

Cross-border credit is also important for the role it plays as the marginal source of funding during credit booms (Borio et al., 2011). Despite being small relative to the total stock of domestic credit, cross-border credit tends to be more volatile and can amplify domestic credit trends (Figure 2.2). Indeed, cross-border bank credit can be an important early warning indicator of banking crises (Aldasoro et al., 2018). Furthermore, changes in cross-border bank claims are representative of the changes in total aggregate liabilities. Figure 2.3 illustrates this point by means of pairwise correlations for our core sample of EMEs. Cross-border bank claims and total liabilities (with and without FDI) are strongly and positively correlated. This correlation is also statistically significant, as illustrated by the simple regression in Table 2.2. The fit of these regressions is particularly good (given the simplicity of the estimation) when looking at total liabilities excluding FDI. Interestingly, even as BIS data adjust for exchange rate movements (see footnote 11), growth rates in international bank claims are more volatile than total and non-FDI international liabilities (which are not adjusted for exchange rate movements).

Table 2.2: Cross-border bank lending and IIP liabilities are strongly related

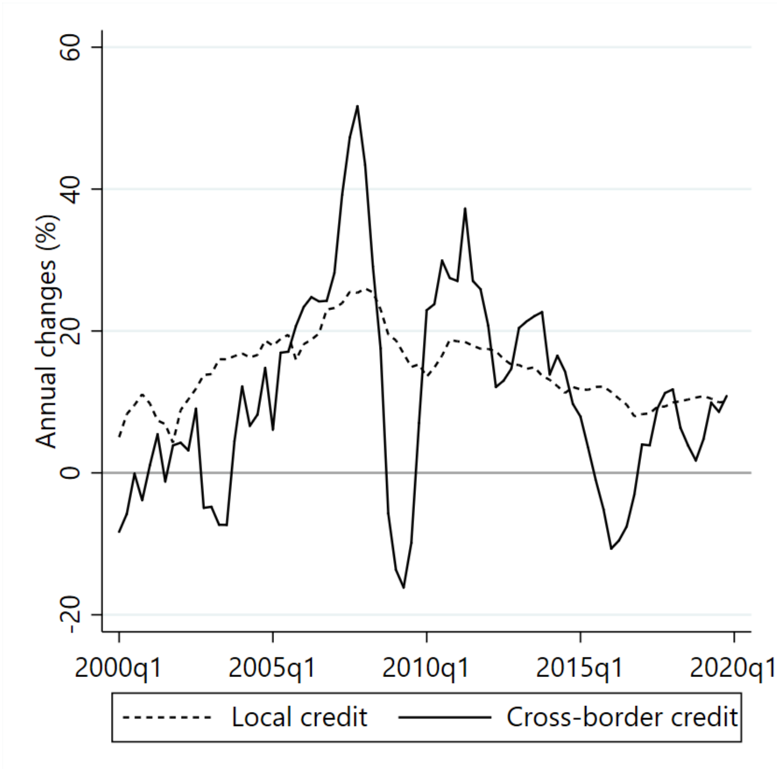
	(1)	(2)
VARIABLES	Total	Total Non-FDI
Banking	0.394***	0.409***
	(0.0152)	(0.0157)
Observations	975	975
R-squared	0.413	0.417
Countries	22	22

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

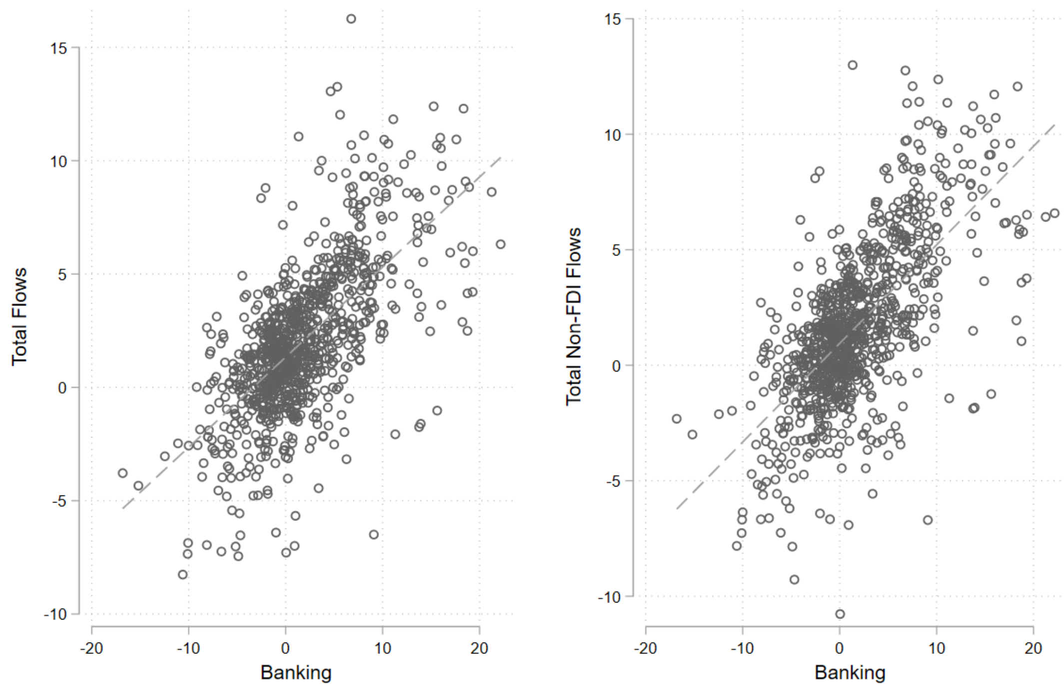
Notes: This table shows the results of a panel regression with country fixed effects of the quarterly growth rates of different measures of gross international liabilities (as reported by the IMF International Investment Position Statistics) on the quarterly growth rate of cross-border bank claims of all BIS reporting banking systems.

Figure 2.2: Cross-border bank claims on EMEs show larger swings than local claims



Notes: This figure shows the growth rate in cross-border claims of LBS-reporting banks to the non-bank sector in EMEs plus local claims of all banks to the private non-financial sector of the same EMEs. Weighted averages, based on four-quarter moving sums of GDP. For the list of countries see the BIS Global Liquidity Indicators.

Figure 2.3: Growth in cross-border bank claims and international liabilities are strongly correlated



Notes: This figure plots the correlation between the growth in cross-border bank claims versus that in total external liabilities from the IIP with (left-hand panel) and without (right-hand panel) FDI. The sample comprises 22 EMEs, as presented in Table 2.1.

2.3 Empirical strategy

Our objective is to recover the causal effect of international bank lending on EMEs. As in many macroeconomic settings, we face an identification problem, as EME domestic outcomes and international banking lending are jointly determined. We use the GIV approach of Gabaix and Koijen (2019) to address this endogeneity problem and identify the causal effect of international bank lending on domestic macro-financial variables.

2.3.1 Understanding GIVs: the basic intuition

To motivate our approach, we start by proposing a reduced form model for a single economy that links the growth of this country's international bank claims ($\tilde{y}_t$) to a macro-financial domestic variable (F_t). The model shows how changes in international bank credit affect, for example, real GDP growth, domestic credit, or corporate spreads. The goal of our estimation is to identify α, the elasticity of the endogenous variable F_t to $\tilde{y}_t$

$$F_t = \alpha \tilde{y}_t + \varepsilon_t. \tag{2.1}$$

We observe the total claims by country of origin (indexed by j). We thus denote by $y_{j,t}$ the growth rate of claims from country j on the domestic economy. We assume in this section that $y_{j,t}$ does not depend on F_t:

$$y_{j,t} = \eta_t + u_{j,t} \tag{2.2}$$

where η_t is a shock common to all j lenders[17] and $u_{j,t}$ is an idiosyncratic, lender-specific, shock. By assumption, let $u_{j,t}$ be orthogonal to η_t and ε_t. We also assume that all j sources of lending have the same sensitivity to η_t.[18]

[17]This captures both recipient country aggregate domestic shocks as well as global shocks such as for example changes in dominant currency monetary policy.

[18]This can be thought of as a small open economy. We do not include control variables to simplify the exposition, but they will be included in the full model presented in subsection 2.3.2, where the assumption of no heterogeneity in sensitivity to common shocks is also relaxed.

Growth in aggregate bank claims is given by the weighted average of growth rates from individual lender countries, where weights are given by the share of source j in the aggregate (s_j)[19]:

$$\tilde{y}_t = \sum_j y_{j,t} \times s_j. \tag{2.3}$$

Importantly, we can not recover α directly from estimating equation (2.1) with OLS, as ε_t and η_t are likely correlated, biasing the estimate of α. An instrument for $\tilde{y}_t$ is needed. Such instrument, which we label z_t, can be constructed from observable data on the j sources of claims. To that end, we exploit the heterogeneity in shares s_j and use the difference between the *share-weighted* growth in claims and the *un-weighted* (or *equally-weighted* by $1/N$) growth in claims, with the latter defined as $\bar{y}_t = \sum_j y_{j,t} \frac{1}{N}$:

$$\begin{aligned}
z_t =& \tilde{y}_t - \bar{y}_t \\
=& \sum_j \left(S_j y_{j,t} - \frac{1}{N} y_{j,t} \right) \\
=& \sum_j \left((\eta_t + u_{j,t}) S_j - (\eta_t + u_{j,t}) \frac{1}{N} \right) \\
=& \sum_j \left(u_{j,t} \left(S_j - \frac{1}{N} \right) \right) \\
=& \tilde{u}_t - \bar{u}_t
\end{aligned} \tag{2.4}$$

where, $\tilde{u}_t$ and $\bar{u}_t$ are the share-weighted and equally-weighted sums of idiosyn-

[19]The aggregate growth rate is approximated by $\frac{\partial \ln \tilde{y}_t}{\partial t} \approx \sum_j s_j \frac{\partial \ln y_{j,t}}{\partial t}$. Again, for the sake of simplicity, we ignore for now that the shares may be time-varying.

cratic shocks, respectively. The difference between share-weighted and equally-weighted claims boils down to the difference between the sums of size-weighted and unweighted idiosyncratic shocks.[20]

The intuition why z_t can be a good instrument is simple. First, the difference between $\tilde{y}_t$ and $\bar{y}_t$ removes the common shock η_t and thus the possibility of endogeneity. This renders z_t exogenous as, by assumption, idiosyncratic shocks are uncorrelated with aggregate shocks (e.g. $E(u_{j,t}\varepsilon_t) = E(u_{j,t}\eta_t) = 0$). That is, idiosyncratic shocks "shift" flows but are not correlated with shocks to the endogenous variable F_t.[21] Second, for z_t to be relevant, $y_{j,t}$ has to be "granular": idiosyncratic shocks to large players give a valid IV for growth in aggregate international lending. That is, there has to be heterogeneity in the share/size distribution, which is clear from line 4 in equation 2.4: if there were no difference between share-weighted and equally weighted errors, z_t would be close to zero and would be a poor instrument. The heterogeneity in the size distribution allows the difference in share-weighted and equally-weighted shocks to correlate with total claims growth (e.g. $E(z_t\tilde{y}_t) \neq 0$).

2.3.2 Endogenous bank lending flows in a panel structure

In this section we present the baseline model, which extends the setting presented in the previous section along four dimensions. First, we allow for a panel structure. We want to capture how N borrowing EMEs, indexed by i, respond to exogenous shocks

[20] Gabaix and Koijen (2019) present a methodology to "optimally extract" such idiosyncratic shocks from the data in order to construct granular instrumental variables.

[21] The exogeneity or exclusion restriction would imply in this case that the difference between share-weighted and equally weighted idiosyncratic shocks to lender countries is uncorrelated with the unexplained part of our borrower country domestic variable of interest (e.g. $E(z_t\varepsilon_t) = 0$).

to international bank lending. Second, we generalize the model by allowing bank lending to depend on our endogenous variables of interest. Thus, in equilibrium, there is simultaneity between bank claims and, for instance, domestic financial conditions, GDP growth, or credit growth. Third, we allow for sensitivity to common factors to be heterogeneous across lending sources for each EME. Fourth, we also include additional controls and allow shares of each lending source to be time-varying for each EME.

Setting up the model. With a panel structure, we index aggregate variables by i for the recipient country. We denote by $y_{i,j,t}$ the growth in bilateral bank claims on borrower country i from lender country j at time t. The weighted sum of these over all lender countries j yields the growth in total international bank claims on country i (the extended version of equation (2.3)): $\tilde{y}_{i,t} = \sum_j s_{i,j,t-1} y_{i,j,t}$, where the weights $s_{i,j,t-1}$ are measured as of the previous period.

As above, we are interested in identifying and estimating the parameter α, which captures the marginal effect of banking flows on the domestic variable $F_{i,t}$:

$$F_{i,t} = \alpha \tilde{y}_{i,t} + \gamma^F X_{i,t}^F + \varepsilon_{i,t} \tag{2.5}$$

where $\varepsilon_{i,t}$ is an aggregate shock and $X_{i,t}^F$ is a vector of borrower country-specific controls. Equation (2.5) is analogous to equation (2.1) in this extended setting.

With the panel structure in mind and allowing for reverse causality, the growth in bilateral claims from country j to country i previously given by equation (2.2) now takes the following form:

$$y_{i,j,t} = \Lambda_{i,j} F_{i,t} + \Lambda^{\star}_{i,j} F^{\star}_{i,t} + \gamma^{Y} X^{y}_{i,j,t} + u_{i,j,t}, \quad (2.6)$$

where $\Lambda_{i,j}$ is a vector of the exposures of these bilateral claims to domestic factors, $F_{i,t}$, [22] $F^{*}_{i,t}$ captures international factors such as global risk appetite or monetary policy in dominant currency countries, and $\Lambda^{\star}_{i,j}$ is the exposure of bilateral claims to these international factors, which also vary across bilateral pairs (i, j). Finally, $X^{y}_{i,j,t}$ stands for a set of controls. Endogeneity in this setting comes from reverse causality. As discussed above, if one were to directly estimate α by OLS, the estimator would likely be biased. Not only domestic factors are affected by aggregate capital flows growth, but also capital flows growth may depend on domestic – observed and unobserved – factors.

There are two critical steps to ensure a clean identification of α. First, we need to recover the idiosyncratic shocks $u_{i,j,t}$ from the data. In principle, there could be many endogenous variables F, so it is not obvious what would be an appropriate specification of equation (2.6). We therefore opt for a non-parametric alternative and estimate the equation for each country i by using principal component analysis (PCA, see below for more details).

The second critical step is to avoid a violation of the exclusion restriction. In our context, this is the assumption that idiosyncratic shocks to bilateral bank lending

[22] Note that these are allowed to vary across bilateral pairs (i, j), so different countries of origin may have different sensitivities to changes in conditions in each recipient country. For some EMEs, cross-border credit intermediated via financial centres could be important. In addition, some country pairs could have strong financial links. Having the factors vary at the bilateral (i, j) level helps us control for this.

($u_{i,j,t}$) only affect domestic EME outcomes ($F_{i,t}$) through total international bank lending ($\tilde{y}_{i,t}$) and thus are orthogonal to unobserved aggregate shocks ($\varepsilon_{i,t}$) in equation (2.5). When the model is just identified the exclusion restriction is untestable, though a violation of our exclusion restriction would require that idiosyncratic shocks affect aggregate outcomes through channels other than aggregate lending flows. We argue that it is non-trivial to come up with a strong justification for why this exclusion restriction may not hold, at least approximately.

Obtaining granular instruments. In order to construct a valid GIV, the idiosyncratic shocks $u_{i,j,t}$ need to be extracted from equation (2.6). To this end, the factors need to be filtered out first. To estimate the factors for each country we run a panel regression as follows:

$$y_{i,j,t} = a_{i,t} + e_{i,j,t}, \tag{2.7}$$

where $e_{i,j,t} = \Lambda_{i,j} F_{i,t} + \Lambda^{\star}_{i,j} F^{\star}_{i,t} + \gamma^{Y} X^{y}_{i,j,t} + u_{i,j,t}$ and $a_{i,t}$ is a fixed time effect for the recipient country i. This model allows for heterogeneous exposures across lenders. As we do not have a priori knowledge of the parametric structure of the loadings ($\Lambda_{i,j}$ and $\Lambda^{\star}_{i,j}$) we follow Gabaix and Koijen (2019) and estimate the common factors in $e_{i,j,t}$ via PCA for each country. To determine the number of factors, we use the method proposed by Bai and Ng (2002) and include an additional factor to take a conservative stance.[23] We use an average of 3 factors per country, with minimum and maximum number of factors of 2 and 6 respectively. Table 2.A.3 shows the distribution of the number of factors across countries used in our analysis. We

[23]Our results are robust to adding more factors.

further validate our choice by conducting the different tests in Bai and Ng (2002), which recommend using at least one factor per country.[24]

Given an estimate for the loading vector, we define $u_{i,t}$ as the vector of the idiosyncratic shocks from the N sources of origin. Then, let Q_i be the $N \times N$ matrix projecting vectors onto a space orthogonal to Λ_i (i.e. the matrix representation of $\Lambda_{i,j}$ and $\Lambda^{\star}_{i,j}$), so that $Q_i\Lambda_i = 0$. Then, $Q_i y_{it} = Q_i u_{i,t}$. The GIV is then given by

$$z_{i,t} \equiv S'_{i,t} u_{i,t} = S'_{i,t} Q_i y_{i,t} = \Gamma'_i y_{i,t} \tag{2.8}$$

where $\Gamma_{i,t} \equiv Q'_i S_{i,t}$, such that

$$z_{i,t} \equiv \Gamma'_{i,t} u_{it}.. \tag{2.9}$$

Our GIV $z_{i,t}$ is a valid instrument as it is formed by idiosyncratic shocks. Our identification assumption is that these idiosyncratic shocks to bilateral relationships are orthogonal to aggregate shocks to country i (i.e. $u_{i,j,t} \perp \varepsilon_{i,t}$). Moreover, we choose the projection matrix Q_i such that $z_{i,t}$ is the optimal GIV.[25] We refer the reader to Proposition 3 in Gabaix and Koijen (2019) for a proof.

We illustrate how to use this instrument in our setting. To do so, we solve the system of equations composed by equations (2.5) and (2.10). We sum equation (2.6)

---

[24]For robustness, we conduct other standard tests that use the Akaike and Bayesian information criteria that also recommend using at least one factor per country. We also test the robustness to an alternative method for deciding the number of factors to be extracted, namely the parallel analysis method Horn (1965) – see Section 2.6.

[25]In particular, we choose $Q_i \equiv I - \Lambda_i \left(\Lambda'_i (V^u)^{-1} \Lambda_i\right) \Lambda'_i (V^u)^{-1}$ where V^u is the variance-covariance matrix of the idiosyncratic shocks $u_{i,j,t}$.

over j, replace equation (2.5), and solve for $\tilde{y}_{i,t}$:

$$\tilde{y}_{i,t} = \gamma M_i X_{i,t} + \tilde{\lambda}_i \alpha M_i \varepsilon_{i,t} + M_i \tilde{u}_{i,t} \tag{2.10}$$

where M_i is the general equilibrium multiplier (which is a function of the individual loadings), $X_{i,t}$ is the vector of controls and $\tilde{\lambda}_i$ is a function of the individual loadings. We rewrite this equation as follows

$$\tilde{y}_{i,t} = \beta z_{i,t} + \tilde{\gamma} X_{i,t} + v_{i,t} \tag{2.11}$$

where $v_{i,t}$ is an unobserved variable, which is correlated with aggregate shocks in (2.5). Under our identification assumptions, $z_{i,t}$ is orthogonal to aggregate shocks, hence can be used as an instrument for the growth in bank lending.

Estimation procedure. In practice, our estimation procedure consists of constructing $z_{i,t}$ – an optimal GIV from the growth rates of bilateral bank claims – and using it as an instrument for the growth in total bank claims to consistently estimate α. After having constructed $z_{i,t}$, the procedure is akin to the usual two-stage least squares (2SLS).

The estimation steps can be summarized as follows:

1. Recover $\hat{u}_{i,j,t}$ from equation (2.6) using PCA.

2. Build the optimal GIV ($z_{i,t}$) using equation (2.9).

3. Estimate 1^{st} stage: regress $\tilde{y}_{i,t}$ on $z_{i,t}$ using equation (2.11).

4. Estimate 2^{nd} stage: regress $F_{i,t}$ on the instrumented $\hat{\tilde{y}}_{i,t}$ using equation (2.5). As long as $E(u_{i,j,t}\varepsilon_{i,t}) = 0$, then $E(z_{i,t}\varepsilon_{i,t}) = 0$ and α is identified.

