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Banks fearing the drought? Liquidity hoarding as a response to idiosyncratic interbank funding dry-ups

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Non-technical summary

Research Question

Previous research has shown that banks increase their liquid assets in the case of a market-wide freeze of funding markets. This study analyses this phenomenon, which is called liquidity hoarding, in the case of bank-specific shocks. Furthermore, the role of banks' internal capital markets channeling these shocks to the regional economies via bank branches is investigated. Finally, the paper sheds light on the effect of emergency liquidity provided by the central bank in altering the liquidity hoarding effect. Data on Brazilian banks and their regional branches are employed for this study.

Contribution

While previous research mainly focused on market-wide liquidity crises at the interbank market, this paper deviates by analyzing liquidity hoarding as a bank-specific phenomenon when the aggregate market remains fully functioning. This approach enables us to identify the underlying motivation why banks increase their liquid assets. The paper further highlights how banks' internal capital markets channel these shocks to the local economy with potential negative effects to the real economy. Additionally, the study examines whether the activation of central bank liquidity facilities alters preferences for holding liquid assets.

Results

The empirical study shows that bank-specific shocks at the interbank market can result in increased demand for liquidity and lower lending activity at affected regional branches. Given the bank-specific nature of these shocks, it is shown that liquidity hoarding is due to precautionary bank behavior to avoid liquidity shortages. Further, the paper finds evidence that emergency liquidity does not alter banks' preference to hold liquid assets.

Nichttechnische Zusammenfassung

Fragestellung

Eine Reihe von empirischen Untersuchungen haben gezeigt, dass Banken beim Zusammenbrechen von Refinanzierungsmärkten eine erhöhte Bereitschaft haben, mehr liquide Mittel anzuhäufen. Dieses Phänomen wird in der Literatur auch als "liquidity hoarding" bezeichnet. Das vorliegende Papier untersucht, inwieweit dieses Verhalten auch im Kontext von bankspezifischen Finanzierungsschocks entstehen kann. Zudem wird analysiert, wie diese bankspezifischen Finanzierungsschocks über interne Kapitalmärkte auf die Filialebene durchschlagen können und ob von der Zentralbank bereitgestellte Notfallliquidität "liquidity hoarding" beeinflussen kann. Die Analyse stützt sich auf brasilianische Geschäftsbanken und deren lokale Filialen.

Beitrag

Während in der bisherigen Forschung der Fokus auf marktweite Liquiditätskrisen des Interbankenmarktes gelegt wurde, betrachtet das vorliegende Papier "liquidity hoarding" als ein bankspezifisches Problem, bei dem der betrachtete Interbankenmarkt insgesamt funktionsfähig bleibt. Dieser Ansatz ermöglicht es die dem "liquidity hoarding" zugrunde liegende Motivation genauer zu verstehen. Darüber hinaus zeigt das Papier, dass diese bankspezifischen Schocks über interne Kapitalmärkte auf die lokale regionale Ebene durchschlagen können, mit potentiell negativen Effekten für die lokale Realwirtschaft. Zudem wird analysiert, ob von der Zentralbank bereitgestellte Notfallliquidität die erhöhte Präferenz für liquide Mittel beeinflussen kann.

Ergebnisse

Die empirische Untersuchung zeigt, dass bankspezifische Interbankenschocks ursächlich für eine erhöhte Liquiditätspräferenz und eine geringere Kreditvergabe bei den betroffenen lokalen Bankfilialen sein können. Aufgrund der bankspezifischen Natur dieser Schocks kann gezeigt werden, dass "liquidity hoarding" als eine Folge von vorsorgeorientiertem Verhalten von Banken zur Vermeidung von Liquiditätsengpässen zu verstehen ist. Zudem zeigt sich, das durch Zentralbanken bereitgestellte Notfallliquidität nicht geeignet ist, um die erhöhte Präferenz von Banken, liquide Mittel zu halten, zu verändern.

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Banks Fearing the Drought? Liquidity Hoarding as a Response to Idiosyncratic Interbank Funding Dry-Ups*

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Abstract

We investigate whether idiosyncratic interbank funding shocks affecting a bank headquarters can trigger a liquidity hoarding reaction by their regional branches. Shock-affected branches of Brazilian banks increase liquid assets and cut lending in the shocks' aftermath compared to non-affected branches within the same municipality, even in absence of a market-wide freeze. These effects increase in branches' reliance on internal funding and vary depending on banks' access to central bank emergency liquidity. Our findings suggest that the geographical fragmentation of branches' funding limits their ability to offset idiosyncratic funding shocks.

Keywords: Interbank funding; Internal capital markets; Financial market structure; Liquidity risk; Central bank interventions

JEL classification: G01; G11; G21.

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1 Introduction

The functionality of the banking sector and thus banks' primary objective to transform current liabilities, such as consumer deposits, into long-term illiquid assets critically depends upon the availability of liquid assets once sudden restrictions on access to funding occur (see, e.g., Diamond and Dybving, 1983). In modern banking, in which various forms of loan commitments have become an essential part of banks' business models (see, e.g., Avery and Berger, 1991), disruptions in banks' funding sources can amplify potential liquidity and maturity mismatches. Thus, in order to avoid such adverse scenarios, liquidity hoarding — a drastic increase in liquid assets — is likely to occur as a reaction to periods of financial distress (see, e.g., Gale and Yorulmazer, 2013).

As banks' liquidity management during recent crises became central in explaining the spread of liquidity risk, most empirical studies have analyzed the occurrence of liquidity hoarding in the context of market-wide disruptions in interbank funding (see, e.g., Freixas, Martin, and Skeie, 2011, Acharya and Skeie, 2011, Acharya and Merrouche, 2013 and Heider, Hoerova, and Holthausen, 2015).[1] The macro-finance narrative in this literature has emphasized how aggregate interbank market dysfunctionality can lead banks to hoard liquid assets, creating a doom loop of scarce available liquidity, funding constraints and reductions in credit to the real economy. However, an important and still unexplored aspect of the liquidity hoarding phenomenon is whether it can also emerge in the context of bank-specific funding constraints, with interbank markets remaining liquid and well-functioning in the aggregate. This question is important, considering the documented capacity of idiosyncratic bank shocks to affect the real economy (see, e.g., Gabaix, 2011 or Amiti and Weinstein, 2018).

This paper fills this gap in the literature by providing first evidence on the link between interbank funding shocks and liquidity hoarding in the absence of a market-wide liquidity dry-up. Moreover, we examine whether these idiosyncratic shocks prompt banks to subsequently cut lending, exploring the link between liquidity hoarding and its potential real economic consequences. While we track bank-specific funding shocks in a market segment in which only bank headquarters participate, we analyze liquidity and lending reactions to these shocks at the level of regional bank branches. We therefore investigate this question in a context in which internal capital markets and market-to-market spillovers — from interbank markets to branches' funding markets — provide a mechanism to explain liquidity hoarding.

Exploiting this setting, the paper contributes to expand the understanding of how bank-specific events can trigger real-economic consequences via disruptions in credit supply. We highlight how idiosyncratic shocks at a headquarters level are transmitted downstream in a bank's corporate organization, leading branches to accumulate liquid assets, negatively affecting credit supply. Despite the bank-specific nature of the shocks, the fact that some branches represent major market players at a sub-national level opens the scope for aggregate consequences for the economy.

How can the bank-branch structure in our data help us to understand the consequences

[1] Theoretical literature on liquidity hoarding has discussed different, however, interrelated sources of liquidity risk. Explanations for the occurrence of liquidity hoarding are, for example, banks' fear of market exclusion (Allen and Gale, 2004a), prevailing Knighting uncertainty in an entire market segment (Caballero and Krishnamurthy, 2008) or the increase in counterparty risk (Acharya and Skeie, 2011).

of bank-specific interbank funding shocks? In principle, one could argue that a more suitable framework could be to trace the bilateral links within an interbank network and to link changes in these networks with banks' management of consolidated liquid assets and lending growth. We argue that, in contrast to that setting, the data structure underlying our analysis is more suitable to identify the mechanisms and financial incentives behind a liquidity hoarding reaction. In this regard, three arguments support the choice of our empirical approach.

First, by separating the organizational level of the banking conglomerate at which funding shocks occur from the level at which liquidity and lending adjustments are analyzed, we reduce concerns of reverse causality in which, for example, weak credit market conditions lead banks to reduce their interbank market exposure. Moreover, the geographical structure of the bank branch level data allows us to saturate a difference-in-difference model, in which banks affected and not affected by a funding shock are compared over an event timeline, with municipality-date fixed effects. In a similar vein to Cortés and Strahan (2017) or Dursun-de Neef (2019), this approach controls for regional shocks, such as common demand conditions, allowing us to focus on the supply-side interpretation of our results.

Second, our setting allows us to investigate the spillovers of shocks in parent banks' interbank funding markets on branches' funding markets. This type of market-to-market spillover is interesting, as it provides a framework to unveil the liquidity risk channels involved in branches' incentives to hoard liquid assets. We depart from the notion that branches are restricted to raise deposits — their main funding source — only within their geographical business areas. This 'geographical fragmentation' of deposit markets makes internal capital markets the main mechanism connecting liquidity-short and surplus regions. We show that the fragmentation of deposit markets leave branches exposed to shocks affecting their headquarters. In line with this argument, bank-specific shocks trigger a precautionary liquidity hoarding reaction by branches more exposed to internal capital markets, with subsequent negative effects on credit. By linking branches' reaction to liquidity risk exposure, our approach contributes to disentangle the precautionary from the speculative motive of liquidity hoarding (see, e.g., Gale and Yorulmazer, 2013).

Finally, focusing the analysis on a within-municipality estimation is important to derive policy lessons from our empirical exercise. Since regional branch markets are relatively concentrated and branches' presence establishes borrower–lender relationships, the corresponding adjustment of a local branch to an idiosyncratic shock affecting its headquarters could have more pronounced consequences for the local economy. Our analysis therefore contributes to a better understanding of the mechanisms explaining the transmission of financial shocks to the real economy.

Consistent with the liquidity hoarding hypothesis, we find compelling evidence that regional branches from banks affected by idiosyncratic interbank funding shocks increase their liquid asset holdings and cut lending compared to branches from non-affected banks in the same municipality. We interpret this asset reallocation from illiquid to liquid assets as reflecting branches' preference to hoard liquid assets when funding risks increase. To shed light this interpretation we use detailed data on branches' internal funding exposure and inspect whether the results change depending on branches' ex-ante reliance on internal funds. We find that both the liquidity and credit growth effects increase when branches fund a larger share of their assets with internal funding. Interestingly, this finding emerges only when relevant branches — i.e. larger branches and branches that contribute to a bank's profit the most — are excluded from the sample. This latter result suggests that headquarters shield relevant branches by reallocating internal funds, as discussed by Cremers, Huang, and Sautner (2011).

These findings survive an extensive list of sensitivity analyses, including different definitions of the empirical model and the interbank funding shocks, as well as tests addressing concerns that our shock-affected versus non-affected categorization may reflect other ex-ante weaknesses in banks' balance sheets.[2]

To provide insights into the capacity of central banks to intervene in these scenarios, we further analyze information on banks' individual access to emergency liquidity facilities activated by the Brazilian Central Bank (BCB) during the period of analysis. We find that the documented liquidity hoarding reaction is incremental in banks' access to emergency liquidity facilities, whereas the reduction in credit by affected branches is moderated when the access to liquidity facilities is large. Importantly, we find that the benchmark results remain in place when excluding banks with the largest access to BCB funding. Therefore, the findings do not emerge from branches being flooded by BCB funding per se. Rather, this factor exacerbates the underlying precautionary motive explaining the results.

