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Abstract

This paper examines the reciprocal lending between Financial Conglomerates in the repo market to better understand both what motivates powerful firms to engage in this type of contemporaneous cross-funding relationships, and, on the other hand, some of the implications that such reciprocal transactions may entail for the agents involved and for the market as a whole. In particular, in terms of the implications we focus on two dimensions: first, the potential effects that reciprocal lending has on the market power of FCs and the competitiveness of the repo market for mutual funds and second, the potential implications that frequent and stable reciprocal lending can have in terms of the industry's systemic risk. Using transaction-level data from the Mexican repo market, we show that reciprocal lending between financial conglomerates is mutually beneficial as it reduces search costs for borrowers and mitigates credit risk concerns for lenders. Further, we find that reciprocal lending favors market concentration of the repo lending in a few powerful funds and increases fund market power. Finally, we find that reciprocal lending also leads to centrality within the financial network and increases the dependence between the parties involved. Interestingly, a higher intensity of reciprocal lending can harmful, but this does not necessarily deteriorates financial stability.

Keywords: Reciprocal lending, collateralized money market, repo, banks, mutual funds, asset managers, market power, financial stability.

JEL Codes: G01, G11, G21, G23, G28, L16, L22, L4.

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1 Introduction

Mexican banks use short-term repo funding to cover their needs for liquidity. The share of repo funding in Mexican banks' portfolio was, on average, 20% between 2010 and 2018. On the other hand, the repo is an important marketplace for mutual funds to invest their money, so long as they can only supply liquidity through this market in Mexico. Indeed, in terms of trading volumes, Mexican mutual funds contribute with 20% of the funding that goes to banks and brokerage houses, on average, and near to the 75% of the volume that is concentrated in banks.

The Mexican mutual fund industry appears to offer a large set of choices for investors, including a variety of portfolios, fees and redemption rates in a fairly competitive market with 587 multi-class funds in operation and 3,425 share classes at year-end 2015. By contrast, the asset management sector is concentrated in a few firms that are owned by financial conglomerates (FCs) that often own commercial banks also. For instance, the seven biggest FCs in Mexico (so-called Group of seven or G7),[1] own mutual fund asset managers (AMs) that are among the biggest. In fact, the five leading AMs, out of 33 that were active at year-end 2015, held combined market shares of 70% of assets under management. All of them are affiliated to some of the G7 FCs.

The regulatory framework of the Mexican repo market constrains Mexican open-ended funds to lend money to banks and brokerage firms only, which implies that a significant share of the liquidity that funds provide is concentrated by commercial banks.[2] Furthermore, evidence shows that between 2006 and 2017 G7 banks obtained funding mainly from funds affiliated to G7 FCs, which implies that most collateralized lending transactions in that period happened between FCs.[3] A striking characteristic of the funding relationships between G7 funds and banks is that 40% of the daily transactions between them were reciprocal. We define reciprocal lending as all of the repo transactions that happens between investment funds and banks owned by a given pair of rival FCs such that the funds of one FC provide some liquidity to the bank of the rival FC and, simultaneously (i.e., within the same time window), a similar transaction happens in the reverse direction. Previous literature on the so-called relationship lending–which designates all transactions made between two parties in a stable fashion–suggests that establishing close ties with a counterpart may be motivated, to some extent, by the need to guarantee access to frequent and stable funding at lower rates. Further, close and stable relationships are a way of

[1] The G7 is composed by Banamex, BBVA Bancomer, Banco Santander Mexico, Banorte, HSBC Mexico, Scotiabank Inverlat and Banco Inbursa.

[2] Counterpart credit risk arising from repo transactions are usually mitigated by restrictions on entities that are eligible as counterparts. For instance, according to the Finanical Stability Board, in the UK, counterparts of regulated funds are generally restricted to European banks, investment firms and insurers, US banks and US broker-dealers. In the US, mutual funds, MMFs and ETFs are generally required to approve counterparts, and cannot lend securities to affiliated counterparts unless they have express approval of the SEC.

[3] Transactions between banks and funds affiliated to the same FC accounted only for 0.4% of all of the transactions that happened in the market between January 2006 and February 2018.

overcoming the informational problems associated to making transactions with new (potentially risky) counterparts (see Furfine (1999); Cocco et al. (2009); Presbitero and Zazzaro (2011); Craig et al. (2015); López-Espinosa et al. (2016). However, there is little evidence as to why FCs would choose to engage in stable reciprocal lending relationships with a counterpart which is also its competition.

This paper examines the reciprocal lending between Financial Conglomerates in the repo market to better understand both what motivates powerful firms to engage in this type of contemporaneous cross-funding relationships, and, on the other hand, some of the implications that such reciprocal transactions may entail for the agents involved and for the market as a whole. In particular, in terms of the implications we focus on two dimensions: first, the potential effects that reciprocal lending has on the market power of FCs and the competitiveness of the repo market for mutual funds and second, the potential implications that frequent and stable reciprocal lending can have in terms of the industry's systemic risk.

Using transaction-level data, we construct a database consisting of fund-bank pairs at daily frequencies and compute a reciprocal lending dummy variable (which equals 1 if funds from a financial conglomerate provide liquidity to a bank from another financial conglomerate, and the transaction in the opposite direction occurs contemporaneously and zero otherwise) which we regress on traditional measures of strength and depth of existing relationship between funds and banks. Given that the decision on whether engaged in a one or two-sided transaction in the repo market are endogenous, alongside reverse causality problems, our general identification strategy consists of exploiting the panel structure of our data to control for observed and unobserved factors at the fund, financial conglomerate and time period levels. Further, we exploit exogenous variation in the data that is related to our reciprocity measures and use instrumental variables estimation techniques.

Our regression results indicate that reciprocal lending in the overnight repo market is positively associated with the strength and depth of the relationship between rival FC-affiliated banks and funds. We also find that funding costs between cross lending transactions are netting out which favors reciprocity in lending. In addition, we find that having a regular source of funding is important for banks and is associated with an increase in the probability to observe reciprocal lending transactions. These results are in line with previous literature according to which multiple interactions generate close ties between a lender and its borrower and might facilitate monitoring and screening (Petersen and Rajan, 1994), which in turns can mitigate problems of asymmetric information about the borrower's creditworthiness and agency costs (Brauning and Fecht, 2017).We also find that under a situation in which supply in the repo market is decreasing and demand is increasing banks rely, to a larger extent, on their established relationships in the overnight market. This suggests that the search costs for borrowers seems to be higher during periods when search frictions were present on the market. Even more, reciprocal lending relationships between banks and funds are preserved during periods when, in addition to search frictions, a higher degree of market uncertainty is present, whereby uncertainty about counterpart credit risk is higher.

Further, we shed light on the effects of reciprocal lending on three fronts: on the competition of investment funds at the repo market, on the importance of commercial banks vis-*à*-vis all other financial institutions in Mexico, and on an overall systemic risk index for the financial industry. First, we construct a lerner index at the fund-level and tailored to the repo market. Second, we construct a proxy at the bank-level for their contribution to systemic risk. For this, we follow a network-based approach and exploit in detail the contagion matrix between all financial institution in all markets, including the repo market. Finally, we construct a proxy for the systemic risk of the Mexican financial industry using market-based data. For all three cases we study their relationship with reciprocal lending metrics.

We find evidence according to which higher levels of reciprocal lending between financial conglomerates increases metrics of concentration for funds as repo liquidity providers. Moreover, that reciprocal lending increases the market power, at the repo market, of those funds. From the perspective of commercial banks, reciprocal lending also increases their importance compared to all other financial institutions in Mexico. Finally, we show that some reciprocal lending metrics increase a system-wide metric of systemic risk, but we also show that some other metrics decrease systemic risk. In particular, we show that metrics associated to the intensity, or strength, of reciprocal lending in the past increase systemic risk, but the opposite occurs with metrics on how dependent financial conglomerates are between them. This has interesting implications for policy makers.

This paper contributes to a strand of literature that studies relationship lending (or relationship banking) according to which financial institutions develop close relationships with borrowers over time (Furfine, 1999; Cocco et al., 2009; Presbitero and Zazzaro, 2011; Craig et al., 2015; López-Espinosa et al., 2016). The importance of close and stable relationships between a lender and a borrower has been widely documented by this literature from both theoretical and empirical perspectives. Boot (2000) provides a comprehensive survey. The main rationale for such a phenomenon is that relationship lending helps to circumvent asymmetric information problems as long as the borrower is the informed part about its own creditworthiness whereas the lender faces adverse selection problems. Therefore, by investing in long-term relationships through repeated interactions with a particular borrower, the lender acquires valuable private information about the borrower, reduces the costs associated to screening and monitoring (Boot, 2000; Brauning and Fecht, 2017), and can benefit from the success of the borrower by charging higher tariffs than a bank that is transaction-oriented (Boot, 2000). Frequent interactions need not happen always through the same channel, as transactions with multiple products has also been taken as an indicator of the strength of bilateral relationships between institutions (Petersen and Rajan, 1994; Furfine, 1999; Brauning and Fecht, 2017). This literature focuses mainly on the relationships between banks and firms, even though their findings can be extended to cases in which banks relate to other financial institutions as lenders or as borrowers (or both). Indeed, Cocco et al. (2009) through a transaction based analysis established that interbank relationships are an important determinant of their ability to access funds, and of the amount of liquidity available in the market. In this paper we particularly study reciprocal lending between rival FC-affiliated banks and funds, where funds are limited by regulation to act as a lenders while banks play as lenders or borrowers in the repo market. So that, we study relationships of a different nature happening in a short-term liquidity market.

In the analysis of the economic implications of reciprocal relationships in lending markets between financial institutions, our paper closely relates to Han and Nikolaou (2016), Brauning and Fecht (2017) and Li (2018). The former studies empirically analyzes the formation and the role of relationships in the Tri-party Repo market, an OTC, secured, funding market. Their results are in line with previous theoretical and empirical literature in unsecured OTC markets, found that relationships helped to reduce search frictions, as stable partnerships can be formed among counterparts with opposite liquidity needs, a process which would lead to an increased tolerance against liquidity shocks. However, their focus is not on reciprocal relationships and not they provide empirical evidence on the effects of that trading mechanism. Brauning and Fecht (2017) study relationship lending in the inter-bank market. Even though their main focus is not to explain reciprocity between a pair of banks, they account for the two-sided nature of interbank relationships by including measures of reciprocity between a pair of banks in their in their analysis. Our empirical exercises include measures of reciprocity that are along the lines of those used by Brauning and Fecht (2017). However, unlike Brauning and Fecht (2017), our focus is on the effects of reciprocal lending relationships between funds and banks of rival FCs on the stability of the financial system and the competitiveness of the mutual fund sector. Li (2018) provides empirical evidence on what she calls "cross-market relationship lending" between banks and prime money market funds (MMFs). Banks and MMFs appear to be circumventing the tight post-crisis regulations by establishing "bundling" arrangements between them that include multiple markets and financial products of both short- and long-term. Her focus is on two funding markets: the certificates of deposits market and the Eurodollar time deposit market. Unlike Li (2018), we are mainly interested in short-term funding relationships that take place in the repo market, and consider a different kind of reciprocity between pairs.

This paper is also related to the literature about determinants of systemic risk. Commercial banks have been extensively studied and several papers have explored the role of size, market power, VaR, leverage, and maturity mismatch (Anginer et al., 2014; Black et al., 2016; Irresberger et al., 2017; Laeven et al., 2016; Varotto and Zhao, 2018; Buch et al., 2019), their dependence on short-term wholesale funding (Karim et al., 2013; Lopez-Espinosa et al., 2013; Mayordomo et al., 2014; Moore and Zhou, 2013), the relevance of non-interest rate income (De Jonghe, 2010; De Jonghe et al., 2015; Bostandzic and Weiβ, 2018; Kamani, Forthcoming), and interconnectedness (Markose et al., 2012; Battiston et al., 2012). Likewise, commercial banks in this paper play a major role as they are the most important financial institution at the financial conglomerate, and consequently whatever happens to them will also affect the latter. The main difference with this strand of literature is that we explore the relationship between banks and funds from rival financial conglomerates, and argue that reciprocal lending at the short-term collateralized money market could have a direct effect on the systemic risk.

In particular, this paper is related to the topic of interconnectedness and systemic risk. Interconnections between financial institutions is an important channel for the propagation of shocks (Allen and Gale, 2000; Gorton and Metrick, 2012; Giglio, 2016), but the relationship with systemic risk is not unambiguously positive as its marginal effect depends on the current level of interconnection (Acemoglu et al., 2015). Different papers have found evidence of a relationship (Tasca et al., 2017; Cai et al., 2018; Roukny et al., 2018; Kanno, Forthcoming) but is difficult to draw broad conclusions as empirical approaches differ. Our paper is the first to evaluate the relationship of reciprocal lending, their strength and depth, and systemic risk. Interestingly, we find that if reciprocal relationships are strong and stable in time for both FCs, then the financial system could gain stability and systemic risk decreases.

A small set of papers study the relationship between non-bank financial institutions and systemic risk. We know regular banks differ from non-bank financial institutions[4] in several aspects of their balance sheet (Hancock and Passmore, 2015; Harutyunyan et al., 2015), and that some of them are relevant liquidity providers to commercial and universal banks (Kodres, 2015; Cañon and Pardo, 2018). Some papers have explored the role of liquidity mismatch, dynamic trading and arbitrage strategies, higher levels of returns, leverage, network structure (Pellegrini et al., 2017; Fung et al., 2008; Hwang et al., 2017; Kanno, 2016), and others have compared the contribution of these types of financial institutions to traditional banks (Adams et al., 2011; Boyson et al., 2010; Bernal et al., 2014) and show the latter are the most important contributor to systemic risk. The main contribution of this paper is that reciprocal lending between financial conglomerates is a funding strategy that partly restores the financial synergies at the group level

[4] These institutions are also categorized as shadow banks and there are several paper just discussing their classification, see (Pozsar, 2008; Pozsar et al., 2012).

(Luciano and Wihlborg, 2018), that are constrained by the regulation which limits the exposures of financial institutions belonging to the same financial conglomerate, but that also shapes the systemic risk.

Finally, this paper also relates to a strand of literature that studies funds affiliated to financial conglomerates (Ritter and Zhang, 2007; Massa and Rehman, 2008; Golez and Marin, 2015; Brief, 2017); and, from a broader perspective, our paper relates to a vast literature that studies the economics of the mutual fund industry (see, for example, Sirri and Tufano (1998); Hortacsu and Syverson (2004); Stein (2005), and many others).

The remaining of the paper is organized as follows. Section 2 presents in detail the role of commercial banks and investment funds in the Repo market, as well as characterize reciprocal lending at the Mexican Repo market. Section 3 describes the empirical strategy including a discussion of our identification approach. Section 4 explores the determinants of reciprocal lending. Section 5 studies the effect of reciprocal lending and competition for investment funds at the Repo market. Section 6 studies the effect of reciprocal lending on the contribution of commercial banks to systemic risk, and on an overall metric of systemic risk. Finally, Section 7 concludes.

2 The fund industry: preliminary evidence

2.1 Organization of the Mexican mutual fund industry

At year-end 2015, the mutual fund asset management companies managed US$ 114 billion through 587 mutual funds, with a little more than two million contracts divided between 28 asset managers in operation. The total assets held by all funds combined amounted to 0.65% of United States mutual funds' total assets in 2015. Mexico is the second Latin American country in terms of net assets held by funds, after Brazil which has total assets of 4.8% of total US mutual funds' assets (ICI, 2017). Most funds are multi-class funds which means there are a number of share classes under the same fund that offer the same portfolio, but differ in their pricing and redemption schemes. By 2017, there were 33 asset managers in charge of 521 mutual funds and 3521 share classes (see Table 2), which means that investors had a large set of choices including a variety of portfolios, fees and redemption rates in a fairly competitive market.

By contrast, the market for asset managers seems to be concentrated in a few firms that belong to large FCs. Table 1 presents a set of characteristics of assets under management by asset managers by the end of 2015 in Mexico. Even though the Herfindahl-Hirshman index (HHI) indicates that the market was competitive according to the US Department of Justice thresholds,[5]

[5] The HHI is a widely accepted measure of market concentration. It is calculated as the sum of the squares of the individual firms' market shares. It ranges between near zero and 10,000. The US Department of Justice interprets

other measures of concentration indicate the market was rather concentrated. In effect, according to concentration ratios, the leading three asset managers concentrated 56.4% of the total assets in the market, and the leading five accounted for 70% of the total assets held by investment funds. All five belong to large FCs that also own commercial banks. Moreover, there is a considerable dispersion in assets managed by different operators. The seventy-fifth percentile asset manager had 14 times more assets under management than the twenty-fifth percentile asset manager. The dispersion is higher if we compare assets of the ninetieth percentile manager and the tenth percentile manager: the former had 66 times more assets than the latter (see Table 1).

Table 1. Characteristics of the investment funds' asset management sector, end of 2015

This table reports summary statistics related to asset values, market concentration and dispersion of assets under management in Mexico by the end of 2015. The row *Financial conglomerate* (= 1 *if yes*) corresponds to a dummy that takes the value of one whenever an asset manager belongs to a Financial Conglomerate; HHI stands for the Herfindahl-Hirshman index; $C5$ corresponds to the concentration ratio, calculated as the total assets of the five largest asset managers, divided by the value of the total assets in the market; $C1$ and $C3$ correspond to concentration ratios for the largest and the three largest asset managers, respectively. The row 75th to 25th percentile ratio is calculated as the asset value of the asset manager in the 75th percentile, divided by the assets of the asset manager in the 25th percentile; 90th to 10th percentile ratio is calculated as the asset value of the asset manager in the 90th percentile, divided by the assets of the asset manager in the 10th percentile.

