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

Abstract

Since the global financial crisis, economic literature has highlighted banks' inclination to bolster up their liquid asset positions once the aggregate interbank funding market experiences a dry-up. To this regard, we show that liquidity hoarding and its detrimental effects on credit can also be triggered by idiosyncratic, i.e. bank-specific, interbank funding shocks with implications for monetary policy. Combining a unique data set of the Brazilian banking sector with a novel identification strategy enables us to overcome previous limitations for studying this phenomenon as a bank-specific event. This strategy further helps us to analyse how disruptions in the bank headquarters' interbank market can lead to liquidity and lending adjustments at the regional bank branch level. From the perspective of the policy maker, understanding this market-to-market spillover effect is important as local bank branch markets are characterised by market concentration and relationship lending.

Keywords: financial crisis, interbank market, liquidity risk

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 like consumer deposits into long-term illiquid assets critically depends on the availability of liquid assets once sudden restrictions in access to funding occur (see, e.g., Diamond and Dybving, 1983). In modern banking, where 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 even amplify potential liquidity and maturity mismatches. Thus, in order to avoid such adverse scenario, liquidity hording – 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 financial crises became front and center in explaining the spread of liquidity risk through interbank markets, most empirical studies have analyzed the occurrence of liquidity hoarding in the context of aggregate – i.e. market-wide – disruptions in interbank funding (see, e.g., Freixas et al.,2011, Acharya and Skeie, 2011, Gale and Yorulmazer, 2013, Acharya and Merrouche, 2013 and Heider et al., 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 sector. However, an important and still unexplored aspect of the liquidity hoarding phenomenon is whether it can also emerge in the context of rather 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 of affecting aggregate dynamics in the real economy (see, e.g., Gabaix 2011 or Amiti and Weinstein, 2018).

This paper fills this gap in the literature by studying 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. In particular, we investigate this

[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, 2004b), prevailing Knighting uncertainty in an entire market segment (Caballero and Krishnamurthy, 2008) or the increase in counterparty risk (Acharya and Skeie, 2011).

question in a context where internal capital markets and market-to-market spillovers provide a mechanism to explain liquidity hoarding. While we track bank-specific funding shocks in a market segment where only bank headquarters participate, we analyze liquidity and lending reactions to these shocks at the regional bank branch level. This setting allows us to unravel the liquidity risk channels driving a liquidity hoarding reaction within a banking conglomerate when its main organizational level – the bank headquarter – is affected by a bank-specific funding shock.

Our overall contribution can be best understood by focusing on why the liquidity hoarding literature might have neglected the role of idiosyncratic funding shocks. First, only very recently, Pérignon et al. (2018) documented how during the global financial crisis important segments of the interbank market faced idiosyncratic liquidity dry-ups, despite of remaining liquid in the aggregate. They show that this was the case, for instance, in the European market of certificates of deposits. We exploit the fact that this phenomenon has not only being restricted to the European context. In fact, it provides also an accurate representation of how interbank markets in emerging countries reacted to recent episodes of global financial distress. We therefore focus our analysis on banks' reaction to idiosyncratic shocks in the Brazilian unsecured interbank funding market. Second, the lack of adequate data and a suitable identification strategy might have impeded previous research from studying our research question. To overcome these limitations, we rely on a granular data set based on regulatory data from the Banco Central do Brasil (BCB). This data set covers granular balance-sheet and income information of the entire universe of banks and their corresponding individual local bank branches that operate within Brazil and its municipalities. This setting enables us to pin down (headquarter) bank-specific interbank funding shocks in the period from January 2008 to December 2009 in an important segment of the local interbank market on a monthly frequency and to trace branches' reaction to these shocks.

How can the bank-branch structure in our data contribute to help us to understand the consequences 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' consolidated liquid assets management 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. To this regard, three arguments support the choice of our empirical approach.

First, by separating the organizational level of the banking conglomerate at which funding restrictions 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 by a funding shock are compared over an event-timeline with regional-time fixed effects on a monthly basis. In similar vein to Gilje et al.(2016) or Cortés and Strahan (2017), this approach controls for regional shocks such as common demand conditions affecting banks within a municipality, 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 market on branches' funding market. This type of market-to-market spillover is interesting as it provides a framework to unravel the liquidity risk channels involved in branches' incentive to hoard liquid assets. We show that branches are likely to be subject to geographical fragmentation of their funding markets, depending to a large extent on local retail deposits and internal funding. This funding friction becomes then the mechanism underlying the reaction of branches' balance sheets to shocks affecting their corresponding headquarters. By linking branches' reaction to liquidity risk exposure, our approach contributes to disentangle the precautionary from the speculative motive of banks hoarding liquidity (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 the idiosyncratic shock of its headquarter could have more pronounced consequences for the local economy. Our analysis can therefore contribute to a better understanding of the mechanisms explaining the transmission of financial shocks to the real economy, especially in countries with fragmented regional financial markets.