Our paper can be placed within a body of literature that empirically investigate liquidity hoarding as a phenomenon that occurs during times of financial distress. To the best of our knowledge, this study is the first to analyze the phenomenon of liquidity hoarding as a reaction to bank-specific funding shocks with market-to-market spillovers due to branches' reliance on internal capital markets. Beyond our focus on a different market mechanism explaining liquidity hoarding, we are not aware of previous studies linking this phenomenon to the features of financial markets in emerging countries. Previous literature has found evidence for the occurrence of liquidity hoarding as a reaction of U.S. banks to the global financial crisis (see, e.g., Cornett, McNutt, Strahan, and Hasan, 2011 or Berrospide, 2013). Other contributions have also shown that the functionality of interbank markets and banking networks is related to the occurrence of liquidity hoarding in the context of market-wide disruptions using European data (see, e.g., Gabrieli and Georg, 2015, Acharya and Merrouche, 2013, or Fourel, Heam, Salakhova, and Tavolaro, 2013).

Our different bank-branch setting shifts the focus towards liquidity risk transmission via internal capital markets as a mechanism explaining liquidity hoarding. This aspect is particularly relevant for emerging countries like Brazil, in which limited financial development leads to a strong dependence on deposit-based funding. Since regional deposit markets are geographically fragmented and can mainly be connected via internal capital markets, liquidity hoarding emerges as a response to limitations that prevent the free allocation of deposits across regions. We are not aware of previous studies unveiling this mechanism as a driver of financial contagion.

[2]Liquidity hoarding may also emerge due to a bank's decision to anticipate a deposit run following an interbank shock, directing its branches to hoard cash. However, this alternative interpretation is unlikely in our setting. First, branches' informational advantage in assessing credit risk makes them central in banks' decision making (see, e.g., Liberti and Mian 2009 and Cortés and Strahan 2017). Second, we can test whether within a given bank, some branches hoard more liquidity depending on their exposure to internal liquidity risk. These tests show that liquidity hoarding is driven by branches with higher internal funding reliance and a low deposit base, which is in line with the notion that branches represent a rather decentralized decision making structure.

Our paper also connects with a broader body of literature that analyzes the lending channel of interbank market shocks. While these studies have primarily examined the lending channel of interbank funding shocks from a cross-border perspective and focused solely on aggregated interbank market disruptions, we provide evidence that idiosyncratic interbank funding shocks can propagate via internal capital markets to regional banking markets within countries. Closer to our study are papers linking liquidity dry-ups in interbank markets with reduction in bank credit (see, e.g., Iyer, Peydró, da Roche-Lopes, and Schoar, 2014). From a cross-border perspective, De Haas and van Lelyveld (2014) and Allen, Hryckiewicz, Kowalewski, and Turmer-Alkanm (2014) find that internal capital markets are relevant in explaining cross-country financial contagion via foreign banks. Additional contributions to the topic of cross-border contagion via interbank markets with effects on lending are from Aiyar (2012), Ongena, Peydro, and van Horen (2015) and Buch and Goldberg (2015). Most related to our approach is a paper by Pérignon, Thesmar, and Vuillemey (2018), who depart from the study of aggregate interbank market dry-ups and describe the occurrence of idiosyncratic shocks in the European market of certificates of deposits. Our findings contribute to unveil the mechanisms through which dry-ups, such as the ones described by Pérignon et al. (2018), can affect the real economy by changing the preference for liquid assets when market frictions preventing the reallocation of liquidity across regions exist.

As we track the interbank market shock through internal capital markets from headquarters to branches, we further contribute to recent literature that focuses on the role of internal capital markets in propagating shocks to the regional economy (see, e.g., Gilje, Loutskina, and Strahan, 2016, Cortés and Strahan, 2017, Dursun-de Neef, 2019, or Levine, Lin, Wang, and Xie, 2018). Bustos, Caprettini, and Ponticelli (2016) relies on the same bank-branch data for Brazil to show how liquidity booms originated in soy-producing regions are transmitted to other economic sectors via bank-branch connections. We exploit this empirical setting with a different purpose, unraveling the role of internal capital markets in shaping a portfolio reallocation towards liquid assets by branches affected by a sudden disruption in their available funding.

Finally, our paper also touches upon a strand in the literature that evaluates the effects of unconventional monetary policy interventions. In particular, Chodorow-Reich (2014) as well as Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru, and Yao (2017) find that emergency liquidity assistance in the U.S. mitigated the impact of the financial crisis on both households and banks. Numerous other contributions in this field have also investigated the intervention of the European Central Bank (ECB) from a macro perspective (see, e.g., Andrade, Cahn, Fraisse, and Mésonnier, 2019, García-Posada and Marchetti, 2016, Heider, Garcia-de Andoain, Hoerova, and Manganelli, 2016, Casiraghi, Gaiotti, Rodano, and Secchi, 2018, or Crosginani, Faria-e Castro, and Fonseca, 2020). In contrast, Carpinelli and Crosignani (2021) study the effectiveness of ECB liquidity interventions on bank loan supply to Italian firms following a wholesale funding dry-up. While the credit effect of these interventions has been well established for developed countries, we provide evidence from an emerging country suggesting that corporate political considerations can limit the effectiveness of central banks' actions if incentives exists to use the proceeds from liquidity injections to build up liquid assets.

The remainder of the paper is organized as follows: Section 2 discusses the theoretical motivation, the data set employed and our empirical methodology. Section 3 presents the benchmark results and the analysis of how these results vary depending on dynamics in internal capital markets. This section also summarizes a set of additional robustness tests. In Section 4, we discuss policy implications derived from banks' access to central bank liquidity facilities. Finally, Section 5 concludes.

2 Methodology and data

2.1 Theoretical motivation

We start by defining two distinct financial markets that interact in explaining the transmission of a parent-bank funding shock to liquidity and lending decisions by its municipal branches. First, parent banks participate in a country level interbank market, obtaining loans from their counterparties and providing their own funding in an over-the-counter fashion. The second market represents branches' market for funding, which rely on two main funding sources: local retail deposits and internal capital markets. These two sources represent 74 percent of total assets for the average branch in our sample.

Based on this setting, we conjecture that bank-specific shocks at the parent-bank level can lead branches to increase their liquid assets and to cut lending. This reaction would occur against the backdrop of increasing expectations of a branch-level funding market freeze, as branches may expect to experience increasing liquidity and rollover risk. Therefore, liquidity hoarding would emerge in our setting as a reaction to liquidity risk exposure in the form of branches' reliance on internal capital markets that become constrained when the main component of a banking conglomerate – namely, its headquarters bank – experiences a significant funding shock.

Why should we expect to observe consequences of sudden bank-specific disruptions in interbank markets in the first place? In principle, under the assumption that interbank market frictions do not exist, these markets should ensure an efficient allocation of liquidity across all market institutions (Allen and Gale, 2004a). In our setting, this argument means that parent banks of branches with the opportunity to finance a positive net present value project should be able to use the interbank market to tap the necessary liquidity, providing it via internal capital markets to the respective branches. The theoretical literature on interbank markets shows, however, that frictions in the form of informational asymmetries may restrict banks' capacity to access interbank funding, even if positive NPV projects exist (see, e.g., Gale and Yorulmazer, 2013). For instance, as counterparty risk becomes difficult to assess banks are less inclined to provide interbank loans. Hence, in this scenario, the interbank market itself becomes a channel that propagates liquidity risks across (and potentially within) banking conglomerates (Freixas et al., 2011).

Building on this idea, our approach features distinct market frictions both at the parent bank and at the branch level that could explain an increase in branches' liquid assets when parent banks become funding constrained. Regarding parent banks, we argue that 2008 and 2009 — the years around the global financial crisis during which we identify events of bank-specific interbank funding shocks — represent a time window with high financial market uncertainty in which interbank lenders were likely to be more sensitive to informational asymmetries (Allen and Gale, 2004b), exposing banks to the risk of sudden disruptions in the availability of interbank funding. We therefore take the likelihood of interbank funding shocks as a given and implement an algorithm explained below to identify the months in which such events occur, distinguishing between affected and unaffected banks.

With respect to branches, we argue that they face a liability-side friction, since they fund their operations in geographically fragmented deposit markets. Branches can neither raise retail deposits in other regions nor can they directly access the country-level interbank market because of their organizational subordination. This phenomenon leads to a problem of funding market incompleteness, in which jurisdictional and organizational barriers prevent a free allocation of liquidity across branches and regions, as it has been shown for the U.S. by Gilje et al. (2016). Such allocation barriers can lead financial market institutions to hold high levels of liquid assets, i.e., they can lead banks to engage in liquidity hoarding (see, e.g., Allen and Gale, 2004a).

Finally, it should be noted that from the perspective of an individual bank there are two competing, though not mutually exclusive, rationales to increase liquid asset holdings. On the one side, banks fearing market exclusion may increase liquid assets in a precautionary fashion. On the other side, banks may accumulate liquidity if they speculate that other affected banks will be forced to sell their assets at fire sale prices (Gale and Yorulmazer, 2013). As we show below, our approach can distinguish this latter speculative motive from the precautionary motive, leading to more precise estimations.

2.2 Identification and empirical model

To analyze the effect of bank-specific interbank funding shocks that occur at the headquarters level of a banking conglomerate on lending and liquidity adjustments at the local bank branch level, we employ the following identification strategy.

First, as bank headquarters experience funding shocks at different points in time, we implement an event-timeline to compare branches of affected vs. non-affected banks around the period where shocks occur. While only affected banks do experience a dry spell in interbank funding, we assign to non-affected banks a "pseudo" shock set at the time where they are the closest to face an actual interbank funding shock. With this setting we compare banks over an event-timeline starting at at $\tau = -24$ and ending at $\tau = 24$, where $\tau = 0$ indicates the month at which a shock occurs. We explain these definitions in detail in Section 2.4.

Second, by separating headquarters from branches we reduce concerns of reverse causality. For example, it would be possible that a bank's reduction in interbank funding is driven by its decision to cut back on lending during times of economic decline. However, when controlling for regional macroeconomic factors by including municipality-date fixed effects, the focus on branches reduces this concern. We exploit the fact that each individual branch represents a marginal share of their respective banking conglomerates, making it unlikely that local conditions in individual regions could affect interbank borrowing decisions.

Third and finally, by exploiting the geographical variation in our data set we can we control for all time-varying factors within a given municipality, including credit demand. For this purpose, we follow previous contributions by applying a within-municipality estimation (see, e.g., Gilje et al., 2016 or Cortés and Strahan, 2017, Dursun-de Neef, 2019).[3]

[3] Originally, the idea of using a within-borrower estimation by including borrower-time fixed effects

In contrast to this procedure, the optimal choice to control for credit demand would be to use credit register data at the borrower level, as suggested by the empirical literature (see, e.g., Iyer et al., 2014, Jiménez, Ongena, Peydró, and Saurina, 2014, or Ioannidou, Ongena, and Peydró, 2015). However, this type of data does not allow for tracing adjustments at the branch level, as it does not report the balance sheets of the branches. Observing branches' balance sheets over time is central to our research question, as it allows us both to improve our identification of a bank-level hoarding reaction and to investigate the drivers of this phenomenon. This latter advantage means that we can explore whether liquidity risk factors, such as branches' geographically fragmented funding markets and organizational subordination provide an explanation for liquidity hoarding.