Variable	Statistic
Number of asset managers (AMs)	28
Assets: summary statistics (Million dollar)	
Min	0.15
Mean	3,957
Median	1,140
Standard Deviation	6,668
Max	27,906
Market concentration	
Financial conglomerate (=1 if yes)	0.57
HHI	1,335
C1	25.18
C3	56.43
C5	69.82
Dispersion of assets under management	
Coefficient of variation	168.50
75th to 25th percentile ratio	14.14
90th to 10th percentile ratio	66.27

Source: Banco de México. Authors' calculations.

Table 2 shows the ownership structure of the leading asset management companies, the number of funds and fund classes they manage and their share of assets under management on the total

the HHI as follows: if HHI< 1500, the market is considered to be unconcentrated; if 1500 ⩽ HHI < 2500, the market is considered to be moderately concentrated; finally, if HHI⩾ 2500 then the market is considered to be highly concentrated (see USDOJ (2010)).

mutual fund assets. Seven of the leading AMs are owned by the largest FCs of Mexico which are also owners of large commercial banks. These FCs are part of the so-called Group of seven or G7 and concentrate a significant share of the fund sector: they manage 52% of the total funds available with a combined share of 77% of total fund assets.

Table 2. Mexican Investment Funds Industry and Asset Management companies in 2017

The table reports characteristics of Mexican asset managers (AM) ordered by their share of assets under management (AUM) at year-end 2017. The first two columns show the ownership structure of asset managers: whether they belong to a financial conglomerate (FC) or not and whether they are part of the group of seven (G7) or not. The G7 group is composed by Banamex, BBVA Bancomer, Banco Santander Mexico, Banorte, HSBC Mexico, Scotiabank Inverlat and Banco Inbursa. The columns labeled as "Number of funds" and "Number of fund classes" show the number of funds and fund classes managed by each AM. The column "Share on total AUM" shows the percentage share of assets under management of that particular AM on the total value of assets in the fund industry in Mexico.

	Ownership		Number of	Number of	Share on
Asset manager ID	FC (=1 if Yes)	G7 (=1 if Yes)	funds	fund classes	total AUM (%)
1	1	1	53	315	24
2	1	1	59	463	20
3	1	1	65	306	12
14	1	0	36	217	7
5	1	1	9	29	6
11	1	1	29	301	6
8	1	1	34	358	5
23	0	0	37	161	4
4	1	1	20	101	4
21	0	0	35	389	2
24	0	0	12	131	1
Other	—	0	132	750	8

Source: Banco de México. Authors' calculations.

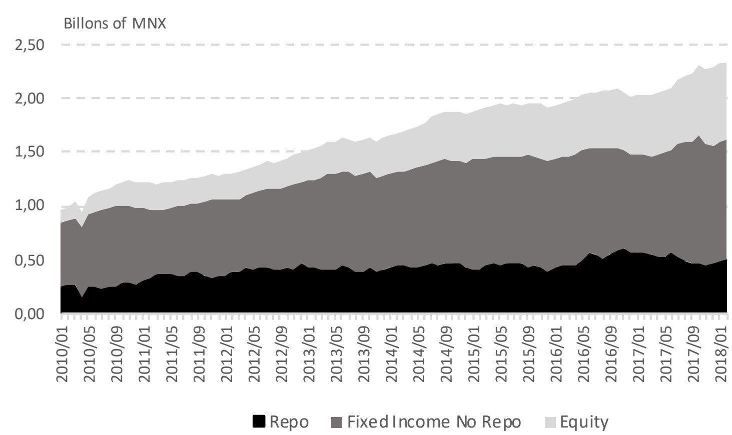
2.2 Preliminary evidence on fund-bank repo transactions

We use transaction level data reported by commercial banks, development banks and brokerage houses to the Mexican central bank every day from January 2006 through February 2018. These data contains detailed information of all of the repo transactions performed by these institutions including the identity of the two parties involved in the transaction, the collateral, the interest rate, the haircuts, etc. In our data, we observe a total of 666.796 transactions performed between commercial banks and mutual funds in 3,040 trading days.

In Mexico, the repo market is regulated by the central bank and, according to this regulation, only banks and brokerage houses are able to perform repo transactions; these institutions act, hence, as the cash borrower (security seller or collateral provider). On the other hand, investment funds, pension funds, firms, treasuries, individuals, state, quasi-state and municipal governments, authorities (e.g., Banco de México), foreign financial institutions, and other financial institutions (e.g., insurance companies) act as the cash lender (security buyer or collateral receiver) and perform reverse repo transactions (López et al., 2017). In particular, according to the Mexican regulation, funds can only provide liquidity at the repo market. Therefore, Mexican asset managers (AMs) actively provide short-term liquidity to banks and brokerage houses at the repo market and, in particular, represent and important source to commercial banks. Figure 1 shows that the (portfolio) share of repo funding is non-negligible and fluctuates historically around 20%.

Figure 1. Funds portfolio by investment type

This figure shows the evolution of funds portfolio investment by type. The portfolio value is given in billions of pesos (MXN). Series correspond to monthly values from January 2010 to February 2018.



Source: Banco de Mexico. Authors' calculations.

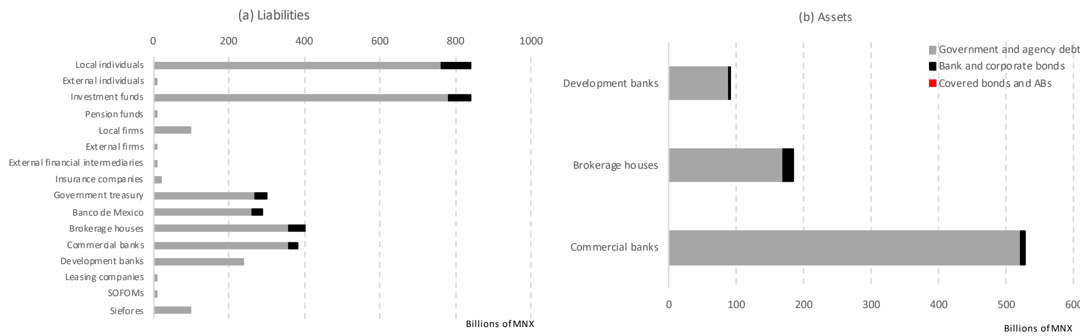
While funds can only supply liquidity through this market, commercial banks, development banks and brokerage houses can do both demand and supply liquidity at the repo. Figure 2 shows that at the asset side, commercial banks mainly lend to other commercial banks and, to a small extent, to brokerage firms.[6] On the liability side, their two main repo funding sources are local (largely non-financial) firms, that use repo market as a mean to obtain extra earnings with cash holdings, and AMs, a heterogeneous group of financial institutions usually affiliated to a FCs, that use that market to acquire liquid set of collaterals and securing earning with cash holdings. By and large, commercial banks use and receive sovereign debt as collateral in repo transactions. Figure 2 also shows that other asset classes, such as corporate bonds, represent a small fraction of the total volume attached to commercial banks.

Even though funds have historically been an important source of funding for commercial banks,

[6] They also lend a small fraction to development banks.

Figure 2. Banks' repo activity by counterpart and collateral type, 2017

This figure shows the asset and liability side of the Bank's balance repo activity. The cash borrower (security seller) is said to perform a repo transaction, whereas the cash lender (security buyer) performs a reverse repo. A repo transaction is a sale that is treated in the books like a loan. The security seller keeps the security on its books, adds the cash received to its assets, and adds a loan to its liabilities.



Source: Banco de México. Authors' calculations.

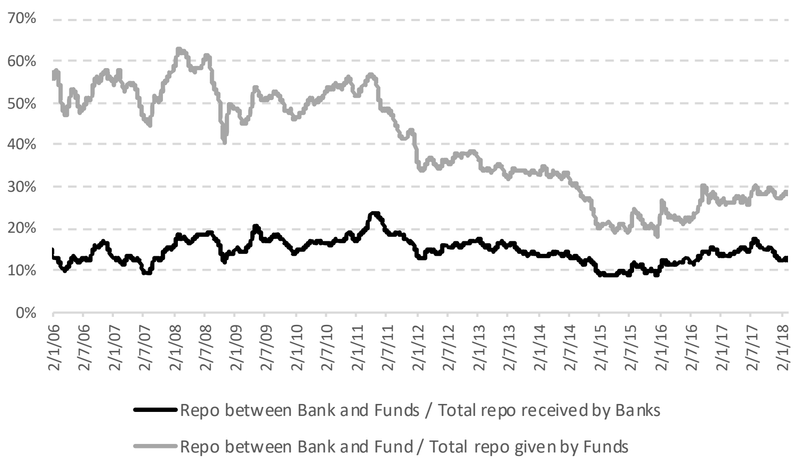
recently, these banks have reduced their dependence on them. Figure 3 presents the relevance of funds to commercial banks and viceversa. We observe that until 2011 banks usually obtained half of their repo funding from funds, this dependence decreased by late 2015 to around 20% and since then it increased again near 30%. On the other hand, commercial banks have always absorbed 10% to 20% of the total repo lending provided by funds. During the financial crisis we did not observe different funding patterns. López et al. (2017) show that the Mexican repo market was resilient during the last financial crisis, the haircuts, rates and volume remained stable even during the worst moments of the crisis.

The total repo funding received by commercial banks, discriminating G7 banks from the other institutions,[7] have evolved as shown in Figure 4. In 2006, G7 banks funded 5.5% of their total claims choosing G7 funds as their most important type of counterpart, closely followed by other institutions with 3.7%. However, at the end of the period it increased to near 6.5%, while the share of repo funding received from other institutions consistently grew since 2006 reaching 15.5% (as the blue line shows on the right panel). Particularly, the share of total claims financed inside G7 increased until 2011, showing a drop until the end of 2015 and a rapid increase at the end of the period (as the black line in both panels show). However, the blue line on the left panel which represents the total repo funding received by banks from funds, shows a totally different pattern, suggesting that the eligible counterparties for investment funds in Mexico can only be banks and brokerage firms, G7 banks mainly funded through asset managers inside G7; this is, using the fund management branches of other major FC in Mexico. This suggests that most securities lending

[7] Other institutions include development banks, brokerage firms, legal persons, legal entities, commercial banks and asset managers different from G7, and other institutions.

Figure 3. Dynamic of the share of funds and banks in the Repo market.

This figure shows the evolution of the liquidity provision ratio in the repo market for banks and funds. Series correspond to one month moving average values. The dataset covers the period from January 2, 2006 to February 8, 2018.

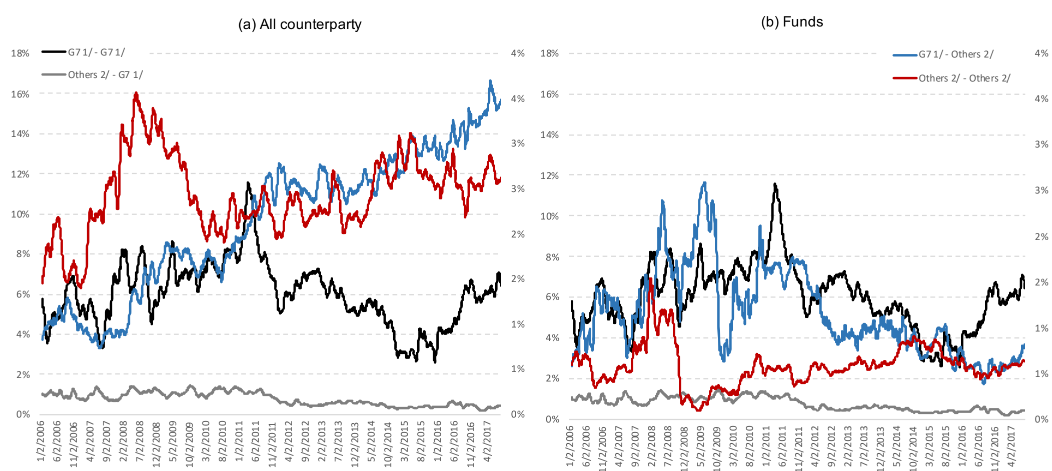


Source: Banco de México. Authors' calculations.

transactions happened between FC affiliated both banks and investment funds.

Figure 4. Total Repo funding received by commercial banks

The graph on the left shows the evolution of the Repo funding received by commercial banks from all type of counterpart; whereas the right graph show the funding received only from mutal fund companies. Graphs on this figure are double Y axis. On the right axis we measure lines black and grey, whereas on the left axis we measure the blue and red lines. In the legend, the institution on the right side is the collateral provider and the one on the left side is the receiver. The dataset covers the period from January 1, 2006 to February 8, 2018.



Source: Banco de Mexico. Authors' calculations.

Figure 5 present metrics of the liquidity provided by funds to commercial banks. The top-left panel shows a sharp increase in the volume of money lent by funds to banks during the Global Financial Crisis and until the first quarter 2011, a decline until the beginning of 2015 and a subsequent increase to pre-2015 levels. The top-right panel shows that the vast majority of transactions are overnight and that during the Global Financial Crisis and the initial phases of the European sovereign debt crisis (2010-2011), the average maturity increased. The middle panel shows the evolution of prices of the repo transactions. We observe expected levels of stress during the Global Financial Crisis; while haircuts fluctuate around zero and present abnormal volatility during the Crisis; the repo rate is always very close to the policy rate, except during periods of stress in which the spread becomes negative.The bottom left panel shows the evolution of the number of banks' trading counterparties in repo market, and the right panel the same thing but for funds. In the case of banks, we observe an increasing trend from the beginning of the period that reaches its maximum level by the end of 2009 and showing a decreasing trend after that; whereas in the case of funds we observe that the number of counterparties is rather stable over time being on average equal 1.5. Moreover, banks have considerably more counterparties than funds, which is due to the fact that commercial banks demand liquidity from a larger set of institutions while funds can only supply liquidity to a reduced set of counterparties.

The fewer number of counterparties for funds suggests that relationships between banks and funds are persistent over time. In fact, Figure 6 shows that the probability of observing a transaction between a given fund-bank pair at t when a transaction between them occurred at *t-1* is higher than 70% in the whole period and it is about 90% from 2008 on, which confirms the persistence in the fund-bank relationships in the repo market.

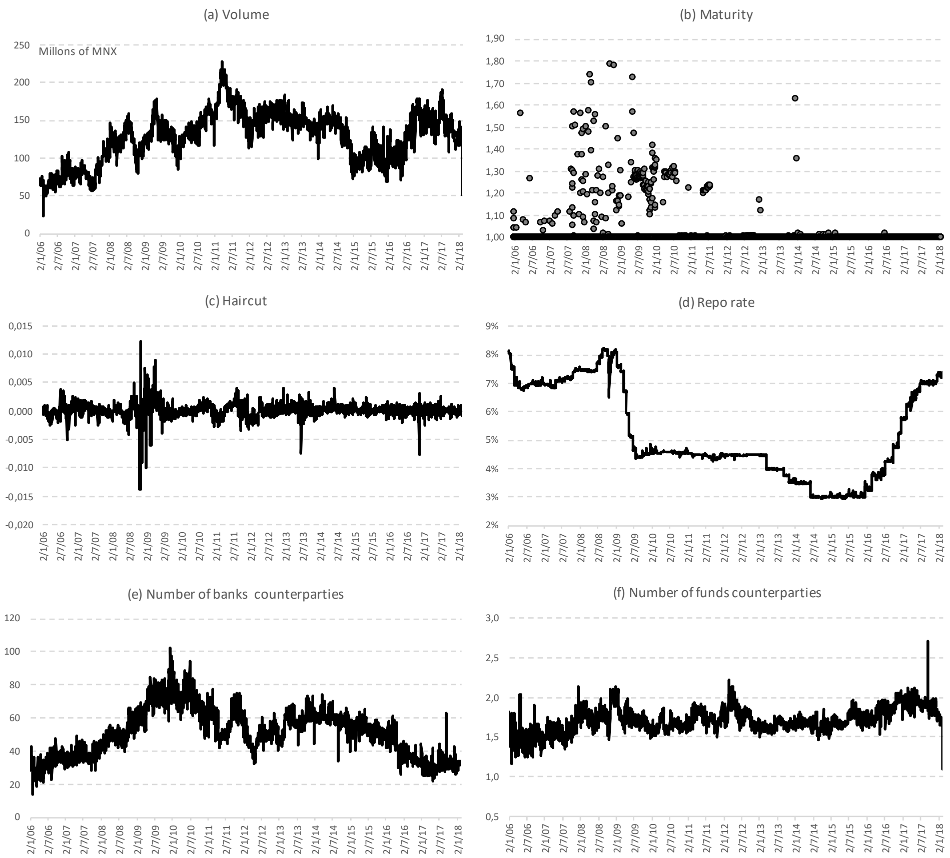
2.3 Descriptive evidence on reciprocal lending between financial conglomerates

As we alredy mention, we define reciprocal lending relationships in the broadest possible sense as all repo transactions between FC affiliated banks and funds in which the latter provide liquidity to a bank owned by a rival FC, and viceversa. This implies that we will only consider as reciprocal lending relationships the set of transactions between FC-affiliated pairs that are two-sided in nature. Figure 7 offers an illustration to this point. It is important to note that these two way transactions need not happen simultaneously (i.e., in the same day) but can happen in different days. We initially consider as reciprocal all of the transactions between banks and funds that belong to rival FCs taking place either contemporaneously or within the following two days. However, more than 90% of the reciprocal transactions over the observation period happened on the same day, reason why we restrict our definition to only contemporaneous transactions.