2.3.3 Dynamic causal effects of international bank lending

Having discussed the core model and the construction of the GIVs, we now present the general empirical model used in the rest of the paper. To assess the dynamic response of EME domestic variables to exogenous shocks to international bank lending, we use Jordà (2005) local projection method with instrumental variables.[26] This allows us to also explore non-linearities such as the effects of different levels of capital controls. Details about this exercise are left to section 2.5.

Statistical design. We denote a given macroeconomic aggregate observed for country i at time t by $F_{i,t}$. Our aim is to characterize the change in this variable over some future time horizon indexed by $h = 0, 1, \cdots, H$. The h period ahead change is denoted by $\Delta_h F_{i,t+h}$, which sometimes we can interpret as the cumulative growth. Following Jordà and Taylor (2016), we are interested in the average cumulative response to international banking lending shocks

$$\begin{aligned} CR(\Delta_h F_{i,t+h}, y_{i,t}, \delta) = \; & \mathbb{E}_t\left(\Delta_h F_{i,t+h} | \tilde{y}_{i,t} = \bar{y}_i + \delta; \mathcal{F}_t\right) \\ & - \mathbb{E}_t\left(\Delta_h F_{i,t+h} | \tilde{y}_{i,t} = \bar{y}_i; \mathcal{F}_t\right) \end{aligned} \tag{2.12}$$

where $\mathcal{F}_t$ is the information set up until t and δ is the size of the shock. We are interested in the limit case where $\delta \to 0$. Since changes in $\tilde{y}_{i,t}$ might not be exogenous, we rely on the GIV $z_{i,t}$ to identify the causal effect of banking flows on macroeconomic

[26] See Ramey (2016) and Stock and Watson (2018).

variables (we include GIV lags). The causal impact at horizon h can be identified as follows:

$$\alpha_h^{IV} = \frac{\lim_{\delta \to 0} CR(\Delta_h F_{i,t+h}, z_{i,t}, \delta)}{\lim_{\delta \to 0} CR(\Delta_0 y_{i,t}, z_{i,t}, \delta)} \tag{2.13}$$

Equation (2.13) can be estimated by assuming that the expectation can be approximated by a local projection. We make this assumption for two reasons: (i) a VAR approach would be parametrically more intensive, and (ii) it is not straightforward to get a Wald representation in the context of time-varying states (e.g. high versus low capital controls). Local projections allow us to deal with non-linearities in a robust and flexible fashion. The first stage equation becomes

$$\tilde{y}_{i,t} \quad = \beta z_{i,t} + \theta z_{i,t} \mathbb{I}_{i,t}^{state} + \psi B_{i,t} + v_{i,t}, \tag{2.14}$$

where $\mathbb{I}_{i,t}^{state}$ is a dummy variable equal to one if country i is in a particular state (e.g. if it has a high level of capital controls). Here $B_{i,t}$ includes all control variables, including panel fixed effects, interacted with the state dummy. The second stage can be approximated by estimating the following sequence of fixed-effects panel regressions:

$$\Delta_h F_{i,t+h} \quad = \alpha^{(h)} \hat{\tilde{y}}_{i,t} + \rho^{(h)} \hat{\tilde{y}}_{i,t} \mathbb{I}_{i,t}^{state} + \kappa_{i,t}^{(h)} \mathbb{I}_{i,t}^{state} + \Omega_{i,t}^{(h)} + \varepsilon_{i,t}^{(h)}, \tag{2.15}$$

where the projection horizon h goes from 1 to H quarters and $\hat{\tilde{y}}_{i,t}$ is the fitted growth rate in bank claims from the first stage. The expressions $\Omega_{i,t}^{(h)}$ and $\kappa_{i,t}^{(h)}$ include control variables and panel fixed-effects. We are interested in $(\alpha^{(h)}, \rho^{(h)})$, which characterize the average cumulative response.

2.4 Data

This section describes the data used to estimate the model presented in section 2.3.3. First we present the bilateral cross-border bank lending data which is key to construct our GIVs. Then we detail other complementary datasets used to construct domestic outcome variables and controls for the estimation.

Cross-border banking. To construct the GIVs we use the BIS locational banking statistics by Residence (LBSR).[27] The data capture the outstanding claims and liabilities of internationally active banks located in BIS reporting jurisdictions vis-à-vis bank and non-bank counterparties residing in more than 200 recipient countries.[28] Positions are recorded on an unconsolidated basis, i.e. transactions between different entities of the same banking group ("intragroup") are included in the data. The BIS LBSR capture around 95% of global cross-border banking activity (Bank for International Settlements, 2015). Three characteristics of the data make it particularly useful for our purposes (Avdjiev and Hale, 2019). The first two are features of how the data are collected, whereas the third is a statistical property of the data.

First, the LBSR are compiled following principles consistent with the balance of payments statistics. As the name indicates, they are based on the *residence* of reporting banks as well as that of their counterparties. Our focus is on the role of banking flows for borrowing EMEs and how their macroeconomic and financial

[27]These data include free, restricted, and confidential observations. We use the latter, which can only be accessed on BIS premises, and it is the only version in which all bilateral lending pairs are observable.

[28]Internationally active banks report to the central bank of the jurisdiction in which they reside. These data are aggregated at the country level and submitted to the BIS.

conditions are affected, with data based on either the system of national accounts or balance of payments. Having a residence perspective is thus better fit for purpose than the alternative of consolidated data.[29]

Second, the LBSR provide a currency breakdown, as well as information on break in series due to the changes in methodology, reporting practice or reporting population. This enables the BIS to compute break- and exchange rate-adjusted changes in amounts outstanding, which approximate underlying flows during a quarter.[30] Comparing these flows with previous stocks allows for the computation of growth rates which are clean of methodological and sample breaks, and movements in exchange rates.[31] These adjusted growth rates will be the focus of our analysis.

Third, and most important for our paper, bilateral cross-border data show a strong degree of concentration (Aldasoro and Ehlers, 2019). At one end, there is a very large number of bilateral links of relatively small size. On the other hand, a few dozen very large bilateral links account for the lion's share of cross-border bank lending volumes (Figure 2.4). The distribution of cross-border bilateral country-level links is extremely unequal: The largest 1% of observed cross-border banking links contribute as much to the total volume as the smallest 99%. With such a

[29]The BIS also collects consolidated banking statistics, which capture the worldwide consolidated positions of internationally active banking groups headquartered in reporting countries, excluding intragroup positions. These data respects balance sheet perimeters rather than national borders, and can be used to, inter alia, decompose banking flows into supply, demand, and common factors as in Amiti et al. (2019).

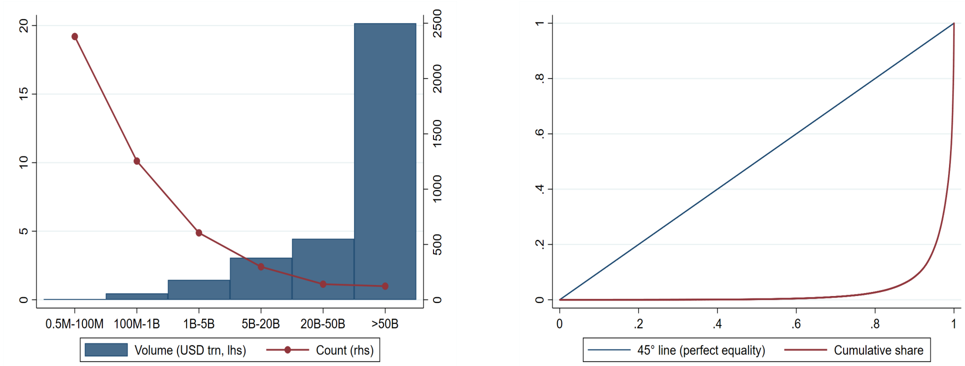
[30]These adjusted changes may still over or underestimate underlying flows due to changes in valuations, write-downs, the under-reporting of breaks, and differences between the exchange rates on the transaction date and that used for conversion of non-US dollar amounts to US dollars, namely average-of-quarter exchange rates.

[31]Throughout the paper we use bilateral country-level claims vis-à-vis all counterparty sectors and in all currencies.

skewed distribution, idiosyncratic shocks can become "granular" and have aggregate effects (Gabaix, 2011), making the LBSR data a natural application of the GIV methodology.[32]

Figure 2.4: Cross-border banking: Small (large) number of large (small) links

(a) Count and volumes by link size (b) Lorenz curve



Notes: BIS locational banking statistics. Data as of end-Q1 2019.

Financial conditions index. The FCI is designed to capture both domestic and global financial price factors in a single parsimonious indicator. We construct FCIs for 22 EMEs using up to 17 price-based variables.[33] The estimation is based on a vector autoregression model with time-varying parameters which takes into account differences in data availability across variables as well as changes in the interaction

[32] In Figures 2.A.1a and 2.A.1b in the Appendix we present further evidence of this high concentration by plotting the median and $25^{th}/75^{th}$ percentiles of the measures of excess Herfindahl and the Gini coefficient for our sample of EMEs.

[33] The variables include interbank spreads, corporate spreads, sovereign spreads, term spreads, equity returns, equity return volatilities, equity implied volatilities, changes in real long-term rates, interest rate implied volatilities, house price returns, the percent changes in the equity market capitalizations of the financial sectors to total market capitalizations, equity trading volumes, expected default frequencies for banks, market capitalizations for equities, market capitalizations for bonds, domestic commodity price inflation rates, and foreign exchange movements.

between them (Koop and Korobilis, 2014). For more details on the methodology, we refer the reader to Adrian et al. (2018); for more details on the sources underlying the different series used for the construction of the FCI, see Chapter 3 in IMF (2017).

Macro and other data. The macroeconomic data used as either additional controls or as left-hand side variables are sourced from the International Financial Statistics of the IMF (GDP, CPI, stock prices, government spreads) and from the credit and property price statistics of the BIS (private domestic credit, housing prices).

We use the measure of de-facto capital controls from the updated dataset of Fernández et al. (2016). We use their composite measure of capital inflow controls. We interpolate the yearly data to obtain quarterly series[34] and compute the median across countries for every quarter. Countries above the median are classified as "high" capital control countries, whereas those below the median are classified as "low" capital control countries.

Final sample. We work with a quarterly unbalanced panel that covers 22 EMEs over the period 1990q1-2018q4. Country selection is mostly constrained by reliable sovereign and corporate spreads data. Table 2.1 presents the list of countries included in the sample, Table 2.3 presents data availability by series and country, and Table 2.4 summary statistics.

[34] Fernández et al. (2016) find that that capital controls are strongly acyclical and have a very small standard deviation at annual frequencies. An alternative would be to assume that capital controls have no variation within years as in Zeev (2019). We prefer interpolation to avoid artificially generating a seasonal effect in the first quarter of each in year in which changes are measured.

Table 2.3: Data by country and variable

Code	Country	NEER		REER		RER US		Sov. Spread		Corp. Spread		Long-term int rate		Short-term int rate		Equity prices	
		start	end	start	end	start	end	start	end	start	end	start	end	start	end	start	end
186	Turkey	94q1	18q4	94q1	18q4	90q1	18q4	96q2	18q4	07q1	17q4	07q2	18q4	16q3	18q4	92q2	18q4
9	South Africa	94q1	18q4	94q1	18q4	90q1	18q4	94q4	18q4	07q3	17q4	90q1	18q4	90q1	18q4	95q1	18q4
213	Argentina	94q1	18q4	94q1	18q4	90q1	18q4	93q4	18q4	01q4	17q4					93q1	18q4
223	Brazil	94q1	18q4	94q1	18q4	90q1	18q4	94q2	18q4	01q4	17q4	07q4	18q4	99q4	18q4	94q4	18q4
228	Chile	94q1	18q4	94q1	18q4	90q1	18q4	99q2	18q4	01q4	17q4			17q2	18q4	92q4	18q4
233	Colombia	94q1	18q4	94q1	18q4	90q1	18q4	97q1	18q4	07q2	17q4	13q1	18q1	17q2	18q4	93q4	18q4
273	Mexico	94q1	18q4	94q1	18q4	90q1	18q4	93q4	18q4	01q4	17q4	01q2	18q4	90q1	18q4	92q2	18q4
293	Peru	94q1	18q4	94q1	18q4	90q1	18q4	97q1	18q4	05q3	17q4	18q2	18q4	18q2	18q4	94q3	18q4
436	Israel	94q1	18q4	94q1	18q4					01q4	17q4						
469	Egypt					90q1	18q4	01q3	18q4	07q1	18q4	15q3	18q4	97q1	18q4	96q4	18q4
534	India	94q1	18q4	94q1	18q4	90q1	18q4	12q4	18q4	04q2	17q4	01q2	18q4	03q1	18q4	94q4	18q4
536	Indonesia	94q1	18q4	94q1	18q4	90q1	18q4	04q2	18q4	01q4	17q4	04q1	18q4	07q2	18q4	92q2	18q4
548	Malaysia	94q1	18q4	94q1	18q4	90q1	18q4	96q4	18q4	01q4	17q4	92q2	18q4	90q1	18q4	92q2	18q4
566	Philippines	94q1	18q4	94q1	18q4	90q1	18q4	93q4	18q4	01q4	17q4	00q1	18q4	90q1	18q4	92q2	18q4
578	Thailand	94q1	0q1	94q1	0q1			97q2	17q4	01q4	17q4						
918	Bulgaria	94q1	00q1	94q1	0q1			94q3	17q4								
922	Russia	94q1	18q4	94q1	18q4	90q1	18q4	97q4	18q4	02q2	17q4	09q2	18q4	10q1	18q4	96q1	18q4
924	China	94q1	18q4	94q1	18q4	90q1	18q4	94q1	18q4	02q2	17q4	05q2	18q4	02q1	18q4	95q4	18q4
926	Ukraine					90q1	18q4	00q2	18q4	06q3	18q4	15q2	18q4	17q2	18q4	05q1	18q4
935	Czech Rep.	94q1	00q1	94q1	00q1			00q2	17q4	12q2	17q4						
944	Hungary	94q1	18q4	94q1	18q4	90q1	18q4	99q1	18q4	12q4	17q4	97q4	18q4	90q1	18q4	96q2	18q4
964	Poland	94q1	18q4	94q1	18q4	90q1	18q4	94q4	18q4	12q1	17q4	99q1	18q4	12q1	18q4	95q1	18q4

Code	Country	FCI		House price ind		Priv dom credt		Real GDP		Private Cons		Investment		Exports		Imports	
		start	end	start	end	start	end	start	end	start	end	start	end	start	end	start	end
186	Turkey	90q1	18q4	10q1	18q4	12q2	18q4	1987q1	18q3	1987q2	17q2	1987q2	16q4	1987q2	17q2	1987q2	17q2
9	South Africa	90q1	18q4	1980q1	18q4	12q2	18q4	1980q1	18q4	1980q1	17q1	1980q1	17q1	1980q1	17q1	1980q1	17q1
213	Argentina	93q4	18q4					90q1	17q1	93q2	17q2	93q2	16q4	93q2	17q2	93q2	17q2
223	Brazil	94q2	18q4	01q1	18q4	12q2	18q4	95q1	17q3	95q2	17q2	95q2	17q2	95q2	17q2	95q2	17q2
228	Chile	92q4	18q4	02q1	18q4	12q2	18q4	1986q1	18q2	96q2	17q1	96q2	17q1	96q2	17q1	96q2	17q1
233	Colombia	90q1	18q4	88q1	18q4	12q2	18q4	94q1	18q4	94q2	16q2	94q2	16q2	94q2	16q2	94q2	16q2
273	Mexico	90q1	18q4	05q1	18q4	12q2	18q4	80q1	18q3	81q2	17q1	81q2	17q1	81q2	17q1	08q2	17q1
293	Peru	94q3	18q4	98q1	18q4	12q2	18q4	80q1	17q1	80q1	17q2	80q1	16q4	80q1	17q2	80q1	17q2
436	Israel			12q2	18q4	12q2	18q4	80q1	18q2	02q1	18q4	02q1	18q4	02q1	18q4	02q1	18q4
469	Egypt	97q1	18q4					02q1	18q4	02q2	14q1	02q2	14q1	02q2	14q1	02q2	14q1
534	India	01q1	18q4	09q1	18q4	12q2	18q4	05q1	17q4	05q2	17q2	05q2	17q1	05q2	17q2	05q2	17q2
536	Indonesia	92q2	18q4	02q1	18q4	12q2	18q4	97q1	18q3	97q2	17q2	97q2	17q1	97q2	17q2	97q2	17q2
548	Malaysia	90q1	18q4	1988q1	18q4	12q2	18q4	88q1	17q1	91q2	17q2	91q2	17q2	91q2	17q2	91q2	17q2
566	Philippines	90q1	18q4	08q1	18q4	12q2	18q4	81q1	18q2	81q2	17q2	81q2	17q2	81q2	17q2	81q2	17q2
578	Thailand			12q2	18q4	12q2	18q4	93q1	18q2	93q2	17q2	93q2	17q2	93q2	17q2	93q2	17q2
918	Bulgaria			12q2	18q4	12q2	18q4	95q1	18q3	96q2	17q2	96q2	17q1	96q2	17q2	96q2	17q2
922	Russia	96q1	18q4	01q1	18q4	12q2	18q4	95q1	18q1	95q2	17q2	95q2	17q2	95q2	17q2	95q2	17q2
924	China	95q4	18q4	05q2	18q4	12q2	18q4	91q4	18q3	92q2	17q2	95q2	17q1	92q2	17q2	92q2	17q2
926	Ukraine	05q1	18q4					00q1	18q2	01q2	14q2	01q2	14q2	01q2	14q2	01q2	14q2
935	Czech Rep.			12q2	18q4	12q2	18q4	94q1	18q3	94q2	17q2	94q2	17q2	95q2	17q2	95q2	17q2
944	Hungary	96q2	18q4	07q1	18q4	12q2	18q4	95q1	18q3	95q2	17q2	95q2	17q2	95q2	17q2	95q2	17q2
964	Poland	92q1	18q4	10q1	18q4	12q2	18q4	95q1	18q3	95q2	17q2	95q2	17q1	95q2	17q2	95q2	17q2

Table 2.4: Summary statistics

Variable	Obs	Countries	Mean	Sd	Min	p25	p50	p75	Max
Total flows	2080	22	1.742	7.423	-31.92	-2.843	1.293	5.411	41.89
GIV	2080	22	-0.866	4.173	-27.88	-2.836	-0.458	1.401	14.93
Endogenous factor	2080	22	6.131	8.659	-31.04	0.973	4.872	10.27	126.6
Capital controls (Index)	1992	22	49.69	30.97	0	20	55	75	100
NEER app. (YoY)	2020	20	-4.661	18.87	-292.6	-7.252	-1.263	3.359	54.94
REER app. (YoY)	2020	20	0.119	11.43	-110.3	-4.099	0.911	5.389	75.72
RER US app. (YoY)	1438	17	-0.510	12.42	-99.00	-6.061	-0.0706	6.514	40.13
Sovereign spread	1844	21	3.565	5.818	-0.0767	1.324	2.120	3.865	66.24
Corporate spread	1199	19	5.128	7.024	0.0293	2.558	3.510	5.078	73.73
FCI	1680	18	0.878	97.11	-642.7	-65.56	-6.319	59.98	376.1
House price (YoY)	1349	19	27.69	44.47	-28.56	-0.250	5.220	49.68	151.3
Stock price (YoY)	1591	20	3.040	14.22	-45.40	-1.563	1.637	6.801	384.7
Equity prices	1777	18	1.975	0.990	0.0116	1.336	1.853	2.457	11.69
Real credit (YoY)	1607	17	7.052	10.53	-70.30	1.750	6.187	12.24	75.32
RGDP (YoY)	1912	22	3.922	4.494	-22.44	2.180	4.337	6.273	43.30
Consumption (YoY)	1758	22	0.348	0.945	-3.450	0.0668	0.180	0.315	11.93
Investment (YoY)	1742	22	0.370	1.561	-5.856	-0.0814	0.233	0.561	19.73
Exports (YoY)	1754	22	0.654	4.722	-166.5	-0.222	0.579	1.511	27.49
Imports (YoY)	1697	22	0.595	4.858	-164.9	-0.251	0.612	1.649	19.34
Trade Balance/GDP (%)	1708	21	1.388	8.284	-23.21	-3.485	-0.317	5.062	71.22
Inflation, CPI (YoY)	1802	18	8.129	11.47	-3.749	2.934	5.076	8.834	161.8
Short term interest rate	1337	17	9.489	10.22	-0.0300	4.100	6.967	10.77	94.94
Long term interest rate	1077	17	7.639	3.961	0.330	4.710	7.046	9.358	26.65

Notes: This table presents the summary statistics for the variables used in the empirical analysis.