To identify the effect of idiosyncratic interbank funding shocks on liquid asset growth, we estimate Eq. 1:

$$\begin{aligned} \Delta Liquidity_{i,m,\tau} = &\alpha_0 + \beta_1 \left[Affected_i \times Shock_\tau \right] + \beta' Bank_{i,m,\tau} \\ &+ \mu_{m,t} + \gamma_{i,m} + \delta_t + \varepsilon_{i,m,\tau} \end{aligned} \tag{1}$$

The panel is structured at the branch-time level, with branches being labeled with subscripts i, m to reflect that they belong to bank i and operate in municipality m. The dependent variable is the monthly (month-on-month) change in log liquid assets of bank branch i located in municipality m at event-time τ, which can represent different actual months t for each bank. Standard errors in this benchmark model are clustered at the headquarters and month level to achieve efficient estimates.[4] Furthermore, we saturate our model by including branch, as well as municipality-date fixed effects based on the underlying actual month t ($\gamma_{i,m}$ and $\mu_{m,t}$, respectively).

Within this specification the interaction $[Affected_i \times Shock_\tau]$ provides the main variable of interest, whose corresponding parameter β_1 represents the difference between affected and non-affected branches in the average change in liquidity growth between the pre- and post shock periods. Therefore, β_1 takes the form of a difference-in-differences estimator. While the first term of the interaction, $Affected_i$, is a time-invariant dummy variable that equals 1 for all branches belonging to an affected headquarters and 0 otherwise, the second term, $Shock_\tau$, is a dummy variable that equals 1 for the period $\tau \geq 0$ and 0 for $\tau < 0$. By construction, all branches i, m that belong to bank i are affected or not in the same way by interbank funding shocks.

To control for headquarters- and branch-specific characteristics, we include various control variables at the headquarters and branch level which are captured by $Bank_{i,m,\tau}$. For the headquarters level, these variables include the size of the bank (captured by the log of total assets), the capital-to-asset ratio, the liquid-to-total-asset ratio, the non-performing loans to total assets ratio (capturing bank's loan portfolio risk) and a ratio of administrative costs to income as a proxy for banks' managerial quality. Similarly, at the branch level, we control for branch size (log of total assets), for internal liquidity exposure (measured by the internal funding to total assets ratio), and for the deposit

has been established in previous literature by Khwaja and Mian (2008) and Schnabl (2012) and was then extended to the regional setting.

[4] In the robustness section, we show that our results will remain unaltered when clustering the standard errors at different levels.

to total assets ratio. We additionally control for branches' income-to-asset ratio.[5] As our dependent variable is defined as a growth rate and all control variables are based on balance sheet items, we use one-month lagged controls to mitigate multicollinearity concerns.

Since an increase in liquid assets is likely to be accompanied by an asset reallocation effect as outlined above, we conjecture that affected branches may have to cut their lending activity to satisfy their liquidity preferences. To test this hypothesis, we substitute the liquid asset growth rate with the lending growth rate as the main dependent variable in Eq. 1 to estimate Eq. 2:

$$\begin{aligned}\Delta Credit_{i,m,\tau} =&\alpha_0 + \beta_2 \left[Affected_i \times Shock_\tau\right] + \beta' Bank_{i,m,\tau} \\ &+ \mu_{m,t} + \gamma_i + \delta_t + \varepsilon_{i,m,\tau}\end{aligned} \tag{2}$$

Specifically, the dependent variable of Eq. 2 is the monthly change in month-on-month log change in outstanding commercial credit at the branch level.[6] Evaluating Eqs. (1) and (2) over the same event-timeline enables us to track the asset reallocation effect between liquidity and credit as a response to the idiosyncratic funding shock. Assuming that liquidity hoarding occurs and crowds out commercial credit, we expect $\beta_1 > 0$ and $\beta_2 < 0$ on average.

2.3 Data and sampling procedure

2.3.1 Data description

We combine granular data on balance sheet and income information from banks' headquarters and their corresponding individual bank branches for the entire universe of the Brazilian banking system.[7] Another dimension of granularity is that this information is available on a monthly basis.[8] To link both datasets, we manually construct an identifier to connect each branch to its corresponding headquarters. Furthermore, the branch data set also includes information on the municipality in which each branch operates. The data used for the analysis is reported in millions of Brazilian Reais (in what follows BRL). This data source has been used to investigate the regional reallocation of credit and the functioning of internal capital markets in Brazil (see, e.g., Coleman and Feler, 2015, Noth and Ossandon Busch, 2017 and Coleman, Correa, Feler, and Goldrosen, 2017).

Both data sets are based on regulatory information from the BCB. The first data set is based on call reports of the BCB and contains unconsolidated data and separate information for each bank's headquarters. The second data set, which contains the

[5] The variables' description can be found in Table A.1 in the Appendix.

[6] Note that Eq. 2 follows Cornett et al. (2011). Focusing on commercial credit further underpins the use of municipality-date fixed effects to control for credit demand. In fact, an underlying assumption of this approach is that demand shocks are relatively homogeneously distributed across banks within a municipality at a given point in time. To the extent that branches' can differ in terms of the credit segments in which they provide lending, observing credit in a particular segment makes a violation of this assumption rather unlikely.

[7] This is ensured by the fact that both datasets contain information on all banks that have a banking license in Brazil. Hence, our dataset is also not restricted to any size limit as any institution is recorded.

[8] Our data set starts in 2005m1 and ends in 2012m1. However, data from both sources is updated regularly by the BCB.

branch-municipality information, is also based on regulatory data from the BCB and is denominated the ESTBAN database. By focusing on retail banking, our sample is less representative of financial centers and major cities, as investment banks are predominantly located there. Apart from this property, bank branch penetration is widely spread across Brazilian municipalities such that our sample accounts on average for approximately 80 percent of total bank assets in 26 out of 27 federal states.[9]

Focusing on Brazil as a major emerging market has additional advantages for our analysis. First, the Brazilian banking sector represents one of the largest banking markets among emerging economies. At the beginning of our sample in January 2005, 127 institutions with a local banking license existed, with aggregated credit accounting for 26 percent of the country's GDP. Second, the geographic size and diversity of the country helps us to add a large heterogeneity to the empirical model, allowing us to investigate how branches' features explain the cross-regional transmission of interbank funding shocks. Finally, a crucial feature of Brazil is that heightened information sensitivity in Brazilian interbank markets was not driven by local factors such as regional housing bubbles but rather by the increase in uncertainty originating in the U.S. mortgage crisis that led to the global financial crisis. Hence, from the Brazilian perspective, the crisis that hit Brazil in 2008 can be understood as an external shock.[10]

2.3.2 Sampling procedure

Our identification strategy further requires the following sampling procedure. First, we only focus on banks that do not close during the sample period. Thereby, we ensure comparability across banks as changes in interbank funding may reflect ex-ante conditions responsible for the bank being closed, merged or acquired. By excluding M&As from our sample, we eliminate concerns that changes in interbank funding are driven by changes in the organizational structure which would be reflected in the new funding structure of the respective bank.

Second, we also exclude all banks that are not continuously active in the interbank market segment that we focus on. This restriction is needed in order to properly apply the Cavallo, Powell, Pedemonte, and Tavella (2015) algorithm used to identify the occurrence of interbank shocks (see below). This restriction also reflects that changes in interbank funding by banks that are not frequently active in this market are likely to be demand-driven. This is, however, relatively unlikely for banks that historically have been continuously using this funding source. Third, since this procedure also excludes complete dry-ups, we can argue that the estimations are driven by the precautionary motive of banks and are not due to the actual event of market exclusion. This second procedure reduces our sample to 51 out of 120 banks, which on average still account for 79 percent of the lending volume of the investigated interbank market segment.

Finally, in line with our within-municipality estimation approach, we only use those municipalities for our analysis that contain at least one affected and at least one non-

[9] Sao Paulo with 67 percent is here the outlier. This is expected as Sao Paulo is the country's biggest financial center.

[10] Even though this statement holds at the country level, it may be the case that individual banks could have been ex-ante more exposed to risks associated with the transmission of the global financial crisis to emerging countries, such as foreign funding reliance. We empirically address these concerns in Section 3.3.

affected branch. This final adjustment ensures the consistency of our estimates and allows us to implement our preferred fixed-effects structure. Ultimately, our final sample contains 4514 bank branches that are active in 1628 municipalities. At the headquarters level, our final sample consists of 46 banks that account on average for 52 percent of total assets and 92 percent of credit outstanding for Brazil's entire banking system.

The branches in the sample vary according to the size of their balance sheets from an average of 2.84 US Dollar mill. of assets in the lowest decile to an average of 3,300 US Dollar mill. of assets in the highest decile. Overall, an average branch has total assets that amount to about 345 US Dollar mill.[11] An average branch is located 679 km away from its headquarters, whereas 22 percent of branches are located at a distance larger than 1000 km from its headquarers. These numbers — calculated using municipalities' geographical centroids as a reference — help to visualize the geographical spread of branches in the sample. Table A.2 in the Online Appendix provides further details on the distribution of bank ownership in the sample: out of a total of 46 banks, 31 are domestic banks and 16 correspond to foreign-owned banks. At the branch level, these numbers translate into 696 out of 4514 branches being foreign owned.

The within-municipality data coverage is high, as the final sample covers an average of 77 percent of total branch assets in the 1628 municipalities considered after excluding banks in the sampling procedure described above. It should be noted that municipalities in the sample vary also according to their degree of urbanization. Using the urban hierarchy definitions published by the Brazilian Institute of Geography and Statistics, we find that 52 percent of the municipalities in the sample correspond to relatively highly urbanized areas, whereas the rest of the sample corresponds to semi-urban municipalities. The relatively large representation of urban municipalities is in line with the notion that bank branches operate mostly in the regional and sub-regional capitals. As a reference, highly urbanized municipalities reported in the sample period an average population of 155,581 inhabitants, whereas other municipalities reported an average population of 32,241 inhabitants.[12]

2.4 Pinning down interbank funding shocks

To pin down bank-specific funding shocks we need both a suitable real context and a specific methodological approach. Interestingly, similar to the European context (see Pérignon et al., 2018), we find that the unsecured local Brazilian interbank market did not experience a complete dry-up during the period from 2007 to 2009. This particular market segment represents local and unsecured interbank lending operations with a maturity of more than 90 days.[13]

[11] These numbers are calculated using an exchange rate of 2.1 US Dollar per Reais as a reference, which is the average exchange rate in the sample period. At the consolidated bank level, the top-5 banks in terms of assets held an average of 83,900 US Dollar mill. of assets in the sample period. Conversely, the smallest 5 banks held on average 187 US Dollar mill. of assets. The average bank reported 13,917 US Dollar mill. of assets on average.

[12] Highly urbanized municipalities correspond to national and regional metropolises, regional capitals, sub-regional urban centers, and smaller zone centers, following the local definitions.

[13] A more detailed description of this particular market segment can be found in Section A.2 in the Online Appendix.