Figure 8, shows the historical evolution of the reciprocal lending in terms of trading volume

Figure 5. Characteristics of lending provided by asset managers to commercial banks

The graph on the top left shows the evolution of the Repo trading volume betwee commercial banks and funds, middle left graph shows the corresponding haircuts and bottom left shows the daily average number of banks counterparties. The top right graph shows the maturity of the repo transactions, middle right graph shows the repo rate and finally the bottom right shows the daily average number of funds counterparties. The dataset covers the period from January 2, 2006 to February 8, 2018.

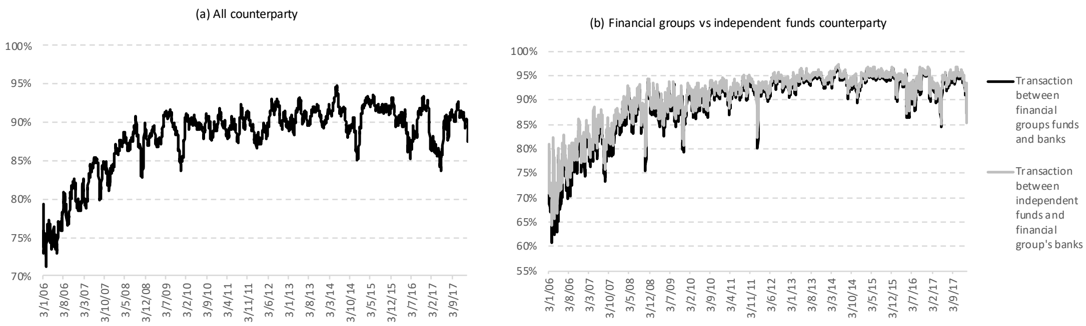


Source: Banco de Mexico. Authors' calculations.

and number of transactions in relative terms. The top panel presents the evolution of the number of loans of both types: one-sided (bilateral) lending and reciprocal lending. The figure shows that there is a considerable number of reciprocal transactions that take place at each day. Compared to the one-sided transactions, the number of reciprocal loans is similar until the end of 2011, however after that on most days the number of reciprocal loans exceeds the one-sided transactions. On the other hand, the bottom panel shows the daily proportion of reciprocal funding transactions between 2006 and 2018. The number of reciprocal funding transactions decreased during the years of the financial crisis and show an increased after 2012, reaching the 50% of the daily transactions in 2018. Moreover, reciprocal lending in terms of trading volume reached values ranging from 15% to 70% with a mean value over the period equal to 42,5%.

Figure 6. Probability of persistence for the repo transactions between banks and funds

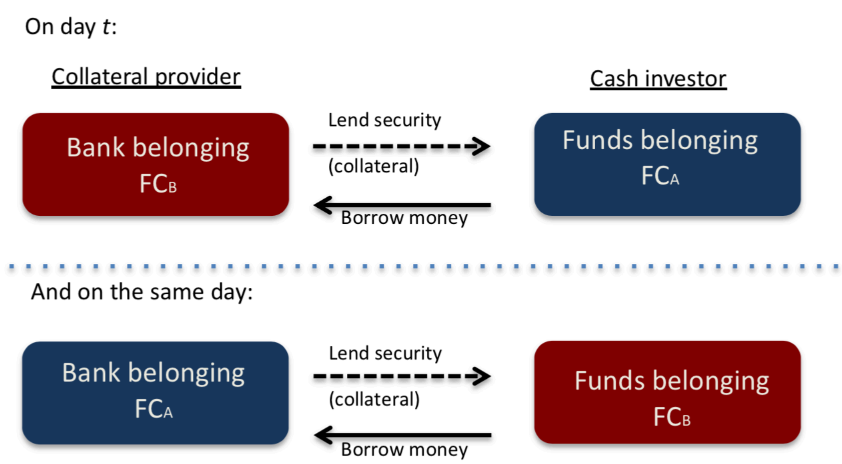
In panel (a) this figure depicts the probability that a transaction observed period *t-1* is observed also *t* for all counterpart. Panel (b) shows the same probability but distinguish between funds part of a financial group from independent funds. The dataset covers the period from January 1, 2006 to February 8, 2018.



Source: Banco de Mexico. Authors' calculations.

Figure 7. Reciprocal lending transactions

This diagram describes the reciprocal lending activity between Funds and banks in Repo Mexican market. The cross lending involves two bilateral repo transactions and the diagram only shows what happen in the opening leg of the repo. In the closing leg these flows are reversed, the cash investor returns the securities to the collateral provider in exchange for cash.



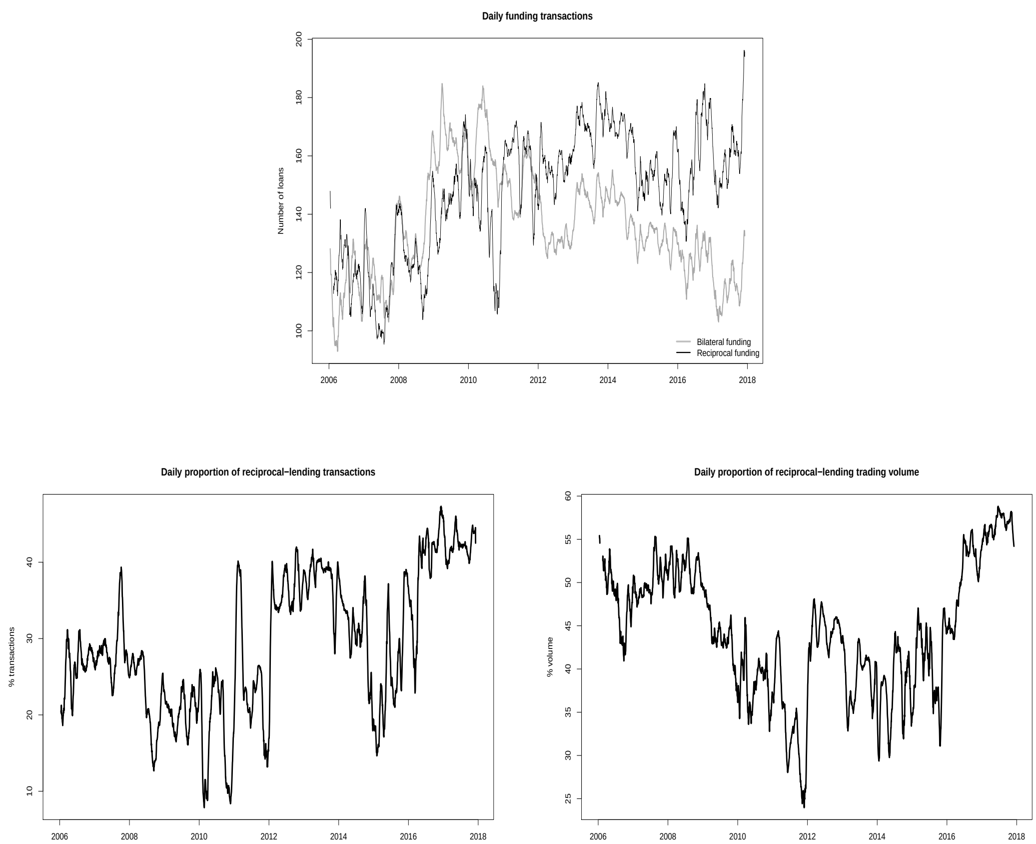
Source: Authors' diagram.

Table 3 shows that banks obtain short-term liquidity from funds that do not belong to their own FC. Only 1.5% of the transactions actually happened between a bank-fund pair belonging to the same financial conglomerate. Even though internal capital markets are not forbidden in Mexico, the National Banking and Securities Commission implemented some regulatory measures to discourage that AMs engage in repo transactions with commercial banks from the same FC.[8]

[8] Banks and brokerage houses are allowed to perform a repo transaction with entities of the same financial group,

Figure 8. Reciprocal lending activity

This figure depicts the 20-day moving average of daily total number of loans both one- and two-sided i.e., reciprocal (top), the 20-day moving average daily number of reciprocal lending transactions as a percentage of the total number of repo transactions (bottom-left) and the 20-day moving average daily total volume of money traded in reciprocal transactions as a percentage of the total volume lent in the repo market that day (bottom-right). The dataset covers the period from January 1, 2006 to February 8, 2018.



Source: Banco de Mexico. Authors' calculations.

Further, we can observe that the volume of transactions is not homogeneously distributed between FCs; in fact, on average 88.8% of the total cross-lending transactions observed between 2006 and 2018 is concentrated by the funds managed by the leading three FCs, and these funds provided liquidity mainly to the three biggest commercial banks in Mexico, which concentrated 81% of the total lending transactions between 2006 and 2018.

The previous evidence raises the following question: Why are reciprocal lending relationships so stable over time? A partial answer to this question is in the pricing of the reciprocal funding transactions. The left panel on Figure 9 presents the weighted average repo interest rate series

however the securities used as collateral for the repo must have the minimum rating from at least two rating agencies including: Standard and Poor's, Moody's and Fitch.

Table 3. Cross-lending between financial conglomerates

Table shows the transactions between banks-AMs pairs as percentage of the total cross-lending transaction in the Repo market, during the period 2006 - 2018.

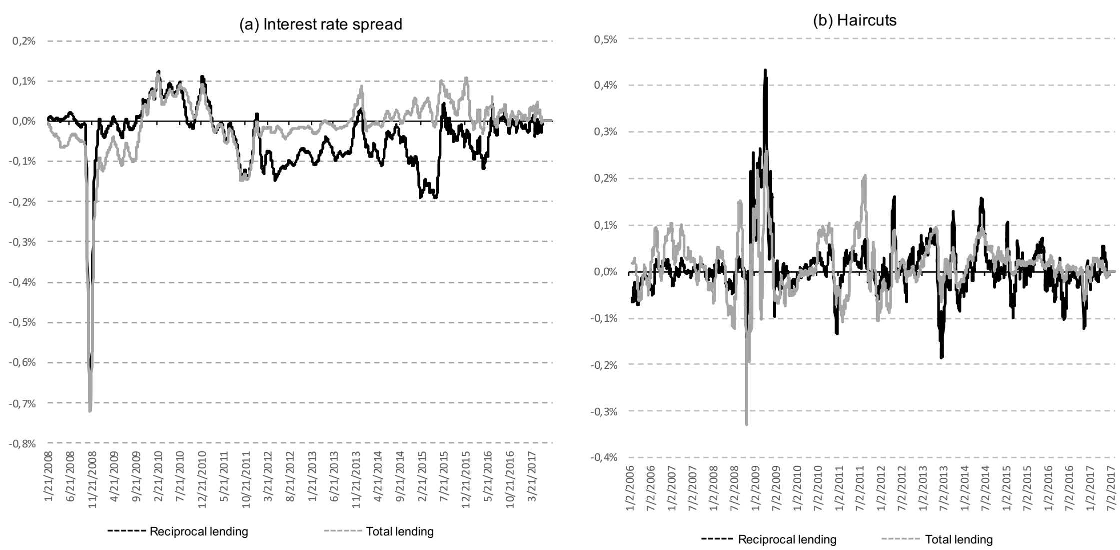
	AM1	AM8	AM2	Other	AM4	Other	Other	AM9	Other	AM3	AM11	Tot AMs
B1	1,5%		28,8%		1,6%	0,3%		1,8%			2,1%	36,0%
B8									1,7%	3,0%		4,8%
B2	10,6%	0,003%			0,1%					23,4%		34,1%
Other				0,05%								0,05%
B4	1,5%		0,1%							0,003%		1,6%
Other	1,8%											1,8%
Other											0,02%	0,02%
B9	0,7%											0,7%
Other		1,5%									0,1%	1,7%
B3		1,7%	9,2%		0,01%							10,9%
B11	8,1%						0,02%		0,3%			8,4%
Tot Banks	24,2%	3,2%	38,2%	0,02%	1,7%	0,3%	0,02%	1,8%	2,0%	26,4%	2,2%	

Source: Banco de México. Authors' calculations.

for two types of transactions: reciprocal lending and bilateral (one-sided) lending. We observe that by late 2011 reciprocal lending transactions were cheaper than the other type of transactions. Moreover, the right panel of Figure 9 presents the haircuts of but for types of transactions. In this case, the only clear difference is that reciprocal lending transaction haircuts are more volatile.

Figure 9. Average daily volume weigthed interest rate spreads and haircuts

In panel (a) this figure depicts the spread between the daily average daily volume weigthed interest rate and the repo rate. Panel (b) shows the daily average volume weigthed haircuts, for both reciprocal lending and total lending. The dataset covers the period from January 1, 2006 to February 8, 2018.



Source: Banco de Mexico. Authors' calculations.

To summarize, the evidence presented in this section suggests that bank-funds repo transactions are concentrated in a few agents which in most cases are affiliated to financial conglomerates. Moreover, during a considerable number of years we observe that funding costs between reciprocal lending transactions are netting out which is consistent with conventional wisdom according to which reciprocal lending is mutually beneficial for the parties involved if the funding conditions net out.

3 Empirical strategy

3.1 Variables of interest

Our main focus is on reciprocal lending transactions between banks and funds in the repo market. We account for reciprocal lending transactions by defining a set o variables that measure the number and the depth and strength of these relationships. In order to capture the former. we define a dummy variable that takes on the value one if we observe that two transactions from funds and banks affiliated to FCs took place contemporaneously and zero otherwise. We observe 196.734 reciprocal lending transactions which correspond to 30% of the total repo transactions between banks and funds over the period from January 1, 2006 to February 8, 2018. Concerning the latter, we construct two indexes along the lines of (Brauning and Fecht, 2017): a lender reciprocity index (LRI) which we compute as the sum of the amount of money that a fund affiliated to a FC i grants to a bank affiliated to a FC l plus the amount of money that a fund affiliated to FC l grants to a bank affiliated to FC i on day t divided by the overall amount of money lent by FC i's funds and FC l's funds on day t. Similarly, a borrower reciprocity index (BRI) which we compute as the amount of money borrowed by bank i from funds affiliated to FC l plus the amount of money borrowed by bank l from funds affiliated to FC i on day t, divided by the overall amount of money borrowed by bank i and bank l on day t.

Formally, the LRI and BRI are given by:

$$LRI_{ilt} = \frac{m_{ilt} + m_{lit}}{\sum_l m_{ilt} + \sum_i m_{lit}}, \qquad BRI_{ilt} = \frac{n_{ilt} + n_{lit}}{\sum_l n_{ilt} + \sum_i n_{lit}} \tag{1}$$

where m_{ilt} is the amount of money lent by funds affiliated to FC i to a bank affiliated to FC l on day t, m_{lit} is the amount of money lent by funds affiliated to FC l to a bank affiliated to FC i on day t; n_{ilt} is the amount of money borrowed by a bank affiliated to FC i from funds affiliated to FC l on day t; and n_{lit} is the amount of money borrowed by a bank affiliated to FC l from funds affiliated to FC i on day t. These variables measure the concentration (depth or dependence) of the lending and borrowing portfolios on the respective borrower and lender. We interpret a high lender reciprocity index as a concentrated credit risk exposure between the funds of the two financial conglomerates involved in the reciprocal funding relationship. As a consequence, funds can have better information about the creditworthiness of their closest borrower bank compared to spot borrowers. Similarly, we interpret a borrower reciprocity index (BRI) as a measure of a borrower's dependency on a particular lender, which in our case implies the interdependence between banks (borrowers) and funds (lenders) of a pair of financial conglomerates.

It is important to note that we also compute the BRI and LRI for those transactions in which we observe one-sided lending relationships; this is, if we observe that a fund lends money to any bank, whether it is affiliated to a FC or not (independent in this case), we compute the BRI and LRI to measure the degree of exposure of both institutions to one another. In this case, the numerator of the respective index in equation (1) will have one of the two components equal to zero.

In addition, we measure the strength (intensity) of the interactions (SI) between bank-fund pairs in the overnight market as the logarithm of one plus the total number of loans granted from lender i to borrower l (denoted by nl_{ilt}) and from lender l to borrower i (denoted by nl_{lit}) , over the last 22 trading days. We also measure the reciprocal interest rate spread which is defined as the bilateral interest rate (to the target rate) between lender i and borrower l minus the bilateral interest rate (to the target rate) between lender l and borrower i on day t. Analogously, we compute the reciprocal haircut spread as the difference between the haircut of the transaction between lender i and borrower l minus the haircut between lender l and borrower i on day t.

$$SI_{ilt} = \log(1 + \sum_{t}^{t-22} nl_{ilt} + nl_{lit}) \tag{2}$$

Table 4 reports summary statistics and pairwise correlations of the reciprocal cross-funding measures. All of the correlations are significant at the 1% level. The variables reported capture different aspects of the cross-funding activity between FC affiliated funds and banks. Our reciprocity indexes, LRI and BRI, are moderately related with a correlation coefficient of 0.44. The strength of the interactions is less correlated with the cross-funding concentration measures, with a correlation of 0.18 and 0.10 respectively. The mean spread between bilateral interest rates in a reciprocal lending relationship is equal to zero, which implies the possibility to net out the transactions, obtaining mutually beneficial funding costs, being advantageous compared to the system. The idea that cross-lending transactions are cheaper than off cross-lending ones is also suggested by the the reciprocal haircut spread.