Overall, 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 reduce lending compared to branches from non-affected banks. This asset reallocation from illiquid to liquid assets reflects bank branches' preference to hoard liquid assets when idiosyncratic funding risks heighten. 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 vs. non-affected categorization may reflect other ex-ante weaknesses in banks' balance sheets. Furthermore, by exploiting information on banks' individual access to emergency liquidity facilities activated by the BCB during the global financial crisis, we provide evidence that branches from banks which had a better access to these facilities relative to their interbank shock size use this additional funding source to build up their liquid assets even further while cutting lending to a lesser extent. These latter findings provide insights on the extent to which liquidity hoarding can render monetary interventions less effective if frictions that prevent the transmission of a monetary stimulus to credit supply exist.

Our study contributes to three main strands in the literature. First, our paper can be related to previous studies that empirically investigate liquidity hoarding as a phenomenon that occurs during times of financial distress. As far as we are aware of, this is the first study that analyzes the phenomenon of liquidity hoarding as a reaction to bank-specific funding shocks with market-to-market spillover effects due to branches' reliance on internal capital markets. Previous literature has found evidence for the occurrence of liquidity hoarding as a reaction of US banks to the global financial crisis (see, e.g., Cornett et al., 2011 or Berrospide, 2013). Other contributions have shown that also the functionality of interbank markets and banking networks is related to the occurrence of liquidity hoarding in the context of market-wide disruptions (see, e.g., Gabrieli and Georg, 2014, Acharya and Merrouche, 2013, or Fourel et al., 2013).

The second strand in the literature we contribute to, analyzes the lending channel of interbank market shocks. While these studies have mainly 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 also propagate via internal capital markets to effect lending decisions at the regional level within a country. For example, Iyer et al. (2014) provide evidence – based on loan level data – that banks which were more reliant on the

European interbank market reported a stronger reduction in credit supply when the interbank market collapsed during the global financial crisis. Analyzing internal capital markets, De Haas and van Lelyveld (2014) and Allen et al. (2014) find that these markets are also relevant in explaining cross-country financial contagion. Additional contributions to the topic of cross-border contagion via interbank markets with effects on lending are from Aiyar (2012), Ongena et al. (2015) and Buch and Goldberg (2015). Departing from the study of aggregate interbank market dry-ups is only Pérignon et al. (2018) who describe the occurrence of idiosyncratic dry-ups in the European market of CDs (certified deposits). Our analysis can help to understand the mechanisms through which dry-ups, like the ones described by Pérignon et al. (2018), can ultimately affect the real economy by changing the preference for liquid assets within a banking conglomerate.

As we track the interbank market shock through internal capital markets from the headquarter to the branch level, we further contribute to a recent literature that focuses on the role of internal capital markets in propagating shocks to the regional economy (see, e.g., Giljie et al., 2016, Cortéz and Strahan 2017 or Levine et al., 2018). In this regard, our paper is the first to evaluate how interbank market shocks propagate from the headquarter level via internal capital markets to the regional branch level.

Finally, our paper also touches a recent strand in the literature which evaluates the effects of unconventional monetary policy interventions. In particular, Chodorow-Reich (2014) as well as Di Maggio et al. (2015) find that emergency liquidity assistance in the US 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 ECB from a macro perspective (see, e.g., Casiraghi et al., 2013, Crosginani et al., 2017, Heider et al. 2016, Andrade et al., 2017, or García-Posada and Marchetti, 2016). In contrast, Carpinelli and Crosignani (2017) study the effectiveness of ECB liquidity interventions

on bank loan supply to Italian firms following a wholesale funding dry-up. In addition to these findings, we provide evidence that an unconventional monetary policy intervention was not able to change banks' preferences to hoard liquidity with potentially severe consequences for the pass-through of unconventional of monetary policy itself.