Figure 1 displays the dynamics of this segment of the interbank market.[14] The solid line in the upper panel depicting the log of aggregated balances remains fairly stable over the crisis period. Even during this period of stress in global financial markets, the Brazilian interbank market remained liquid and well-functioning in the aggregate. The dashed line in the bottom panel shows, however, that the volatility of flows in this market increased during the financial crisis with a peak in the middle of 2009. This finding indicates that even though the market did not suffer from an aggregate disruption, uncertainty about counterparty risk may have restricted the access of certain banks to this market. Henceforth we refer to the segment of interest in the interbank market as interbank borrowing.[15]

We exploit these dynamics of interbank borrowing to apply an algorithm to identify and pin-down the moment in time when a bank is hit by an idiosyncratic interbank funding shock. The shocks we identify are similar to a partial dry-up of a bank-specific funding source. We rely on a time series approach in the spirit of Cavallo et al. (2015) that was originally used to identify sudden stops in capital flows. Our adjusted approach can be described in the following way.

First, based on the previously discussed theoretical considerations and descriptive evidence, we define the period from January 2008 to December 2009 as the period in which we would expect the algorithm to detect potential idiosyncratic shocks. Second, we calculate the bank-specific funding growth rate in this market segment $\Delta\widetilde{IB}_{i\tau}$ by subtracting the average growth rate of all other banks in this market from bank i's own interbank funding growth rate. In a robustness test, we also calculate these idiosyncratic growth rates $\Delta\widetilde{IB}_{i\tau}$ using a multifactor residual model (see, e.g., Pesaran, 2006 or Buch, Doepke, and Stahn, 2009). Third, similar to Cavallo et al. (2015) the condition specified in Eq. 3 is applied to identify whether and at which point in time a bank experienced a sudden disruption in interbank funding.

$$\Delta\widetilde{IB}_{i\tau} \leq \frac{\sum_{\tau=-12}^{12}\widetilde{IB}_{i\tau}}{12} - 2\sigma_{i\tau} \tag{3}$$

According to this condition, a bank is classified as being affected by an interbank funding shock if its idiosyncratic growth rate $\Delta\widetilde{IB}_{i\tau}$ falls below the second standard deviation of its 12-month historical mean in the period from January 2008 to December 2009. If this condition is met, the start (end) of the shock is set at the month when $\Delta\widetilde{IB}_{i\tau}$ plunges below (exceeds) the first standard deviation of its historical mean. Based upon this procedure, we find that 18 out of 46 banks are classified as being affected, while the remaining 28 banks will be used as the control group. These 18 'affected' banks own

[14] Figure A.1 in the Online Appendix displays the relative importance of this market segment over time.

[15] The balance sheet data provided by the BCB distinguishes between different categories of interbank funding. These categories include interbank deposits, interbank borrowing, foreign interbank funding, liabilities from derivatives and interbank relations. Interbank deposits represent the largest category in the sample (aprox. 50 percent). Interbank borrowing, the variable used for our analysis, represents another 25 percent of total interbank liabilities on average. Interbank relations — a category that includes smaller positions such as debts payable and obligations with correspondents — together with foreign interbank funding and derivative positions account for the remaining share of total interbank funding. On average, banks in the sample finance 14 percent of their total assets with interbank borrowing. Section A.2 in the Online Appendix provides further details on the composition of Brazilian banks' interbank funding.

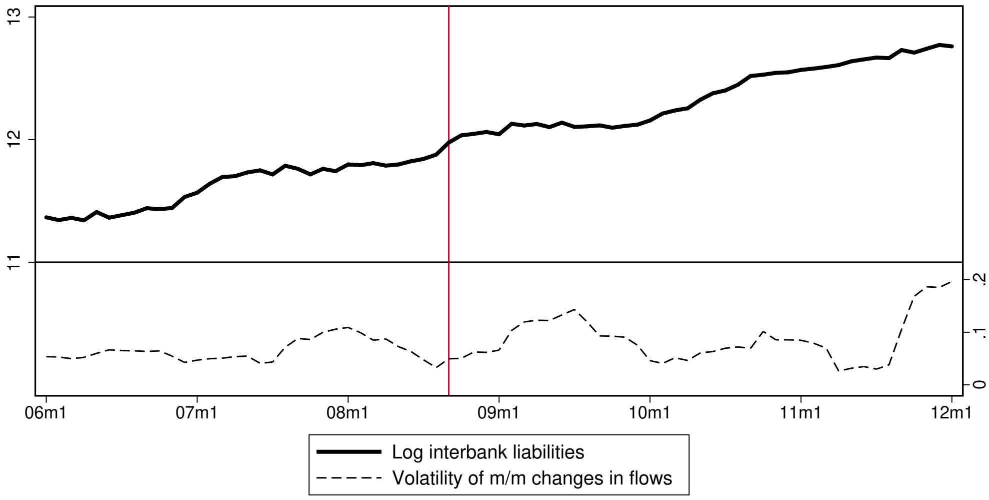

Figure 1: Interbank borrowing volume and volatility

NOTES: This figure depicts the evolution of the log amounts outstanding (in millions of BRL) of aggregate interbank borrowing over time. The dashed line in the bottom panel displays the underlying volatility of these volumes. This volatility is calculated as the standard deviation of monthly changes in flows over the past 12 months on a rolling window. The vertical red line marks as a reference the month at which Lehman Brothers collapsed (September 2008).

2,365 branches, as opposed to the 2,149 branches belonging to non-affected banks. To analyze the effect of these shocks on liquid assets growth, we assign a pseudo-shock to the non-affected banks at the particular month at which the distance between $\Delta\widetilde{IB}_{i\tau}$ and the threshold is minimized.[16]

Departing from the notion that we do not observe an aggregate freeze or major liquidity drop in the Brazilian interbank market under investigation, we define idiosyncratic interbank market shocks as events in which a drastic reduction in a bank's available interbank funding occurs despite the absence of an aggregate liquidity freeze. While this definition follows closely the one by Pérignon et al. (2018), our empirical approach to pin down shocks differs from this latter study. While they define 'interbank runs' as periods in which a bank loses 50% or more of its certificates of deposits' funding over a 50-days period, we shift the focus to large deviations in banks' secular trends in interbank funding growth. This approach allows us to mitigate concerns about 'false positives' arising from irregular trends in banks' funding that could be wrongly attributed to supply-driven shocks. As in Pérignon et al. (2018), the shocks we document imply that the loss of funding by a few banks should not be necessarily associated with a market that becomes dysfunctional in the aggregate, even in the period of the global financial crisis.

[16] In the Online Appendix (Section A.2) we discuss this procedure in greater detail. The shocks we identify are also well distributed within the period from January 2008 to December 2009 (see Figure A.2). Tables A.1 and A.2 in the Online Appendix report further descriptive statistics on the affected banks.

2.5 Descriptive statistics and identification assumptions

The main descriptive statistics are reported in Table 1. where the first four columns display the mean, the standard deviation, the minimum and the maximum value of all variables for the entire sample period, the next columns report the mean of the affected and non-affected groups and the difference in means of both groups in the pre-shock period. In the last columns, we also report whether this difference is statistically significant by employing the test of normalized differences of Imbens and Wooldridge (2009) (col. VII) and a simple t-test of differences in means (col. VIII). The test of normalized differences assesses the overlap between bank groups without the sample size affecting the analysis.

We find that shock-affected branches had on average a larger internal funding ratio and a lower deposit to total asset ratio. At the headquarters level, affected banks were on average more liquid and held a larger share of non-performing loans in their portfolio. As shocks in our setting occur at the headquarters level, the results concerning structural differences between headquarters are more important for our analysis. In this regard, we find rather mixed results. While a higher liquidity ratio for the affected group points to the fact that affected banks had stronger fundamentals, the higher non-performing loan to total loans ratio indicates the opposite. To reduce the concern that these ex-ante differences drive our results, we implement robustness tests in which these bank features compete against the shock-affected dummy in driving the difference-in-differences estimation. [17]

Apart from these explanatory variables, Table 1 additionally reports whether we find evidence of a violation of the parallel trend assumption in the pre-shock period — i.e., when the group-specific dependent variables are not on a parallel trajectory before the shock occurs. We first test whether growth rates are at a similar level. The final column of the first two rows shows that there is no statistically significant difference in the average liquidity and credit growth rates between each group. The third and fourth rows of the last column provide a further test for the violation of the parallel trend assumption, focusing on the first difference of the dependent variables in the pre-shock period. Again, we do not find any statistically significant difference between affected and not-affected branches.

The parallel trend of banks' credit and liquidity growth can be visually verified in Figure A.3 in the Online Appendix. This Figure depicts the average liquidity and lending growth rates of affected and non-affected branches over the event-timeline. However, this visual representation is based on averages per banks and can still hide bank-specific factors leading to violations of the parallel trend assumption. We therefore implement a further test in which we regress the growth rates of liquidity and credit on the $Affected_i$ dummy from Eqs. 1 and 2. This regression is performed only in the pre-shock period and is saturated with municipality-date fixed effects. The results, reported in Table A.7 in the Online Appendix, show no statistically significant relationship between $Affected_i$ and the liquidity or credit growth rates. Importantly, this results holds both for the full pre-shock period as well for narrower definitions of the pre-shock period.

Even though Table 1 suggests that the occurrence of interbank shocks is not strongly

[17] The t-statistic tests of differences in means show some diverging results. While they confirm the similarity of the pre-shock trends in credit and liquidity growth, they also show that affected headquarters can be seen as larger, more capitalized, and more liquid banks. These differences emerge due to the fact that t-statistics weight the individual subsamples by their size (see a detailed discussion in Imbens, 2015).

Table 1: Summary statistics

	Mean	S.d.	Min.	Max.	Affected: Yes	Affected: No	Diff.	T-stat.
	I	II	III	IV	V	VI	VII	VIII
Dep. variables:								
Δ Log liquidity	-0.023	0.701	-1.971	2.055	-0.105	-0.129	-0.024	-0.590
Δ Log credit	0.010	0.940	-2.761	2.869	0.055	-0.284	-0.339	0.860
Dif. Δ Log liquidity	-0.026	1.376	-3.625	3.831	-0.101	-0.135	-0.035	-0.581
Dif. Δ Log credit	0.007	1.844	-4.996	5.361	0.056	-0.290	-0.346	0.872
Headquarters:								
Bank size	12.195	1.173	8.763	13.369	12.260	11.859	-0.401	1.790
Capital / assets	0.074	0.040	0.036	0.253	0.075	0.073	-0.002	-5.955
NPL / Credit	0.171	0.074	0.038	0.287	0.203	0.126	-0.077*	0.686
Adm. Cost / assets	0.004	0.002	0.001	0.011	0.004	0.004	0.000	0.342
Liquidity / assets	0.012	0.005	0.002	0.022	0.014	0.010	-0.004*	-2.314
Branches:								
Branch size	3.534	1.355	1.073	8.746	3.528	3.308	-0.220	-0.220
Deposits / assets	0.750	0.266	0.058	0.998	0.691	0.812	0.121*	0.534
Income / assets	0.020	0.011	0.005	0.056	0.020	0.021	0.002	-1.852
Internal funding	0.173	0.262	0.000	0.874	0.233	0.108	-0.125*	-1.776
Assets								

Notes: This table reports the summary statistics for the working sample. Cols. I to IV report the mean, the standard deviation (S.d.), the minimum, and the maximum value for each variable for the entire sample period. Cols. V and VI report the mean for the group of affected and non-affected branches separately in the pre-shock period. Col. VII reports the difference in means between affected and non-affected banks. Employing the normalized difference in means method of Imbens and Wooldridge (2009), * denotes whether the respective difference is statistically significant. This test does not find any statistically significant difference in means for the first difference of our dependent variables in the pre-shock period (see third and fourth row). Hence, we do not detect any violation of the parallel trend assumption. Col. VIII reports a test of difference in means in the form of a t-statistic.

related, ex-ante, to bank characteristics, we performed additional tests to check the presence of systematic sorting. First, we run linear probability regressions estimating the occurrence of an interbank market shock as explained by banks' characteristics. For this purpose we collapse the panel at the bank level taking averages across branches in the pre-shock period. We then run regressions of the shock-dummy on bank and branch controls. These regressions show that bank or branch characteristics are largely unrelated with the occurrence of interbank shocks, neither for individual variables, nor for a model in which we include all variables simultaneously (see Table A.3 in the Online Appendix).[18]

In a second exercise, we explore interbank interest rates to check whether interbank shocks can be attributed to changes in banks' own demand for funds. Specifically, we test

[18] If anything, Table A.3 shows some weak evidence of a negative relationship between the ratio of banks' administrative costs to assets and the affected categorization. This relationship vanishes, however, when all control variables enter the model simultaneously.

whether the interest rates of interbank borrowing change in the 12-month run-up to the shock. As bank-specific interest rates in the interbank market are not publicly available, we take the amount of interest paid relative to the loan amount outstanding in the interbank market for each individual bank per month. We find that this interest rate proxy increases for affected relative to non-affected banks only one month in advance of shocks, suggesting that funding shocks are not driven by changing bank funding preferences. This test is reported and discussed in greater detail in Table A.4 in the Online Appendix.