2.5 Estimation results

This section presents the main results of the paper. First, we show our core results. We find that an increase in international banking flows has a causal effect on financial conditions: interest rate spreads compress, nominal and real exchange rates appreciate, and financial conditions indices loosen. Moreover, this increase in inflows also causes an expansion of domestic activity led by a strong effect on private credit and moderate yet significant effect housing prices, together with investment growth and a trade balance deterioration. Second, we investigate how these causal effects are affected by different levels of capital controls. In particular, we contrast *high* versus *low* capital controls using the composite capital inflow controls indicator of Fernández et al. (2016). An above-median (i.e. high) level of capital controls is associated with more muted responses of financial conditions, equity and house prices, credit, GDP, investment and imports. For countries with below-median values of the capital inflow control measure (i.e. relatively low prevalence of capital controls), the causal effects discussed in the baseline case are strong. Our findings suggest that capital inflow controls can afford countries some degree of flexibility in dealing with the effects arising from cross-border bank flows.

2.5.1 The causal effect of cross-border bank lending on EMEs

Here we present the results for our baseline model for the full sample of 22 EMEs (see Table 2.1) where the interaction term in equations (2.14) and (2.15) is not included.

Our GIVs are relevant. Table 2.5 shows the t-statistics of the first stage of each of the regressions. In all cases, our GIVs are statistically significant.[35]

Table 2.5: First stage statistics for linear model

depvar	Coef.	SE	R^2	Countries	Observations
NEER	0.946***	(0.027)	0.843	20	1707
REER	0.946***	(0.027)	0.842	20	1707
RER US	0.964***	(0.025)	0.877	17	1309
Sov spread	0.867***	(0.060)	0.755	21	1549
Corp spread	0.869***	(0.077)	0.727	19	955
FCI	0.878***	(0.064)	0.775	18	1523
Housing prices	0.969***	(0.037)	0.852	19	1069
Stock prices	0.884***	(0.069)	0.784	20	1443
Equity prices	0.884***	(0.062)	0.764	18	1424
Credit growth	0.962***	(0.023)	0.884	17	1451
Real credit	0.960***	(0.023)	0.883	17	1463
RGDP	0.885***	(0.058)	0.781	22	1900
Consumption	0.944***	(0.028)	0.853	22	1662
Investment	0.947***	(0.028)	0.855	22	1639
Exports	0.942***	(0.029)	0.854	22	1657
Imports	0.944***	(0.029)	0.851	22	1584
Trade Balance	0.857***	(0.070)	0.765	21	1627
FX debt	0.879***	(0.064)	0.784	18	1580
Inflation	0.881***	(0.064)	0.784	18	1580
Short-term interest rate	0.936***	(0.029)	0.864	17	1059
Long-term interest rate	0.911***	(0.048)	0.838	17	822

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the t-statistics for the GIV in the first stage corresponding to regressions depicted in panels (2.5) and (2.6)

[35]We come back to this in Section 2.7.2, where we show that many alternative instruments from the literature are not relevant in similar first stage regressions.

Overall, we find that international bank lending has an expansionary effect in the economy and financial markets. Figures 2.5 and 2.6 present the cumulative causal effect of a one standard deviation shock to cross-border bank lending on EME domestic financial and macro variables respectively.

Financial conditions loosen as a result of a positive shock to international bank lending. Exchange rates, however measured, appreciate: as shown in Figures 2.5a to 2.5c the nominal effective exchange rate, as well as multilateral and bilateral (vis-à-vis the US dollar) real effective exchange rates appreciate noticeably in response to a shock to international bank lending, especially in the short term (i.e. up to one year). Cross-border flows and the associated exchange rate fluctuations influence macroeconomic and financial stability in EMEs through domestic financial conditions. Just as exchange rates appreciate, sovereign and in particular corporate spreads (both in USD) also narrow (Figures 2.5d and 2.5e, respectively). Domestic short and long-term interest rates fall and equity prices increase (Figures 2.5f to 2.5h). More broadly, financial conditions as measured by the FCI loosen significantly (Figure 2.5i).[36] The response of all these financial variables differs significantly from zero in the short term (quarters 1 to 4). The easing of financial conditions can foster the rise of asset prices, in the limit contributing to unsustainable bubbles. The most important domestic asset price is housing. Real house prices increase following a shock to cross-border bank lending (Figure 2.5j). [37] This result is in line with the findings

[36]We do not find any clear or significant effect on other domestic variables underlying the construction of the FCI when analyzed in isolation, such as interbank spreads, real interest rate, trading volatility, or domestic commodity prices.

[37]When we run several methodological robustness checks (see Section 2.7), we lose the statistical significance in the estimation involving real house prices. The point estimate of Figure 2.5j remains broadly unchanged.

of Cesa-Bianchi et al. (2018). The magnitude of the effects we uncover, however, is notably smaller.

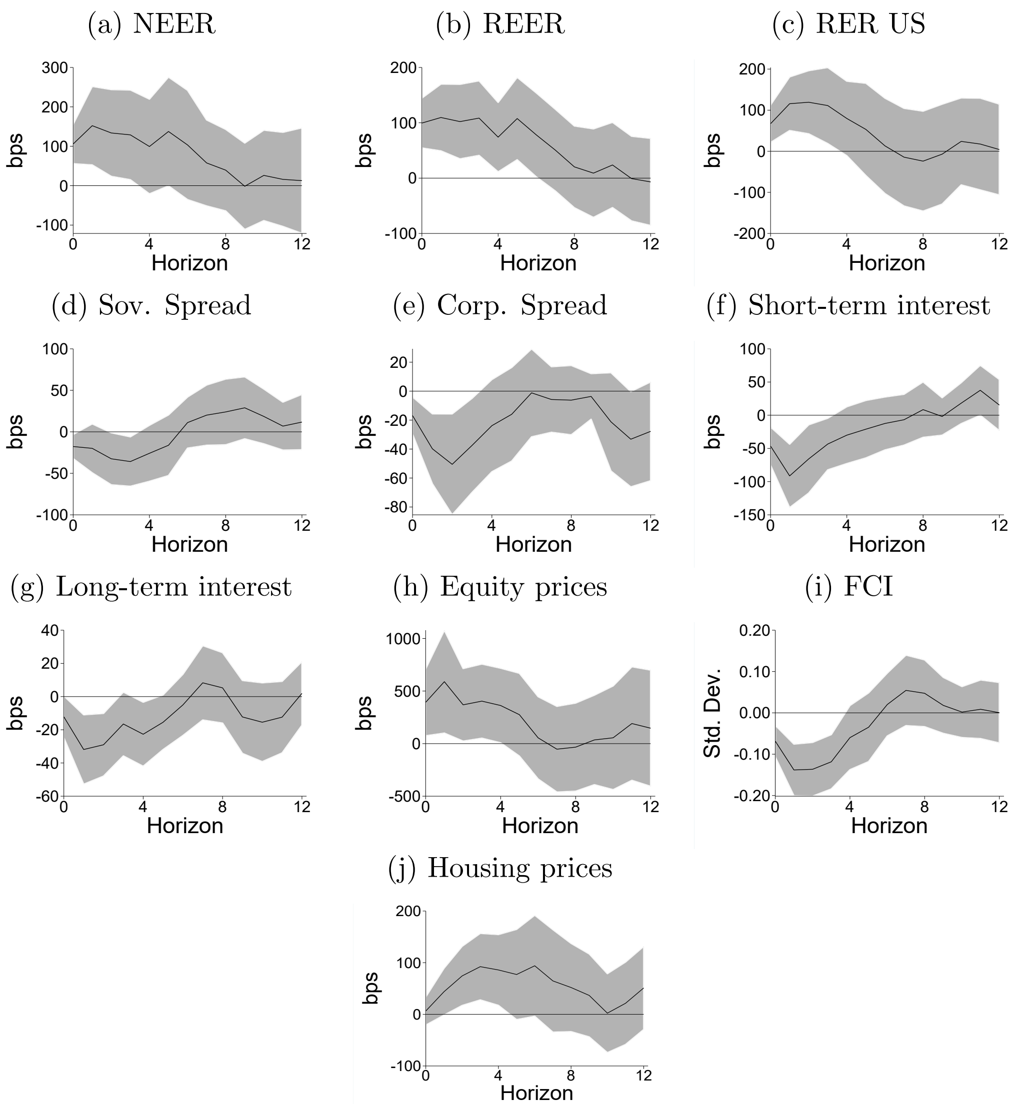
An exogenous increase in cross-border banking flows also has effects on domestic credit markets. Nominal domestic private credit growth increases significantly after four quarters following a shock to cross-border bank lending (Figure 2.6a), in line with di Giovanni et al. (2019) and Borio et al. (2011). This is also reflected in a significant increase in the real stock of credit, which materializes after a few quarters (Figure 2.6b). This is in line with the literature emphasizing the financial channel of exchange rate appreciation (Bruno and Shin, 2015a,b), that tends to be more pronounced for EMEs (Banerjee et al., 2020). The interpretation is that as financial conditions ease and the exchange rate appreciates, the relaxation of balance sheets allows for non-financial leverage to increase.

Finally, shocks to international bank lending also affect the real economy. There is a significant effect on real GDP growth and a fall in inflation, as shown in Figures 2.6c and 2.6d. While there is no significant effect on consumption (Figure 2.6e, in contrast to Cesa-Bianchi et al. (2018)), the boost to domestic activity is associated with an increase in investment (Figure 2.6f)[38] and imports (Figure 2.6h). This, together with the lack of a significant effect on exports (Figure 2.6g) is consistent with the deterioration in the trade balance (Figure 2.6i).

Interestingly, while real GDP is boosted especially in the short term, the effect on credit is larger and significant at longer horizons (beyond 4 quarters). These results are consistent with a relaxation of balance sheets that allows for non-financial leverage to increase.

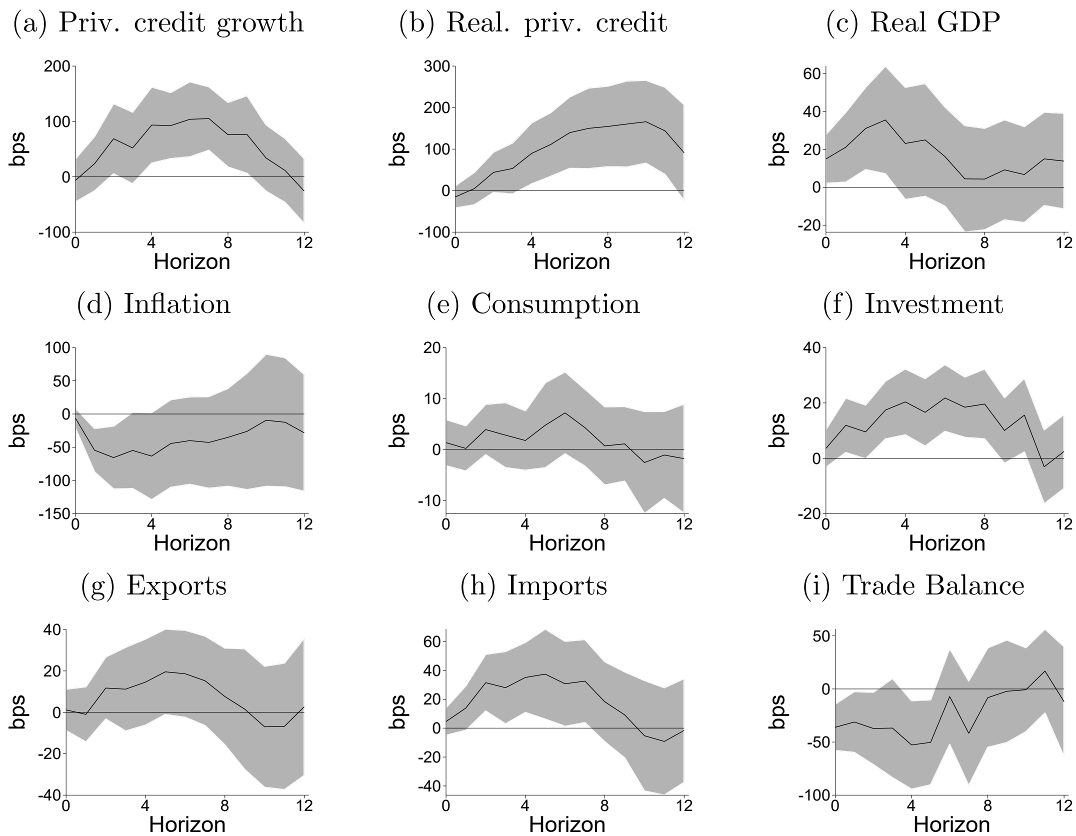
[38] Unfortunately we can not disentangle whether this is driven by construction or machines and equipment, due to lack of sufficient cross-country data availability.

Figure 2.5: Cumulative causal effect of international bank lending on financial variables



Notes: This panel shows the cumulative impact of a one standard deviation exogenous international banking lending (black like) and its 90% confidence interval (grey area) on: the log of the nominal effective exchange rate ($NEER$), log of real effective exchange rate ($REER$), log of the bilateral real exchange rate vis-à-vis the US dollar ($RER\,US$), domestic short-term interest rates, domestic long-term interest rates, sovereign spread (in USD), corporate spread (in USD), equity prices measured by the price-to-earnings ratio, a standarized financial conditions index (FCI) which decreases when financial conditions are looser, and the log of real housing price index. The country sample is presented in Table 2.1, with data from 1990Q1 to 2018Q4. The estimation is done by 2SLS using our GIV as instrument. Standard errors are robust to heteroskedasticity and autocorrelation.

Figure 2.6: Cumulative causal effect of international bank lending on macro variables



Notes: This panel shows the cumulative impact of a one standard deviation exogenous international banking lending (black like) and its 90% confidence interval (grey area) on the log real private domestic credit, private domestic credit quarterly growth, log real gross domestic product ($RGDP$), log change (year-on-year) in consumption price index, log real private consumption, log real investment, log real imports, and log real exports, and the trade balance as a share of GDP. The country sample is presented in Table 2.1, with data from 1990Q1 to 2018Q4. The estimation is done by 2SLS using our GIV as instrument. Standard errors are robust to heteroskedasticity and autocorrelation.

They are also consistent with cross-border bank lending being a contributor to domestic credit booms and the build up of domestic vulnerabilities (Cesa-Bianchi et al., 2018, 2019; Borio et al., 2011; Aldasoro et al., 2018).

Using OLS instead of a GIV approach can lead to large estimation biases. Table 2.6 shows the largest differences between the OLS estimates and our results when both are significative.[39] The overall picture that emerges from the OLS estimations is that interest rates fall by less, and asset prices and real variables increase by more relative to the GIV results. This is consistent with unobserved demand shocks playing a role that at least partially offset the pure supply shock captured by the GIV.[40]

2.5.2 The role of capital controls

In this subsection we explore whether the effects of international bank lending on domestic EME outcomes differ depending on the level of capital inflow controls. We use the full non-linear model as specified in equations (2.14) and (2.15) and include interaction terms between the GIV-instrumented banking flows and dummies that define relevant states. As discussed in Section 2.4, we use the dataset of Fernández et al. (2016) and define as "high" and "low" capital control countries respectively as

[39] In general, the estimation is not precise enough for a Hausman test to reject the null hypothesis of coefficient equality, so the comparison between point estimates can only be made heuristically. Still, the magnitudes of the difference between statistically significant point estimates are large and suggest that OLS coefficients are biased. Note that the approach used is a conservative choice. In some cases in which the GIV estimates are not statistically different from zero and OLS are statistically significant, the differences are larger. This tends to happen in the medium/longer horizons.

[40] Given that the OLS estimates are significative for private domestic consumption at a one year horizon, but are not significative for exports, it could be interpreted as unobserved domestic demand shocks playing a larger role than unobserved foreign demand shocks.

Table 2.6: Largest differences between OLS and GIV estimates for linear model

	OLS	IV	Difference	Time
$NEER$ (bps)	107.76	152.25	-44.49	2
$REER$ (bps)	129.73	74.04	55.69	4
$RER\,US$ (bps)	176.12	111.24	64.88	3
Sov. Spread (bps)	-27.06	-35.83	8.77	3
Corp. Spread (bps)	-37.62	-50.54	12.92	2
Short-term interest rate (bps)	-41.88	-91.39	49.51	1
Long-term interest rate (bps)	-8.85	-29.03	20.18	2
Equity prices (bps)	964.34	563.87	400.47	1
FCI (s.d.)	-0.05	-0.12	0.07	3
Housing prices	33.25	60.50	-27.25	2
Credit growth (bps)	146.67	93.45	53.22	4
Real credit (bps)	135.25	89.64	45.61	4
$RGDP$ (bps)	52.00	35.46	16.54	3
Inflation (bps)	-16.49	-65.62	49.13	2
Consumption (bps)	n.a.	n.a.	n.a.	n.a.
Investment (bps)	8.63	11.59	-2.96	2
Exports (bps)	n.a.	n.a.	n.a.	n.a.
Imports (bps)	21.52	31.21	-9.69	2
Trade Balance/GDP (bps)	-53.01	-37.22	-15.79	2

Notes: This table shows the largest differences between the point estimates from OLS and GIV estimations and the time horizon at which these occur. The GIV estimates correspond to the regressions depicted in panels (2.5) and (2.6). Results are reported for the cases in which both OLS and GIV estimates are significatively different from zero.

those above and below the median of all countries for any given quarter. We use the one-quarter lag of the capital control index in order to limit endogeneity concerns. We refer the reader to Fernández et al. (2016) for details on the data.

The effects of international bank lending on domestic EME outcomes are notably stronger for countries with relatively lower scores on the capital inflow control index. Panels 2.7 to 2.11 present the estimated causal effects of international bank lending shocks on selected financial and macro variables for "low" and "high" levels of capital controls, as well as the differential effect (i.e. low minus high). Overall, the evidence shows that the effects are larger and significative for countries with lower levels of capital control. The differences with respect to countries with high capital inflow controls are significative in several cases. [41]

The nominal and real effective exchange rate appreciation caused by international bank lending is stronger for countries with lower levels of capital controls (Figures 2.7a to 2.7i). The difference between low and high capital control countries is significant in the case of he nominal effective exchange rate (Figure 2.7c). For other financial variables, the differences between low and high countries are starker.[42] Equity prices rise for countries with low scores (Figure 2.8d), whereas for countries with high scores equity prices in fact decline one year after the shock (Figure 2.8e). Accordingly, the difference between the two states is large and significant (Figure 2.8f). Financial conditions as measured by the FCI loosen in both low and high countries

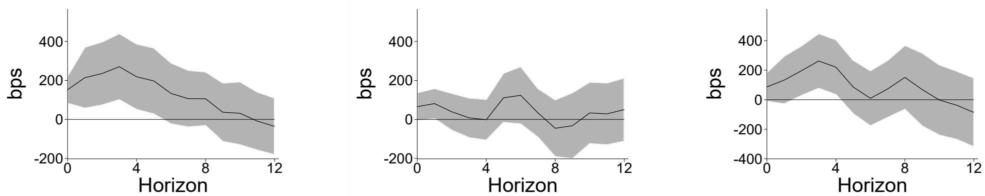
[41] An important caveat of these results is that we do not control for the potential endogeneity of capital controls. There could be underlying structural features of the countries that influence both their sensitivity to international bank flows and their choice of capital inflow controls, as well their intensity. Our approach is in line with that used in Zeev (2017). An additional qualification of our approach is that it is not an analysis of the effects of *changes* in capital controls. Such analysis would directly speak to how these controls affect the magnitude of inflows.

[42] The one exception are sovereign spreads, see Figures 2.8a to 2.8c.