The rest of the paper is organized as follows: Section 2 discusses the theoretical motivation, the data stet employed and our empirical methodology. Section 3 presents the baseline results and additional robustness tests. In Section 4, we shed further light on the asset reallocation effect by analyzing the conditional effect of the idiosyncratic shock on liquidity hoarding conditional on bank's individual access to emergency liquidity facilities of the BCB, and finally, Section 5 concludes.

2 Methodology and data

In this Section, we provide a detailed discussion on the theoretical motivation, the empirical model (Section 2.1), the data set (Section 2.2) and the Cavallo et al. (2015) algorithm (Section 2.3) which we employ to examine the effect of idiosyncratic interbank funding shocks on liquidity and credit adjustments at the regional bank branch level. Additionally, we provide information on the summary statistics of our baseline sample (Section 2.4).

2.1 Theoretical motivation and identification strategy

2.1.1 Theoretical considerations

Our approach starts by defining two distinct financial markets that interact in explaining the transmission of a parent-bank level funding shock to liquidity and lending decisions by 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 (OTC) fashion. The second market represents branches' market for funding, which includes two main liquidity sources: local retail deposits and internal capital markets. These two funding sources represent 74% of total assets for the average branch in our sample. Ultimately, these branches decide whether to use their liabilities to provide loans to firms and households in the municipality where they operate or to build up liquid asset buffers predominantly in the form of cash. As explained below, we approach our research question by tracing the spillovers of liquidity shocks in the former (parent-bank level) interbank market on the latter market in which local branches seek to obtain their funding.

Based on this setting, we conjecture that bank-specific shocks in the parent-bank level interbank market can lead branches of those institutions to increase its liquid assets and to cut lending. This reaction would occur in 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 themselves constrained when the main component of a banking conglomerate – namely its headquarter bank – experiences a significant funding shock.[2]

But why should we expect to observe consequences of sudden bank-specific disruptions in interbank markets like the ones described above in the first place? In principle, under the assumption that interbank market frictions do not exists, these markets should ensure an efficient allocation of liquidity across all market institutions (Allen and Gale, 2004b). In our setting this argument means that parent banks of branches with the opportunity to finance a positive-NPV (net present value) local 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 which can also lead to adverse selection 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 evaluate in a context of aggregate uncertainty, banks are also less inclined to provide liquidity in the form of loans to other market participants via the interbank market. 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 theoretical foundation, our approach features distinct market frictions both at the parent bank and at the branch level that in combination can explain an increase in branches' liquid assets when parent banks are affected by interbank funding shocks. 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 are likely to be more sensible to informational asymmetries and adverse selection (Allen and Gale, 2004a), exposing banks to the risk of sudden disruptions in the

[2] This approach differs from previous attempts to empirically identify drivers of banks' liquidity hoarding, in which the main frictions involved relate to liquidity commitments on the asset-side of the balance sheet. For instance, Cornett et al. (2011) show that US banks' exposure to credit lines lead them to hoard liquid assets in periods in which the TED-spread increases. Our approach highlights that liquidity risk in the liabilities' side of the balance-sheet also matters when it comes to understand banks' preferences between liquid assets and lending.

availability of interbank funding. We therefore take the likelihood of interbank funding shocks as given and implement an algorithm explained below to identify months on which such events occur, distinguishing between affected from unaffected banks.

With respect to branches, we argue that they face a fundamental liability-side friction since they operate in geographically fragmented markets. They can neither raise retail deposits in other regions nor can they directly access the country-level interbank market because of their organizational subordination to their headquarters. This leads to a problem of funding market incompleteness, in which jurisdictional and organizational barriers prevent a free allocation of liquidity across branches. Such allocation barriers can lead financial market institutions to hold excessively high levels of liquid assets relative to the efficient level of liquidity, i.e. banks engage in liquidity hoarding (see, e.g., Allen and Gale 2004a).

Finally, it should be noted that in the case of aggregate disruptions in the interbank market there are two competing, however, non-exclusive rationales from the perspective of an individual bank to increase liquid asset holdings. First, banks fearing market exclusion might want to increase their liquid asset positions in order to avoid any losses that would occur under a fire sale scenario. This *precautionary motive* for liquidity hoarding implies that banks prevent future funding restrictions and their associated financial losses by building up liquidity buffers they can rely on in case of need. Alternatively, banks might accumulate liquidity if they speculate that other banks affected by disruptions in the interbank market will sale their assets at fire sale prices (Gale and Yorulmazer, 2013). Our approach has the advantage that it can distinguish this latter *speculative motive* from the *precautionary motive*. In fact, as we compare within each municipality shock-affected branches from non-affected ones over an event-timeline in which shocks occur at different points in time, we can link the increase in affected-branches' liquid assets with the *precautionary motive* that we conjecture may drive branches' adjustment.