Third, we show in Section 3.3 that our analysis can be replicated by excluding, for instance, banks that experienced the largest average drops in credit during the shock period. These banks could have cut interbank funding demand as a consequence of facing a large reduction in credit demand. Also, the analysis can be performed by excluding interbank 'market makers', that is, banks that are net lenders in the interbank market and that could have cut interbank funding following a drop in credit demand. The main results remain, however, unaltered when these groups of banks are excluded.

Finally, it should be noted that our estimation is performed using a sample of banks that never fully halted their funding activities in the interbank market. Moreover, the interbank market we focus on remained liquid and active in the aggregate. These arguments and preliminary tests support the notion that the shocks we identify are supply-driven and cannot be related to a systematic sorting according to banks' fragilities or credit demand-side conditions. Therefore, the interbank shocks we identify can be seen as reflecting supply-driven dry-ups in interbank funding to individual banks at different points in time.

3 Results

3.1 Benchmark results

Table 2 reports the benchmark results for the estimation Eqs. 1 and 2 in cols. I to III and IV to VI, respectively. Cols. I and IV use neither control variables nor fixed effects, whereas cols. II and V include headquarters and branch controls as well as branch and date fixed effects. Finally, cols. III and VI report the results for our preferred specification, i.e., we include control variables for both levels of the organizational structure of banks and saturate our model with municipality-date fixed effects.

Across all specifications, we find compelling evidence for both the liquidity hoarding and the asset-reallocation effect on lending of idiosyncratic interbank funding shocks. For our preferred specifications (i.e., III and VI), the difference-in-differences parameter is statistically significant at the 5-percent level at least. This idiosyncratic interbank funding shock increases liquidity by 13 percentage points (henceforth: p.p.) on average, i.e., affected branches report on average a 13 p.p. higher liquidity growth rate than non-affected branches in the post-shock period compared to the pre-shock period. As this effect captures 18.6 percent of the within variation of the liquidity growth rate (70 p.p.), this effect is sizeable from the perspective of its economic significance. Furthermore, the idiosyncratic interbank funding shock decreases the credit growth rate by approximately 27.3 p.p. on average (i.e., the difference-in-differences effect). This effect accounts for 29

Table 2: Benchmark Results

Dep. var:	**Δ Log Liquidity**			**Δ Log Credit**		
	I	**II**	**III**	**IV**	**V**	**VI**
Affected X Shock	0.116***	0.144*	0.130**	-0.291***	-0.267*	-0.273**
	(0.006)	(0.076)	(0.059)	(0.008)	(0.144)	(0.121)
Shock	0.268***	-0.09	-0.087	0.591***	0.118	0.106
	(0.004)	(0.058)	(0.054)	(0.006)	(0.096)	(0.09)
Affected	0.001			0.374***		
	(0.004)			(0.006)		
Headquarters controls:						
Size (log total assets)		0.214	0.277**		0.343	0.382
		(0.181)	(0.135)		(0.369)	(0.303)
Capital / Assets		0.036	0.135		-0.065	0.188
		(0.743)	(0.532)		(1.799)	(1.402)
NPL / Credit		0.322	0.489		-0.949	-0.652
		(0.537)	(0.424)		(0.922)	(0.784)
Adm. Cost / Income		11.042	11.618		54.998	52.647
		(22.19)	(15.999)		(40.937)	(32.371)
Liquidity / Assets		4.442*	3.719*		5.319	5.147
		(2.211)	(2.057)		(4.29)	(3.552)
Branch controls:						
Size (log total assets)		0.350***	0.388***		0.554***	0.558***
		(0.042)	(0.044)		(0.067)	(0.072)
Deposits / Assets		0.545***	0.682***		-0.109	-0.325
		(0.196)	(0.219)		(0.451)	(0.405)
Income / Assets		7.958***	9.188***		6.463***	7.968***
		(1.655)	(1.47)		(2.045)	(2.038)
Internal funding / Assets		-0.08	-0.108***		-0.675***	-0.683***
		(0.065)	(0.027)		(0.096)	(0.109)
Branch FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	Yes	.	No	Yes	.
Municipality x Date FE	No	No	Yes	No	No	Yes
Observations	214,063	214,061	196,667	214,063	214,061	196,667
R-squared	0.054	0.121	0.397	0.069	0.187	0.435

Notes: This table reports the empirical results of the benchmark estimation. Columns I to III report the results when estimating liquidity growth, whereas columns IV to VI report estimations of credit growth. For growth rates, we use log changes of the respective variables. Columns I and IV contain neither control variables at the headquarters nor at the branch level nor any type of fixed effects structure. Columns II and V include headquarters and branch controls as well as branch and time fixed effects (on a monthly basis). Columns III and VI report the results for the preferred specification which includes all control variables and branch as well as municipality-date fixed effects. For all equations, we use standard errors that are clustered at the headquarters and date level and ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively. The variables are defined in Table A.1 in the Appendix.

percent of the within-variation of the lending growth rate (94 p.p.).[19]

An interesting question is whether the parallel effect of the interbank shock on liquidity and lending can also be associated with other adjustments in branches' balance sheets. For example, does the shock exposure lead affected branches to shrink their size, or to take on more risk to compensate for the reduced credit supply? To explore these related questions, we perform tests in which we replace the dependent variable in our benchmark model by the growth rates of total branches' assets, deposits, and internal funding. We also estimate the effect on the monthly change in branches' return on assets.

The results, reported in Table A.5 in the Online Appendix, depict some interesting dynamics: as expected, affected branches suffer a loss of internal funding, which is partially compensated by an increase in total deposits. This compensation is, however, of small economic magnitude compared to the effect on internal funding growth. The shock also leads affected branches to reduce the overall size of their balance sheet, whereas we find no statistically significant effect on branches' returns. These results are in line with the notion that liquidity risk is transmitted via internal capital markets and that the fragmented structure of regional deposit markets limit branches' capacity to offset the loss of internal funds.

3.2 Dynamics in internal capital markets

The results in the previous section suggest that intra-bank linkages help to explain the spread of liquidity risk across regions when bank-specific interbank shocks occur. This interpretation builds on the assumption that regional branches face limits to substitute the loss of internal funding: while raising local deposits could mitigate the effect of the shock, branches are restricted to raise deposits only within their geographical business areas and remain therefore exposed to a fragmented structure in regional deposit markets.

With this limitation in place, we would expect the liquidity and credit effects to increase in branches' reliance on internal funding. However, headquarters are also likely to cut internal funding heterogeneously across branches in the presence of principal-agent frictions between branches and headquarters (see, e.g., Scharfstein and Stein, 2000; Degryse, Matthews, and Zhao, 2018). For example, banks may decide to support branches with a higher influence within the banking group, as well as branches that matter the most for the group's profits (see, e.g., Cremers et al., 2011; Cetorelli and Goldberg, 2012).

Given these conjectures, we next evaluate the implications of dynamics in internal capital markets for our analysis. We look explicitly at branches' dependence on internal funding and ask whether the benchmark results increase in branches' internal funding reliance. With this test we check whether frictions related to the geographically fragmented structure of deposit markets help to explain the results. Econometrically, we add to the benchmark model an interaction term between the difference-in-difference estimator and a dummy proxying for branches' internal funding exposure. We define this dummy as 1 if a branch reports in the pre-shock period an average internal to total funding ratio above the sample median. Alternatively, we also compute a 'negative' measure of internal

[19] In Table A.10 in the Online Appendix, we provide evidence that these benchmark results are also robust to the inclusion of the loan to asset ratio and the mortgage to asset ratio at the branch level, as well as the interbank funding to total funding ratio, a foreign currency exposure measure and the mortgage to asset ratio at the headquarters level.

Table 3: Dynamics in internal capital markets (A)

	Internal fund. ratio		**Deposit ratio**	
Dep. var:	ΔLiq.	ΔCred.	ΔLiq.	ΔCred.
	I	**II**	**III**	**IV**
Affected X Shock X Frisk	0.185***	0.14	-0.211***	-0.049
	(0.063)	(0.085)	(0.04)	(0.074)
Affected X Shock	0.041	-0.355**	0.237***	-0.236*
	(0.068)	(0.138)	(0.061)	(0.117)
All constitutional terms included	Yes	Yes	Yes	Yes
All controls included	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
Municipality x Date FE	Yes	Yes	Yes	Yes
Observations	196,667	196,667	196,667	196,667
R-squared	0.398	0.431	0.4	0.435

Notes: This table reports the results when introducing to Eq. 1 and 2 an interaction term between $[Affected_i \times Shock_\tau]$ and variables capturing branches' reliance on internal capital markets for funding. The table considers the ratio of internal liabilities to total liabilities (cols. I and II) and the ratio of deposits to assets (cols. III and IV). These variables are computed as dummy variables ($Frisk$) equal to 1 for branches with an average pre-shock ratio above the sample median and 0 otherwise. The dependent variable is the log change in liquid assets (ΔLiq.) in cols. I and III, and the log change in outstanding credit (ΔCred.). All control variables and the fixed effects structure are based on our preferred within-municipality specification of cols. III and VI from Table 2. Standard errors that are clustered at the headquarters and month level. ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

funding reliance by generating a dummy equal to 1 if a branch reports in the pre-shock period an average deposit to total funding ratio above the sample median. Table 3 reports the corresponding results.

We find that the liquidity hoarding effect is driven by branches with a higher ex-ante share of internal funding to total liabilities. Conversely, a higher reliance on local deposits mitigates the liquidity hoarding effect. Interestingly, these non-linearities only affect the liquidity growth equations, while the effect of the shock on lending remains unaltered when introducing the differentiation by branches' internal funding dependence. [20]

These results raise the question of why the ratio of internal funding does not affect the benchmark estimation of credit growth. One explanation could be hidden in headquar-

[20] An alternative interpretation of our benchmark findings could suggest that bank headquarters direct branches to hoard liquidity in anticipation of a run by depositors following a funding withdrawal by (more informed) interbank lenders. However, the results from Table 3 suggest that this alternative hypothesis is unlikely to explain the results. First, the fact that liquidity hoarding increases in branches' internal funding (col. I) implies a heterogeneous response within banks. Second, a larger deposit base reduces the liquidity hoarding reaction instead of exacerbating it (col. III).