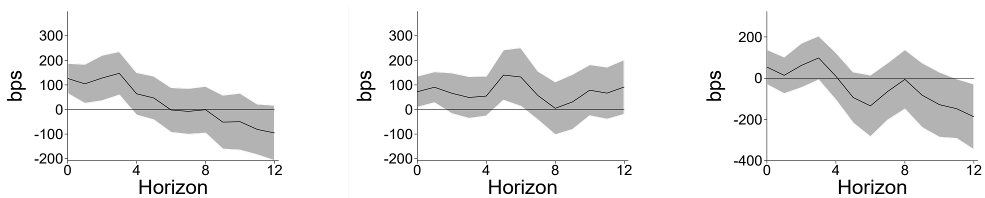
Figure 2.7: Cumulative causal effect of international bank lending on selected financial variables (rows) for low, high capital controls, and their difference (columns)

NEER

(a) Low (b) High (c) Low-High

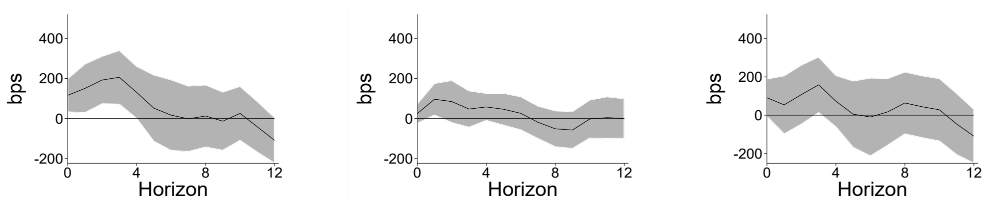


REER



(d) Low (e) High (f) Low-High

RER US



(g) Low (h) High (i) Low-High

Notes: This Figure shows the total cumulative impact of a one standard deviation exogenous international bank lending on selected financial variables for "low" and "high" levels of controls to capital inflows (measured with the index in Fernández et al. (2016) and groups defined as in Section 2.4), and the differential cumulative effect of "high" relative to "low" levels of capital controls. The country sample corresponds to Table 2.1, with data from 1990Q1 to 2018Q4. The estimation is done by 2SLS using our GIV as instrument. Standard errors are robust to heteroskedasticity and autocorrelation.

(Figures 2.9a and 2.9b), but this loosening is stronger for the former group. Furthermore, for countries with stricter controls, there is a reversal after 5-6 quarters, when financial conditions begin to tighten.The picture that emerges is of financial conditions loosening significantly more in countries with low levels of capital controls (Figure 2.9c). Finally, high capital control countries do not witness domestic house price appreciation, whereas for low capital control countries there is a significant rise in housing prices (Figures 2.9d to 2.9f). Interestingly, the increase in house prices for low capital control countries swiftly reverses after around 8 quarters.

The expansionary effect of cross-border bank claims on macroeconomic variables is also stronger for countries with lower levels of capital controls. Credit growth responds by more to an increase in international bank lending when capital controls are lower, and the difference between low and high is statistically significant (Figures 2.10a to 2.10c). Real GDP growth increases in response to international bank lending shocks when capital controls are lower (Figure 2.10d), whereas the effect for countries with high capital controls and the difference between low and high are not statistically significant (Figures 2.10e and 2.10f, respectively). Finally, investment and imports present patterns similar to those observed for credit growth (Figures 2.11a to 2.11f).

Taken together, the evidence presented in this section is consistent with the notion that capital controls can be effective in moderating the boom in financial and macroeconomic conditions associated with increased inflows.

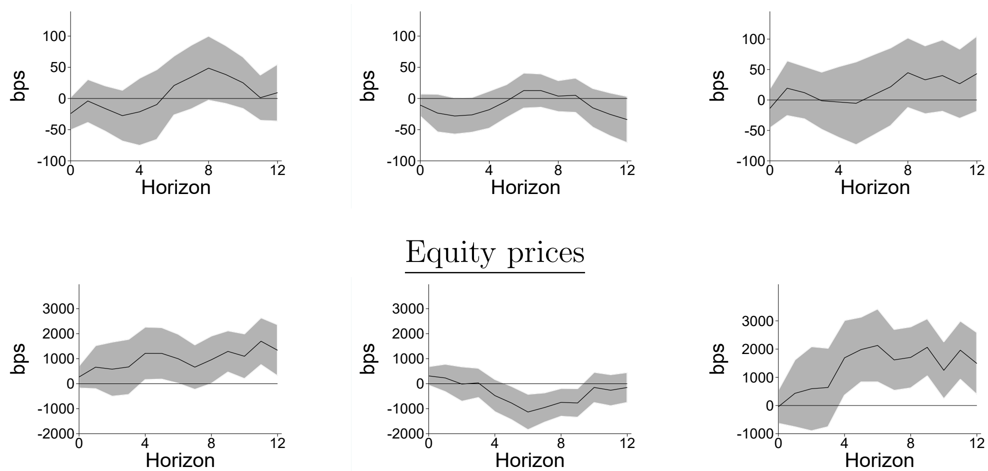
2.6 Robustness

In this section we discuss the robustness of the GIVs. We first argue that our GIVs are likely to satisfy the exclusion restriction, and argue why a narrative validation

Figure 2.8: Cumulative causal effect of international bank lending on selected financial variables (rows) for low, high capital controls, and their difference (columns)

Sovereign Spread

(a) Low (b) High (c) Low-High



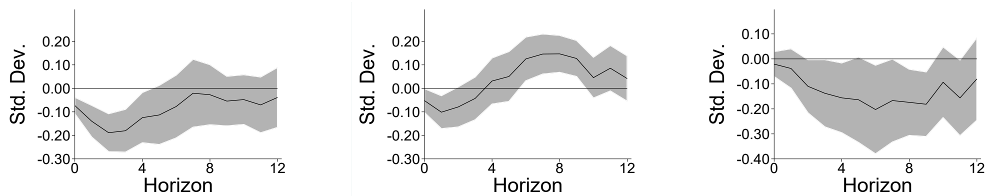
(d) Low (e) High (f) Low-High

Notes: This Figure shows the total cumulative impact of a one standard deviation exogenous international bank lending on selected financial variables for "low" and "high" levels of controls to capital inflows (measured with the index in Fernández et al. (2016) and groups defined as in Section 2.4), and the differential cumulative effect of "high" relative to "low" levels of capital controls. The country sample corresponds to Table 2.1, with data from 1990Q1 to 2018Q4. The estimation is done by 2SLS using our GIV as instrument. Standard errors are robust to heteroskedasticity and autocorrelation.

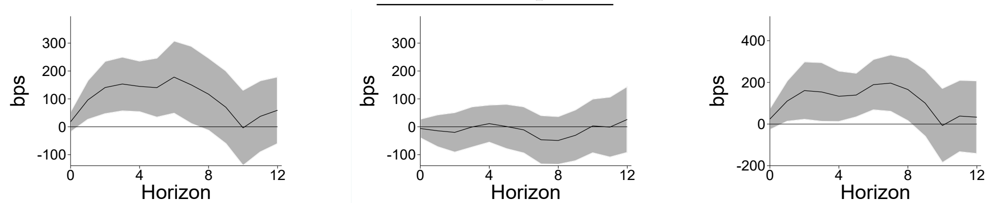
Figure 2.9: Cumulative causal effect of international bank lending on selected financial variables (rows) for low, high capital controls, and their difference (columns)

<u>*FCI*</u>

(a) Low (b) High (c) Low-High



<u>Real house prices</u>



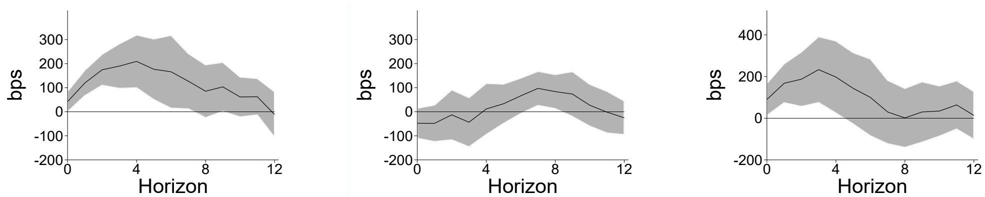
(d) Low (e) High (f) Low-High

Notes: This Figure shows the total cumulative impact of a one standard deviation exogenous international bank lending on selected financial variables for "low" and "high" levels of controls to capital inflows (measured with the index in Fernández et al. (2016) and groups defined as in Section 2.4), and the differential cumulative effect of "high" relative to "low" levels of capital controls. The country sample corresponds to Table 2.1, with data from 1990Q1 to 2018Q4. The estimation is done by 2SLS using our GIV as instrument. Standard errors are robust to heteroskedasticity and autocorrelation.

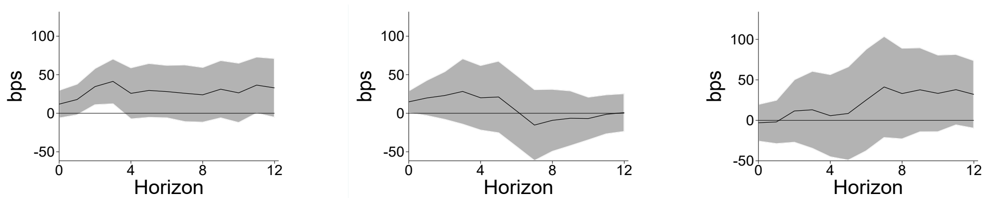
Figure 2.10: Cumulative causal effect of international bank lending on selected macro variables (rows) for low , high capital controls, and their difference (columns)

Credit growth

(a) Low (b) High (c) Low-High



Real GDP



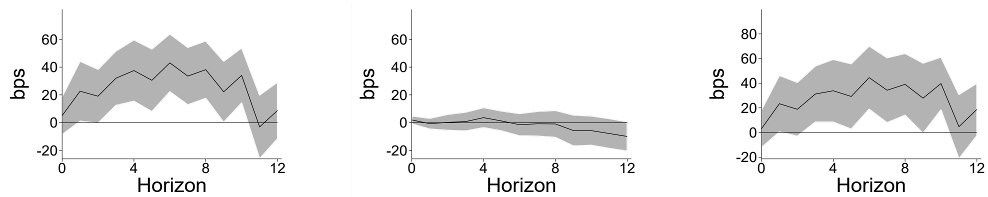
(d) Low (e) High (f) Low-High

Notes: This Figure shows the total cumulative impact of a one standard deviation exogenous international bank lending on selected macro variables for "low" and "high" levels of controls to capital inflows (measured with the index in Fernández et al. (2016) and groups defined as in Section 2.4), and the differential cumulative effect of "high" relative to "low" levels of capital controls. The country sample corresponds to Table 2.1, with data from 1990Q1 to 2018Q4. The estimation is done by 2SLS using our GIV as instrument. Standard errors are robust to heteroskedasticity and autocorrelation.

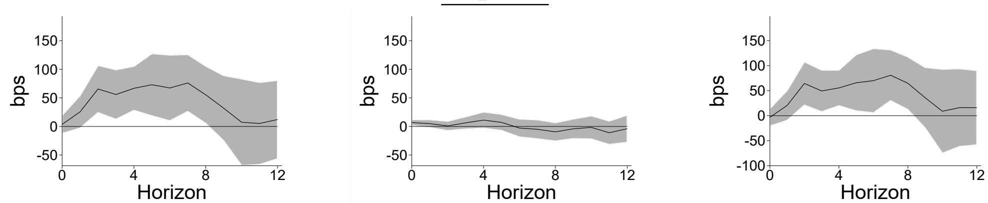
Figure 2.11: Cumulative causal effect of international bank lending on selected macro variables (rows) for low , high capital controls, and their difference (columns)

Investment

(a) Low (b) High (c) Low-High



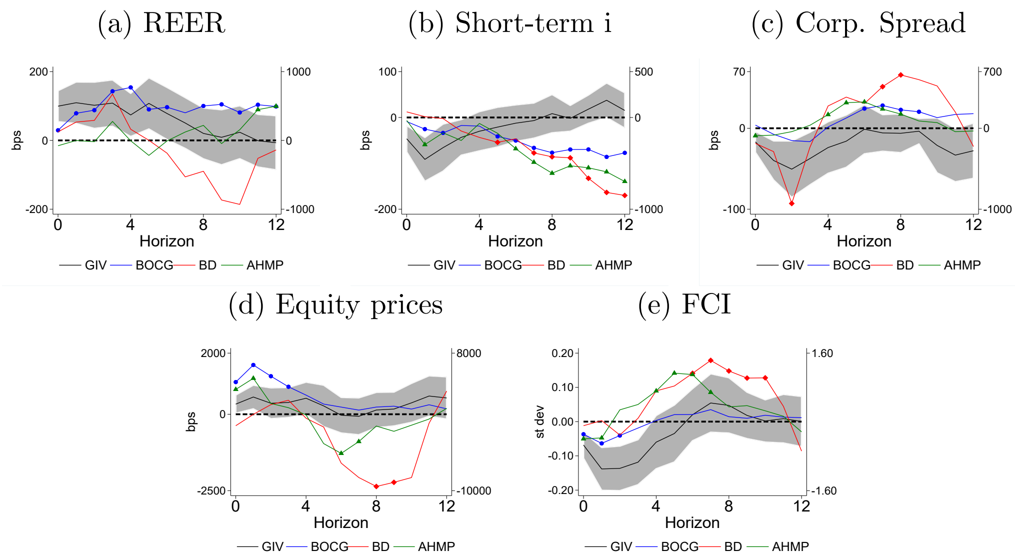
Imports



(d) Low (e) High (f) Low-High

Notes: This Figure shows the total cumulative impact of a one standard deviation exogenous international bank lending on selected macro variables for "low" and "high" levels of controls to capital inflows (measured with the index in Fernández et al. (2016) and groups defined as in Section 2.4), and the differential cumulative effect of "high" relative to "low" levels of capital controls. The country sample corresponds to Table 2.1, with data from 1990Q1 to 2018Q4. The estimation is done by 2SLS using our GIV as instrument. Standard errors are robust to heteroskedasticity and autocorrelation.

Figure 2.12: Cumulative causal effect of international bank lending using GIV (left-hand axis) and alternative instrumental variables (right-hand axis) for selected financial variables



Notes: This Figure compares the cumulative impact of a one standard deviation exogenous international bank lending shock with three instruments on selected variables. The black line and grey area shows the point estimate and 90% confidence interval of our GIV as in Figures 2.5 and 2.6. The colored lines show the estimated effect of alternative IVs and have markers when it is significative at a 90%. The blue line shows the estimated effect of constructing an IV as Blanchard et al. (2016) ($BOCG$) using the LBSR data, the red line shows the estimated effect of using US broker-dealers' leverage (BD) as IV, and the green line shows the estimated effect of using the "common" component of Avdjiev et al. (2020). The selected variables are the log of real effective exchange rate ($REER$), domestic short-term interest rates, corporate spread (in USD), equity prices measured by the price-to-earnings ratio, and a standardized financial conditions index (FCI) which decreases when financial conditions are looser. The country sample is presented in Table 2.1, with data from 1990Q1 to 2018Q4. The estimation is done by 2SLS using each of the four IVs. Standard errors are robust to heteroskedasticity and autocorrelation.

strategy is hard to defend in our context. We then move to the key robustness checks we perform when computing the GIVs. These pertain to the sample of countries used, the method to extract endogenous factors and the role of crises.

Robustness of the exclusion restriction. Given our empirical setup, the primary threat to identification comes from the idiosyncratic shocks used to construct the GIVs potentially affecting domestic variables not only through growth in international bank lending. That is, a violation of the exclusion restriction could occur if the bilateral idiosyncratic shocks $u_{i,j,t}$ affect domestic outcomes through channels other than movements in international banking flows ($\tilde{y}_{i,t}$). Additional influences via such channels are referred to as "spillover effects" (Jordà et al., 2019). Such effects would only occur if a lending or a recipient country experienced a country-specific shock that could affect unobservables in the structural equation (2.6) and therefore affect domestic outcomes. As the idiosyncratic shocks are by construction orthogonal to aggregate factors that drive total international bank lending flows and that would include expectation terms, we are skeptical of a possible violation of the exclusion restriction. Moreover, the data on bilateral relationships is not observed in real time or may directly be confidential so it is even harder to argue how it could drive domestic outcomes indirectly through unobserved factors.

Narrative validation. Gabaix and Koijen (2019) suggest a narrative approach as an alternative validation of GIVs. This consists of selecting the top shocks – say, based on some threshold approach or simply selecting the top five/ten shocks – and then browsing the news for relevant information of what occurred around the dates of these shocks. This is a good alternative validation approach when the underlying data is of high frequency. Contrary to some of the applications in Gabaix and Koijen (2019) that use daily data, our analysis is based on quarterly data. This unfortunately prevents us from applying a narrative validation strategy to our idiosyncratic bilateral lending shocks. It is hard to unambiguously pin down idiosyncratic shocks to an event occurring on any given day when the observations are at quarterly frequency.

Constant sample of reporters. New reporting countries enter the reporting population of the BIS banking statistics over time. While we account for this when computing growth rates,[43] a valid concern is that such changes can affect the shares we use to compute the GIVs. We thus perform a robustness check using a constant sample of reporting countries, namely those that constitute the reporting population at the beginning of our sample period. We take this one step further and also do not consider entries or re-entries, e.g. we disregard observations in which a given lender initiates a previously non-existent bilateral relationship with one of our borrower countries, or if stops and then resumes a relationship. We recalculate the GIVs, including the shares, and replicate the entire analysis. Our baseline results are robust this change. Figures 2.A.3 and 2.A.4 present the impulse response functions to cross-border bank lending shocks for financial and macro variables respectively. The results are virtually indistinguishable from those discussed in Section 2.5.1 (compare with Figures 2.5 and 2.6 respectively).[44]

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[43]As discussed in more detail in Section 2.4, we deal with this issue by using growth rates that account for changes in the number of countries reporting to the BIS, as well as changes in the reporting population within a country, methodological changes such as different thresholds used for reporting, and accounting for exchange rate effects.

[44]Note this is a more stringent version of considering a constant sample that includes entries and exits of bilateral relationships. We also performed such analysis and the baseline results also

Alternative estimation of factors. A key step in the construction of our instrument is the correct extraction of the commonality across bilateral lending flows. We use principal components and follow the method in Bai and Ng (2002). We follow the IC_{p2} criterion, as in Gabaix and Koijen (2019). In the baseline estimates we take a conservative stance and include an additional factor to those recommended by this criteria. To verify that the selection method of the number of factors is not driving our results, we use the parallel analysis method as in Horn (1965). Results are robust to using this alternative method for extracting factors, as shown in Figures 2.A.5 and 2.A.6. Table 2.A.3 presents the summary statistics of the number of factors across countries for different samples and methods. Our baseline estimation is the most conservative in terms of factors included – on average it selects three factors oer country. On average, the parallel analysis method recommends less factors by country (2.5). Using alternative methods for computing the optimal number of factors may deliver less or more factors for individual countries, however. For example, there is one country for which the parallel analysis method recommends 4 factors less than the baseline, whereas there is another country for which it recommends two more factors than the baseline. In any event, the results we obtain are robust using alternative methods and samples.

Dealing with crises. A potential concern is that our instrument is systematically capturing the variation from domestic crises and that our results are therefore driven by these extreme events. To address this, we check if our instrument systematically reflects the extreme movements from domestic crises. We define large shocks as events where our instrument is 2 or more standard deviations below the mean. We check

remain robust. These results are available upon request.

whether these large shocks coincide with a domestic crisis episode. To do so, we use the definition of a systemic crisis from Laeven and Valencia (2020), which includes banking, currency, and sovereign debt crises, as well as events of restructuring of sovereign debt. These large shocks coincide only 7 times out of the total 58 crises that we observe in our sample (see Table 2.A.5). Moreover, in most of these events, there are no important aggregate outflows from these countries. These observations reassure us that our instrument is not picking up systematically extreme outflows correlated with domestic conditions.

We perform an additional robustness check to verify that our results are not impacted by these events. We estimate the impulse response functions ignoring the events in Table 2.A.5. The results are presented in Figures 2.A.7 and 2.A.9 and show that our results are almost invariant without these events.