We use the time dimension of the data to include in our models the interaction terms of our relationship variables with a dummy variable for periods with greater financial uncertainty. We construct two variables: one for the crisis period beginning on August 9, 2007 and finishing

Table 4. Reciprocal lending variables: summary statistics and pairwise correlations

The table reports the statistic summary for the reciprocal funds-bank relationship variables and their correlations. The dataset covers the period from January 1, 2006 to February 2, 2018.

Variable	Mean	Stand. dev	Min	Max	# Obs
LRI_{ilt}	0.27	0.22	0	1	666,796
BRI_{ilt}	0.28	0.22	0	1	666,796
SI_{ilt}	4.58	0.67	1.10	5.80	666,796
Variable	LRI_{ilt}	BRI_{ilt}	SI_{ilt}		
LRI_{ilt}	1				
BRI_{ilt}	0.44	1			
SI_{ilt}	0.19	0.07	1		

around June 2010 and other based on the Financial System Stress Index (IESF in Spanish), which equals one if on a given day the index is over their historical mean plus one standard deviation. Empirical evidence have shown that in periods characterized by higher uncertainty in the market private information about counterpart risk become more important for the allocation and pricing of liquidity. So that, a positive effect on reciprocal lending probability is an indication that reciprocal lending between banks and funds from different financial conglomerates indeed mitigates uncertainty about for example counterpart risk. López et al. (2017) provide evidence that shows that Mexican repo market was resilient during the recent financial crisis.

As control variables we consider fund conglomerate, bank and time fixed effects. Moreover, in our analysis we control for other time-varying borrower (bank), time-varying lender (FCs affiliated funds), and time-varying bank-fund pair lending transaction characteristics. A description of these variables and summary statistics are presented in Table B.1 and Table B.3 of the Appendix.

3.2 Identification

In this section we discuss the challenges we face in the identification of the coefficients related to our reciprocity measures and discuss our assumptions, the exogenous information we exploit as instrumental variables and their validity in the context of each of the models we specify.

Our general empirical strategy consists of testing several hypothesis with the help of the data described before and reduced-form models, one for each testable hypothesis we consider. In general, two main concerns to identification are common to all of our regressions: selection problems (derived from the fact the decision on whether engaged in a one or two-sided transaction in the repo market are endogenous) and reverse causality problems.

Our general identification strategy consists of exploiting the panel structure of our data to control for observed and unobserved factors at the fund, financial conglomerate and time period levels. Further, we exploit exogenous variation in the data that is related to our reciprocity measures and use instrumental variables estimation techniques. In particular, we observe, on a daily basis, detailed information of exposures of every major financial institution with any counterpart, irrespective of their nationality or residence. Specifically, we observe both assets and liabilities. Moreover, for each of these categories we can distinguish exposures associated to debt bond issued by Mexican financial institutions, from very short-term liquidity sources, and from exposure coming from derivatives, and other markets such as the repo. Of this information we use the number of foreign counterparts and the associated dollar volume of transactions with these counterparts for every bank as instrumental variables.

Our identification assumption is, therefore, that after controlling for observed and unobserved fund and financial conglomerate characteristics and market-level aggregate shocks, the exposure variables we use contain information about the liquidity requirements of Mexican banks, but are not correlated wiht the specific shocks of our regressions. In the corresponding section, we discuss in more detail which is the specific endogeneity problems associated to that estimation exercise and how we address it.

4 Why does FC-affiliated banks and funds establish reciprocal lending relationships?

In this section we explore the reasons why banks and funds both may have some incentives to develop a mutually beneficial relationship and trade with each other in the reciprocal manner we defined. Specifically, we analyze how reciprocal lending relationships affect the probability of a two-sided transaction occurring.

4.1 Close ties and cheap funding

Reciprocal cross-lending can be beneficial to funds and banks. According to Boot (2000), multiple interactions generate close ties between a lender and its borrower and might facilitate monitoring and screening, which in turns can mitigate problems of asymmetric information about the borrower's creditworthiness and agency costs. Counterpart risk is a key factor in the repo market as repo deals build on the trust in counterparties, so building close ties in repo market is of fundamental importance, even more because counterpart risk has significant impacts on repo spreads (Taylor (2009); Krishnamurthy (2010); Gorton and Andrew (2012)).

On the other hand, Petersen and Rajan (1994) show that a firm with close ties to its institutional creditor should have a greater availability of financing and lower cost of funding.

So that, we test whether reciprocal lending in the overnight market is positively associated with the strength and depth of the two-sided relationship between the FC-affiliated banks and funds.

H1: *Reciprocal lending is positively associated with the strength and depth of the relationship between banks and funds from rival financial conglomerates.*

To test this we define D_{ilt} as an observed binary variable, which takes on the value one if we observe that funds from a financial conglomerate (lender) i grants an overnight loan to bank from another financial conglomerate (borrower) l on day t and the reciprocal lending transaction occurs contemporaneously; and zero otherwise. We estimate a the following binary choice model,

$$D_{ilt} = I(X_{ilt}\beta + \epsilon_{ilt} \geq 0) \tag{3}$$

where $I(.)$ is an indicator function, X_{ilt} is a a vector of observed regressors, and β a corresponding coefficient vector, with ϵ_{ilt} an unobserved iid logistic error. The key explanatory variables in X_{ilt} are LRI_{ilt} and BRI_{ilt}, which measure the depth of the reciprocal lending relationship. A positive and significant coefficient indicates that a higher lender's (borrower's) dependency on a particular borrower (lender) leads to a higher probability for reciprocal cross-funding. As an alternative measures we consider SI_{ilt} which measure the strength of the interactions between bank-funds pairs. A high SI indicates higher number of reciprocal interactions between pairs.

In addition we test if this cross-lending is motivated by the possibility to have access lower cost of funding we consider as explanatory variables the reciprocal interest rate spread and the reciprocal haircut spread. We measure the reciprocal interest rate spread (Spr_{ilt}) as the bilateral interest rate (to the target rate) between lender i and borrower l minus the bilateral interest rate (to the target rate) between lender l and borrower i on day t. Analogously, we compute the reciprocal haircut spread ($Spr.h$) as the difference between the haircut of the transaction between lender i and borrower l minus the haircut between lender l and borrower i, on day t. Spreads near to zero indicate that funding costs between cross lending transactions are netting out, which should favours reciprocity in lending bank-funds pair transactions.

H2: *Reciprocal lending is positively associated with netting out pricing conditions*

Table 5, presents the estimation results considering different specifications and reporting results coming from maximum likelihood estimation and the second stage regression of the control function method. We include the total amount of the liabilities with foreign counterparts on three different categories: debt securities, repo and derivatives, and call money as instrumental variables. In addition we control for market level shocks and for fund and bank level shocks to identify the effect of relationship lending variables over the likelihood of reciprocal trading transactions.[9]

[9] In the proposed approach, the first stage regression involves a linear model of the relationship variables on the

We find that the estimated coefficient of the borrower reciprocity index and lender reciprocity index are both positive and highly significant across different models. This result indicates that the probability to engage in a reciprocal lending relationship increases with the concentration (depth) of borrowing/lending transactions. This result provides support for the view that banks mutually provide liquidity to each other, but through their affiliated funds. In addition, it is in line with previous literature according to which asymmetric information about borrower's creditworthiness is of main importance. Despite the convenience given by collateral, the primary concern in a repo should always be the creditworthiness of the counterpart. It is well known that the primary credit risk in a repo is on the seller, so that a good quality seller should be allowed to drive the decision to transact. In addition we find that an increase in the haircut spread of the cross-funding transaction implies a lower probability for a reciprocal lending relationship. This implies that cross funding conditions net out. In other words, banks that trade liquidity more frequently with a specific fund counterpart, trade at almost the same haircut rate.

To further explore the formation of reciprocal lending relationships we include variables that evaluate the stability of the relationship between bank-funds pairs. $Stab.f_{ilt}$ represents the dependence (in terms of stable or regular source of funding) of funds from a financial conglomerate i on bank l and $Stab.b_{ilt}$ represents the bank l dependence on funds from financial conglomerate i. These variables are measure as the total number of lending transactions between funds-bank pair at time t divided by total number of transactions of the firm during the last 22-days. Following Li (2018), we alternatively measure relative importance and bargaining power of fund i and bank l by counting the numbers of their counterparties on day t. We measure the number of counterparties with variables $counter.b_{it}$ and $counter.f_{it}$ as the number of number of funds(banks) who lend(borrow) to(from) bank(funds) l at time $t-1$ and the number of banks who borrow from fund i at time $t-1$, respectively. More funds or banks counterparties should be both negatively associated with reciprocal cross-funding.

Model (2) presents the specification when we also include stability and bargaining power variables. The dependence of a bank on a particular FC-affiliated funds in terms of funding is positive and statistically significant, which means that is more likely to establish a reciprocal lending relationship. This results appears to suggest that keep an stable relationship over time is important for borrowers, as frequent interactions on repo market seem to be crucial conduit for the liquidity that banks need. However, it is not the case from the point of view of FC-affiliated funds. These findings suggest that for funds is more important to concentrate their lending activity and hold a deeper relationship, than perform daily interactions with specific counterpart. Indeed,

instrumental variables, and the second stage regression is a logistic regression of the outcome on the reciprocal lending adjusting for the first stage residual. Results for the first-stage regression are not reported but they are available under request.

Table 5. Cheaper and stable funding relationship hypothesis

The table reports the estimated parameters of the logit model with endogenous regressors and the second stage regressions, and their corresponding standard errors in parentheses. In the case of control function results we report adjusted standard errors to the first-stage estimation error. The dependent variable is a dummy that equals one if funds from a financial conglomerate (lender) i grants an overnight interbank loan to bank from another financial conglomerate (borrower) j at day t, and zero otherwise. Control variables include pair-transaction characteristics, lender-specific characteristics, borrower-specific characteristics, aggregate Repo market conditions and aggregate market conditions, which are describe in TableB.1. In addition, fund and bank financial conglomerate and year fixed effects are considered. We are using transaction level daily data and the dataset covers the period from January 1, 2006 to February 28, 2018. The symbols *,**,*** denote significance at the 10%, 5% and 1% level, respectively. We use bootstrap to obtain corrected standard error in the control function approach.

	Logit					Control Function Approach				
Variable	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Constant	-8,97***	-8,64***	-8,48***	-7,85***	-23,85***	-105,29***	-116,20***	-104,05***	-116,36***	-15,43***
	(0,36)	(0,37)	(0,36)	(0,38)	(0,37)	(2,74)	(2,90)	(2,77)	(2,95)	(2,95)
LRI_{ilt}	13,89***	13,76***	13,35***	14,31***		294,67***	329,03***	291,67***	333,94***	
	(0,15)	(0,16)	(0,16)	(0,16)		(9,54)	(10,08)	(9,66)	(10,25)	
BRI_{ilt}	7,42***	7,43***	7,12***	7,45***		252,92***	275,91***	252,12***	274,07***	
	(0,14)	(0,15)	(0,15)	(0,15)		(4,74)	(5,02)	(4,80)	(5,09)	
SI_{ilt}					2,89***					2,74***
					(0,04)					(0,05)
$Spr.h_{ilt}$	-42,19***	-41,01***	-44,38***	-42,96***	-38,27***	-37,9***	-36,63***	-39,81***	-38,55***	-44,16***
	(2,46)	(2,41)	(2,51)	(2,46)	(2,14)	(2,48)	(2,43)	(2,53)	(2,48)	(2,52)
$Stab.b_{lit}$		5,96***		5,85***	5,84***		6.41***		6.28***	5.95***
		(0,09)		(0,09)	(0,08)		(0,09)		(0,09)	(0,09)
$Stab.f_{lit}$		-1,08***		-1,20***	-0,22**		-0,67***		-0,80***	-1,24***
		(0,07)		(0,07)	(0,07)		(0,07)		(0,07)	(0,07)
$SI_{ilt} \times d.u_t$					-0,45***					-0,29***
					(0,03)					(0,03)
$LRI_{ilt} \times d.u_t$			-7,71***	-4,67***				-9,42***	-6,19***	
			(0,64)	(0,67)				(0,65)	(0,69)	
$BRI_{ilt} \times d.u_t$			14,08***	-2,49**				15,65***	1,58	
			(0,78)	(0,92)				(0,80)	(0,97)	
$Spr.h_{ilt} \times d.u_t$			127,11***	112,10***	95,63***			115,45***	118,79***	109,39***
			(19,36)	(19,72)	(23,03)			(19,73)	(20,21)	(23,54)
$Stab.b_{ilt} \times d.u_t$				6,17***	6,81***				5,60***	6,37***
				(0,19)	(0,28)				(0,22)	(0,28)
$Stab.f_{ilt} \times d.u_t$				-0,93**	0.05				-1,68***	0,33
				(0,29)	(0,44)				(0,39)	(0,21)
# Obs	414163	414163	414163	414163	414163	414163	414163	414163	414163	414163
$AdjR^2$	0,8206	0,8215	0,8302	0,8328	0,7782	0,8108	0,8116	0,8200	0,8235	0,7782
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Banco de México. Authors' calculations.

empirical evidence shows that on average a fund trades with 1.5 banks daily, while banks trades with minimum 20 funds. With respect to bargaining power variables, they are both statistically and economically significant. Thus more bank or funds counterparties are both associated with less probability to engage in a reciprocal lending relationship.

In order to assess whether bank-funds pair relationships were more important during periods when uncertainty was presumably elevated we include in our model interaction terms of our relationship variables with the dummy variables for periods of higher uncertainty described before, denoted $d.u_t$. If the interaction term with relationship variables has a positive effect on the reciprocal cross-funding probability, these results would be further indications that reciprocal relationship lending indeed mitigates uncertainty about counterpart risk. Models (3) and (4) in Table 5 present the results. The coefficient of the interaction terms are significantly different from zero. Thus, we find evidence that during the crisis period reciprocal lending relationships depend on the the concentration (depth) of borrowing/lending transactions. In particular, during times of elevated uncertainty banks rely on frequent and stable relationships. However, funds were less likely to privilege their habitual borrowers concentrating even more their credit risk exposure with them. Also, during the crisis or higher uncertainty periods the probability of reciprocal lending relationship increases even though haircuts spread increases. While in calm periods lower spread margins requirements favor reciprocal lending relationships. Gorton and Andrew (2012) show evidence for increased haircuts during the 2007-09 crisis, which increased borrowing costs and made access to credit harder. This suggest that during higher uncertainty periods the pricing strategy of reciprocal lending transactions change, turning to be less advantageous for both of them, however this not a hurdle to cross-funding between FCs.

We repeat the exercise considering variable $SI_{i,j,t}$ as substitute relationship variable that measure the strength of the relationship and report regression results in Model (5). Regression results including SI variable are similar to those of the baseline model. In fact, this relationship measure is positively associated with the probability to reciprocal lending and significant at the 1% level. This suggest that a stronger dependence between banks and funds, not only in terms of amount of short-term funding but in the number of transactions over time as well, actually makes reciprocal lending more likely.

Comparing the results in which we did not use instruments for the relationship metrics with those coming from the control function approach in Table 5 emerged interesting results. First, the level of significance of all variables and their signs remain essentially unchanged once we control for the endogeneity of relationships. However, the magnitude of the estimated coefficients shows an considerable change in some cases. In particular, the coefficients on BRI and LRI variables greatly increased, while for the SI there is a mild variation in the magnitude of the estimated coefficient. This result suggests that the endogeneity problem, in general, does not affect the inference regarding the causal link between relationship variables and reciprocal lending.

4.2 Mitigating search frictions

We hypothesized that reciprocal cross-funding relationships may have a positive effect on mitigating problems associated with costly counterpart search. Previous literature suggest that search frictions affect the bargaining and negotiation in the repo market, having an impact on assets prices (Duffie et al. (2002)). An increase in the number of sellers (borrowers) and a reduction in the number of buyers (lenders), lead the price drops in part because of the higher fraction of assets held by distressed traders, but importantly, also by the worsened bargaining position of sellers (Duffie et al. (2007)). Empirical results in the interbank lending market suggest that when market is tight it is more difficult to find a new counterpart, hence, the search cost for borrowers is high, and banks may rely on their established relationships in the overnight market to a larger extent (Brauning and Fecht (2017)). Therefore, established reciprocal credit relations could have a substantial impact on mitigating that frictions.

H3: *Reciprocal lending mitigates search frictions for banks.*

To test this hypothesis, we use the same specification than before but now we consider a measure for market tightness. Following Brauning and Fecht (2017) and Bech and Monnet (2016) we compute the number of lenders divided by number of borrowers participating in the repo market on day t. We compute the dummy variable $Tight.d_t$, which equals one if the day is in the lowest quantile of the distribution of the Market tight, and is zero otherwise. In addition, we use the total number of daily loan transactions between funds and banks $Trans_t$ and analogously construct the dummy variable $Trans.d_t$. We thus include the interaction terms relationship variables with a proxy for periods of high search frictions. A positive coefficient for the BRI interaction term means that when search cost for borrowers is high, banks may rely on their established relationships in the overnight market to a larger extent.