Table 4: DYNAMICS IN INTERNAL CAPITAL MARKETS (B)

	Bank's assets		**Bank's net income**	
Dep. var:	ΔLiq.	ΔCred.	ΔLiq.	ΔCred.
	I	**II**	**III**	**IV**
Affected X Shock X *Frisk*	0.143***	-0.095**	0.169***	-0.080*
	(0.035)	(0.044)	(0.034)	(0.043)
Affected X Shock	0.116***	-0.161**	0.076*	-0.185*
	(0.034)	(0.073)	(0.044)	(0.096)
All constitutional terms included	Yes	Yes	Yes	Yes
All controls included	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
Municipality x Date FE	Yes	Yes	Yes	Yes
Obs.	120,660	120,660	122,089	122,089
R-squared	0.480	0.521	0.471	0.507

NOTES: This table reports the results of adding to Eq. 1 and 2 an interaction term between $[Affected_i \times Shock_\tau]$ and a dummy variable equal to 1 for banks with a ratio of internal liabilities to total liabilities above the median and 0 otherwise ($Frisk$). The dependent variable is the log change in liquid assets (ΔLiq.) in cols. I and III, and the log change in outstanding credit (ΔCred.) in cols. II and IV. The table reports this exercise for two subsamples. In cols. I and II the estimation considers only branches which are below the 75th percentile of the distribution of the share of branches in their bank's total assets. In cols. III and IV the estimation considers only branches which are below the 75th percentile of the distribution of the share branches in their bank's net income. These two variables are measured as pre-shock averages. All control variables and the fixed effects structure are based on our preferred within-municipality specification of columns III and VI from Table 2. Standard errors that are clustered at the headquarters and month level. ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

ters' heterogeneous treatment of branches according to their importance within banks. As outlined above, we shall expect — following previous literature — that more relevant branches will get a preferential access to internal funding. These branches could subsequently cut back on lending to a lesser extent. To the extent that relevant branches represent a small proportion of a bank's branches, excluding them from the exercise reported in Table 3 could shed light on whether normal (non-relevant) branches cut back on lending by more when being largely exposed to internal funding.

In line with this argument, we evaluate whether the results from Table 3 vary when we exclude from the sample branches that are below the 75th percentile of the within-bank distribution of branches' share in banks' assets or branches' share in banks' net income. If branches above these thresholds get a preferential access to internal funding, we shall expect that excluding them from the analysis would provide a clearer picture of how internal funding exposure affects the liquidity and credit dynamics of average branches.

The results from this exercise are reported in Table 4. For simplicity, we consider only the dummy build on the ratio of internal to total funding as our proxy for branches' internal funding reliance. In columns I and II we drop branches below the 75th percentile of the within-bank distribution of branches' share in a bank's assets. In columns III and IV we drop branches below the 75th percentile of the within-bank distribution of branches' share in a bank's net income. These shares are computed as pre-shock averages. As in the previous exercise, we find that the positive effect of the shock on liquidity growth increases in branches' reliance in internal funding (cols. I and III). The main difference with the previous results emerge in columns II and IV: when relevant branches are excluded, we find that the negative effect on credit increases in branches' internal funding reliance.

These results are meaningful in terms of economic magnitudes. When large branches are excluded (cols. I and II), affected branches exposed to internal funding report an increase in liquid assets growth that is 14.3 p.p. larger than the increase reported by other affected branches. This number represents 19.5 percent of the standard deviation of liquidity growth in the sample. The negative effect on credit growth is 9.5 p.p. larger for branches exposed to internal funding (col. II), what represents 10 percent of the standard deviation of credit growth.[21]

Taken together, the exercises reported in Tables 3 and 4 provide additional evidence that the benchmark effects are driven by the transmission of liquidity risk via internal capital markets. However, this conclusion relates to relatively small- and medium-sized branches that are arguably more exposed to fragmented deposit markets. Also, our findings depend on the exclusion of branches' that represent a large share of banks' net income. This finding connects to the notion that banks actively use internal capital markets to support entities with a larger influence and importance, as previously discussed, i.e., in Cremers et al. (2011).[22]

3.3 Robustness analysis

We run a number of robustness tests aimed at exploring the validity and stability of our benchmark results. First, we test in Table 5 whether we find similar results when restricting the sample period. We consider two different exercises. First, we gauge the short-term effect of the shocks by keeping only the observations between τ= -12 and τ = +12, that is, 25 months around the shock. Second, to inspect whether the results prevail in the long run we drop all observations between τ= -12 and τ = +12, keeping the remaining 24 months in the sample. These results are reported in Table 5.

While we find that our results can be verified for these two different sample periods, we also find that the effect is larger when looking at the months between τ = 13 and τ = 24 (cols. III and IV). Unreported t-tests suggest that the difference between the 'short' vs. 'long' effects is, however, only statistically significant when estimating credit growth.

[21] We further tested the sensitivity of these results by adding bank headquarters-date fixed effects. The results reported by Table 4 remain quantitatively and qualitatively stable. These results are available upon request.

[22] The fact that we find no differential effects on credit growth for branches deferentially exposed to internal capital markets in Table 3 could also be attributed to policy interventions. For example, liquidity facilities implemented by the central bank could 'flood' branches' balance sheets with liquid assets that are not further transmitted to credit supply. If branches more dependent on internal funding also get larger proceeds from these interventions, then Table 3 could reflect a disconnection between the liquidity and credit growth results. We therefore carefully address this concern in Section 4.

Table 5: Robustness — short vs. long-term impact

Specification:	**Short-term impact [only τ-12 to τ+12]**		**Long-term impact [drop τ-12 to τ+12]**	
Dep. var:	ΔLiq.	ΔCred.	ΔLiq.	ΔCred.
	I	**II**	**III**	**IV**
Affected X Shock	0.069*	-0.078**	0.189**	-0.401***
	(0.038)	(0.039)	(0.091)	(0.100)
Controls included	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
Municipality x Date FE	Yes	Yes	Yes	Yes
Observations	97,922	97,922	90,133	90,133
R-squared	0.400	0.431	0.465	0.504

Notes: This table reports robustness tests in which we either restrict the sample to the 24 months around the shock (see cols. I and II) or exclude the 24 months around the shock (cols. III and IV). While the first specification gauges the short-term impact of shocks, the second evaluates whether shocks are also relevant on a longer horizon. All control variables and the fixed effects structure are based on our preferred within-municipality specification of cols. III and VI from Table 2. Standard errors that are clustered at the headquarters and month level. ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

The larger coefficient on col. IV could be related to an overall reduction in the balance sheet size by certain affected branches. This is a plausible explanation given the fact that we find that shocks lead to a reduction in affected branches' total assets (see Table A.5 in the Online Appendix). In line with this argument, we find that the estimation on col. IV becomes statistically insignificant when excluding branches that reported a large drop in total assets in the shock period. This extension is reported in Table A.11 in the Online Appendix.

In an additional test, we employ a dynamic parameter approach in which we evaluate the difference-in-differences effect at a monthly frequency for each point in time. Figure A.5 in the Online Appendix depicts the corresponding results. It shows a positive 'on impact' effect of the shock on liquidity growth, whereas the negative effect for credit growth emerges around three months after the shock. This lagged effect on credit supports our interpretation of the credit adjustment being driven by an asset reallocation reaction.

In Table 6, we provide two additional robustness tests. First, we find that our results are also robust when we collapse the timeline to two observations per branch, that is, one for the pre-shock and one for the post-shock period. As difference-in-differences estimators are potentially suffering from serial correlation of the error terms (see Bertrand, Duflo, and Mullainathan, 2004), we transform our data to two cross-sections — one for the pre- and one for the post-shock period. For this approach, we compute the average of each variable for the pre- and post-shock periods per bank branch. Cols. I and II of

Table 6: Robustness — sensibility analysis

Specification:	Collapsed time period		Excluding financial centers	
Dep. var:	ΔLiq.	ΔCred.	ΔLiq.	ΔCred.
	I	**II**	**III**	**IV**
Affected X Shock	0.066***	-0.217***	0.163***	-0.245**
	(0.024)	(0.044)	(0.053)	(0.123)
Controls	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
Municipality x Date FE	Yes	Yes	Yes	Yes
Observations	8,366	8,366	147,385	147,385
R-squared	0.749	0.765	0.405	0.445

Notes: This table reports the results of two robustness tests. First, columns I and II report the results for liquidity and credit growth when collapsing the pre- and post-shock period into two single periods to address potential concerns about auto-correlated error terms (see: Bertrand et al., 2004). Second, cols. III and IV replicate the benchmark results when excluding the financial centers of Sao Paulo and Rio de Janeiro. All control variables and the fixed effects structure are based on our preferred within-municipality specification of cols. III and VI from Table 2. Standard errors are clustered at the headquarters and month level. ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

Table 6 depict the corresponding results of this approach for liquidity and credit growth respectively. Overall, we find similar results compared to our benchmark estimation, with an improvement in the precision of the estimates.

To ensure that our results are not driven by Brazil's financial centers — i.e., Sao Paulo and Rio de Janeiro — we exclude these federal states from our analysis. This procedure does not alter our benchmark results (see cols. III and IV of Table 6). We also perform a placebo test by randomly selecting the groups of affected and non-affected banks, reporting the corresponding results in Figure A.4 in the Online Appendix. In this exercise we first draw random numbers between 0 and 1 (with 8 decimals) from a uniform distribution, assigning each drawn number to a branch. Second we sort branches according to the random numbers and labeled the first 2365 branches as $Affected = 1$, mirroring the 2365 affected branches in the sample. The other 2144 branches are labeled as $Affected = 0$. We run this exercise 100 times replicating each time our benchmark estimation. Figure A.4 plots the corresponding estimated coefficients with their 5 percent confidence intervals. After 100 iterations we found that only 4 percent of the draws render positive and significant coefficients when estimating liquidity growth, while only 2 percent of the draws render the negative and significant coefficients observed in the benchmark model when estimating credit growth.

In addition to these robustness checks, Table 7 reports that our results are robust to alternative clustering of standard errors and when using the change in liquidity to lagged

Table 7: Robustness – S.E. clustering and relative growth

Specification:	**S.E. cluster UF X date**		**S.E. cluster Region X date**		**Relative growth rate**	
Dep. var:	**Δ Liq.**	**Δ Cred.**	**Δ Liq.**	**Δ Cred.**	**Δ Liq.**	**Δ Cred.**
	I	**II**	**III**	**IV**	**V**	**VI**
Affected X Shock	0.130***	-0.273***	0.130***	-0.273***	0.001*	-0.112***
	(0.037)	(0.06)	(0.026)	(0.056)	(0.001)	(0.027)
Controls included	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality x Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	196,667	196,667	196,667	196,667	196,667	196,667
R-squared	0.397	0.435	0.397	0.435	0.41	0.462

Notes: This table reports the results of robustness analyses of our benchmark estimation. The first two columns provide evidence that our results remain robust when the standard errors are clustered by the federal unit-date level (UF stands for federal unit, the Brazilian federal states), or when clustered at the municipality-date level (columns III and IV). Columns V and VI report the results when using the change in liquid assets and commercial loans scaled by one-month-lagged total assets as the dependent variables, respectively. All control variables and the fixed effects structure are based on our preferred within-municipality specification of columns III and VI from Table 2. Standard errors in columns V and VI are clustered at the headquarters and date level and ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

total assets and the change in loans to lagged total assets as an alternative definition of the dependent variables.