We further investigate the events presented in Table 2.A.5. For the countries that experience a crisis that coincides with a large reduction in our instrument, we verify and eliminate from our estimates lender countries that satisfy the following criteria: (1) are small in terms of the historical share of total claims to the country of destination and (2) experience large increases in cross border claims during the event under consideration. The presence of these outlier observations overestimates the average bilateral growth rate and therefore might lead to the identification of large negative shocks. For example, the bilateral relationship between Colombia and the Netherlands at the end of the 1990s was characterized by economic cooperation for the peace negotiations in Colombia. In the quarter that we identify, we observe a large capital inflow from the Netherlands to Colombia. However, the Netherlands accounts for a relatively small share of total claims on Colombia, and we thus consider the bilateral growth rate during the 1998 crisis as an outlier. To that extent, the behavior of the Netherlands in this period is not representative of the bilateral claims, and we eliminate it from our sample as a robustness check.

The results from this robustness check are presented in Figures 2.A.9 and 2.A.10. Again, the impulse responses summarizing the effect of cross-border bank claims on EME domestic macro and financial variables look notably similar to those in the baseline results.

2.7 Alternative IVs and the global financial cycle

2.7.1 GIVs and the global financial cycle

A growing literature in international macro-finance emphasizes the importance of the global financial cycle (Rey, 2015). This focuses on how global financial conditions affect individual economies – especially EMEs – and is intimately related to international bank lending. To be a meaningful instrument, our GIVs should not be capturing developments in the global financial cycle.

The GIVs we construct from bilateral cross-border bank lending are orthogonal to measures of the global financial cycle.[45] Table 2.A.4 presents regressions of our GIVs on the three global financial cycle measures. The coefficients for all the cycle variables are very small, statistically insignificant, and the fit of the regression is vir-

[45] We focus on the three key indicators used to measure this cycle: (i) the price-based indicator developed in Miranda-Agrippino and Rey (2015) and updated in Miranda-Agrippino et al. (2020), which is the most common measure of the global financial cycle and focuses on the common component in a large number of global risky asset prices; (ii) a quantity-based measure based on the first principal component of capital flows across countries (Cerutti et al., 2019b); and (iii) the VIX as a measure of global risk aversion (di Giovanni et al., 2019).

tually indistinguishable from zero.[46] This is a reassuring finding, as it is a necessary condition for our GIVs to be valid. We revisit this issue in Section 2.7.2 when we discuss the validity of other possible instruments used in the literature.

Instead, international bank lending and measures of the global financial cycle are correlated (Rey, 2015; Bruno and Shin, 2015a,b). Table 2.A.1 presents regressions of international banking flows on the three measures of the global financial cycle discussed above, controlling for country fixed effects.[47] The global financial cycle as most commonly measured ($GFCy$) shows a statistically significant and strong correlation with banking flows. An increase in $GFCy$ (i.e. an upswing in the global financial cycle) is associated with increased banking flows. Similarly, if the upswing in the global financial cycle is measured by means of the common component of capital flows across countries ($PC1$), there is an associated increase in banking flows. Finally, an increase in global risk aversion as measured by a higher VIX is associated with lower banking flows.

2.7.2 GIVs and alternative instruments

Finally, in this subsection we compare our GIVs with alternative instruments taken from the literature. These instruments can be categorized into two groups. A first group has poor first stage statistics properties for international banking claims; these instruments are thus not relevant. A second group is significant in the first stage but correlates strongly with the global financial cycle, and thus fail to be excludable:

[46] Results are identical when considering the global financial cycle measures one at a time or in pairs. We do not present them for the sake of space; they are available upon request.

[47] We refer to the three cycle measures as $GFCy$, $PC1$ and VIX, respectively.

these affect domestic outcomes through many channels, including non-observables, and renders their estimates biased.

We consider the following alternative instruments. Work on international credit supply shocks has used the excess bond premium measure of Gilchrist and Zakrajšek (2012) [48] and the leverage of the US broker-dealer sector (Cesa-Bianchi et al., 2018) as exogenous shocks to capital flows to EMEs. We use these as alternative instruments, which we label *EBP* and *BD* respectively. Recently, Avdjiev et al. (2020) (AHMP henceforth) apply the methodology proposed by Amiti and Weinstein (2018) to the LBSR data and decompose US dollar-denominated cross-border bank claims into a "common" component that can be thought of capturing the global financial cycle, a "host" component that captures developments that affect lender countries' claims, and a "borrower" component that captures developments on the recipient country end.[49] We thus consider their *Host* and *Common* series as alternative IVs.[50] Finally, we compute a Bartik-type of instrument inspired by the approach used in Blanchard et al. (2016) but applied to our data and which we label *BOGC*. For a given EME i, we take the growth rate of cross-border bank claims on all other EMEs ($j \neq i$), and use it as an instrument for the growth rate of claims on country i. More concretely, we define the instrument as follows: $z_{i,t}^{BOGC} = \sum_j S_{i,j,t-1} g_{j,-i,t}$, where $S_{i,j,t-1}$ is the initial exposure of country i to country j. We define $g_{j,-i,t}$ as the growth rate of claims on all other EMEs. Note that, contrary to the instrument in Blanchard et al. (2016), the Bartik-type instrument used here varies significantly across countries

[48]See (Zeev, 2019).

[49]In Appendix 2.B we discuss in more detail how their methodology relates to ours and how we can use it to test a necessary condition for the validity of our GIV.

[50]We compute them for claims in all currencies and not just US dollar claims.

because the exposures to each lender vary in the cross-section.[51]

Table 2.A.2 presents the results for the first stage of the 2SLS. EBP and $Host$ are not relevant instruments for cross-border banking flows. The instruments that have a positive correlation with cross-border bank flows are the $Common$ component of international banking flows computed using AHMP's methodology, the leverage of US broker-dealers (BD) and the Bartik-type of instrument constructed for any country i by using the growth of claims to all EMEs other than i ($BOGC$).

While the correlation of these three instruments with banking flows makes them relevant, they are unlikely to fulfill the exclusion restriction. As columns (3) to (5) in Table 2.A.4 show, the three IVs are highly correlated with the three different measures of the global financial cycle discussed earlier, namely the price-based factor of Miranda-Agrippino and Rey (2015), the VIX, and the first principal component of capital flows.[52] As noted in Section 2.7.1, cross-border bank flows are also highly correlated with the measures of the global financial cycle (Table 2.A.1). On the contrary, our GIVs are not (column (1) in Table 2.A.4).[53]

We use these alternative instruments for banking flows to recompute impulse

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[51]In principle one could find more IVs in the literature on spillovers from US monetary policy to EMEs. Examples include the narrative monetary policy shocks originally proposed in Romer and Romer (2004), or the high-frequency monetary policy and news shocks from Nakamura and Steinsson (2018a) or Miranda-Agrippino and Ricco (2017). The channels through which these would act, however, would not allow us to identify the causal effect of exogenous changes in international bank lending as they would capture all ways in which these spillovers affect domestic outcomes and thus are not excludable. They correlate strongly with measures of the global financial cycle. Furthermore, and consistent with the findings in Ramey (2016), these shocks tend to produce weak instruments as they tend to perform poorly in the first stage of our model.

[52]Somewhat surprisingly, $Common$ and BD also correlate positively with the VIX.

[53]The results in this table are robust to alternative specifications were we consider one global financial cycle indicator at a time or in pairs. These results are available upon request.

response functions and contrast them with those obtained in our baseline results. Figures 2.12 and 2.A.2 we present the IRFs for selected outcome variables when we use *Common*, *BD*, and *BOGC* as IVs. The estimated effects are significative in some cases, though not all.[54]

Estimated effects using alternative IVs are an order of magnitude larger than when using our *GIVs*. While in many cases the sign of the effect is similar when using *GIV* or the alternative IVs, the latter have effects of magnitude between 4 (domestic long-term interest rate, equity prices) to 8 times larger (*FCI*, *RGDP*) than when using the *GIVs*. In some instances, these effects seem implausibly large.

We interpret this as evidence of a bias in the alternative IVs, related to their strong correlation with the global financial cycle. This bias emerges from the various channels through which changes in global risk-taking appetite affect EMEs *above and beyond* the increase in capital inflows. Such catch-all changes are likely to reflect a number of simultaneous changes affecting both demand and supply. The significant and large effect on exports that we obtain when using the alternative IVs is an example of this: a global increase in risk-taking appetite not only relaxes each EME financial constraints and boosts growth through investment and credit growth, but it also raises global growth and gives a sizable boost to exports. Another interesting result is that some measures of financial conditions (corporate and sovereign spreads, *FCI*, equity prices) show some statistically significant reversal effects at longer horizons when using the alternative IVs. Together with the statistically significant increases in consumption after a few quarters, this points to demand shocks.

[54]We omitted the results of other variables where estimates are not significative at all. These results are available upon request.

2.8 Conclusion

In this paper we estimate the causal effects of cross-border bank lending on EME domestic financial and macroeconomic conditions. Our approach differs from the literature that uses EME-specific firm-level data or event studies to achieve identification at the micro level, and thus does not provide a full picture of macro effects.

We address the endogeneity of banking flows – an important component of capital flows – by leveraging the heterogeneity in the size distribution of bilateral cross-border bank lending. Using confidential BIS data, we construct granular instrumental variables for international bank lending. Our GIVs improve upon available instruments in the literature to the extent that they are exogenous to recipient country characteristics and unrelated to potential confounding factors such as the global financial cycle.

International bank lending loosens financial conditions and boosts the economy of emerging markets. Financial condition indices ease, sovereign and corporate spreads narrow, and real exchange rates appreciate. Similarly, domestic private credit grows, as do real GDP and imports. We also find significant though quantitatively small effects on house prices.

These effects are significantly weaker for countries that resort to capital inflow controls. Such measures, it seems, can thus help EMEs temper the effects of cross-border flows, in line with Forbes et al. (2015), Zeev (2017), Pasricha (2017) and Nier et al. (2020). In a world of international risk spillovers (Kalemli-Özcan, 2020), macroprudential policies can be important to smooth the effects of changes in risk sentiment, which can be particularly harmful for EMEs.

The framework we present lends itself to answering a number of interesting questions in the international finance literature, which we leave for future research. For example, we could explore the calibration of macroprudential policies in order to better isolate domestic financial stability risks from foreign capital flow surges.

2.A Appendix: Additional Figures and Tables

Table 2.A.1: International banking flows and the global financial cycle

	(1)	(2)	(3)	(4)	(5)
	Banking Flows	Banking Flows	Banking Flows	Banking Flows	Banking Flows
$GFCy$	0.0218***	0.0145***	0.0190***		0.0107***
	(0.00162)	(0.00250)	(0.00170)		(0.00258)
$PC1$		0.00768***		0.0149***	0.00860***
		(0.00202)		(0.00132)	(0.00201)
VIX			-0.00103***	-0.00133***	-0.00110***
			(0.000205)	(0.000198)	(0.000205)
Observations	2,435	2,435	2,435	2,435	2,435
R-squared	0.070	0.075	0.080	0.080	0.086
Country FE	YES	YES	YES	YES	YES
Countries	22	22	22	22	22

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. This table shows the results of a panel regression with country fixed effects of the growth in international bank claims on different measures of the global financial cycle. $GFCy$ stands for the global financial cycle as computed by Miranda-Agrippino and Rey (2015) and updated in Miranda-Agrippino et al. (2020). $PC1$ stands for the first principal component of capital flows to all countries (constructed as in Cerutti et al. (2019b)). VIX stands for the CBOE Volatility Index.

Table 2.A.2: First stage significance for alternative instruments

Dep Var/ Instrument	GIV	EBP	Host	Common	BD	BOGC
NEER	***			***	**	***
REER	***			***	**	***
RER US	***			**	**	***
Sov spread	***			***	**	***
Corp spread	***			***	*	***
FCI	***			***	***	***
Housing prices	***			***	***	***
Stock prices	***			***	**	***
Equity prices	***			***	***	***
Credit growth	***			***	**	***
Real credit	***			***	**	***
RGDP	***			***	**	***
Consumption	***			***	*	***
Investment	***			***	*	***
Exports	***			***	*	***
Imports	***			***	*	***
Trade Balance	***			***	*	***
Inflation, consumer prices	***			***	***	***
Short-term interest rate	***			***	**	***
Long-term interest rate	***			***	***	***

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the results of first stage regressions of alternative instruments on cross-border bank lending growth. *GIV* is our granular instrumental variable for cross-border lending, *EBP* is the excess bond premium by Gilchrist and Zakrajšek (2012), *Host* and *Common* come from the decomposition of international bank lending growth rates in Avdjiev et al. (2020) (see Appendix 2.B), *EBP* is the external bond premium constructed by Gilchrist and Zakrajšek (2012), as used in Zeev (2019). *BD* stands for the leverage of the US broker-dealer sector, as used in Cesa-Bianchi et al. (2018). *BOGC* is an instrument constructed using the LBSR data following Blanchard et al. (2016).

Table 2.A.3: Number of factors selected by model

	Baseline	Constant sample	Crisis	Parallel analysis
Mean	3.00	2.82	2.95	2.50
sd	1.69	1.56	1.62	0.67
Min	2.00	2.00	2.00	2.00
p25	2.00	2.00	2.00	2.00
p50	2.00	2.00	2.00	2.00
p75	3.00	3.00	3.00	3.00
Max	6.00	6.00	6.00	4.00
Av. diff. w.r.t. Baseline	.	-0.18	-0.05	-0.50
Min. diff. w.r.t. Baseline	.	-4.00	-1.00	-4.00
Max. diff. w.r.t. Baseline	.	1.00	0.00	2.00

Notes: This table presents the summary statistics of the number of factors selected for each model after removing the average growth rate. The columns *Crisis*, *Constant sample* and *Parallel analysis* present the statistics for the robustness scenarios described in Section 2.6. The mininum (maximum) difference with respect to the baseline compute the minimum (maximum) difference of factors selected by the models across individual countries. For instance, the value of -4.00 in the second to last row for the *Parallel analysis* column implies that there is at least one country for which this method selects four factors less than the benchmark method. Similarly, the last row indicates that there is at least one country for which this method selects two factors more than the baseline.

Table 2.A.4: GIV and alternative IVs for international banking flows and the global financial cycle

	(1)	(2)	(3)	(4)	(5)
VARIABLES	*GIV*	*Host*	*BOGC*	*Common*	*BD*
$GFCy$	-0.000183	-0.700***	0.0394***	6.066***	4.490***
	(0.00154)	(0.151)	(0.00339)	(0.614)	(0.864)
$PC1$	-0.000350	0.438***	0.0131***	0.112	2.461***
	(0.00120)	(0.117)	(0.00264)	(0.479)	(0.675)
VIX	-7.39e-05	-0.0831***	-0.00363***	0.246***	0.287***
	(0.000122)	(0.0120)	(0.000269)	(0.0487)	(0.0684)
Observations	2,435	2,355	2,435	111	116
R-squared	0.000	0.025	0.303	0.689	0.592
Country FE	YES	YES	YES	NO	NO
Countries	22	22	22		

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the results of regressing different IVs for international banking flows on measures of the global financial cycle: $GFCy$ stands for the global financial cycle as computed by Miranda-Agrippino and Rey (2015) and updated in Miranda-Agrippino et al. (2020). $PC1$ stands for the first principal component of capital flows to all countries (constructed as in Cerutti et al. (2019b)). VIX stands for the CBOE Volatility Index. The IVs correspond to our GIV, a Blanchard et al. (2016)-type of instrument ($BOGC$), US broker-dealers' leverage (used by Cesa-Bianchi et al. (2018)), and the "common" component from Avdjiev et al. (2020).

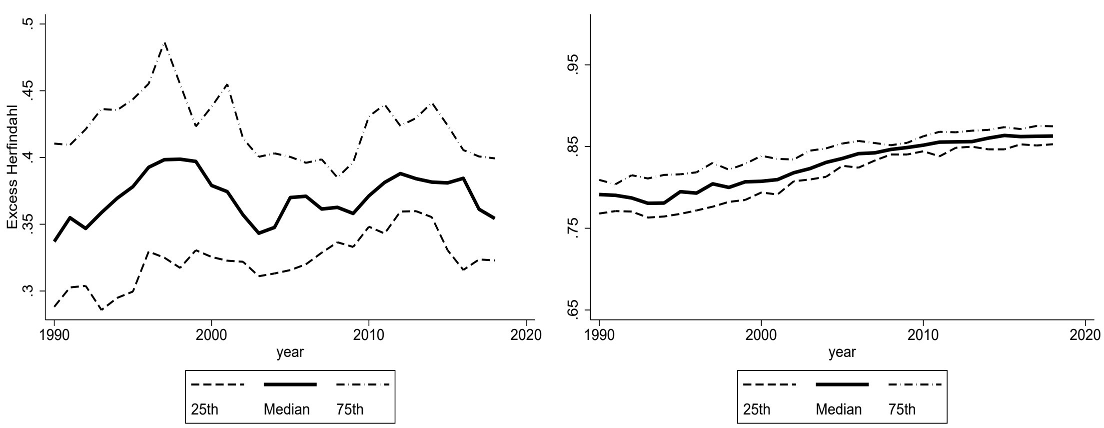
Table 2.A.5: Domestic crises and GIV

Country	Year	Standardized Banking Flows	Standardized GIV
Argentina	2014	-0.719	-2.254
Brazil	1990	-0.569	-2.054
Bulgaria	1996	0.533	-2.832
Chile	1990	-1.345	-2.128
Colombia	1998	-0.984	-2.154
Czech Republic	1996	0.414	-3.683
Malaysia	1997	-1.657	-3.370
Turkey	2000	1.052	-2.064
Ukraine	2015	-0.794	-2.504

Notes: This table presents the events identified as a domestic crises as in Laeven and Valencia (2020) where the GIV is two standard deviations or more below the average.