The regression results are presented in Table 6. Model (1) confirms the above-mentioned empirical prediction. As we expected the likelihood of reciprocal lending on days of high market tightness depends strongly and positively on the deepness existing relationship for borrowers. However, for funds a high market tightness could increase their bargaining power, leading to a reduced needing to rely on established lending relationships. However, Model (2) shows a tight market having a different effect when during a higher uncertainty period when they are interacted with LRI. This means that when uncertainty was presumably elevated and few funds lenders face many borrowers banks, they now are willing to establish reciprocal relationships, motivated may be on the possibility to negotiate favorable conditions. But under this market conditions banks instead tend to not restrict their liquidity funding to those counterparties with whom they most deeply interacted. In terms of the pricing conditions, we find that even under a tightness situation reciprocal lending strongly depends on both trades happening at almost the same haircut rate.

Model (3) shows results considering as a relationship variable the strength of the relationship. Regression results show that even after interaction terms are included, the strength of the interaction variable is positive, meaning that it significantly increases the probability of reciprocal lending. However, when there are very few lenders willing to extend loans the number of loans granted over the last month reduces the likelihood of reciprocal lending, meaning that funds do not restrict their lending to those counterparties with whom they most frequently interacted. But past frequent interactions between pairs of bank and funds might to be particularly important on days when few lenders face many borrowers and in addition the uncertainty in the market is elevated.

Table 6. Search friction hypothesis

The table reports the estimated parameters of the logit model with endogenous regressors and the second stage regressions, and their corresponding standard errors in parentheses. In the case of control function results we report adjusted standard errors to the first-stage estimation error. The dependent variable is a dummy that equals one if funds from a financial conglomerate (lender) i grants an overnight interbank loan to bank from another financial conglomerate (borrower) j at day t, and zero otherwise. Control variables include pair-transaction characteristics, lender-specific characteristics, borrower-specific characteristics, aggregate Repo market conditions and aggregate market conditions, which are describe in TableB.1. In addition, fund and bank financial conglomerate and year fixed effects are considered. We are using transaction level daily data and the dataset covers the period from January 1, 2006 to February 28, 2018. The symbols *,**,*** denote significance at the 10%, 5% and 1% level, respectively.

	Logit			Control Function Approach		
Variable	(1)	(2)	(3)	(1)	(2)	(3)
Constant	-9,08***	-10,99***	-22,80***	-105,21***	-126,10***	-18,21***
	(0,37)	(0,36)	(0,34)	(2,75)	(2,92)	(0,42)
LRI_{ilt}	14,37***	14,66***		294,77***	309,56***	
	(0,16)	(0,17)		(9,57)	(9,98)	
BRI_{ilt}	7,09***	7,06***		251,96***	338,95***	
	(0,15)	(0,15)		(4,75)	(5,66)	
SI_{ilt}			2,59***			2,86***
			(0,04)			(0,05)
$Spr.h_{ilt}$	-42,02***	-41,40***	-36,88***	-39,05***	-37,52***	-44,27***
	(2,51)	(2,55)	(2,18)	(2,53)	(2,57)	(2,62)
$LRI_{ilt} \times tight.d_t$	-7,47***	-8,44***		-6,13***	-6,24***	
	(0,52)	(0,66)		(0,53)	(0,69)	
$BRI_{ilt} \times tight.d_t$	7,04***	5,98***		6,02***	5,64***	
	(0,66)	(0,84)		(0,63)	(0,90)	
$SI_{ilt} \times tight.d_t$			-0,07			-0,07***
			(0,03)			(0,01)
$Spr.h_{ilt} \times tight.d_t$	-16,40	-41,09**	-41,09**	29,68	-4,05	-54,05***
	(13,55)	(15,28)	(15,28)	(12,68)	(15,39)	(16,68)
$LRI_{ilt} \times d.u_t \times tight.d_t$		9,86***			8,82***	
		(2,10)			(2,13)	
$BRI_{ilt} \times d.u_t \times tight.d_t$		-9,04***			-9,97***	
		(2,21)			(2,32)	
$SI_{ilt} \times d.u_t \times tight.d_t$			0,07			0,12**
			(0,03)			(0,03)
$Spr.h_{ilt} \times d.u_t \times tight.d_t$		550,57***	1430,04***		620,35***	1160,99***
		(125,19)	(140,59)		(140,30)	(131,99)
# Obs	414163	377061	377061	414163	377061	377061
$AdjR^2$	0,8112	0,8051	0,7566	0,8209	0,8186	0,8112
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Source: Banco de México. Authors' calculations.

Finally, results of the second-stage regression in the control function approach show that the statistical significance and the signs of the estimated coefficient remains unchanged. The magnitude for variables measuring the concentration of the lending relationships considerably increased, instead the intensity of the relationship showed a slightly change.

5 Effects of reciprocal lending on the fund industry

Now we are turning to analyze the effects of reciprocal lending on the industry of asset managers. We empirically explore how reciprocal lending affects market concentration and market power of FC affiliated funds in the repo market. Based on the preliminary evidence presented above, our hypoyhesis is as follows:

H4: *Reciprocal lending relationships increase market concentration and market power of FC affiliated funds at the repo market.*

5.1 The competitiveness of funds at the Repo market

Reciprocal relationships between financial institutions are good from several perspectives. However, they may also involve negative implications specially when such relationships are held between institutions with a significant market share as they may imply that lending is concentrated by the few groups already dominating the market. This may favor more concentration, higher market power for the bigger firms and hurt smaller independent funds.

We empirically explore the effects of reciprocal lending between financial conglomerates on the competitiveness of funds in the repo market by regressing a daily Herfindahl-Hirschman Index (HHI) for the lending transactions between funds and banks on our reciprocity measures, the frequency of interactions between the pair of institutions involved in the transaction, and observed market characteristics. The daily HHI Index measures the level of concentration of the lending provided by investment funds to banks in the Repo market in one day. Our right-hand side variables of interest are the borrower reciprocity index (BRI) and the frequency of interactions. Given that our HHI is a market-level measure, meaning that it is common to all of the transactions observed at t, we aggregate our data up to the market level which implies that our main regressors are averages across funds of the individual levels. Our specification is as follows:

$$HHI_t = \beta_1 \overline{BRI}_t + \beta_2 \overline{FI}_t + \mathbf{X}_t \boldsymbol{\beta}_3 + \phi_t + \varepsilon_t$$

where $\overline{BRI}_t$ is the average borrower reciprocity index across transaction pairs (fund-bank) at day t; $\overline{FI}_t$ is the average, across transaction pairs (fund-bank), frequency of interactions, $\mathbf{X}_t$ are observed market characteristics that are common to all funds and banks and ϕ_t are time fixed-effects that capture unobserved characteristics at the market level that vary over time and control for a time trend.

Further, in order to explore the effects of reciprocity at the individual level, we perform a similar regression but using fund level market shares as the dependent variable. We compute market shares as the amount of money lent by fund j to banks at day t on the total amount of money lent by funds to banks in similar operations in the repo market that day. In this regression, we are able control for observed and unobserved characteristics of both lenders and borrowers that do not vary across periods by including fund and FC dummy variables. In particular, we estimate:

$$s_{jt} = \lambda_j + \alpha_1 BRI_{jt} + \alpha_2 FI_{jt} + \mathbf{X}_t \boldsymbol{\beta}_3 + \xi_l + \eta_t + \varepsilon_{jt}, \tag{4}$$

where s_{jt} is the percentage market share of fund j on the total amount of money lent to banks in the repo market at date t, BRI_{jt} is the borrower reciprocity index of fund j, averaged across fund j's bank counterparts at day t; FI_{jt} is the average, across banks, frequency of interactions, $\mathbf{X}_t$ are observed characteristics at the market level and λ_j, ξ_l, η_t are fund, financial conglomerate and time fixed-effects.

Identification. In the two regressions, there is an endogeneity issue with the BRI because some of the information we use in its computation is also used to compute the dependent variable of the respective regression. As a consequence, a shock to the market concentration index (respectively, fund j's market share) will also cause a change in the BRI. We address this issue by using information on the exposure of banks to a number of foreign counterparts as instrumental variables in both regressions and estimating them by two-stage least squares. In particular, in this section we include the total amount of the liabilities with foreign counterparts on three different categories: debt securities, repo and derivatives, and call money; the square of each of these and the interactions between them as instrumental variables. The identifying assumption is, therefore, that after controlling for market level shocks in the first regression, and for fund and FC level shocks as well in the second regression, along with exogenous variation that is correlated with our reciprocity measure, we are able to isolate the effect of reciprocal lending on the market structure.

Results. We report the results in Tables 7 and 8. Columns 1 and 3 include observed market characteristics that vary with time, whereas columns 2 and 4 include week dummies. Our preferred specifications, which includes market level unobserved factors and instrumental variables, are displayed in column 4 of the respective Table.

In the HHI regression results are as expected. Our reciprocity measure $BRI\,Daily\,Mean$ is positive across regressions which is consistent with our prior according to which reciprocal lending favors market concentration. This is, the higher the amount of transactions between two groups, the more concentrated the market will be in the hands of the big financial groups, which hold the largest market shares. The magnitude of its coefficient considerably increases in our preferred specification (column 4) which suggests that, compared to its analogous in column 2, the endogeneity problem was causing a downward bias. Moreover, the coefficient of *frequency of* *interactions* is positive and significant in all of the regressions. This is in line with the result described above, meaning that the more frequently two agents make transactions, the more concentrated the market will be.

Table 7. Regression results for Herfindahl-Hirschman Index (HHI)

The table reports the estimated parameters of a linear model and the corresponding robust standard errors in parentheses. The dependent variable is a daily Herfindahl-Hirschman Index (HHI) for the lending transactions between funds and banks in the Repo market. Control variables include the frequency of interactions between the pair of institutions making a transaction and observed market characteristics that vary with time, which are described in Table B.1. In addition, we account for financial conglomerate, fund and week fixed effects. Our dataset covers the period from January 1, 2006 to February 28, 2018. The symbols *,**,*** denote significance at the 10%, 5% and 1% level, respectively.

	Dependent variable: Herfindahl-Hirschman Index			
	OLS		IV	
Variables	(1)	(2)	(3)	(4)
BRI Daily Mean	9.77***	13.95***	8.94***	65.68**
	(1.78)	(7.10)	(3.21)	(32.54)
Frequency of Interactions	562.49***	534.32***	563.5***	660.31***
	(67.75)	(64.07)	(67.04)	(104.21)
TIIE 28	-323.48**		-315.9**	
	(158.74)		(160.1)	
Mexico (IESF)	-1068.74***		-1,051***	
	(156.68)		(163.4)	
IPC	0.00		-0.00	
	(0.00)		(0.01)	
Interbank Funding Rate	1055.15***		1,048***	
	382.54		(377.5)	
Government Funding Rate	-2151.37***		-2,097***	
	(656.82)		(700.1)	
Exchange Rate	68.31***		66.63***	
	(8.75)		(10.16)	
VIMEX	7.99***		7.86***	
	(2.15)		(2.17)	
EMBI	-1.33		-1.18	
	(1.70)		(1.72)	
Target Rate MEX	-252.60**		-251.8**	
	(123.26)		(123.4)	
Target Rate USA	-120.01		-107.5	
	(116.89)		(117.8)	
Target Rate EU	188.28***		187.7***	
	(23.92)		(23.99)	
Premium Rate – Repo	1658.69**		1,604*	
	(804.20)		(851.8)	
Total Loans – Repo	0.00*		-6.48e-11*	
	(0.00)		(0)	
Constant	-210.57	-276.31	-210.3	-1038.04**
	(284.30)	(171.96)	(282.9)	(514.03)
Observations	1,505	1,786	1,505	1,786
R-Squared	0.19	0.71	0.19	0.53
First stage R-Squared	——-	——-	0.53	0.82
Week FE	No	Yes	No	Yes

Source: Banco de México. Authors' calculations.

Columns 1 and 2 of Table 8 shows that the coefficient of our reciprocity variable is negative when the endogeneity issue is present. Once we address it, the coefficient turns positive consistent with what is expected: reciprocity favors higher market shares in the already bigger funds. The coefficient of frequency of interactions is positive, significant and of similar magnitude in columns 2 and 4 which are the specifications that include a higher number of controls. This result is consistent with conventional wisdom according to which the more frequent (and stable) the relationships are between a pair of lender-borrower, the better the position of the lender in the market.

Table 8. Regression results for funds' market shares

The table reports the estimated parameters of a linear model and corresponding robust standard errors in parentheses. The dependent variable is the daily market share of fund j on the total amount of money lent by funds to banks on the repo market. Control variables include the borrower reciprocity index, the frequency of interactions between the pair of institutions making a transaction and observed market characteristics that vary with time, which are described in Table B.1. In addition, week, financial group and fund fixed effects are considered. We are using transaction level daily data and the dataset covers the period from January 1, 2006 to February 28, 2018. The symbols *,**,*** denote significance at the 10%, 5% and 1% level, respectively.

	Dependent variable: percentage market share			
	OLS		IV	
Variables	(1)	(2)	(3)	(4)
BRI Daily Mean	-0.124***	-0.058***	0.314***	0.332***
	(0.002)	(0.004)	(0.013)	(0.100)
Frequency of Interactions	-0.099***	0.080***	-0.111***	0.082***
	(0.008)	(0.010)	(0.009)	(0.011)
TIIE 28	-2.021***		-6.001***	
	(0.129)		(0.186)	
Mexico (IESF)	-3.446***		-13.39***	
	(0.202)		(0.363)	
IPC	8.01e-05***		2.47e-05***	
	(4.74e-06)		(5.23e-06)	
Interbank Funding Rate	-1.259***		2.702***	
	(0.435)		(0.484)	
Government Funding Rate	3.717***		-26.48***	
	(0.617)		(1.100)	
Exchange Rate	0.187***		1.088***	
	(0.010)		(0.029)	
VIMEX	0.089***		0.154***	
	(0.003)		(0.003)	
EMBI	0.010***		-0.076***	
	(0.002)		(0.003)	
Target Rate MEX	1.220***		0.689***	
	(0.163)		(0.191)	
Target Rate USA	2.731***		-3.775***	
	(0.130)		(0.247)	
Target Rate EU	0.125***		0.502***	
	(0.023)		(0.026)	
Premium Rate – Repo	-1.617**		29.25***	
	(0.772)		(1.201)	
Total Loans – Repo	-0***		-0***	
	(0)		(0)	
Constant	0.556**	4.766***	-0.676***	1.236
	(0.218)	(0.164)	(0.239)	(0.915)
Observations	359,200	414,223	359,200	414,223
R-Squared	0.05	0.35	0.05	0.33
First stage R-Squared	—-	—-	0.38	0.82
Week FE	No	Yes	No	Yes
Finantial conglomerate FE	No	Yes	No	Yes
Fund FE	No	Yes	No	Yes

Source: Banco de México. Authors' calculations.

5.2 Effects on the market power of funds affiliated to financial conglomerates

Does reciprocal lending increase market power of funds affiliated to financial conglomerates? The evidence we have found so far about the concentration of repo funding transactions in a few financial conglomerates and the reciprocity in their relationships suggests that this kind of transactions may help financial conglomerate affiliated funds to increase their market power.

In order to check this empirically, we back out a fund-level Lerner index as a measure of market power and use it as our outcome variable. According to theory, the Lerner index is a function of the marginal cost of production, which is not observed in our data. However, in a context of Bertrand competition, the optimal pricing rule of a firm in a symmetric equilibrium with differentiated products equals the Lerner index to the inverse of the elasticity of demand. Our strategy to back out the fund-level Lerner index is to develop a reduced-form structural model of supply and demand, following the standard literature of demand estimation in empirical Industrial Organization. Our focus is on the repo market for lending services, in which banks, the demand side, face short-term liquidity needs whereas investment funds supply lending products to banks at an interest rate. The fund sector consists of a number of single product firms that set the interest rates of their lending products according to a Bertrand competition conduct.

We perform our estimation in two steps. First, we set out a supply and demand model for the repo market of short term funding, we estimate the demand using our data set of fund-bank transactions, compute own price elasticities of demand, and apply the standard formula to compute a fund-level Lerner index. Second, we regress our Lerner index on reciprocity measures and other controls.

A. First step: a stylized structural model to back out a Lerner index

Supply side. Suppose that there are F funds in the repo market, indexed by $f = 1, \ldots, F$ each of which supplies liquidity through lending services. For the sake of simplicity, we will aggregate all of the credits made by a given fund in a single product indexed by the same subscript of the fund. We are thereby assuming that funds are single-product firms.[10] The variable profit of fund f derived from its lending activities in the repo market is given by:

$$\Pi_f = (r_{ft} - c_{ft}) M s_f(\mathbf{r}_t),$$

where r_{ft} is the weighted average interest rate of the lending given by f at time t, c_{ft} is the marginal cost, s_{ft} is the market share of fund f at time t, $\mathbf{r}$ is the $F \times 1$ vector of interest rates of all funds in the market, and M is the size of the lending market, which we take as all of the money borrowed by banks in the repo market from any firm providing liquidity at time t, including investment funds. We assume that funds compete in setting interest rates and that a pure-strategy Bertrand-Nash equilibrium in prices exist. Therefore, the interest rate of the lending supplied by fund f must satisfy the first order condition:

$$s_f(\mathbf{r}_t) + (r_{ft} - c_{ft}) \frac{\partial s_f(\mathbf{r}_t)}{\partial r_{ft}} = 0.$$

We have, therefore, a system of F equations, one for each of the funds (products) existing in

[10] This is a restrictive view of how the market works in reality, in which the funding provided to a particular borrower is characterized by a particular amount of money, a given interest rate, a given maturity, and a given collateral. Lending products provided by the same fund to different borrowers are, therefore, heterogeneous.

the market. Solving fund f's equation for its interest rate-cost margin yields, for $f = 1, \ldots, F$:

$$r_{ft} - c_{ft} = \frac{1}{-\frac{\partial s_f(\mathbf{r}_t)}{\partial r_{ft}}} s_f(\mathbf{r}_t). \tag{5}$$

This optimal pricing rule allows us to back out a Lerner index for each fund at each period t. Dividing by the interest rate yields:

$$LI_t \equiv \frac{r_{ft} - c_{ft}}{r_{ft}} = \frac{1}{\eta_{ft}}, \tag{6}$$

with:

$$\eta_{ft} = -\frac{\partial s_f(\mathbf{r}_t)}{\partial r_{ft}} \frac{r_{ft}}{s_f(\mathbf{r}_t)},$$

being the own price elasticity of demand for product f in period t. Due to the fact that the Lerner index is a function of the demand elasticity, it is not necessary to observe the marginal costs of investment funds to estimate the Lerner index, but to have a good estimate of the own price elasticity of demand.