A further concern relates to the supply-driven interpretation of the interbank market shocks. Affected banks could have reduced their demand for interbank funds when facing a contemporaneous drop in credit demand, creating an omitted variable bias. Also, our results could be potentially explained by banks that are relevant lenders in the interbank markets and that could have been hit themselves by funding shocks associated with drops in credit demand. Even though our identification strategy controls for branches' common demand trends at the municipality level, we address these concerns by replicating our benchmark estimation excluding (i) banks that faced the largest drops in aggregate credit during the shock period, and (ii) banks that can be considered as 'market makers' in the interbank market. The results, reported in Table A.6 in the Online Appendix, confirm that our findings remain in place when these groups of banks are excluded from the analysis, supporting the supply-driven interpretation of the identified shocks.[23]

The differences-in-differences effect can also be driven by other bank characteristics

[23] In the first test, we drop banks facing an average drop in credit in the shock period above the 90th percentile of the credit growth distribution. In the second test, we exclude banks that are above the 90th percentile in the distribution of the average ratio of net interbank credit to total assets. We consider these latter banks as 'market makers'.

Table 8: Summary of results — horse-race against bank traits

Dep. var:	ΔLiq.	ΔCred.
Reported parameter:	Affected X Shock	Affected X Shock
	I	**II**
Included competing variable:		
Bank size X Shock	0.106**	-0.307***
	(0.045)	(0.106)
Capital ratio X Shock	0.135**	-0.263**
	(0.055)	(0.113)
Liquidity ratio X Shock	0.137**	-0.273**
	(0.054)	(0.118)
(Adm. cost / Income) X Shock	0.131**	-0.273**
	(0.06)	(0.109)
NPL ratio X Shock	0.150***	-0.247***
	(0.034)	(0.089)
State ownership X Shock	0.109***	-0.293**
	(0.027)	(0.11)
Foreign ownership X Shock	0.208***	-0.100**
	(0.045)	(0.05)
Foreign funding X Shock	0.157***	-0.238**
	(0.054)	(0.106)

Notes: This table summarizes the results of a 'horse race' estimation including both the difference-in-differences interaction $[Affected_i \times Shock_\tau]$ and other competing interaction terms. Col. I reports results for liquidity growth, whereas col. II reports the results for credit growth. Each row reports the difference-in-differences parameter of the variable $[Affected_i \times Shock_\tau]$ when including the non-linearity that is stated on the right-hand side of each row. For all interactions including the competing non-linearities, all constitutive terms of the interaction are included as individual variables. The variable Foreign Ownership is a dummy variable that equals one if the bank is at least 50 percent owned by a company headquartered abroad. Foreign Funding is the ratio between interbank funding from non-domestic sources relative to total assets. State ownership is also a dummy variable that equals one if a bank is state-owned. All control variables and the fixed effects structure are based on our preferred within-municipality specification of cols. III and VI from Table 2. Standard errors that are clustered at the headquarters and month level. ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

correlated with bank risk, leading to omitted variable bias. This would be the case, for example, if (as shown in Table 1) affected banks report ex-ante a higher credit risk exposure. Hence, we also address the ex-ante sorting of banks. We run multiple so-called "horse-races", that is, we include competing interaction terms between the post-shock dummy and bank characteristics that could be related to banks' exposure to liquidity risk. Table 8 summarizes these results, reporting the coefficient for our difference-in-differences estimator —, i.e., β_1 and β_2 of Eqs. 1 and 2 — when different interactions between the interbank shock and other bank characteristics listed on the left hand-side of Table 8 are included in the model.

We test if our results hold when including in our benchmark model interaction variables between the shock and the following variables: bank size, capital to assets ratio, headquarters' liquid assets ratio, headquarters' administrative cost to income ratio, and headquarters' non-performing loans ratio. Across these different specifications, our benchmark results are confirmed. Importantly, the variables identified in Table 1 as having statistically significant differences between affected and non-affected banks do not affect our findings when entering the model interacted with $Shock_\tau$. For instance, the fact that we found affected parent banks to have a larger NPL ratio in the pre-shock period does not imply that the NPL ratio confounds the definition of $Affected_i$.

To address concerns of state-owned banks affecting the results, we also include a competing interaction between a state-owned dummy and the shock variable, with our results remaining in place.[24]

Given that the identified interbank shocks occur in a period around the global financial crisis, a natural concern is whether banks' foreign exposures can confound the effect on liquidity and credit. The results from Table 8 suggest, however, that this factor is not a major concern for the estimation, as the results are robust to including foreign ownership or headquarters' ratio of foreign interbank liabilities as competing interaction variables. Alternatively, we also performed tests in which the variable $Affected_i$ is replaced by proxies for foreign exposure capturing banks' ties to the U.S. market in the period prior to the identified shocks.

These results, reported in Table A.8 in the Online Appendix, show no evidence of branches' liquidity or credit reacting to banks' foreign funding exposure, foreign ownership, or direct U.S. ties via the presence of related entities in the U.S. market. These results suggest that the benchmark effects are not driven by direct cross-border contagion during the global financial crisis. Finally, we confirm that our results remain unaltered when we (i) exclude banks facing a funding shock between October 2008 and March 2009 at the peak of the global financial crisis, as well as when (ii) we include a triple interaction term with a dummy identifying this period (see Table A.9 in the Online Appendix).

It should be noted that despite these latter results, banks' U.S. ties can still pay a role in the analysis. For example, the fact that the we identify supply-driven interbank shocks may imply that banks that are net-lenders in the domestic interbank market reduce their interbank credit supply as a consequence of their own U.S. exposures. We discussed above that the results remain unaltered when excluding these 'market makers' from the sample. However, we cannot rule out the possibility that these banks are being themselves affected by financial contagion originated in their U.S. exposures. While we lack the necessary bilateral interbank data to explore this hypothesis further, future research could shed light on how banks' foreign exposures can trigger domestic interbank shocks when affected banks are relevant domestic market makers.

We also test whether the results remain robust to an alternative parametric estimation of the idiosyncratic growth rates used to identify the shocks. For this purpose, we compute the interbank funding growth rate $\Delta\widetilde{IB}_{i\tau}$ using a multifactor residual (MFR) model (see, e.g., Pesaran, 2006 or Buch et al., 2009). This approach has been previously used in the literature to retrieve idiosyncratic components of entity-specific growth rates, and

[24] Table A.12 in the Online Appendix provides additional evidence that the difference-in-differences effect of our benchmark estimation also survives additional horse races against non-linearities that are based on the remaining branch control variables.

Table 9: Robustness – MFR-model-based idiosyncratic growth rates

Dep. var:	**∆ Liquidity**		**∆ Credit**	
	I	**II**	**III**	**IV**
Affected X Shock	0.209***	0.223***	-0.187*	-0.226**
	(0.061)	(0.048)	(0.111)	(0.109)
Controls included	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
Time FE	Yes	.	Yes	.
Municipality X Date FE	No	Yes	No	Yes
Observations	162,512	155,982	162,512	155,982
R-squared	0.129	0.387	0.2	0.441

Notes: This table reports robustness tests when calculating the idiosyncratic funding growth rate using a multifactor residual (MFR) model (see, e.g., Pesaran, 2006 or Buch et al., 2009). The results are reported for liquidity growth (cols. I and II) and credit growth (cols. III and IV). While columns I and III use the same specification as columns II and V of Table 2, i.e., including all control variables and time and branch fixed effects, columns II and IV include municipality-date fixed effects (benchmark specification Table 2 columns III and VI). Standard errors that are clustered at the headquarters and date level and ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

it enables us to filter out observed and unobserved macroeconomic variations. Similar to Buch et al. (2009), we calculate the idiosyncratic component in the following way. First, we use the individual interbank funding growth rate as our dependent variable and regress it on a set of macroeconomic variables in bank-specific time series regressions. This time series approach filters out aggregate variation so that the residual term of the model captures the idiosyncratic growth rate of bank i. Finally, we employ this estimated growth rate to implement the Cavallo et al. (2015) algorithm.[25] Table 9 reports the results. While columns I and III report results with time fixed effects, regressions in cols. II and IV include municipality-date fixed effects. These results confirm our main findings.

[25]Following Buch et al., 2009 we use the following domestic and foreign macroeconomic control variables on a monthly basis (sources are in parenthesis): Brazil Economic Activity Index growth as a proxy for GDP growth (BCB), change in unemployment rate (Brazilian Institute of Geography and Statistics, BIGS), change in the monetary policy SELIC rate (BCB), change in the average overnight interbank rate in Brazil (BCB), change in the IMF Commodity Price Index (IMF), net exports' growth rate (Brazilian Institute of Geography and Statistics, BIGS), TED Spread (St. Louis Fed) and the US Industrial Production Index growth rate (St. Louis Fed). We also include as a proxy for unobserved macroeconomic variables the sample means of the following bank level variables: ratio of liquid to total assets, ratio of debt to equity, credit growth rate, total assets growth rate and interbank borrowing growth rate. For each bank i these latter variables are computed as the sample average of all other banks.

4 Policy implications for central banks

Our findings connect to discussions on the effectiveness of lender-of-last-resort interventions. If banks have incentives to hoard a proportion of the proceeds obtained from central bank liquidity facilities, then the lending channel of these interventions could be impaired. This challenge is foremost relevant for emerging economies like Brazil with lower degrees of financial development. With limited derivative markets, bank branches depend on deposit-based funding to a larger extent (see Loutskina and Strahan, 2009). The fact that branches cannot freely raise deposits in other regions via channels different than internal capital markets creates incentives to precautionary hoard cash in periods of stress.

Lender-of-last-resort interventions also matter because they can provide an alternative explanation for our findings. For instance, our results can be seen as emerging from a liquidity flooding phenomenon, in which central bank liquidity floods branches' balance sheets with liquid assets that only partially translate into credit supply. If this is the case, the precautionary motive for liquidity hoarding outlined above would not be the main driver of our results. The analysis requires therefore carefully exploring the implications of central bank liquidity interventions for our findings.

We next address these implications by exploring whether a wider access to emergency liquidity affects our benchmark findings, using individual bank balances vis-à-vis liquidity facilities activated by the BCB in the period of analysis. During the global financial crisis the BCB provided extraordinary liquidity facilities to banks in Brazil. These facilities were activated soon after the collapse of Lehman Brothers (September 2008) and provided additional funding for banks to stabilize their funding structure. Figure A.6 in the Online Appendix displays the aggregated balances vis-à-vis these emergency liquidity facilities.

Using these data is not without limitations, as banks which were more dramatically hit by interbank funding shocks may have received preferential access to this facility. Also, our data does not allow us to explore the political economy of these interventions. Accounting for this drawback, we first compute the average ratio of BCB balances to total liabilities during the 6 months following the beginning of a funding shock. We then weight this ratio by the peak-to-trough log change in interbank borrowing around the shock, which proxies for the size of funding shocks. As this bank-specific and shock-weighted measure is hard to interpret economically, we normalize the final measure $\widetilde{CBI}_i$ by transforming the statistic into a continuous variable distributed between 0 and 1.[26]

We investigate whether the impact of the shocks is moderated by banks' access to liquidity facilities by estimating a triple interaction model of Eqs. 1 and 2. The results reported in Table 10 show that the effect of the shocks on liquidity growth increases with $\widetilde{CBI}_i$. Conversely, the negative effect on credit diminishes with $\widetilde{CBI}_i$. Figure 2 confirms this finding by plotting the marginal effects of the shocks for the full distribution of $\widetilde{CBI}_i$. While the effect on liquidity growth is still in place for banks with an average $\widetilde{CBI}_i$, it increases for banks with a larger access to central bank liquidity. Similarly, the effect on credit growth is statistically significant for a large proportion of the distribution of $\widetilde{CBI}_i$, becoming insignificant for banks with a large access to central bank liquidity.