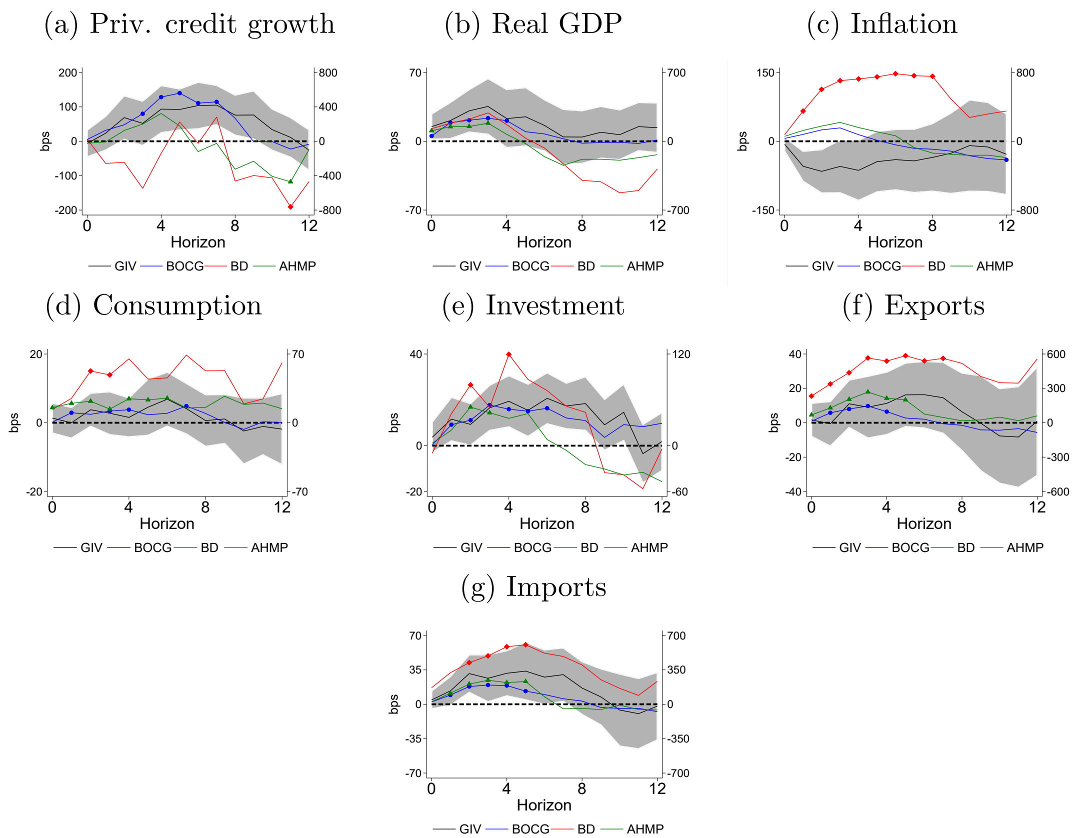
Figure 2.A.1: Concentration in cross-border banking

(a) Excess Herfindahl (b) Gini



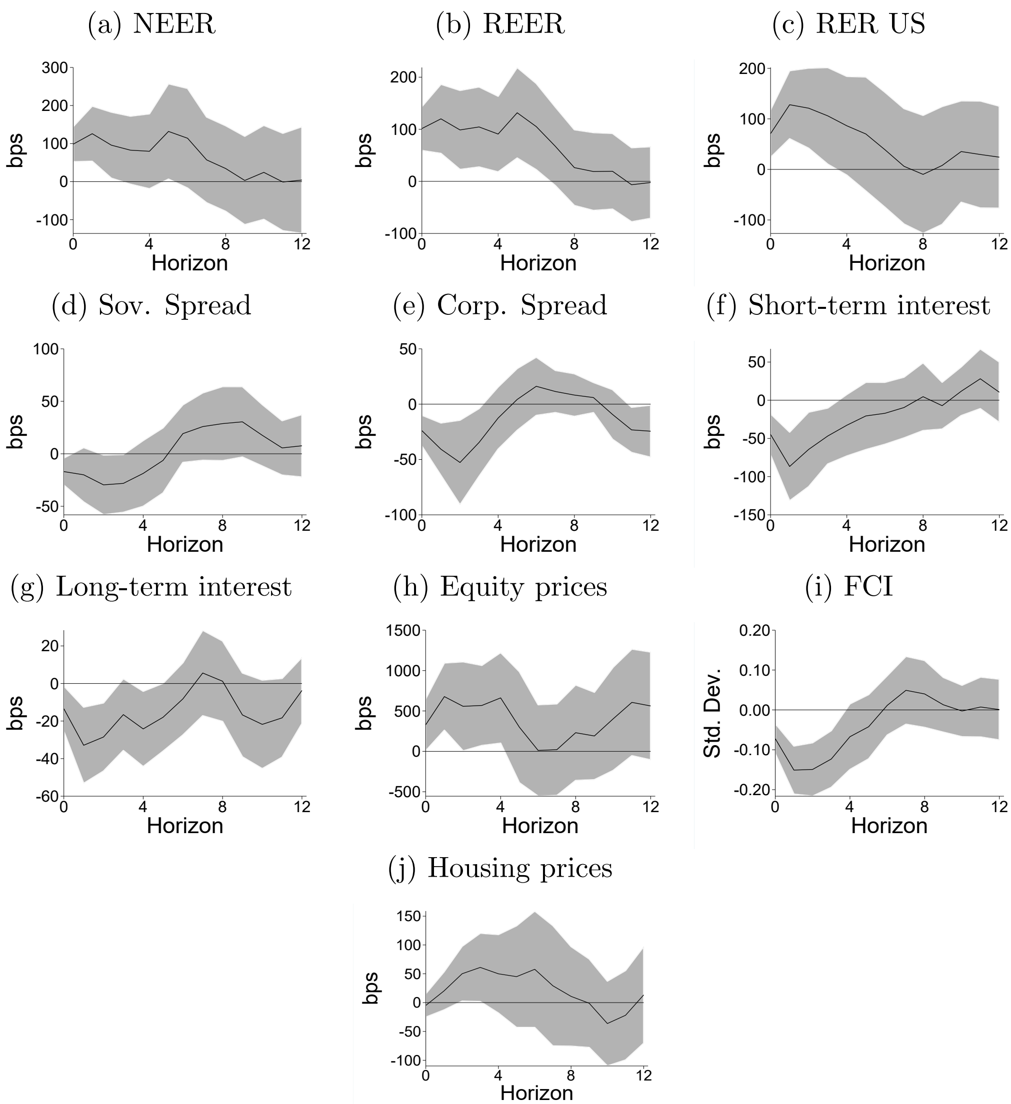
Notes: This figure shows the median, 25th, and 75th percentiles of the excess Herfindahl index (left-hand panel) and the Gini coefficient (right-hand panel) for cross-border bank claims on EMEs. Excess Herfindahl is computed as $h_{i,t} = \sqrt{-\frac{1}{N} + \sum_j^N S_{j,t}^2}$, where i, t and j index the recipient country, year and lender country respectively. The sample of recipient countries comprises 22 EMEs, as presented in Table 2.1.

Figure 2.A.2: Cumulative causal effect of international bank lending using GIV (left-hand axis) and alternative instrumental variables (right-hand axis) for selected macro variables



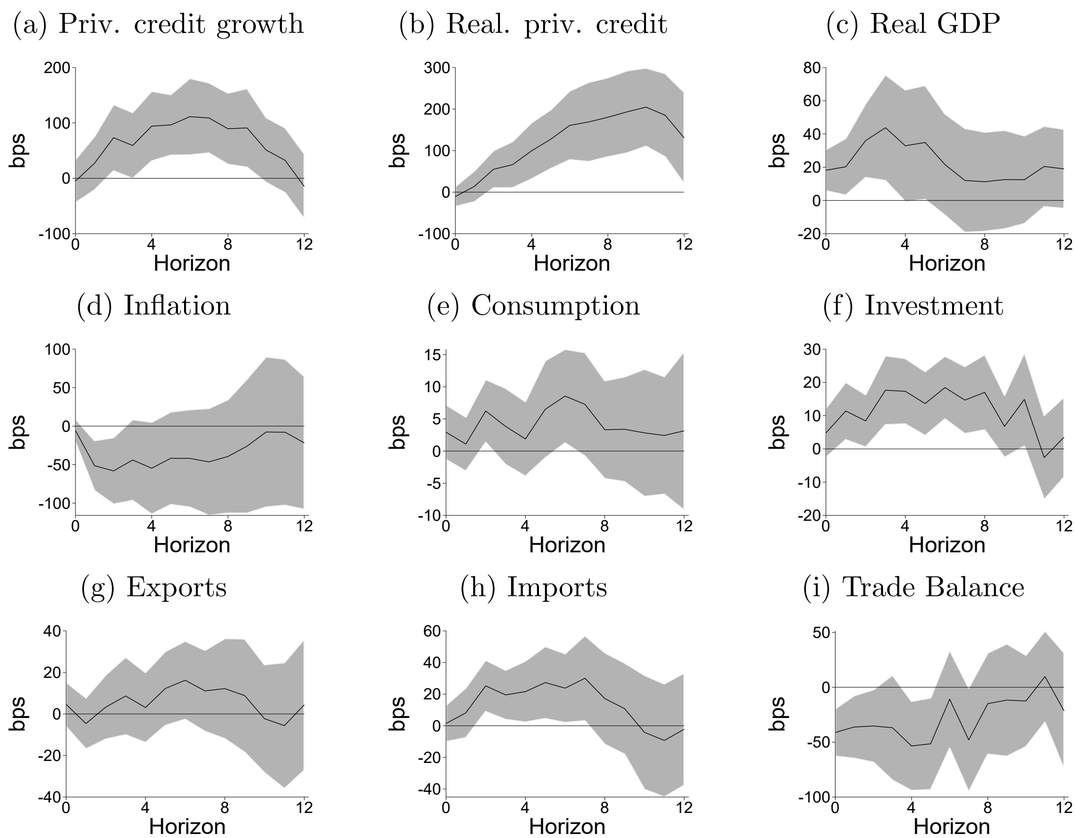
Notes: This Figure compares the cumulative impact of a one standard deviation exogenous international bank lending shock with three instruments on selected variables. The black line and grey area shows the point estimate and 90% confidence interval of our GIV as in Figures 2.5 and 2.6, the blue line shows the point estimate (with markers when it is significative at a 90%) corresponding to using an IV constructed as in Blanchard et al. (2016) (*BOCG*) but with LBSR data, the red line shows the point estimate (with markers when it is significative at a 90%) corresponding to using US Broker Dealers' leverage (*BD*) as IV, and the green line shows the estimated effect of using the "common" component of Avdjiev et al. (2020). The selected variables are domestic private credit growth, real GDP growth, inflation, investment, consumption exports and imports. The country sample is presented in Table 2.1, with data from 1990Q1 to 2018Q4. The estimation is done by 2SLS using each of the four IVs. Standard errors are robust to heteroskedasticity and autocorrelation.

Figure 2.A.3: Effect of international bank lending on financial variables – constant sample



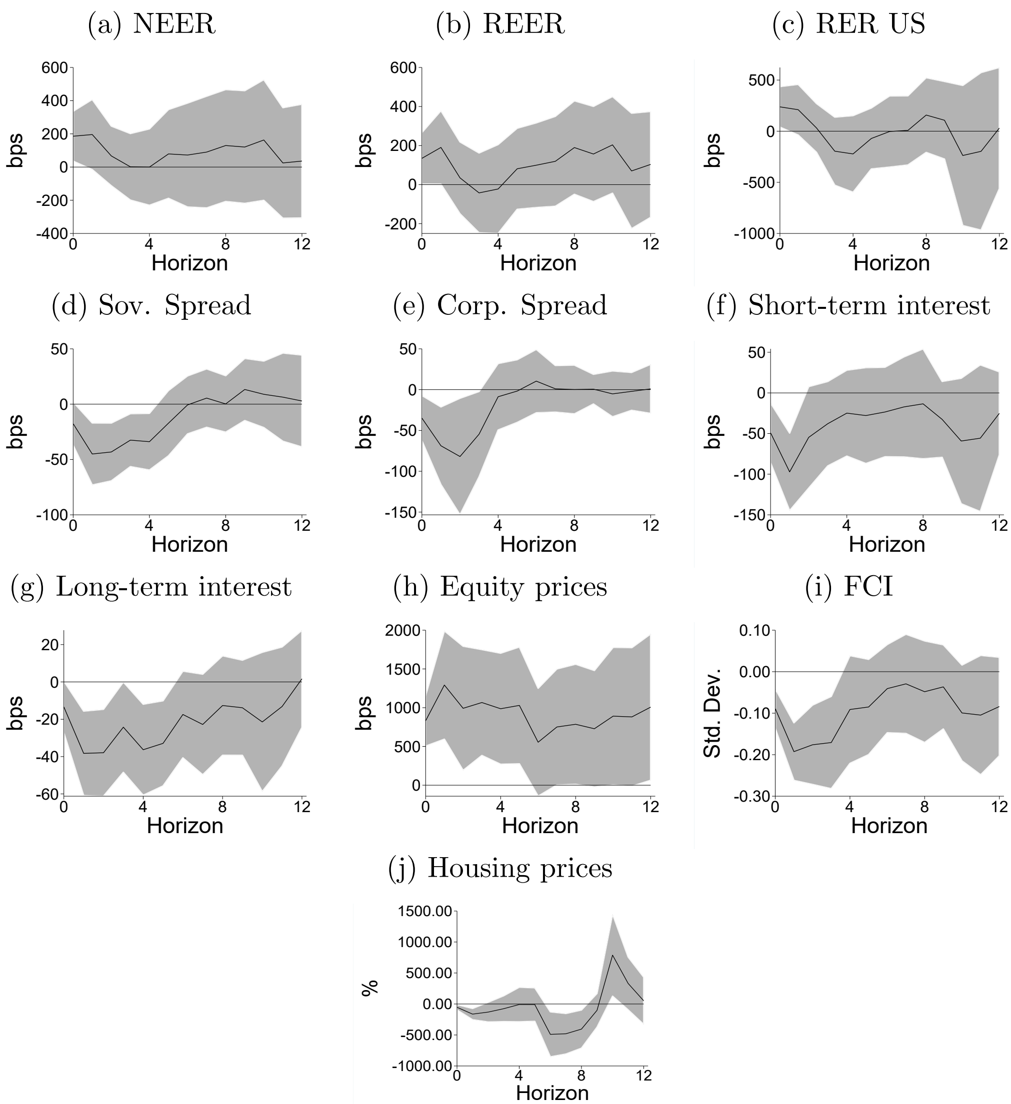
Notes: Robustness check: constant sample of reporting countries. The Figure shows the cumulative impact of a one standard deviation exogenous international banking lending (black like) and its 90% confidence interval (grey area) on: the log of the nominal effective exchange rate ($NEER$), log of real effective exchange rate ($REER$), log of the bilateral real exchange rate vis-à-vis the US dollar ($RER\ US$), domestic short-term interest rates, domestic long-term interest rates, sovereign spread (in USD), corporate spread (in USD), equity prices measured by the price-to-earnings ratio, a standarized financial conditions index (FCI) which decreases when financial conditions are looser, and the log of real housing price index. The borrower country sample is presented in Table 2.1, with data from 1990Q1 to 2018Q4. The estimation is done by 2SLS using our GIV as instrument.

Figure 2.A.4: Effect of international bank lending on macro variables – constant sample



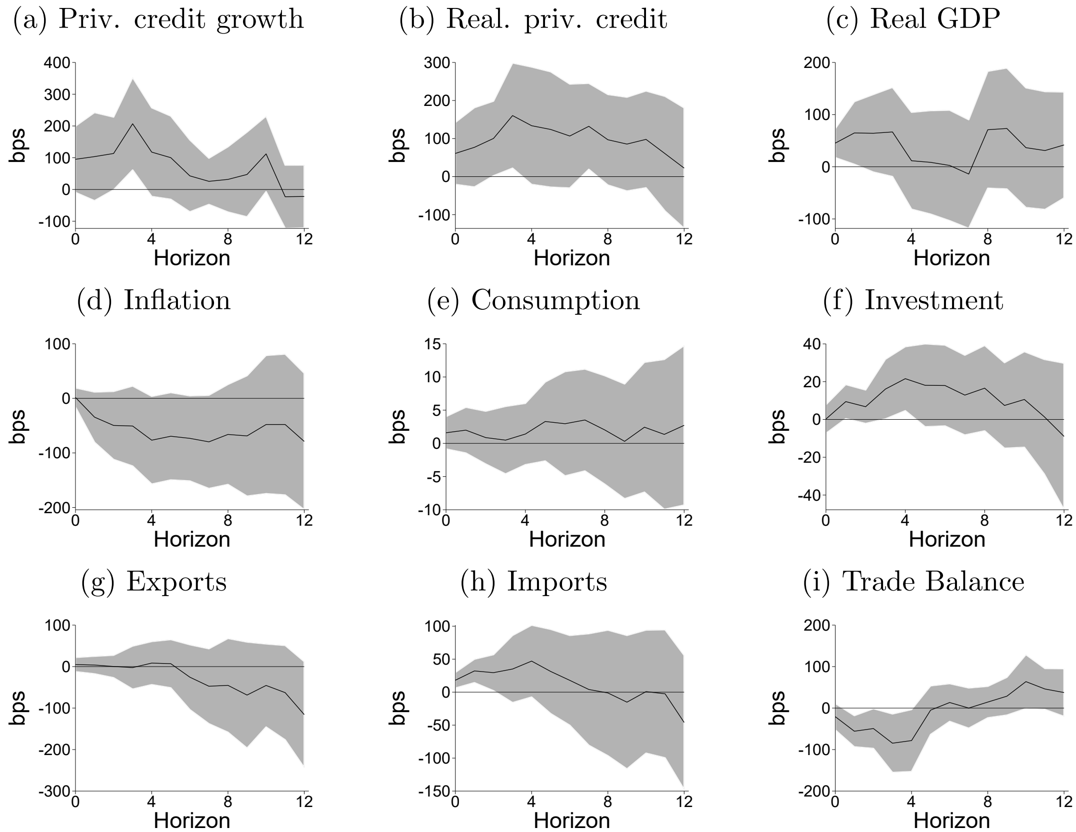
Notes: Robustness check: constant sample of reporting countries. The Figure shows the cumulative impact of a one standard deviation exogenous international banking lending (black like) and its 90% confidence interval (grey area) on the log real private domestic credit, private domestic credit quarterly growth, log real gross domestic product ($RGDP$), log change (year-on-year) in consumption price index, log real private consumption, log real investment, log real imports, and log real exports, and the trade balance as a share of GDP. The borrower country sample is presented in Table 2.1, with data from 1990Q1 to 2018Q4. The estimation is done by 2SLS using our GIV as instrument. Standard errors are robust to heteroskedasticity and autocorrelation.

Figure 2.A.5: Effect of international bank lending on financial variables – alternative method for extracting factors



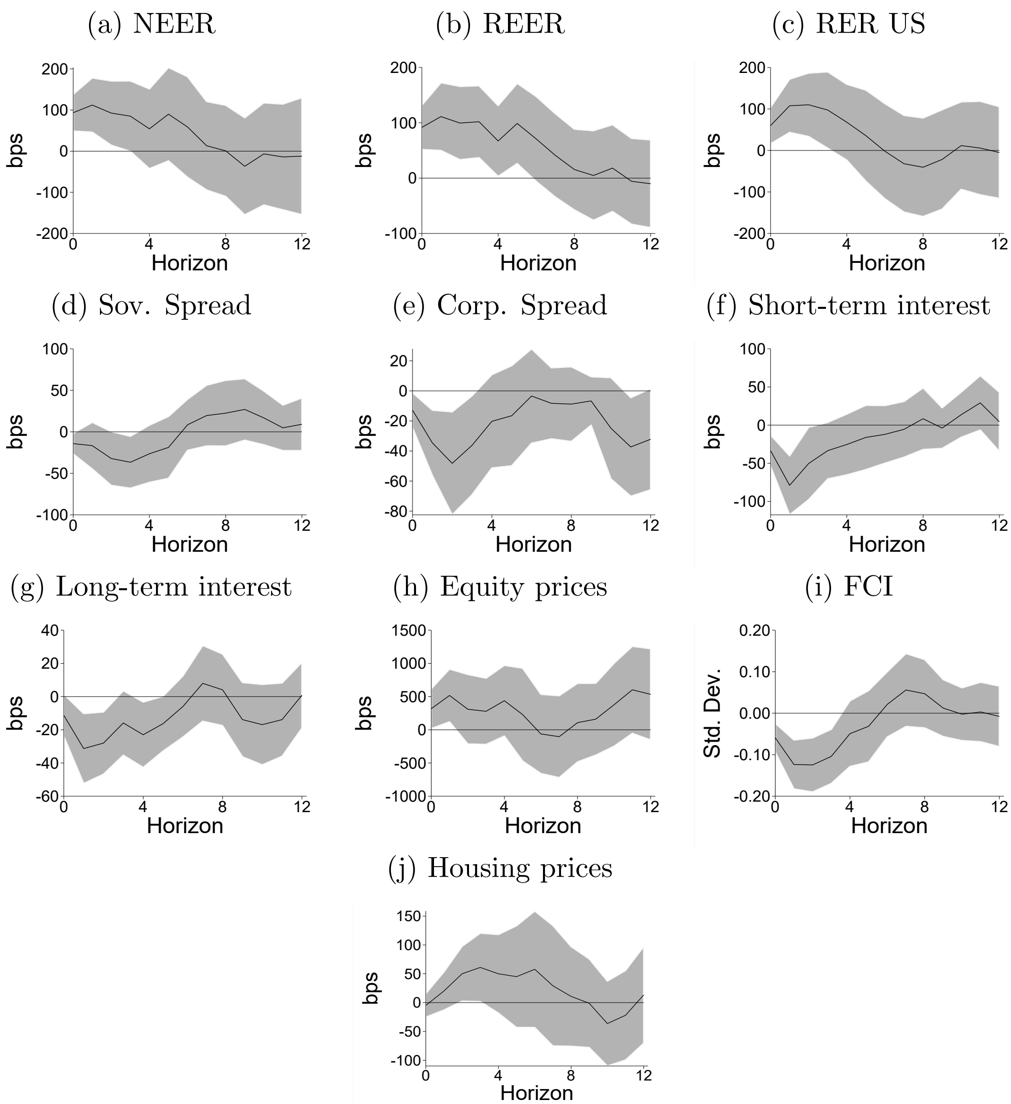
Notes: Robustness check: endogenous factors are extracted using the parallel analysis method as in Horn (1965) instead of the method of Bai and Ng (2002). The Figure shows the cumulative impact of a one standard deviation exogenous international banking lending (black like) and its 90% confidence interval (grey area) on: the log of the nominal effective exchange rate ($NEER$), log of real effective exchange rate ($REER$), log of the bilateral real exchange rate vis-à-vis the US dollar ($RER\ US$), domestic short-term interest rates, domestic long-term interest rates, sovereign spread (in USD), corporate spread (in USD), equity prices measured by the price-to-earnings ratio, a standarized financial conditions index (FCI) which decreases when financial conditions are looser, and the log of real housing price index.