2.1.2 Identification and empirical model

In order to analyze the effect of bank-specific interbank funding shocks that occur at the headquarter-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 affected with non-affected branches at the moment in time when the funding shock occurs.[3] This event-timeline starts at $\tau = -24$ and ends at $\tau = 24$, where $\tau = 0$ indicates the date at which the shock hits the respective headquarter. For further robustness, we also use different time window definitions.

Second, by separating the bank headquarter – where we document the occurrence of shocks – from the branch level at which liquidity and lending adjustments are analyzed, we avoid the potential concern of reverse causality. For example, it would be possible that bank's reduction in interbank funding is driven by its decision to cut lending during times of economic decline. However, when controlling for macroeconomic factors by including actual time fixed effects, focusing on branch outcomes reduces this concern. This is because each individual branch with its marginal size relative to the respective banking conglomerate is unlikely to affect the interbank borrowing of the main headquarter.

Third and finally, by exploiting the geographical variation and structure within our dataset and introducing municipality-time fixed effects, we control for all time varying factors within a given municipality including common demand effects. In principle, we follow previous contributions by applying a within-municipality estimation (see, e.g., Gilje et al., 2016 or Cortés and Strahan, 2017).[4]

In contrast to this procedure, the optimal choice to control for credit demand would be the use of credit register data at the borrower level, as suggested by the empirical literature (see, e.g., Iyer et al. 2014, Jiménez et al., 2014, or Ioannidou et al., 2015). However, this type of data does not allow to trace adjustments at the branch level, as it does not report the balance-sheets of branches providing the credit. 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 liquidity hoarding reaction and to investigate the financial drivers of branches' liquidity adjustments. This latter advantage means that we can explore whether liquidity risk factors such as branches' geographically fragmented funding market and organizational subordination provide an explanation for liquidity hoarding.

[3] This procedure further implies for a proper comparison between affected and non-affected branches to set a date at which the non-affected headquarter experiences a "pseudo" shock. Since this is not trivial, we discuss this issue in section 2.3 in greater detail.

[4] Originally, the idea of using a within-borrower estimation by including borrower-time fixed effects has been established in previous literature by Khwaja and Mian (2008) and Schnabl (2012) and was then extended to the regional setting.

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

$$\Delta Liquidity_{i,m,\tau} = \mu_{m,t} + \omega_{i,m} + \beta_1 [\,Affected_i \times Shock_{i,\tau}] + \theta' Bank_{i,m,\tau-1} + \varepsilon_{i,m,\tau} \qquad (1)$$

As our dependent variable, we use the monthly (month-over-month) change in log liquid assets of bank branch i located in municipality m at event-time τ. Standard errors in this bassline model are clustered at the headquarter-time level to achieve efficient estimates.[5] Furthermore, we saturate our model by including branch as well as municipality-date fixed effects on a monthly basis (see $\omega_{i,m}$ and $\mu_{m,t}$, respectively).

Within this specification the interaction, $[\,Affected_i \times Shock_{i,\tau}]$, is our variable of interest whose corresponding parameter β_1 presents the difference in the average liquidity growth rates between affected and non-affected branches in the post-shock when accounting for pre-shock differences. While the first term of the interaction, $Affected_i$, is dummy variable that equals 1 for all branches belonging to an affected headquarter and 0 otherwise, the second term, $Shock_{i,\tau}$, is a dummy variable that equals 1 for the period $\tau \geq 0$ and 0 for $\tau < 0$.

To control for headquarter- and branch-specific characteristics, we include various control variables at the headquarter and branch level which are captured by $Bank_{i,m,\tau-1}$. For the headquarter level, these include the size of the bank (captured by the log of total assets), the capital to assets ratio, the liquid asset to total assets ratio, the non-performing loans to total assets ratio (capturing bank's loan portfolio risk) and a ratio of administrative costs to income to proxy for managerial quality. Similarly, at the branch-level, we control for branch size (log of total assets), and for internal liquidity exposure (measured by the internal funding to total asset ratio), and for the deposit to total asset ratio. We additionally control for the income-to-assets ratio. By saturating our model with municipality-date fixed-effects $\mu_{m,t}$ on a monthly frequency, we control for time varying factors at the municipality level such as common demand effects. 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 in order to avoid