[26] The construction of the $\widetilde{CBI}_i$ index is discussed in greater detail in Section A.4 in the Online Appendix.

Table 10: LIQUIDITY HOARDING AND EMERGENCY LIQUIDITY FACILITIES

Sample:	**Full**		**low** $\widetilde{CBI}_i$		**high** $\widetilde{CBI}_i$	
Dep. var:	ΔLiq. **I**	ΔCred. **II**	ΔLiq. **III**	ΔCred. **IV**	ΔLiq. **V**	ΔCred. **VI**
Affected X Shock X $\widetilde{CBI}_i$	0.473***	0.609***				
	(0.087)	(0.149)				
Affected X Shock	-0.068	-0.607***	0.164***	-0.195**	0.140***	-0.244*
	(0.046)	(0.130)	(0.029)	(0.075)	(0.006)	(0.065)
Obs.	196,667	196,667	156,841	156,841	26,852	26,852
R-squared	0.400	0.439	0.444	0.478	0.540	0.596

NOTES: This table reports the results of estimating adjusted versions of Eq. 1 and 2 exploring the implications of emergency liquidity facilities activated by the BCB for the benchmark results. Cols. I and II estimate a triple interaction model in which the variable $[Affected_i \times Shock_\tau]$ is further interacted with a shock-weighted measure of banks' access to emergency liquidity facilities activated by the BCB ($\widetilde{CBI}_i$). Cols. III and IV report a replication of the benchmark model for the subsample of banks with a measure of $\widetilde{CBI}_i$ below the 75th percentile of the respective bank-level distribution. Cols. V and VI replicate this latter exercise for banks with a measure of $\widetilde{CBI}_i$ above the 75th percentile of the relevant distribution. All constitutive terms of the interaction terms and control variables are included in the regressions. Standard errors that are clustered at the headquarters and month level. ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

These results imply that a 1 standard deviation increase in $\widetilde{CBI}_i$ leads to a 18 p.p. larger effect on liquidity growth (0.38 x 0.473) and to a 23 p.p. lower effect on credit growth (0.38 x 0.609). Therefore, while the effect on credit is effectively moderated by the policy intervention, the results also suggest that branches accumulate a portion of the proceedings as cash when being affected by a funding shock. This dynamic may well reflect a situation in which central bank liquidity leads to a flooding of cash that ultimately increases credit supply by affected branches. However, the differential effect of $\widetilde{CBI}_i$ seems to operate on top of the precautionary motive for liquidity hoarding, considering that the effects on liquidity and credit growth remain in place when excluding banks with large $\widetilde{CBI}_i$ (see cols. III and IV in Table 10).[27]

These findings complement existent evidence on the effectiveness of unconventional monetary interventions. The lending channel of such interventions has been profusely explored in recent literature (see, e.g., Crosginani et al., 2020). Our analysis adds to these findings the idea that in countries with less developed financial markets the effectiveness of unconventional monetary interventions can be limited by precautionary liquidity hoarding reactions emerging from geographically fragmented deposit markets.

[27] To verify that the measure $\widetilde{CBI}_i$ does not explain our benchmark findings by itself, we run regressions replacing the variable $Affected_i$ by a dummy equal to 1 for banks with a value of $\widetilde{CBI}_i$ above the 75th percentile of the respective distribution. We find no statistically significant results in these regressions (see Table A.13 in the Online Appendix).

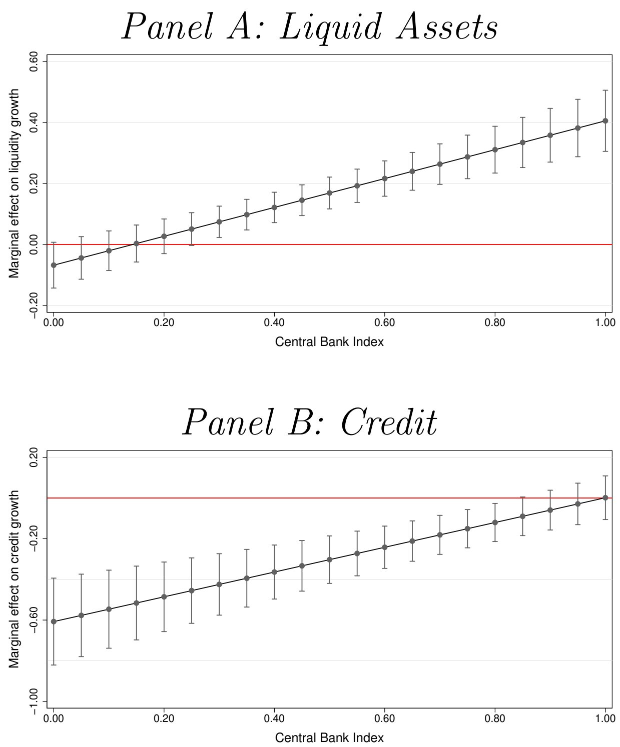

Figure 2: Marginal Effect conditional on BCB liquidity

Notes:: This figure illustrates the marginal effects at the 95% confidence level of a non-linear extension of Eqs. 2 (Panel A) and 2 (Panel B), in the form of $\Delta Liquidity_{i,m,\tau} = \alpha_0 + \beta_1[Shock_\tau \times Affected_i \times \widetilde{CBI_i}] + ...$ and $\Delta Credit_{i,m,\tau} = \alpha_0 + \beta_1[Shock_\tau \times Affected_i \times \widetilde{CBI_i}] + ...$, respectively. The solid line represents the marginal effect of the difference-in-differences for particular levels of $\widetilde{CBI_i}$. The whiskers represent the corresponding 95 percent confidence interval. These marginal effects are based on cols. I and II of Table 10.

5 Conclusion

This study explores how idiosyncratic shocks in interbank funding can prompt banks' regional branches to increase their liquid asset positions and reduce credit supply. Our key finding is that branches tend to hoard liquid assets and to subsequently cut credit after their headquarters experience a funding shock in the absence of an aggregate market freeze. We obtain these findings by exploiting a matched bank-branch sample covering all banks in Brazil.

Our results emerge as a result of frictions preventing liquidity reallocation across regions: while branches are limited to raise deposits only within their geographical business areas, internal capital market remain the main mechanism connecting liquidity-short and surplus regions. We show that when internal capital markets become disrupted by idiosyncratic shocks, branches more exposed to internal funding increase liquidity and cut back on lending the most. However, this latter result emerges only after the most relevant branches within banks are excluded from the sample, suggesting that headquarters actively support relevant branches in periods of stress.

Our results show that a combination of banks' changing preferences towards liquid assets and institutionally constrained regional deposit markets can explain the transmission of idiosyncratic funding shocks to lending. This finding is relevant for policymakers, as idiosyncratic shocks transmitted to concentrated regional bank markets can have severe implications for local economies in the presence of granular effects. Hence, our approach highlights particular frictions that may be relevant for future regulatory innovations. Policies fostering financial inclusion and financial development can help to widen branches' deposit base, improving regional capacities to cushion against shocks. The development of well-regulated derivatives markets can also help to break the link between internal funding access and local credit supply.

While we do find that the effect of the shocks on credit growth is mitigated by banks' access to central bank liquidity, we also find that a share of these proceedings ends up accumulated in branches' liquid assets. This finding is likely reflecting that precautionary liquidity hoarding partially limits the pass-through of liquidity interventions. Moreover, the fact that branches are heterogeneously affected can trigger unintended distributional effects of these interventions across regions and economic sectors. Future research could examine whether the mechanisms unveiled in this paper can be associated with this type of distributional effects in the real economy.

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A Appendix: Variables Definitions

Table A.1: VARIABLES DEFINITION

Variable	Definition	Unit
Headquarters variables		
Shock	Dummy equal to 1 during the 24 months after the occurrence of an interbank shock.	0 or 1
Affected	Dummy equal to 1 if a branch's headquarters was affected by an interbank shock in the period between January 2008 and December 2009.	0 or 1
Interbank borrowing	Log of credit obligations from borrowing and onlending in the interbank market computed as log of BRL mill.	log
Borrowing rate	Ratio of expenses from interbank borrowing to total interbank borrowing.	rate
Bank size (log BRL mill.)	Total size of a bank's balance sheet computed as the log of total assets measured in millions of BRL.	log
Capital / Assets	Ratio of equity to total assets.	rate
NPL / Credit	Ratio of non-performing to total outstanding credit. Non-performing credits are credit reporting some delay in its re-payment record. The ratio is computed by dividing the volume of non-AA-rated credits (maximum risk category) to total credit.	rate
Adm. Cost / Income	Ratio of administrative costs as reported in banks' income statements to total income	rate
Liquidity / Assets	Ratio of liquid to total assets at the headquarters level. Liquid assets are defined as cash holdings.	rate
Foreign ownership	Dummy variable equal to 1 if a bank is owned by a foreign financial institution and 0 otherwise.	0 or 1
Foreign funding / Assets	Ratio of interbank funding originated outside Brazil and total assets.	rate

NOTES: This table provides a description of the main variables used for the empirical analysis reported in the paper. Sources are reported in parentheses.

Table A.1: Variables definition (continued)

Variable	Definition	Unit
Headquarters variables		
State ownership	Dummy variable equal to 1 if a bank is owned by a Brazilian state entity.	0 or 1
$\widetilde{CBI}_i$	Average ratio of liabilities from the BCB to total liabilities in the six months after the interbank shock divided by the size of the interbank shock. The variable is normalized in a scale from 0 to 1.	rate
Branch variables		
Δ Log credit	monthly change in log of outstanding commercial credit.	growth rate
Δ Log liquidity	monthly change in log of liquid assets defined as cash holdings.	growth rate
Branch size (log BRL mill.)	Total size of a branch's balance sheet computed as the log of total assets measured in millions of BRL.	log
Deposits / Assets	Ratio of sight plus saving deposits to total assets.	rate
Income / Assets	Ratio of income as reported in branches' income statements to total assets.	rate
Internal funding / Assets	Ratio of internal (intra-group) liabilities to total assets.	rate
Frisk	Dummy equal to 1 for branches with a pre-shock average ratio, above the sample median, for either the ratios of internal funding or deposits to total liabilities.	0 or 1
Variables used in the Online Appendix		
Mortgage to asset rat.	Ratio of outstanding mortgage credits to assets at the headquarters level	rate
Interbank deposits rat.	Ratio of interbank deposits to total liabilities at the headquarters level	rate
Foreign currency exp.	Ratio of net FX-denominated liquid assets to total assets at the headquarters level	rate
Mortgage to asset rat. (BR)	Ratio of outstanding mortgage credits to assets at the branch level	rate
Loan to asset rat.	Ratio of outstanding credits to assets at the branch level	rate
U.S. Branch	Dummy variable equal to 1 if a bank has a related entity (a branch, subsidiary, or its own foreign headquarters) located in the U.S.	0 or 1

Notes: This table provides a description of the main variables used for the empirical analysis reported in the paper. Sources are reported in parentheses.