Figure 2.A.6: Effect of international bank lending on macro variables – alternative method for extracting factors



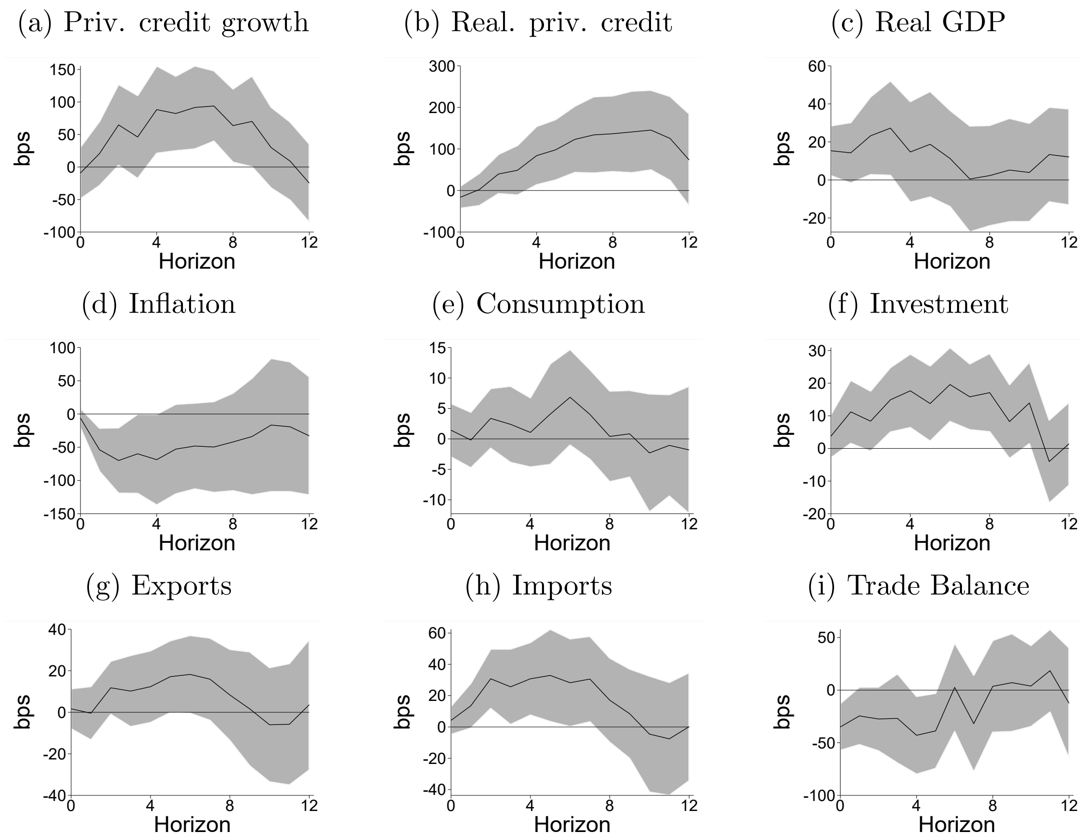
Notes: Robustness check: endogenous factors are extracted using the parallel analysis method as in Horn (1965) instead of the method of Bai and Ng (2002). The Figure shows the cumulative impact of a one standard deviation exogenous international banking lending (black like) and its 90% confidence interval (grey area) on the log real private domestic credit, private domestic credit quarterly growth, log real gross domestic product ($RGDP$), log change (year-on-year) in consumption price index, log real private consumption, log real investment, log real imports, and log real exports, and the trade balance as a share of GDP. The borrower country sample is presented in Table 2.1, with data from 1990Q1 to 2018Q4. The estimation is done by 2SLS using our GIV as instrument. Standard errors are robust to heteroskedasticity and autocorrelation.

Figure 2.A.7: Effect of international bank lending on financial variables – excluding crises



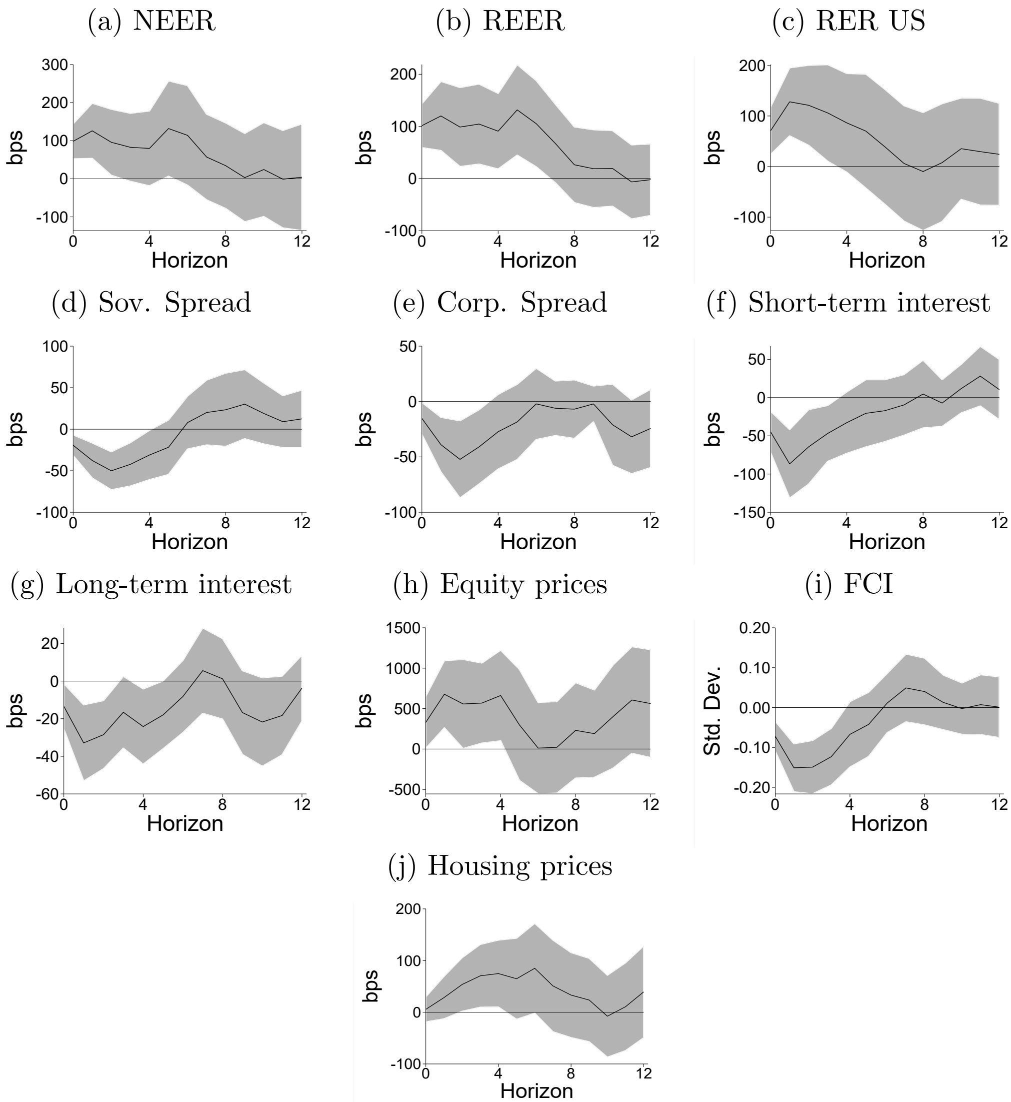
Notes: Robustness check: excluding crises (see Table 2.A.5). The Figure shows the cumulative impact of a one standard deviation exogenous international banking lending (black like) and its 90% confidence interval (grey area) on: the log of the nominal effective exchange rate ($NEER$), log of real effective exchange rate ($REER$), log of the bilateral real exchange rate vis-à-vis the US dollar ($RER\ US$), domestic short-term interest rates, domestic long-term interest rates, sovereign spread (in USD), corporate spread (in USD), equity prices measured by the price-to-earnings ratio, a standarized financial conditions index (FCI) which decreases when financial conditions are looser, and the log of real housing price index. The borrower country sample is presented in Table 2.1, with data from 1990Q1 to 2018Q4.

Figure 2.A.8: Effect of international bank lending on macro variables – excluding crises



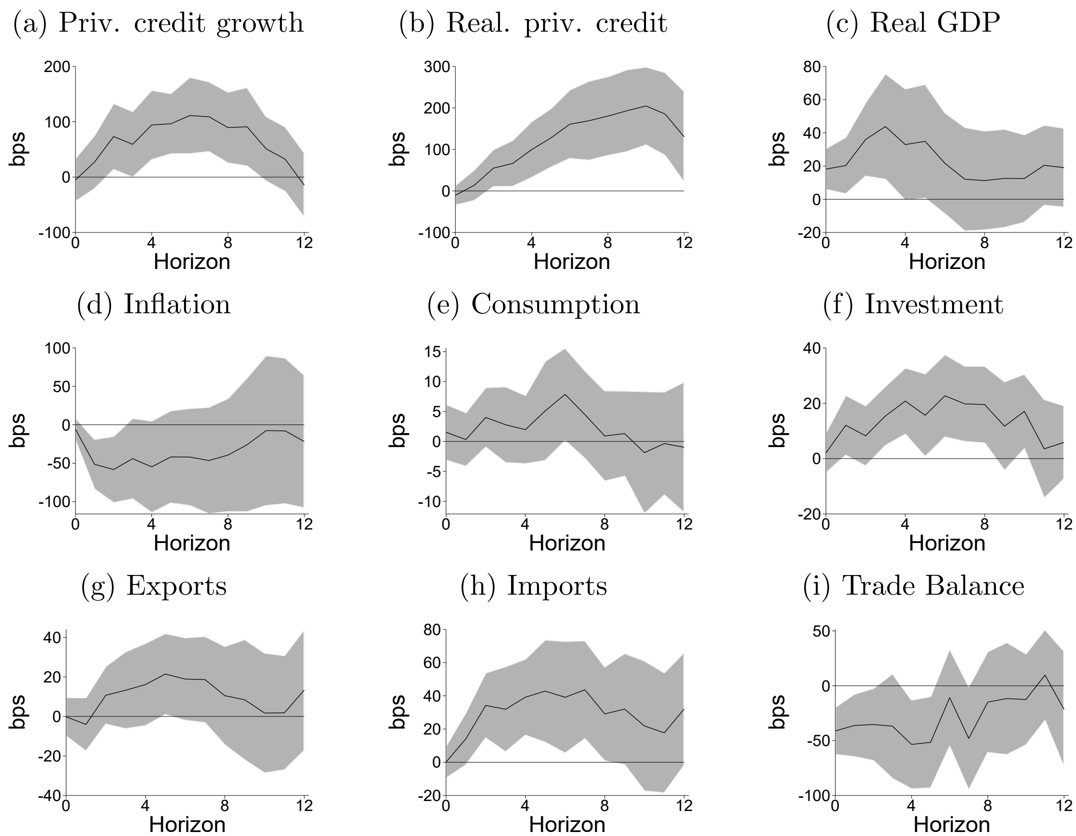
Notes: Robustness check: excluding crises (see Table 2.A.5). The Figure shows the cumulative impact of a one standard deviation exogenous international banking lending (black like) and its 90% confidence interval (grey area) on the log real private domestic credit, private domestic credit quarterly growth, log real gross domestic product ($RGDP$), log change (year-on-year) in consumption price index, log real private consumption, log real investment, log real imports, and log real exports, and the trade balance as a share of GDP. The borrower country sample is presented in Table 2.1, with data from 1990Q1 to 2018Q4. The estimation is done by 2SLS using our GIV as instrument. Standard errors are robust to heteroskedasticity and autocorrelation.

Figure 2.A.9: Effect of international bank lending on financial variables – excluding potentially problematic lenders around crises



Notes: Robustness check: manually excluding potentially problematic lenders in crises episodes (see Table 2.A.5). The Figure shows the cumulative impact of a one standard deviation exogenous international banking lending (black like) and its 90% confidence interval (grey area) on: the log of the nominal effective exchange rate ($NEER$), log of real effective exchange rate ($REER$), log of the bilateral real exchange rate vis-à-vis the US dollar ($RER\ US$), domestic short-term interest rates, domestic long-term interest rates, sovereign spread (in USD), corporate spread (in USD), equity prices measured by the price-to-earnings ratio, a standarized financial conditions index (FCI) which decreases when financial conditions are looser, and the log of real housing price index. The borrower country sample is presented in Table 2.1, with data from 1990Q1 to 2018Q4.

Figure 2.A.10: Effect of international bank lending on macro variables – excluding potentially problematic lenders around crises



Notes: Robustness check: manually excluding potentially problematic lenders in crises episodes (see Table 2.A.5). The Figure shows the cumulative impact of a one standard deviation exogenous international banking lending (black like) and its 90% confidence interval (grey area) on the log real private domestic credit, private domestic credit quarterly growth, log real gross domestic product ($RGDP$), log change (year-on-year) in consumption price index, log real private consumption, log real investment, log real imports, and log real exports, and the trade balance as a share of GDP. The borrower country sample is presented in Table 2.1, with data from 1990Q1 to 2018Q4. The estimation is done by 2SLS using our GIV as instrument. Standard errors are robust to heteroskedasticity and autocorrelation.

2.B GIVs and bank lending growth decompositions

In this Appendix we compare our approach with a decomposition based on the seminal contribution by Amiti and Weinstein (2018). The original methodology in Amiti and Weinstein (2018) was devised to separate firm demand shocks from bank supply shocks in the context of bank-firm lending data.[55] The method was subsequently applied to BIS Consolidated Banking Statistics in Amiti et al. (2019), who decompose bank lending growth rates into common, idiosyncratic supply and idiosyncratic demand factors.

Recently, Avdjiev et al. (2020) (AHMP henceforth) apply the method to the three banking datasets of the BIS, including the one we focus on here (LBSR). They decompose US dollar-denominated cross-border bank claims from the LBSR into three components: a "common" component that can be thought of capturing the global financial cycle, a "host" component that captures developments that affect lender countries' claims, and a "borrower" component captures developments on the recipient country end. This last component captures both developments that are specific to each recipient country but also the idiosyncratic shocks to the bilateral lending relationship between that recipient country and each lender country.[56] Put differently, a particular EME can be exposed to a shock to the international bank lending it receives, that simultaneously affects all other EMEs. That would be a

[55]The method is a variation on weighted least squares that can also accommodate the appearance of new lending relationships. It therefore can exactly decompose macro moments in the data into the contributions of lenders, borrowers and a common factor.

[56]The goal of the exercise in Avdjiev et al. (2020) is entirely different from the one pursued here. They use the decomposition as part of a larger regression exercise to disentangle the effect of home versus host country prudential and monetary policies, as well as the spillovers generated by them.

"common" shock. This EME could also be affected by a shock that is specific to one of its sources of lending (e.g. a regulation change in a given lender country that does not spillover to other lender countries); that would be captured by "host". Lastly, international bank lending to this EME could change due to some shock within its borders (e.g. a policy change) or some change specific to a bilateral lending relationship such as one source country changing its lending to that particular EME.

The validity of our GIVs could be questioned if they were to be correlated with the "common" or "host" component.[57] Given that "borrower" captures a domestic "factor" and the idiosyncratic bilateral shocks, this exercise is not sufficient to ensure the excludability of our GIVs. For that, we trust that our conservative approach to estimate factors and extract truly idiosyncratic bilateral shocks grants us a clean identification strategy.

We compare our GIVs with the decomposition in AHMP in three ways. As a first pass, we test whether the endogenous factors we remove from the data (see section 2.3.2) to extract idiosyncratic bilateral lending shocks are indeed capturing global shocks ("common"), shocks to lender countries ("host"), and/or aggregate shocks in recipient EMEs ("borrower"). To do so, we build a measure of the endogenous factors as follows:

$$E_{i,t} = \sum_{k} \hat{\hat{\lambda}}_{k,i} \hat{F}^{i}_{k} \tag{2.B.1}$$

where $\hat{\hat{\lambda}}_{k,i}$ is the estimated aggregate exposure to the estimated factor $\hat{F}^{i}_{k}$ (with k being the number of factors). This measure captures the aggregate growth of claims that is explained by the estimated endogenous factors.

[57]In the main body of the paper we also consider these two as alternative instruments for cross-border bank lending shocks.

We then estimate the following regression:

$$E_{i,t} = \beta_b borrower_{i,t} + \beta_h host_{i,t} + \beta_c common_t + \delta_i + \nu_{i,t}, \tag{2.B.2}$$

where *borrower*, *host*, and *common* come from AHMP,[58] δ_i is a country fixed effect and $\nu_{i,t}$ is an unobservable variable.

Columns (1) to (3) in Table 2.B.1 shows the results for different time periods (full sample, pre- and post-GFC). Overall, the three components from AHMG are highly significant and positively correlated with the endogenous factors we extract with our methodology.[59]

Our second test consists of analyzing the correlation of our GIVs with the three components in the AHMP decomposition. Columns (4) to (6) in Table 2.B.1 presents the results. Our instrumental variable is not correlated with the common shock, which is consistent with the findings in section 2.7.1. It is not correlated with the "host" shock either. Instead, it exhibits a stronger correlation with the "borrower" factors. Our interpretation is that our instrument captures shocks that are specific to the bilateral credit relationships that are not correlated to other confounding factors specific to the lending country. For instance, monetary policy shocks in the US might disproportionately affect lending from the US to all the destination countries. At the same time, US monetary policy affects domestic conditions through other channels. The evidence provided in Table 2.B.1 captures the fact that our filtering process

[58] Avdjiev et al. (2020) decompose cross-border bank lending in USD. We apply their methodology to lending in all currencies.

[59] The significance of the host and common factors depends on the sample considered. In particular, post great financial crisis, these factors become more important when explaining the commonality of bilateral flows across countries, which is consistent with Amiti et al. (2019).

cleans these confounding factors.

Table 2.B.1: Avdjiev et al. (2020) decomposition, endogenous factors and GIVs

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$E_{i,t}$	$E_{i,t}$	$E_{i,t}$	GIV	GIV	GIV
Host	0.0862*	0.225***	-0.0255	0.0137	-0.00240	0.0133
	(0.0453)	(0.0684)	(0.0393)	(0.0150)	(0.0277)	(0.0161)
Borrower	0.196***	0.214***	0.169***	0.0285***	0.0233***	0.0397***
	(0.00754)	(0.00850)	(0.0149)	(0.00656)	(0.00775)	(0.00842)
Common	0.182***	0.188***	-0.0827	-0.0226	-0.0261	-0.0288
	(0.0245)	(0.0237)	(0.0948)	(0.0153)	(0.0163)	(0.0343)
Observations	2,371	1,579	880	2,371	1,579	880
R-squared	0.2397	0.3388	0.0977	0.0193	0.0137	0.0401
Countries	22	22	22	22	22	22
Sample Period	Full	Pre-GFC	Post-GFC	Full	Pre-GFC	Post-GFC

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the results of regressing our measure of estimated endogenous factors in columns (1) to (3) (see equation 2.B.1) and our GIV ($z_{i,t}^{GIV}$) in columns (4) to (6) on Avdjiev et al. (2020) exact decomposition of international bank lending growth rates into ”common”, “borrower”, and “host” components in Columns (1) to (3), including country fixed effects.

Our third test consists of analyzing how our estimated idiosyncratic shocks correlate with the decomposition in AHMP. We show that only for large lenders there is a positive correlation with “borrower” factors. We regress all the idiosyncratic shocks (alternatively, those from the most important regions – whose bilateral share is higher than 20% – or the largest lender only) on the three components from AHMP's decomposition. Columns 1 to 3 in Table 2.B.2 present the results. We find that the estimates are statistically significant only for large lenders. This gives us some reassurance, as on average all the shocks are not correlated – only through those countries that can have an aggregate effect on banking flows. As a final test, column 4 in Table 2.B.2 shows that the average shock $\bar{u}_{i,t}$ (see equation (2.4)) is not correlated with any measure from AHMP's decomposition.