Demand side. The demand model presented in this section is in the spirit of the discrete-choice literature (in particular, Berry (1994) and Nevo (2000)). Banks, indexed by $i = 1, 2, \ldots, I$ face a multiple-choice decision among f funds in each period. Assume that the conditional indirect utility of bank i from choosing fund f, for borrowing some amount of money from it at time t is given by:

$$u_{ift} = \mathbf{x}_f \boldsymbol{\beta} - \alpha r_{ft} + \xi_f + \phi_t + \xi_{ft} + \varepsilon_{ift} \tag{7}$$

where $\mathbf{x}_f$ is a (row) vector of observable product (fund) characteristics, r_{ft} is the interest rate of product f in period t, ξ_j captures the mean valuation of the unobserved product (fund) characteristics that do not vary with time, ϕ_t accounts for time-varying characteristics that are common to all transactions in the market, and ξ_{ft} captures the unobserved characteristics of product (fund) f that vary with time. $(\alpha, \boldsymbol{\beta})$' are parameters to be estimated. Finally, ε_{ift} is an additively separable mean-zero random shock that captures idiosyncratic individual preferences.

We assume that banks' choice set includes an "outside good", which may capture all other liquidity sources not considered in this analysis (such as lenders other than funds in the repo market and so on). It also accounts for the no borrowing from any fund option. Normalizing its mean utility to zero, the indirect utility derived by bank i from the outside option writes as $u_{i0t} = \varepsilon_{i0t}$.

A key assumption of this model is that banks choose at most one fund for borrowing money at each period t. The fund chosen is the one giving the highest utility. For given unobserved demand shocks, $(\boldsymbol{\varepsilon}_{it})$, bank i will choose fund f if:

$$u_{ift} \geqslant u_{ikt}, \; \forall\, k = 0, 1, \ldots, F.$$

Assuming that the shocks to utility ε_{ijt} are independent of the product characteristics and of each other (i.i.d.), and drawn from a Type 1 Extreme Value distribution, the market share of fund f at time t is given by:

$$s_f(\mathbf{X}, \mathbf{r}_t) = \frac{\exp(\mathbf{x}_f\boldsymbol{\beta} - \alpha r_{ft} + \xi_f + \phi_t + \xi_{ft})}{1 + \sum_k \exp(\mathbf{x}_k\boldsymbol{\beta} - \alpha r_{kt} + \xi_k + \phi_t + \xi_{kt})}, \tag{8}$$

where $\mathbf{X}$ is the matrix of observed characteristics of all of the included funds and $\mathbf{r}_t$ is the vector of all of the interest rates of lending transactions between funds and banks in the repo market.

Demand elasticities. The fund level own and cross price elasticities are given by:

$$\eta_{fkt} = \frac{\partial s_{ft}}{\partial r_{kt}} \frac{r_{kt}}{s_{ft}} = \begin{cases} -\alpha(1 - s_{ft}) r_{ft} & \text{if } \; f = k, \\ \alpha s_{kt} r_{kt} & \text{if } \; f \neq k. \end{cases} \tag{9}$$

Identification. Following Berry (1994), we can rewrite equation (8) as a linear model as follows:

$$\log\, S_{ft} - \log\, S_{0t} = \mathbf{x}_f\boldsymbol{\beta} - \alpha r_{ft} + \xi_f + \phi_t + \xi_{ft}, \tag{10}$$

where S_{ft} is the observed market share of fund f at time t and S_{0t} is the observed market share of the outside option at t, which is given by:

$$S_{0t} = 1 - \sum_f S_{ft}. \tag{11}$$

Our identification strategy follows the standard literature that estimates the demand of differentiated products. In particular, it follows Nevo (2001) and exploits the panel structure of the data to identify the parameters of the demand model independent of the supply side. The unobserved fund and time effects that are captured in our model by the parameters ξ_f and ϕ_t, respectively, are identified by introducing both fund and time dummy variables in the model. The residual fund-time variation captured by ξ_{ft} is not identified and plays the role of the error term of the model presented in equation (10).

There is, thus, a challenge to identification that is related to the potential endogeneity of interest rates, which is standard in the literature of demand estimation and stems, in this context, from the potential correlation of interest rates with unmeasured product characteristics that vary with time or shocks to demand for funding that are common to all banks in the market, which are all captured by the error term of the model, ξ_{ft}. Funds may try to adjust interest rates in response to changes in needs for funding or preferences for product characteristics (e.g., maturities and collaterals) that are unobserved to the econometrician.

In order to correct this issue, we use information on the exposure of banks to a number of foreign counterparts as instrumental variables. In particular, in this section we include the total amount of the liabilities with foreign counterparts on three different categories: debt securities, repo and derivatives, and call money, and the interactions between them as instrumental variables. According to evidence and industry wisdom, the repo interest rate is highly correlated with other money market interest rates The identifying assumption is, therefore, that after controlling for market-level aggregate shocks and unobserved product characteristics, the aggregate liabilities of banks with foreign counterparts contain information of the interest rates observed in the Mexican repo market (e.g., the bargaining power of banks to negotiate the interest rates of their liabilities), but are not correlated with the shocks to demand.

Results. We estimate the model given by equation (10) using two-stage least squares. We report the estimation results in Table 9. Columns 1 and 2 show the demand model estimated without correcting the endogeneity of interest rates. Columns 3 and 4 are analogous to columns 1 and 2 but correcting the endogeneity problem. Our preferred specification is that of column 4, which accounts for fund, bank and time fixed-effects. As expected, the coefficient of the interest rate is negative, which means that the demand for liquidity is downward sloping, implying that the amount of liquidity demanded decreases with the interest rate.

Table 10 reports the distribution of the estimated own price elasticities backed out using equation (9) from the results of our preferred specification. Results show that there is no important differences between funds managed by financial conglomerate owned asset managers and those managed by independent asset managers. Further, mean elasticities are close to -3, which suggests that banks are elastic, on average, to changes in the interest rate because they have multiple funding sources.

B. Second step: evidence on the effects of reciprocity on market power

With the estimated elasticities in hand, we are able to compute a daily fund-level Lerner index according to equation (6) which we use as our outcome variable in this step. Our specification is

Table 9. Demand model results

The table reports the estimated parameters of the demand model and the corresponding robust standard errors in parentheses. The dependent variable corresponds to the difference in the logs of the market share of fund f at time t and the market share of the outside option, which is defined as $\log S_{ft} - \log S_{0t}$, where S_{ft} is the observed market share of fund f at time t and S_{0t} is the observed market share of the outside option at t computed according to equation 11. Fund and week fixed effects are considered. We are using transaction level daily data and the dataset covers the period from January 1, 2006 to February 28, 2018. The symbols *,**,*** denote significance at the 10%, 5% and 1% level, respectively.

	OLS		IV	
Variable	(1)	(2)	(3)	(4)
Weighted average interest rate	-2.730***	0.076***	-27.83***	-0.721**
	(0.021)	(0.006)	(0.391)	(0.294)
Frequency of interactions	-0.607***	0.019***	-0.856***	0.008*
	(0.008)	(0.002)	(0.011)	(0.005)
Weighted average maturity	0.616***	0.153***	0.794***	0.151***
	(0.101)	(0.018)	(0.124)	(0.018)
Constant	8.648***	-12.47***	123.9***	-9.169***
	(0.224)	(0.420)	(1.813)	(1.286)
Fund fixed effects	No	Yes	No	Yes
Finantial conglomerate FE	No	Yes	No	Yes
Week Fixed effects	Yes	Yes	Yes	Yes
R-squared	0.03	0.97	0.03	0.97
First-stage R-squared	——	——	0.99	0.99
Observations	410,110	410,110	410,110	410,110

Source: Banco de México. Authors' calculations.

Table 10. Distribution of estimated own price elasticities by fund affiliation

This table reports summary statistics of the distribution of estimated own price elasticities of funds' lending products according to whether a fund's asset manager is affiliated to a financial conglomerate or independent.

Fund affiliation	Mean	SD	Percentile 10	Median	Percentile 90
Financial conglomerate	-2.989	0.788	-4.395	-2.936	-2.151
Independent	-2.994	0.724	-3.445	-3.064	-2.189
Total	-2.990	0.779	-4.357	-2.941	-2.160

Source: Banco de México. Authors' calculations.

as follows:

$$\widehat{LI}_{ft} = \alpha_f + \beta_1 BRI_{flt} + \beta_2 LRI_{flt} + \beta_3 FI_{flt} + \mathbf{X}_{flt}\boldsymbol{\lambda} + \xi_l + \phi_t + \nu_{flt} \tag{12}$$

where BRI_{flt} is the borrower reciprocity index of fund f and bank l at t, LRI_{flt} is the lender reciprocity index of fund f and bank l at t, FI_{flt} stands for the frequency of interactions between fund f and bank l at t, $\mathbf{X}_{flt}$ is a matrix of observed characteristics of the transactions made that day, such as the weighted average haircut and maturity, and α_j, ξ_l, ϕ_t are fund, bank group and time fixed-effects. Finally, ν_{flt} is a zero-mean disturbance.

Identification. In this regression there are three potentially endogenous variables: the two reciprocity indices, BRI and LRI, and the weighted average haircut of the transactions made by fund f and bank l. The reciprocity measures are potentially correlated with the error term because a shock to market power may also affect the willingness of a counterpart to engage in reciprocal transactions and the amount of the reciprocal transactions. Similarly, the haircut is potentially endogenous because it is the result of the bilateral bargaining of the two parties involved in a transaction; hence, a shock to market power would potentially affect the average haircut of the transactions made with a particular counterpart. We deal with these problems by using instrumental variables and estimating the model (12) by two-stage least squares. We follow a similar strategy to correct the endogeneity issues of the two reciprocity measures as in previous regressions. In particular, we use information on the exposure of banks to a number of foreign counterparts as instrumental variables. In particular, in this section we include the total amount of the liabilities with foreign counterparts on three different categories: debt securities, repo and derivatives, and call money, and the interactions between them as instrumental variables.

On the other hand, we use the haircuts of past transactions of a fund-bank pair as instrumental variables for the contemporaneous average haircut of that pair. The identification assumption is that past haircuts are not correlated with the contemporaneous shocks to the fund level Lerner index.

Results. We report the results in Table 11. Our preferred specification is shown in column 2 of the Table and all of the estimates are statistically significant and of the expected sign. The coefficients of the borrower's reciprocity index (BRI) and the frequency of interactions are positive meaning that the higher the dependence of the fund's counterparties on it the higher the market power of the fund. Furthermore, the more frequent are the interactions between a bank and a fund, the higher is the market power of the investment fund. Conversely, the estimate of the Lender's reciprocity index (LRI) is negative, suggesting that the market power of a fund decreases with its dependence on its counterparties. Further, the coefficient of the average haircut is negative, which is consistent with conventional wisdom according to which the higher the haircut, the riskier a counterpart is which can increase the costs of a transaction and lower the fund's market power. Finally, the coefficient of the average maturity of the lending operation is positive, which suggests that the market power of a fund is higher when their provide liquidity for longer periods. .

Table 11. Regression results for the fund-level Lerner index

The table reports the estimated parameters of the linear model and the corresponding robust standard errors are given in parentheses. The dependent variable is a daily fund-level Lerner index. All regressions include fund, bank and week fixed effects. We are using transaction level daily data and the data set covers the period from January 1, 2006 to February 28, 2018. The symbols *,**,*** denote significance at the 10%, 5% and 1% level, respectively.

Variable	OLS	IV
BRI	0.015***	0.040***
	(0.000)	(0.005)
LRI	-0.007***	-0.028***
	(0.000)	(0.003)
Frequency of interactions	0.002***	0.002***
	(0.000)	(0.00)
Weighted average haircut	-0.007	-0.078**
	(0.008)	(0.034)
Weighted average maturity	0.002***	0.002***
	(0.000)	(0.001)
Constant	0.334***	0.336***
	(0.002)	(0.002)
Fund fixed effects	Yes	Yes
Bank group fixed effect	Yes	Yes
Week Fixed effects	Yes	Yes
R-squared	0.98	0.97
Average 1st-stage R-squared	—	0.45
Observations	389,695	365,290

Source: Banco de México. Authors' calculations.

6 Effects on banks and systemic risk

Now we evaluate how reciprocal lending between financial conglomerates affect the overall fragility of the financial system. The literature on the determinants of systemic risk is extensive but have not studied the impact of reciprocal lending between financial conglomerates (see Qin and Zhou (2019) appendix). Though, a related strand of literature discusses the interconnectedness between financial institutions. Allen and Gale (2000) argue that higher levels of interconnectedness turn the financial system more and more fragile because of the risk of contagion.[11] That is, if financial institutions become more interconnected, then if one of them faces a idiosyncratic shock, their financial counterparts will also be affected, and now smaller sized shock can turn to be much larger for the sake of the contagion of other financial institutions. Later, Acemoglu et al. (2015) argue, that interconnectedness' between financial institutions is a more subtle matter. Higher

[11] See also Brauning and Fecht (2017); Giglio (2016); Gorton and Metrick (2012).

levels of interconnectedness turn as beneficial, but until a point in which the downside of higher contagion outweigh the benefits (See Acemoglu et al. (2010, 2017); Kanno (Forthcoming) for further intuition).

We can find other arguments against a hard look on interconnectedness as in (Allen and Gale (2000)). The literature of relationship banking, Brauning and Fecht (2017), Li (2018), and Cocco et al. (2009), points out additional benefits of having strong ties between counterparts of financial transactions. Financial conglomerates can reduce transactions costs, and search costs, in their daily funding requirements by creating strong ties, such as with reciprocal lending at the Repo market.

We consider two related hypotheses. First, we want to check the incentives of commercial banks, given that they are by far the larges group of financial institutions, to engage into a reciprocal lending behavior with funds from a competing financial conglomerate.

H5a: *Higher levels of reciprocal lending benefits banks vis-à-vis other financial institution.*

To evaluate how reciprocal lending between financial conglomerates affects the individual contribution of banks to the systemic risk, we use the debt rank, DebtRank, as a proxy. The latter, introduced by Battiston et al. (2012), is a network-based index where the nodes in a directed network represent the financial institutions, and the links represent the financial dependencies. Intuitively, the DebtRank of a node i "is a number measuring the fraction of the total economic value in the network that is potentially affected by the distress or the default of the node i."

We calculate the DebtRank for Mexico using the same methodology propose in Battiston et al. (2012). This metric is data demanding as we need to know the positions (e.g. assets and bonds, derivatives, and call money) by each bank (fund), and potentially any other financial institution, at all other banks and funds. Also we need to know for each financial institution the assets and equity at each point in time. All this information is available at Banco de Mexico. The main advantage of the DebtRank against other network-based measures is that it avoids the bias associated to having cycles in the adjacency matrix. Few papers have used financial institution level, network-based proxies for systemic risk (Thurner and Poledna (2013)), because it is very hard to acquire this granular level of data. The benefit of doing so, which at the same time is limitation of other non-network-based proxies (Blanco et al., 2018; Silva et al., 2018; Kanno, 2016), is that the DebtRank account for the contagion between financial institutions.[12]

[12] There are other forms of interconnectedness (Tasca et al., 2017; Cai et al., 2018; Roukny et al., 2018; Kanno, Forthcoming) but ours is the first paper addressing reciprocal lending.

The econometric specification is the following,

$$\begin{aligned} DebtRank_{lt} =& \alpha_i + \eta_l + \lambda_t + Collat_t + \beta_1 RL_{ilt} + \beta_2 Fund_{it} + \beta_3 Bank_{lt} \\ &+ \beta_4 Pair.repo.trans_{ilt} + \beta_t X_t + \epsilon_{lt} \end{aligned}$$

where RL_{ilt} are the different metrics of reciprocal lending between funds from financial conglomerates i and banks belonging to financial conglomerate l at time t at the Repo market, $Fund_{it}$ are the fund(lender)-specific characteristics at t, $Bank_{lt}$ are the bank(borrower)-specific characteristics at t, $Pair.repo.trans_{ilt}$ are the pair-transaction characteristics at t, X_t are other time varying covariates, and α, η, λ, and $Collat$ are lender financial conglomerate, borrower financial conglomerate, time, and collateral fixed effects, respectively.