Table 2.B.2: Avdjiev et al. (2020) decomposition and idiosyncratic shocks

	(1)	(2)	(3)
VARIABLES	Id. Shocks	Id. Shocks	Id. Shocks
Common	0.0271	0.170	0.0706
	(0.0651)	(0.235)	(0.248)
Host	0.0104	-0.0910	0.113
	(0.0825)	(0.138)	(0.157)
Borrower	-0.00276	0.206*	0.203*
	(0.0188)	(0.118)	(0.0979)
Observations	38,098	2,245	2,724
R-squared	0.000	0.007	0.006
Lender Sample	All	Top 1	Top 20

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the results of regressing our standardized bilateral shocks ($u_{i,j,t}$) on Avdjiev et al. (2020) exact decomposition of international bank lending growth rates into "common", "borrower", and "host" components.

Taken together, the findings from this section suggest that: (i) the filtered factors capture information that should be excluded from a valid instrument, as they are correlated with the global shocks and aggregate shocks to lenders; (ii) our GIVs are uncorrelated with global and aggregate shocks to lenders, and somewhat correlated with the partition of the data ("borrower") that partly captures idiosyncratic bilateral shocks; and (iii) only the largest idiosyncratic shocks are correlated with the “borrower” factor, thus in line with the size-based identification strategy we pursue.

CHAPTER 3

Identifying The Effects of Foreign Exchange Intervention: Evidence from Sovereign Bond Benchmarks

What are the effects of foreign exchange intervention? In this chapter, we address this question and estimate the causal effect of foreign exchange intervention for a set of emerging economies. Theoretically, the effect of foreign exchange intervention depends on the risk-bearing capacity of financial intermediaries. Limited risk-bearing capacity of financial intermediaries shows as Uncovered Interest Parity deviations that depend on the amount of risk held by intermediaries. To identify the risk-bearing capacity, we use the variation from information free flows of passive investors around rebalancing dates for a set of emerging economies. Our estimates show that to achieve a 10% foreign exchange depreciation in one week, the required foreign exchange intervention is between $0.02-$5.06 Billion dollars, and about 0.15% of annual GDP for the median country.

3.1 Introduction

Emerging market economies have faced large swings in capital inflows. Policymakers in these economies have resorted to a set of policy tools to curb the effects of capital flows. The literature documents the extensive use of foreign exchange intervention to cope with misalignment of the exchange rates and exchange rate volatility. The rationale for foreign exchange intervention to influence the exchange rate is the imperfect substitution across financial assets and to operate through the portfolio balance channel.

The effectiveness of foreign exchange intervention and its opportunity cost is yet a remaining question in the literature. Identifying the effects of foreign exchange intervention on the exchange rate is challenging, as foreign exchange interventions are correlated with capital inflows and the global financial cycle. At the same time, capital inflows are correlated with domestic activity.

In this paper we assess the effectiveness of foreign exchange interventions for a set of emerging market economies. Theoretically, the effects of foreign exchange intervention on the exchange rate depends on the risk-bearing capacity of financial intermediaries. Therefore, identifying the effect of foreign exchange intervention relies on the identification of the elasticity of supply of active intermediaries. We identify the risk-bearing capacity using the variation from information free flows that affect the total risk bared by financial intermediaries and are not correlated with the macroeconomic conditions. We build an instrument that uses the variation around rebalancing dates and comes from mechanical rebalancing of the sovereign bond benchmark index.

We find that the information free flows in local currency bonds cause an appreciation of the exchange rate and a decrease in both the uncovered and covered interest rate differentials. Our preliminary estimates imply that one standard deviation in the information free flows causes a between 40 to 71-basis points appreciation of the currency. We also show that the information free flows cause a decrease in the uncovered and covered interest parity differentials, which is in line with the view of limited risk-bearing capacity of financial intermediaries. These results imply that the required foreign exchange intervention to sustain an annualized 10% depreciation in one week is of the order between 0.02-5.06 billions. For the median country, we our results imply that about 0.25% of annual GDP is necessary to sustain that depreciation level.

3.2 Literature Review

This paper is related to three broad streams of literature: the literature on financial frictions and exchange rates, the literature on the international portfolio rebalancing, and the literature on foreign exchange intervention.

The theoretical literature on the determination of the exchange rates and capital flows show that, under imperfect financial markets, the uncovered interest rate differentials depend on capital inflows, and the risk-bearing capacity of financial intermediaries. Itskhoki and Mukhin (2019) shows that a persistent shock to international asset demand can explain the exchange rate disconnect. The resulting exchange rate is in this type of models admits a micro-foundation as in previous papers with limited arbitrage and financial frictions (Jeanne and Rose, 2002; Gabaix and Maggiori, 2015b; Cavallino, 2019). Our paper contributes to this brand of research by estimating the elasticity of the uncovered interest parity with respect to an exogenous shock to the international asset demand. Our estimates can discipline this variety of macro-models and the risk-bearing capacity of intermediaries.

There is a recent interest on the effects of portfolio rebalancing in international asset pricing. Camanho et al. (2018) examines international equity allocations and find that excess foreign returns influence portfolio rebalancing, capital flows and currencies. Koijen and Yogo (2020) estimates the elasticity of investors demand for local currency bonds in a global portfolio approach. We focus on information free portfolio rebalancing of sovereign benchmark investments and use those to causally identify the elasticity of supply of active investors, which govern the risk-bearing capacity of intermediaries. Pandolfi and Williams (2019b) and Raddatz et al. (2017) show that those information free flows affect bond prices and liquidity. We focus on the causal effect of information free flows on the exchange rate through the Uncovered Interest Parity, and estimate the effect of foreign exchange intervention.

There is a vast empirical literature on the foreign exchange intervention. Numerous papers focus on a case study to assess the effectiveness of foreign exchange intervention[1]. Other papers focus on a panel approach with high and low frequency data Adler et al. (2019); Fratzscher et al. (2019) . We depart from the literature and assess the effect of foreign exchange intervention through a specific mechanism: the risk-bearing capacity of intermediaries.

[1]See Adler et al. (2019) for a detailed literature review

3.3 Data

The main data source is the Index Composition and Statistics reports from J.P. Morgan. These reports include monthly information on benchmark weights and rebalancing for the sovereign bonds benchmarks. The most widely followed benchmark indices for emerging market bonds are the J.P. Morgan Emerging Market Bond Index (EMBIG; for dollar-denominated bonds) and the J.P. Morgan Government Bond Index-Emerging Markets (GBI-EM; for local currency bonds). We focus on the GBI-EM Global Diversified, as it is the most widely used and has the property of mechanical rebalancing from the diversification rules.

Our sample includes a panel of 16 countries from 2014 to 2021. The 16 countries in the index are Brazil, Chile, Colombia, Hungary, Indonesia, Malaysia, Mexico, Nigeria, Peru, the Philippines, Poland, Romania, Russia, South Africa, Thailand, and Turkey. We combine the reports with daily data of exchange rates and government yields from Datastream. We complement this information with CIP deviations for each country from Du et al. (2018) and Du and Schreger (2016).

3.4 Empirical Setting

The uncovered interest rate differential in a family of models with imperfect substitution across assets implies a positive relationship between the UIP premia and the financial intermediaries risk-bearing capacity:

$$i_t - E_t \Delta e_{t+1} - i_t^* = \chi_{1,t} d_t^*, \tag{3.1}$$

where i is the nominal interest rate on local currency bonds, $i^\star$ is the nominal interest rate on foreign currency bonds, e is the nominal exchange rate and $d_t^\star$ is the financial intermediaries position. Here $\chi_{1,t}$ captures the risk-bearing capacity of financial intermediaries. This term in many micro-foundations relates to the financial intermediaries aggregate risk aversion. When financial intermediaries are able to absorb the excess liquidity in the market,$\chi_{1,t}$ is zero and the UIP holds.

In equilibrium, market clearing implies

$$d_t^\star = -b_t^\star + n_t^\star + f_t^{star}, \tag{3.2}$$

where $b^\star$ is the households demand for foreign bonds, $n^\star$ is the position of passive investors (or noise traders), and $f^\star$ is the government demand, and will be our policy choice variable.

Following Lustig and Verdelhan (2011), we can iterate forward and write

$$\mathbb{E}_t e_{T+t+1} - e_t = \mathbb{E}_t \sum_{j=0}^{T} \left(i_{t+j} - i_{t+j}^* \right) + \mathbb{E}_t \sum_{j=0}^{T} \chi_{1,t+j} n_{t+j}^* + \mathbb{E}_t \sum_{j=0}^{T} \chi_{1,t+j} \left(b_{t+j}^* - f_{t+j}^* \right). \tag{3.3}$$

Therefore, the exchange rate dynamics depends on the expected realization of the passive investors, households and government demands, as well as the interest rate differentials.

In partial equilibrium, we could identify the effect of foreign exchange rate intervention by estimating $\chi_{1,t+j}$ from the variation in n_t^*. We discuss the implications of the general equilibrium approach in section 3.5.2

Assuming noise traders are passive investors with buy-and-hold portfolios unless rebalancing occurs implies:

$$n_t^* = \begin{cases} \left(\frac{n_{t-1}^*}{R_{t-1}^*}\right) R_t^* & \text{o.w} \\ \psi_t R_t^* & \text{if} \quad t = \text{rebalancing date} \end{cases}$$

Therefore, at the rebalancing date:

$$\begin{aligned} n_t^* = \psi_t R_t^* = & \underbrace{\psi_t R_t^* - \left(\frac{n_{t-1}^*}{R_{t-1}^*}\right) R_t^*}_{\text{flows implied by rebalancings}} + \underbrace{\left(\frac{n_{t-1}^*}{R_{t-1}^*}\right) R_t^*}_{\text{market value buy-and-hold}} \\ = & \quad \text{FIR}_{c,t} \qquad + \qquad \text{market value}_{c,t}^{BH}. \end{aligned}$$

The term FIR captures information free flows, as long as rebalancing are purely mechanical and do not depend on the domestic conditions. Moreover, we call this flows "information free" to the extend that information arrives earlier at the announcement date, and therefore the market discounts that information in advance.

The exogeneity assumption implies that the information free flows are not correlated with domestic conditions through other channels. In partial equilibrium, this also implies that, controlling for the observed interest rate differentials (and households and government positions), expected future realizations of nominal interest rate differentials, net exports, and policy is exogenous.

We follow Pandolfi and Williams (2019b) and define

$$F\tilde{I}R_{c,t} = \frac{A_t(\omega_{c,t} - \omega_{c,t}^{BH})}{MV_{c,t-1}}, \tag{3.4}$$

where c denotes the country. In this setting,$\omega_{c,t}$ is the country-weight after rebalancing; A_t is the total index market value, $MV_{c,t-1}$ is the market value of country c in the index from $t-1$ and $\omega^{BH}_{c,t}$ is the buy-and-hold weight of the index [2]

3.5 Empirical Results

We estimate:

$$e_{c,t+h} - e_{c,t-1} = \gamma_0^h(i^l_{c,t} - i^{us}_t) + \beta^h_{FIR}FIR_{c,t} + \gamma_1^h Mkt^\star_{c,t-1} + \delta_c + \varepsilon^h_{c,t}, \tag{3.5}$$

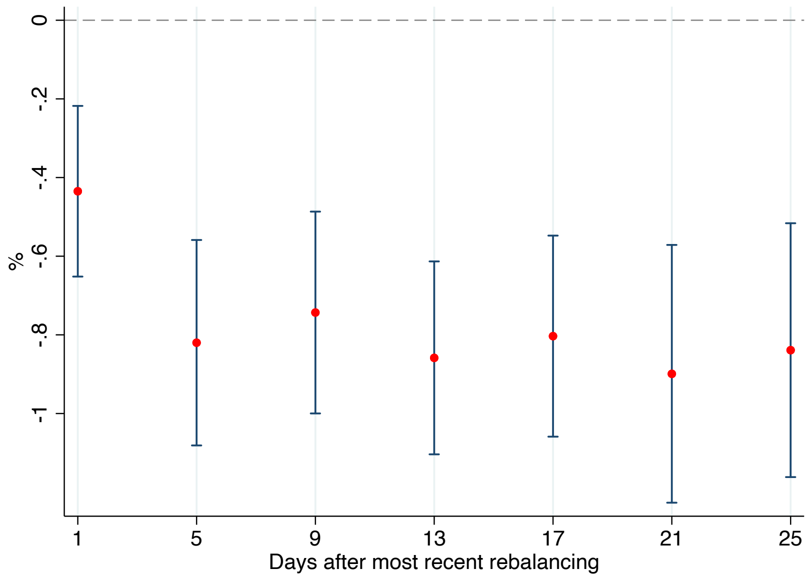
for $h > 0$ around the announcement dates. We control for the one-year government bond yields differentials with respect to the U.S., $i^l_{c,t} - i^{us}_t$, and initial market value of the country, $Mkt_{c,t-1}$. We allow for country level fixed effects.

Table 3.1 presents our results around rebalancing dates for the regression in equation 3.6. Our regression predicts between 42 to 80 basis points foreign exchange appreciation after 1 standard deviation shock in information free flows. This estimates are in line with the results in Pandolfi and Williams (2019b). We also show that the return differentials are not significant and can not explain the exchange rate dynamics around rebalancing dates. Figure 3.1 presents the estimated impulse response function of the cumulative exchange rate after 1 standard deviation shock to the information free flows.

We also estimate of information free flows on CIP deviations. Figure 3.2 presents the estimated impulse response function. We estimate a reduction of 5 basis points

[2]For simplicity, we assume all international mutual funds following GBI-EM act like passive funds. Therefore, $\omega^{BH}_{c,t}$ = Par-value$_{c,t-1}$ $\times$ Dirty price$_{c,t}$.

Figure 3.1: Exchange rate and FIR



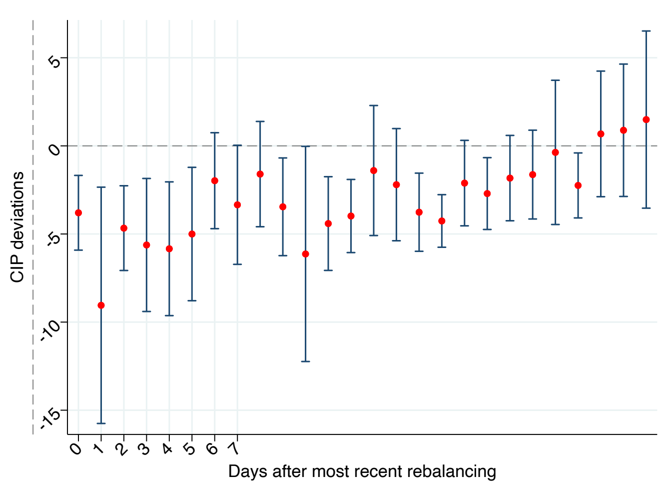
Notes: The confidence intervals are displayed at 90 % level. Exchange rate change are cumulative (since -1 day of rebalancing) and in units of local currency. Interest rates are daily yields of one-year government bonds.

Table 3.1: Exchange rates change on FIR and one-year government bonds yield

	(1)	(2)	(3)	(4)	(5)	(6)
	$t+1$	$t+5$	$t+9$	$t+13$	$t+17$	$t+21$
FIR	-0.423**	-0.806***	-0.708***	-0.744***	-0.718***	-0.781***
	(0.219)	(0.254)	(0.263)	(0.271)	(0.248)	(0.275)
$i_t^{1y} - i_t^{*1y}$	-0.130	-0.847	-3.012	2.787	1.438	0.448
	(5.804)	(3.110)	(2.319)	(5.727)	(2.512)	(0.860)
Obs.	400	620	744	619	757	621
R^2	0.0588	0.0821	0.0489	0.0642	0.0549	0.0494
Adj.R^2	0.019	0.058	0.028	0.039	0.034	0.024

Notes. * $p < 0.1$, ** $p < 0.10$, *** $p < 0.05$. Standard errors in parentheses

Figure 3.2: CIP and FIR



Notes: The confidence intervals are displayed at 90% level. CIP (since -1 day of rebalancing) and in units of local currency. Interest rates are daily yields of one-year government bonds.

on impact after a 1 standard deviation shock on information free flows. The effect vanishes over time as displayed in 3.2 .

3.5.1 The effect of sterilized intervention

To assess the effect of foreign exchange intervention, we estimate

$$e_{c,t} - e_{c,t-1} = \gamma_0^h (i^l_{c,t} - i^{us}_t) + \beta^c_{FIR} FIR_{c,t} + \gamma_1 Mkt^{\star}_{c,t-1} + \delta_c + \varepsilon_{c,t}, \qquad (3.6)$$

where t denotes a week after the announcement. Note that we allow for heterogeneous effects across countries, as different currencies may have heterogeneous liquidity. Therefore, the term β^c_{FIR} is country specific.

To assess the effect of foreign exchange intervention we estimate:

$$\tilde{\beta}_c = \beta^c_{FIR} \frac{\bar{A}}{M} \bar{R} \times \text{Benchmarked assets}, \tag{3.7}$$

where $\frac{\bar{A}}{M}$ is the inverse of the country c's average weight and $\bar{R}$ is the average gross return. The term labeled as "Benchmarked assets" refers to an estimate of the total benchmark driven investments. We use 200 billion dollars for our preliminary estimates, which is in line with the JPM Survey estimates.

The required foreign exchange intervention to sustain a $T\%$ depreciation is

$$f = \frac{T\%}{\tilde{\beta}_c} \tag{3.8}$$

Table 3.2 presents our estimates of the required foreign exchange intervention to achieve a 10% depreciation in one week. The median country requires an intervention of 0.53 billion dollars. We standardize in terms of annual GDP in column 2. The median country requires 0.15 percent of annual GDP to achieve a 10% depreciation. However, the responses across countries are heterogeneous. We see that some dollarized economies have a harder time when it comes to curb the exchange rate volatility and the effects of capital flows. Peru requires 0.99 percent of annual GDP to achieve a 10% depreciation of the currency. This result highlights that imperfect financial markets differ across countries and currencies and the effectiveness of foreign exchange intervention.

Table 3.2: FXI required to sustain 10% depreciation

Country	Billion dollars	% to annual GDP
Argentina	0.03	0.01
Brazil	4.97	0.34
Chile	0.14	0.06
Colombia	0.35	0.13
Czech Republic	0.24	0.10
Hungary	0.29	0.18
Indonesia	1.15	0.11
Malaysia	1.87	0.56
Mexico	5.06	0.47
Peru	1.99	0.99
Philippines	0.02	0.01
Poland	1.79	0.30
Romania	0.20	0.08
Russia	0.44	0.03
South Africa	1.18	0.39
Turkey	0.62	0.21
Median	0.53	0.15
Average	1.27	0.25
Min	0.02	0.01
Max	5.06	0.99

Notes: This table presents the foreign exchange rate intervention required to sustain a 10% depreciation in a 1 week horizon. We use a total benchmark vale equal to 200 billion dollars, the average market share an a 5% average return. In column 2, we standardize as the share with respect to annual GDP as of 2020.

3.5.2 Threats to identification

Our identification strategy relies on information free flows being exogenous with respect to the evolution of the demand of households for local currency bonds. In practice, this demand will evolve according to the equilibrium of the balance of payments. This adjustment is typically slow, and therefore for short horizons we believe our identification strategy holds.

We could also allow for endogenous policy and households demand. When doing so, we could estimate the impulse response function as follows:

$$e_{t+h} - e_{t-1} = \gamma_0^h(i_t^l - i_t^{us}) + \gamma_2^h e_{t-2} + \beta_{FIR}^h FIR_t + \gamma_1^h n_{t-1}^\star + \varepsilon_t^h, \qquad (3.9)$$

where e_{t-2} is the exchange rate at the announcement date.

3.6 Conclusion

In this chapter we estimate the effect of foreign exchange intervention. We leverage from benchmark-related investment flows and the observed portfolio rebalancing. Our preliminary results suggest that the median country requires 0.15 percent of GDP to achieve a 10% depreciation of the currency. We also show that the effects are heterogeneous across countries, highlighting heterogeneity in the risk-bearing capacity of financial intermediaries.

This paper is a building block for policy analysis and the identification of the effects of exchange rate intervention. We will consider the optimal exchange rate intervention in future work, as well as the implications of limited risk-bearing capacity on the available policy tools when it comes to curb the effects of capital inflows.

Our paper also highlights the effects of information free flows and benchmark-driven investments. We show that these flows can explain UIP and CIP differentials for a set of emerging economies. The importance of benchmark-driven investments in local currency bonds in sovereign bonds has increased over time. This imposes a trade-off for policy makers: currency mismatches may reduce, but the effects on exchange rate volatility should be explored further.

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