The parameters of interest, collected at β_1, may suffer from several biases. The main bias we are concerned is the endogeneity bias. For this specification, the higher the contribution of a bank to systemic risk the more important the bank is compared to other institutions in the network. Thus, larger banks are very attractive to other less important banks, and they are more likely to establish a reciprocal lending relationship if they want to. A second argument, that applies more to G7 banks, is that they are aware that reciprocal lending might increase the risk-taking of financial conglomerates involved. Thus, banks with a large contribution to systemic risk have incentive to tame down their reciprocity after reaching a *certain level*. Both arguments led us to think that the metrics of reciprocal lending might be correlated with the error term.

Selection bias is another issue to address. The argument is that only certain type of banks are interested in engaging into reciprocal lending activities. For the Mexican financial industry the main driving characteristic is if banks and funds belong to a G7 group. For our sample, the members of the G7 group has been always the same, thus by including different type of fixed effect this source of bias is attenuated.

We propose using as instruments both the number of foreign counterparts, and the associated dollar volume, for every bank on a daily basis. These instruments will capture the effect of external shock to the balance sheet of banks. A possible drawback would be that some banks might have just few foreign counterparts, but this is not an important issue as we are allowing Mexican counterparts that operate outside Mexico. Also, a large fraction of the reciprocal transactions occur between conglomerates belonging to the G7, which mostly are foreign financial institutions. The instruments are also not related to the dependent variable. Foreign shocks should not affect the contribution of individual financial institutions to systemic risk, nor system-wide metrics of systemic risk, because a very important fraction of conglomerates are either from the United States or Europe, and were simultaneously affected by the external shock during our sample.

Finally, we included week fixed effects as they certainly capture information relevant for the relationship between the external shocks that instruments capture and the metrics of reciprocal lending. On the other hand, given we already included year and day fixed effect at the specification, week fixed effects should not correlate with the debt rank.

Second, we explore if higher levels of reciprocal lending correlates with the systemic risk.

H5b: *Higher levels of reciprocal lending reduce systemic risk if financial conglomerates establish deep and long-term relationships.*

We follow a conservative approach and pick near-coincident indicators to evaluate how the reciprocal lending between financial conglomerates in Mexico affect the overall fragility of the financial system, and we use a standard (rolling-window) principal component technique, IESF, as a proxy.[13] The latter was introduced the Hakkio and Keeton (2009), which is calculated by the Mexican Central Bank and the Kansas Fed, and has been used in the literature as a proxy of systemic risk, Camlica (2016), Aramonte et al. (2013), Singh and Singh (2016), Carbo-Valverde and Sanchez (2013).

We calculate the IESF for Mexico using the same methodology as proposed in Hakkio and Keeton (2009).[14] The IESF combines variables that characterize the most important sectors of the Mexican financial system. The IESF captures the idea that a systemic risk measure should be higher when all the financial system becomes unstable. We calculate the IESF using 30 variables that characterize different sectors of the Mexican financial system: country risk (five variables), the debt market (nine variables), the equity market (four variables), the credit market (six variables), the derivatives market (three variables), and the foreign exchange market (three variables). A brief description of all variables can be found at the appendix.

The econometric specification is as the previous one, but now the dependent variable is $IESF_t$. The identification of parametrer β_1 might suffer from endogeneity and selections biases. The arguments for both biases, given the relevance of G7 banks in the Mexican financial system, pretty much follow through. For example, if the systemic risk increases for an external shock, then G7 banks will have incentive to modify their reciprocal lending decisions. Finally, we use the same instrumental variable technique as before.

Table 12 presents individual regressions for metric of reciprocal lending, and each column should not be understood as one regression. For example, we observe in column one that six

[13] As a robustness check we also used the composite indicator of systemic stress, CISS, of the European Central Bank as it is also a well known near-coincident index. We used the same inputs as IESF for its calculation.

[14] The main feature of IESF is that it is a measure that increases when financial stress is "simultaneously" observed in different sector across the whole financial system. Market data from the different sectors were obtained by Banco de Mexico, Bloomberg, and the Mexican market price provider called Valmer (an acronyms for "Valuación Operativa y Referencias de Mercado").

variables ($Freq.inter_{ilt}$,BPI_{ilt}, BRI_{ilt}, $DOFG_{ilt}$, SI_{ilt}, $STABF_{ilt}$) show statistically significant in a regression with $IESF_t$ as dependent variable, and where we use different covariates, banks FE, and time FE. Odd columns present the estimates using $IESF_t$, and even columns estimates using $DebtRank_{lt}$. Finally, columns one and two use time varying covariates, bank and time fixed effect. The next two columns additionally use fixed effects for the financial conglomerate providing liquidity. Columns five and six (last two columns) are like the first two columns (columns three and four) but including collateral fixed effects.

We apply instruments variables for all specifications. Standard errors are clustered around the interaction of borrower financial conglomerate, lender financial conglomerate and days.

Along most specifications in Table (12), in particular for the last two columns which include collateral fixed effects, we observe most variables are statistically significant, often at 5% or 1%. On terms of their sign, relevant variables keep the sign with both dependent variables. Such is the case for LRI_{ilt}, BRI_{ilt}, $DOFG_{ilt}$ and $STABB_{ilt}$. Variables $Freq.inter$, LPI_{ilt}, BPI_{ilt} and SI_{ilt} flip sign between both dependent variables. Later we will see that most of the latter set of variables turn out not to be statistically significant with a richer set of controls along different specifications. All these insights hold even by replacing ten lagged variables, as they are now, with five and twenty days lagged variables.

Table 13 presents the results from the main econometric specifications. The first four columns present models with different sets of fixed effects for the proxy for the individual contribution to systemic risk, DebtRank(DR). The last four columns present those for the systemic risk proxy for the whole Mexican financial industry, IESF.

In both sets of regressions we include time varying covariates, some of them are banks specific, others fund specific, and other are Repo transactions specific. Also, all regressions include banks fixed effects, and day interacted by year fixed effect. Columns one and two do not include collateral fixed effects, while columns three and four includes them. Columns two and four include fixed effects for financial conglomerates providing liquidity, the other columns do not. Finally, in all cases standard errors are clustered on the combination of borrower financial conglomerate, lender financial conglomerate, and day. The latter is particularly important for the analysis where the dependent variable is a system-wide metric of systemic risk as this variable only changes with time.

The last four columns of Table (13) address the effect of reciprocal lending on the contribution of banks to systemic risk, vis-$\grave{a}$-vis other financial institutions, not only incorporating into the analysis their effect at the Repo market but on the entire financial industry. For all specifications, besides using the instruments described in Section (3), we also include week fixed effect because there are certainly unobserved factor that determine along the month reciprocal lending, but do

Table 12. Individual regressions pooled into one table

The table reports the estimated parameters of the linear model and corresponding *values* in brackets. The dependent variables are either the system wide systemic risk index, $IESF_t$, or the bank-level contribution to systemic risk, $DebtRank_{lt}$. Controls include fund level covariates, bank level covariates and Repo level covariates. In addition, lender financial conglomerate, borrower financial conglomerate, time, and collateral fixed effects, are considered. As IVs we use the dollar volume of foreign exposures through the asset side and liability side, as well as week fixed effect. We are using transaction level daily data and the dataset covers the period from January 1, 2006 to February 28, 2018. The symbols *,**,*** denote significance at the 10%, 5% and 1% level, respectively.

	$IESF_t$	$DebtRank_{lt}$	$IESF_t$	$DebtRank_{lt}$	$IESF_t$	$DebtRank_{lt}$	$IESF_t$	$DebtRank_{lt}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Freq.inter_{ilt-10}$	-3.477***	0.082***	-3.378***	0.068***	-4.322***	0.063**	-3.840***	0.052*
	[0.699]	[0.027]	[0.621]	[0.024]	[0.779]	[0.031]	[0.684]	[0.028]
LPI_{ilt-10}	0.057	0.003	-0.088**	-0.002	-0.154***	0.014***	-0.291***	0.002
	[0.035]	[0.003]	[0.042]	[0.004]	[0.055]	[0.005]	[0.067]	[0.005]
BPI_{ilt-10}	6.493***	-0.132	5.402***	-0.144	6.570***	-0.260**	5.036**	-0.275**
	[2.193]	[0.124]	[2.034]	[0.118]	[2.142]	[0.114]	[1.980]	[0.109]
LRI_{ilt-10}	0.008	-0.006*	-0.100**	-0.019***	0.052**	-0.010***	-0.120**	-0.022***
	[0.023]	[0.003]	[0.051]	[0.006]	[0.025]	[0.004]	[0.053]	[0.007]
BRI_{ilt-10}	-0.324***	0.005	-0.584***	-0.012***	-0.339***	0.001	-0.605***	-0.013***
	[0.073]	[0.005]	[0.114]	[0.004]	[0.073]	[0.005]	[0.119]	[0.004]
$DOBG_{ilt-10}$	-0.055	0.014***	-0.052*	0.021***	-0.142***	0.016***	-0.033	0.020***
	[0.033]	[0.003]	[0.030]	[0.005]	[0.035]	[0.004]	[0.027]	[0.005]
$DOFG_{ilt-10}$	-0.288***	0.013***	-0.341***	-0.008***	-0.269***	0.011***	-0.415***	-0.006***
	[0.074]	[0.004]	[0.077]	[0.002]	[0.077]	[0.004]	[0.090]	[0.002]
SI_{ilt-10}	-0.135***	0.020***	-0.133***	0.018***	-0.138***	0.022***	-0.128***	0.018***
	[0.021]	[0.003]	[0.026]	[0.002]	[0.022]	[0.002]	[0.026]	[0.002]
$STABB_{ilt-10}$	0.093	0.040***	0.310**	0.057***	0.187**	0.050***	0.280*	0.055***
	[0.066]	[0.015]	[0.154]	[0.016]	[0.085]	[0.011]	[0.151]	[0.016]
$STABF_{ilt-10}$	-0.705***	-0.005	-0.723***	0.013***	-0.920***	-0.005	-0.725***	0.006*
	[0.188]	[0.003]	[0.200]	[0.005]	[0.280]	[0.003]	[0.193]	[0.003]
# Obs	86,963	85,991	86,963	85,991	86,962	85,990	86,962	85,990
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Collateral FE	NO	NO	NO	NO	YES	YES	YES	YES
Year × Day FE	YES	YES	YES	YES	YES	YES	YES	YES
GBorrower FE	YES	YES	YES	YES	YES	YES	YES	YES
GLender FE	NO	NO	YES	YES	NO	NO	YES	YES

not affect the contribution to systemic risk.

We can observe that irrespective of the specification three variables yield statistically significant estimates. While BRI_{ilt} shows a negative sign, $STABB_{ilt}$ and $DOBG_{ilt}$ show a positive sign, and this is very interesting as we detect that not every metric of reciprocal lending yields the same qualitative effect. The latter two metrics capture the dependence of a banks on a particular fund to obtain liquidity ($STABB_{ilt}$), measured by the number of transactions on the overall number of transactions by that bank, or the dependence of a fund on a particular bank to position their excess

Table 13. Reciprocal lending and systemic risk

The table reports the estimated parameters of the linear model and corresponding *values* in brackets. The dependent variables are either the system wide systemic risk index, $IESF_t$, or the bank-level contribution to systemic risk, $DebtRank_{lt}$. Controls include fund level covariates, bank level covariates and Repo level covariates. In addition, lender financial conglomerate, borrower financial conglomerate, time, and collateral fixed effects, are considered. Standard errors are clustered on the combination of borrower financial conglomerate, lender financial conglomerate, and day. As IVs we use the dollar volume of foreign exposures through the asset side and liability side, as well as week fixed effect. We are using transaction level daily data and the dataset covers the period from January 1, 2006 to February 28, 2018. The symbols *,**,*** denote significance at the 10%, 5% and 1% level, respectively.

	$IESF_t$				DR_t			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$Freqinter_{t-10}$	0.419**	0.238	0.077	0.216*	0.043	0.046	0.053**	0.038
	[0.188]	[0.162]	[0.144]	[0.125]	[0.038]	[0.040]	[0.026]	[0.031]
BPI_{t-10}	-3.106***	-3.623***	-3.908***	-3.389***	-0.210	-0.289	-0.267	-0.325**
	[0.937]	[0.825]	[0.883]	[0.795]	[0.223]	[0.191]	[0.177]	[0.156]
BRI_{t-10}	-0.162***	-0.193***	-0.162***	-0.187***	-0.012**	-0.016***	-0.011**	-0.016***
	[0.030]	[0.034]	[0.031]	[0.033]	[0.005]	[0.004]	[0.005]	[0.004]
$STABB_{t-10}$	0.076*	0.021	-0.033	0.024	0.025**	0.020**	0.020***	0.017**
	[0.045]	[0.035]	[0.037]	[0.034]	[0.010]	[0.008]	[0.007]	[0.008]
$DOBG_{t-10}$	0.116***	0.091***	0.116***	0.091***	0.007*	0.018***	0.009***	0.019***
	[0.026]	[0.022]	[0.026]	[0.021]	[0.004]	[0.004]	[0.003]	[0.004]
SI_{t-10}	-0.030**	-0.034***	-0.020	-0.034***	0.003	0.002	0.004*	0.003
	[0.015]	[0.013]	[0.012]	[0.012]	[0.002]	[0.003]	[0.002]	[0.003]
Observations	66,235	66,235	66,233	66,233	65,537	65,537	65,536	65,536
Adj R2	0.454	0.603	0.410	0.626	0.143	0.171	0.215	0.198
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Collateral Class FE	NO	NO	YES	YES	NO	NO	YES	YES
Year#Day FE	YES	YES	YES	YES	YES	YES	YES	YES
GBorrower FE	YES	YES	YES	YES	YES	YES	YES	YES
GLender FE	NO	YES	NO	YES	NO	YES	NO	YES

liquidity ($DOBG_{ilt}$), measure by the dollar volume funding on the overall funding provided to banks. Both cases differ from BRI_{ilt} which is the dependence of the both financial conglomerates on each other, captured as the dollar volume reciprocal funding on the overall funding banks obtained with all funds. While BRI_{ilt} is a variable capturing the joint dependence of financial conglomerates, variables $STABB_{ilt}$ and $DOBG_{ilt}$ just capture a one-sided point of view of such relationship.

Finally, we study the effect of reciprocal lending on an overall metric of systemic risk. Along the first four columns of Table (13) we detect robust estimates with different signs. $DOBG_{ilt}$ again is showing that when funds depend more on a single bank to position their excess liquidity, then systemic risk will increase. The reason for it relies on the already low number of counterparts funds have, see Section (2). As funds dependence increases, banks are more prone to risk taking, and contagion risk also rises given a default of banks. Second, the rest of statistically significant estimates, BPI_{ilt}, BRI_{ilt} and SI_{ilt}, have a negative sign and represent the dependence of a bank of a particular fund (BPI_{ilt}) over the last month, and the joint number of transactions between both financial conglomerates (SI_{ilt}) during the last month. These results are pointing out that when reciprocal lending is deep and stable for both financial conglomerates, then systemic risk decreases.

Finally, we want to emphasize that the strongest effects are those of BPI_{ilt}, BRI_{ilt} and SI_{ilt}. We find this interesting in itself as many policy makers have the natural inclination to assume that any modality of reciprocity at the Repo market could undermine the stability of the financial system. And indeed, this is the case from the point of view of the funds, but because they already have a low number of counterparts. Unfortunately, we are unable from our work to make any welfare statement, and we leave this point to further research.

7 Conclusions

This paper examines a recurrent behavior of financial conglomerates in Mexico in which, at the repo market, commercial banks from one group, say group A, obtain short-term liquidity from funds from another financial conglomerate, say group B, and simultaneously, funds from group A provide short-term liquidity to the commercial bank of group B. We label this behavior as reciprocal lending. Restrictions on entities that are eligible as counterparties is a typical regulatory strategy to mitigate counterpart credit risk arising from repo transactions. In Mexico, however the regulatory framework constraints funds to provide liquidity to banks if they belong to the same financial conglomerate. Nevertheless, the evidence shows that the 40% of the lending relations between FC-affiliated bank-funds pairs are reciprocal.

For this matter, we exploit detailed transaction level data, with daily frequency, provided by Banco de Mexico, since 2006 until 2018. The dataset not only includes all transactions at the Repo market, but also the daily exposures of commercial banks and fund with all other financial institutions in Mexico. The first hypothesis we test is if measures of reciprocal lending do affect the probability that financial conglomerates engage in this type of reciprocal behavior. In particular, we find evidence that reciprocal lending is explained as a mechanism in which financial conglomerates can acquire cheap and stable short-term funding. Additionally, we explore of search costs and find that when the Repo market is tight, banks rely more on their established relationships compared to what funds do.

We explore the effect of reciprocal lending on funds and banks. Firstly, we find evidence that higher levels of reciprocal lending benefits funds in their repo lending activity. In particular, there is a positive relationship between reciprocal lending and market concentration of funds at the repo market. Also, there is a positive relationship between reciprocal lending and funds' Lerner index at that same market. Secondly, we also find a positive relationship between reciprocal lending and banks' DebtRank, which is a proxy for the importance of commercial banks vis-*à*-vis all other financial institutions in Mexico.

Finally, we evaluate the reciprocal between reciprocal lending and systemic risk, and find evidence that as reciprocal turns more intense during the last month the systemic risk increases, but the opposite holds when the depth of the relationship increases. Interestingly, for policy making this results opens the question of which is the right level of reciprocal lending to be allowed.

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Appendix

A Price dispersion and market structure of funds by sectors

Price dispersion in the AM industry is an important feature that has previously been documented by the literature. Sirri and Tufano (1998) provide evidence according to which observed heterogeneity in fees and fund performance is due to a higher expenditure in marketing and more media attention. Hortacsu and Syverson (2004) address the issue of a significant price dispersion among the funds in the S&P 500 index funds despite their apparent level of product homogeneity, and find that some of this price heterogeneity is rationalized by search frictions.

Heterogeneity in prices appears to be a salient feature of the AM industry in Mexico as well. Table A.1 shows the mean price and price dispersion measures by fund sector (we use Morningstar categories). There is a remarkable dispersion in the sectors specialized in money markets. In fact, the Euro, Mexico and US money market sectors present a dispersion in prices ranging from 6.6 to 9.9 measured as the ratio between the seventy-fifth and the twenty-fifth percentiles. Two other sectors with considerable price dispersion are the "Guaranteed", with 6.6 percentile ratio, and the "Global equity large cap" with 8.8 percentile ratio. Unreported results consider the same dispersion measures for independent AMs. We find that within sector price dispersion is less important among independent funds, and consequently, they barely set homogeneous pricing.

Finally, Table A.2 presents concentration measures by sector aggregating fund classes of the same family into a single fund. In general, there are a few funds in most sectors, which explains why the HHI is large in those cases indicating high concentration. Moreover, it appears that more than six funds in a sector is enough to have almost an unconcentrated sector according to the HHI. A look at alternative indicators of concentration gives a clearer idea of how concentrated sectors are and, in particular, allows us to see that there are funds that dominate their respective sector. The third column of Table A.2 reports the *C1* measure of concentration. It shows, for example, that the largest fund in the "Agressive Allocation" sector, in which there are seven funds competing, holds 20.2% of the assets invested; there are more remarkable examples. The largest fund in the "Asia Equity" sector, with only two funds, holds almost 80% of the assets invested; the largest fund in the "Euro Fixed Income" sector, with three competitors, holds 52% of the assets; finally, the leading fund in the "Miscellaneous" sector, with four funds in total, holds about 46% of the assets.

Table A.1. Price dispersion within sector

The table reports the mean price and price dispersion measures by fund sector as of the end of 2017, according to Morningstar categories. N corresponds to the number of funds in each sector. The column $75th$ to $25th$ is the 75th percentile divided the 25th percentile of prices; the column $90th$ to $10th$ is the 90th percentile divided by the 25th percentile of prices.

Sector	N	Mean price	Coefficient of Variation	$75th$ to $25th$ percentile ratio	$90th$ to $10th$ percentile ratio
Aggressive Allocation	87	164	0.69	3.3	27.5
Asia Equity	24	145	0.62	2.2	55.0
Cautious Allocation	172	129	0.59	2.2	20.9
Emerging Markets Equity	47	167	0.54	2.2	7.7
Euro Money Market	21	62	0.78	6.6	9.9
Europe Equity Large Cap	41	177	0.62	3.3	31.9
Global Equity Large Cap	112	122	0.79	8.8	100.1
Guaranteed	93	100	0.73	6.6	42.9
Inflation Linked	123	101	0.60	3.3	6.6
Mexico Equity	329	174	0.67	3.3	20.9
Mexico Fixed Income	1431	95	0.95	3.3	12.1
Mexico Money Market	68	71	0.87	6.6	172.7
Miscellaneous	90	151	0.66	3.3	7.7
Moderate Allocation	224	123	0.57	3.3	5.5
Other Fixed Income	120	93	0.58	2.2	6.6
US Equity Large Cap Blend	74	161	0.62	2.2	16.5
US Money Market	59	53	0.79	9.9	110.0

Source: Banco de México. Authors' calculations.

B Control variables

C Systemic risk metrics

In the literature of systemic risk there is a wide set of metrics, such as Acharya et al. (2017), ?, Brownlees and Engle (2016).[15]. Giglio et al. (2016) and Kleinow et al. (2017) argue that we do not have a unique systemic risk measure, and probably because of the elusive nature of the phenomenon, the way to proceed in practice is to use a combination of different metrics.

As a first step, we follow a conservative approach and pick near-coincident indicators as we do not want to take a stand of which systemic risk index better captures the build up of risk.[16] Another reason to use a near-coincident indicator is that a large group of well know systemic risk

[15] See Qin and Zhou (2019) for a broader list.

[16] This type of metrics are not able to identify two or three years in advance materialization of a systemic episode, but do excel identifying the imminence of their occurrence within a window of months. In practice, policy makers frequently use them.

Table A.2. Market concentration measures by sector

The table reports concentration measures for sectors aggregated by fund classes, as of the end of 2017. N corresponds to the number of funds in each sector. $C1$ and $C4$ are measures of concentration which are equal to the sum of the percentage market shares of the largest and four larger funds, respectively.

Sector	N	HHI	C1 (%)	C4 (%)
Aggressive Allocation	7	1,772	20.2	75.2
Asia Equity	2	6,628	78.5	100
Cautious Allocation	8	1,342	14.2	56.7
Emerging Markets Equity	2	5,676	68.4	100
Emerging Markets Fixed Income	2	5,142	58.4	100
Euro Fixed Income	3	4,226	52.0	100
Euro Money Market	9	1,308	13.7	54.7
Europe Equity Large Cap	4	3,144	33.3	100
Global Equity Large Cap	8	1,492	18.1	65.7
Global Fixed Income	24	544	6.4	25.1
Guaranteed	119	104	1.5	6.0
Inflation Linked	9	1,146	16.2	50.2
Mexico Equity	9	1,860	25.3	77.5
Mexico Fixed Income	17	883	10.8	43.1
Mexico Money Market	7	1,932	23.6	80.1
Miscellaneous	4	3,973	45.6	100
Other Fixed Income	4	2,720	35.3	100

Source: Banco de México. Authors' calculations.

indexes are of low frequency, and our data has a daily frequency. Moreover, it has been shown that other market-based measures of systemic risk with a similar frequency only adds a small predictive power, and might not even help at all for systemic episodes wh in nature than 2008 Financial Crisis[17] As a second step, we construct a data demanding, network-based proxy for the contribution of individual financial institutions to a default of the whole financial system.

To evaluate how the reciprocal lending between financial conglomerates in Mexico affect the overall fragility of the financial system, we use a standard (rolling-window) principal component technique, IESF, as a proxy.[18] The latter was introduced the Hakkio and Keeton (2009), which is calculated by the Mexican Central Bank and the Kansas Fed, and has been used in the literature as a proxy of systemic risk, Camlica (2016), Aramonte et al. (2013), Singh and Singh (2016), Carbo-Valverde and Sanchez (2013).

We calculate the IESF for Mexico using the same methodology as proposed in Hakkio and

[17] See Arsov et al. (2013) and Shang et al. (2015) for further details.

[18] As a robustness check we also used the composite indicator of systemic stress, CISS, of the European Central Bank as it is also a well known near-coincident index. We used the same inputs as IESF for its calculation.

Table B.1. Control variables description

Lenders corresponds to funds belonging to a financial conglomerate and the borrower corresponds to a bank from another financial congomerate that rely on Repo funding to lever up their balance sheet. We only consider trading days.

Variables	Definition
	Pair-transaction characteristics
$rate_{ilt}$	Overnight interest rate negotiated by lender i and borrower l at day t
$maturity_{ilt}$	Maturity of the repo transaction between lender i and borrower l at day t
$term_{ilt}$	Specified term of the repo negotiated by lender i and borrower l at day t
$cash_{ilt}$	Initial cash loan negotiated by lender i and borrower l at day t
$loans_{ilt}$	Cash loans negotiated by lender i and borrower l during the last 22 days preceding day t
$n.trans_{ilt}$	Number of loans granted from lender i to borrower l during the last 22 days preceding day t
$n.trans.d_{ilt}$	Number of loans granted from lender i to borrower l at day t
$Freq.inter_{ilt}$	Frequency of interactions measure defines as logarithm of one plus the number of days a fund i has lent to bank l over the last 22 days preceding day t
$collateral_{ilt}$	Type of security sold (collateral) by borrower l to lender i at day t
$spread.collateral_{ilt}$	collateral interest rate spread (to the interbank intesrest rate) at day t
	Lender-specific characteristics
$Assets.f_{it}$	Total assets (in MNX millions) according to balance sheet record of month preceding day t.
$PR.f_{it}$	Page Rank value for borrower i at day t
DoF_{it}	Amount lent by funds belonging financial conglomerate i to bank j at day t divided by total lending of financial conglomerates funds i at day t
$TP.Rank_{it}$	Interest rate quantile
$HC.Rank_{it}$	haircut quantile value
$Flujo_{it}$	Funds Net flow at day t
$Liq.f_{it}$	Liquidity index for lender i at day t
$counter.f_{it}$	Number of counterparties (number of banks who borrow from funds i) of lender i at day $t-1$
$Stab.f_{ilt}$	Number of transactions between funds belonging financial conglomerate i and bank l at day t, divided by the total number of transactions of financial conglomerate funds during the last 22 days preceding day t
$G7.f_i$	Dummy variable that equals one if lender i belong to the 7 biggest financial conglomerates in Mexico
$d.f_i$	Dummy variable that equals one for funds belonging financial conglomerate i and zero in other case
	Borrower-specific characteristics
$Assets.b_{lt}$	Total assets (in MNX millions) according to balance sheet record of month preceding day t.
$Liq.b_{lt}$	Liquidity index for borrower l at day t
$PR.b_{lt}$	Page Rank value for borrower l at day t
$z.score.b_{lt}$	z-score measure proposed by Cheng et. al (2017) as a measure of default risk at day t
DoB_{lt}	Amount borrowed by bank l from funds of financial conglomerate i at day t divided by total borrowing of bank l at day t
$Stab.b_{lit}$	Number of transactions between bank l and funds belonging financial conglomerate i at day t divided by the total number of transactions of bank l, during the last 22 days preceding day t
$counter.f_{lt}$	Number of counterparties (number of funds who lend to bank l) of borrower l at day $t-1$
$G7.b_{lt}$	Dummy variable that equals one if borrower l belong to the 7 biggest financial conglomerates in Mexico
$d.b_l$	Dummy variable that equals one for Bank belonging financial conglomerate l and zero in other case

Keeton (2009).[19] The IESF combines variables that characterize the most important sectors of

[19] The main feature of IESF is that it is a measure that increases when financial stress is "simultaneously" observed in different sector across the whole financial system. Market data from the different sectors were obtained by Banco de Mexico, Bloomberg, and the Mexican market price provider called Valmer (an acronyms for "Valuación Operativa y Referencias de Mercado").

Table B.2. continued: Control variables description

Lenders corresponds to funds belonging to a financial conglomerate and the borrower corresponds to a bank from another financial congomerate that rely on Repo funding to lever up their balance sheet. We only consider trading days.

Variables	Definition
	Aggregate Repo market conditions
$repo.rate_t$	Repo rate at day t
$repo.amount_t$	
$nf.repo_t$	Non-financial repo divided by total repo at day t
	Aggregate market conditions
$TIIE_t$	Mexico 28 days equilibrium interbank interest rate at day t
$IESF_t$	Mexico financial stress index at day t
$Govt.rate_t$	Banco de Mexico's reference rate at day t
$Interbank.rate_t$	Mexico 28 days interbank interest rate at day t
$Vimex_t$	Mexico volatility index at day t
$EMBI_t$	Emerging Market Bond Index at day t
$Exchange.rate_t$	Mexican exchange rate to US dollar (MNX/USD) at day t
$S\&P/BMV(IPC)_t$	Indice de precios y cotizaciones at day t
$Market.tight_t$	Number of lenders divided by number of borrowers at day t
$Tight.d_t$	Dummy variable that equals one if day t is in lowest quantile of Market tight at day t and zero otherwise.
$Trans_t$	Number of total overnight loans granted by funds to banks at day t
$Trans.d_t$	Dummy variable that equals one if day t is in lowest quantile of Market tight at day t and zero otherwise.
$d.u_t$	Dummy variable that equals one from 9 August 2007 to 30 June 2010 (crisis period), or if on a given day the IESF index is over their historical mean plus one standard deviation and zero otherwise

the Mexican financial system. The IESF captures the idea that a systemic risk measure should be higher when all the financial system becomes unstable. We calculate the IESF using 30 variables that characterize different sectors of the Mexican financial system: country risk (five variables), the debt market (nine variables), the equity market (four variables), the credit market (six variables), the derivatives market (three variables), and the foreign exchange market (three variables). A brief description of all variables can be found at the appendix.

Later, to evaluate how reciprocal lending between financial conglomerates affects the individual contribution of banks to the systemic risk, we use the debt rank, DebtRank, as a proxy. The latter, introduced by Battiston et al. (2012), is a network-based index where the nodes in a directed network represent the financial institutions, and the links represent the financial dependencies. Intuitively, the DebtRank of a node i is a "is a number measuring the fraction of the total economic value in the network that is potentially affected by the distress or the default of the node i."[20]

As with the previous metrics, we calculate the DebtRank for Mexico using the same methodology propose in Battiston et al. (2012). This metric is data demanding as we need to know the positions (e.g. assets and bonds, derivatives, and call money) by each bank (fund), and potentially any other financial institution, at all other banks and funds. Also we need to know for each financial institution the assets and equity at each point in time. All this information

[20] See Battiston et al. (2012).

Table B.3. Sumary statistics of control variables

The table Reports the statistic summary of variables used in the empirical analysis. The number of observations depends on the unit of observation of the respective variable. The dataset covers the period from January 1, 2006 to February 28, 2018. Variables in millions of Mexican pesos (MNX)

Variable	Mean	Stand. dev	Min	Max	# Obs
Pair-transaction characteristics					
$rate_{ilt}$	5.08	1.61	2.38	8.75	666796
$maturity_{ilt}$	1.03	0.16	1	24	666796
$cash_{ilt}$	587828	1308656.7	0	24423050	666796
$term_{ilt}$					666796
$loans_{ilt}$	11148560	25522954.2	0	421952395	666796
$n.trans_{ilt}$	18	5.98	1	22	666796
$n.trans.d_{ilt}$	1.52	1.45	1	38	666796
$Freq.inter_{ilt}$					666796
$Collateral_{ilt}$					666796
$spread.collateral_{ilt}$	0.89	2.04	-6.08	9.49	666796
Lender-specific characteristics					
$Assets.f_{it}$	10129706814	14764003921.9	276922	127914000000	380630
$PR.f_{it}$	0	0.0008	0	0.01	631305
DoF_{it}	0.22	0.20	0	1	666796
$TP.Rank_{it}$	0.05	0.28	0	1	631111
$HC.Rank_{it}$	0.45	0.29	0	1	615067
$Flujo_{it}$	-444538	313790477.9	-33345040639	10901677911	90432
$Liq.f_{it}$	0.82	0.26	0	1	380630
$counter.f_{it}$	1.71	1.09	1	12	666910
$Stab.f_{ilt}$	0.42	0.25	0	1	666796
$G7.f_{it}$	0.65	0.47	0	1	666910
Borrower-specific characteristics					
$Assets.b_{lt}$	747181	512884.1	1487	2027395	618928
$Liq.b_{lt}$	0.42	0.14	0.10	0.94	618928
$PR.b_{lt}$	0.05	0.04	0	0.15	631393
DoB_{lt}	0.32	0.25	0	1	666796
$stab.b_{lit}$	0.33	0.24	0	1	666796
$counter.b_{lt}$	51.5	40.15	1	139	666910
$G7.b_{lt}$	0.68	0.46	0	1	666910
$z.score.b_{lt}$	0.81	0.09	0.02	1	431284
Aggregate Repo market conditions					
$repo.rate_t$	4.75	1.51	2.93	8.21	2657
$repo.amount_t$					2657
$nf.repo_t$	0.82	0.03	0.72	0.91	2657
Aggregate market conditions					
$TIIE_t$	5.15	1.59	3.27	8.8	2657
$IESF_t$	0.26	0.14	0.08	1	1047
$Govt.rate_t$	4.79	1.48	2.99	8.24	2657
$Interbank.rate_t$	4.82	1.53	2.96	8.34	2657
$Vimex_t$					1047
$Exchange.rate_t$					1047
$S\&P/BMV(IPC)_t$					1047
$Market.tight_t$	14.20	1.71	9.14	20.77	3040
$Tight.d_t$	0.23	0.42	0	1	3040
$Trans_t$	223.4	29.38	64	374	3040
$Trans.d_t$	0.25	0.43	0	1	3040
$Crisis_t$	0.14	0.35	0	1	3040

is available at Banco de Mexico. The main advantage of the DebtRank against other network-based measures is that it avoids the bias associated to having cycles in the adjacency matrix. Few papers have used financial institution level, network-based proxies for systemic risk (Thurner and Poledna (2013)), mostly because it is very hard to acquire this granular level of data. The great benefit of doing so, which at the same time is limitation of other non-network-based proxies (Blanco et al. (2018), Silva et al. (2018), Kanno (2016)), is that the DebtRank account for the contagion between financial institutions.[21]

[21] There are other forms of interconnectedness (Tasca et al., 2017; Cai et al., 2018; Roukny et al., 2018; Kanno, Forthcoming) but ours is the first paper addressing reciprocal lending.