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

multicollinearity concerns.[6]

Since an increase in liquid assets is likely to be accompanied by an asset reallocation effect as outlined in the introduction, we conjecture that affected branches will reallocate from illiquid to liquid assets. Therefore, branches may have to cut their lending activity in order to satisfy their liquidity preferences. To this end, we substitute the liquid asset growth rate by the lending growth rate as the main dependent variable in Eq. (1) to estimate Eq. (2):

$$\Delta Credit_{i,m,\tau} = \mu_{m,t} + \omega_{i,m} + \beta_2\left[Affected_i \times Shock_{i,\tau}\right] + \theta' Bank_{i,m,\tau-1} + \varepsilon_{i,m,\tau} \qquad (2)$$

Specifically, the dependent variable of Eq. (2) is the monthly change in month-over-month log change in total commercial credits at the branch-level.[7] 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.

2.2 Data and sampling

2.2.1 Data set

To identify idiosyncratic shocks at the headquarter level as well as to trace their effects on the regional branch level requires a unique dataset. For this purpose, we combine granular data on balance sheet and income information of banks' headquarters and their corresponding individual bank branches of the entire universe of the Brazilian banking system.[8] Another dimension of granularity is that this information is available on a monthly basis.[9] To link both datasets, we manually construct an identifier to connect each branch to its corresponding headquarter.[10] Furthermore, the branch data set also

[6] In a robustness test, we find that our baseline results remain unaltered irrespectively of whether we include lagged controls or non-lagged controls. The corresponding result tables are available upon request.

[7] Note that Eq. (2) is in line with 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.

[8] 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.

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

[10] To connect the corresponding headquarter to its bank branch, we had to align and identify bank names in both

includes information on the geographical location at the municipality level in which each branch operates. Finally, the bank branch information is aggregated up for each bank at the municipality level, such that the data is structured at the bank-municipality-month-level.

Both data sets are based on regulatory information from the BCB.[11] The first data set is based on call reports of the BCB and contains unconsolidated data and separate information for each bank's headquarter. The second data set, which contains the branch-municipality information is also based on regulatory data from the BCB and is called the ESTBAN database. By focusing on retail banking, our sample is less representative for financial centers and major cities as particularly investment banks are predominantly located there. Apart from this, bank branch penetration is widely spread across Brazilian municipalities such that our sample accounts for around 80 percent of total bank assets in 26 federal states.[12]

Despite of the obvious suitability of our data base to investigate the cross-regional transmission of interbank funding shocks, focusing on Brazil as a major emerging market and BRIC member state has additional advantages for our analysis. Since 127 bank institutions with an official banking license exist at the beginning of our sample (i.e. January 2005), which aggregate loan volume amounted for 26 percent of the Brazil's GDP in 2005, Brazil has one of the most diverse, developed and largest banking systems relative to other emerging markets. Additional heterogeneity and the granular geographical structure further helps us to investigate the shock transmission from headquarters to regional bank branches. Finally, another 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 the increase in uncertainty stemmed from the US mortgage crisis leading to the global financial crisis. Hence, from the Brazilian perspective, the crisis that hit Brazil in 2008 can be understood as an external shock.[13]

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databases manually.

[11] See Appendix A.1 for further details on the data collection process.

[12] There are in total 27 federal states in Brazil. The remaining state, Sao Paulo, is with 67 percent here the outlier. This is expected as Sao Paulo is the country's biggest financial center.

[13] 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 3.2.

2.2.2 Sample selection

Our identification strategy further requires the following sampling procedure. First, we only focus on banks that do not become defunct over the entire sample period. Thereby, we ensure comparability across banks as changes in interbank funding might reflect ex-ante conditions responsible for the bank becoming defunct. By excluding also 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 funding structure of the respective bank(s).

Second, we also exclude all banks that are not continuously active in the interbank market segment that we focus on. This adjustment is due to the following reasons:

First, this restriction is needed in order to properly apply the Cavallo et al. (2015) algorithm.[14] Second, changes in interbank funding of banks that are not frequently active in this market segment are likely to be demand driven. This is, however, relatively unlikely to be the case for banks that historically have been continuously using this particular funding source. Third, since this procedure also excludes complete dry-ups, we can argue that the empirical results obtained from our analysis 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 accounts for 79 percent of the lending volume of the investigated interbank market segment.

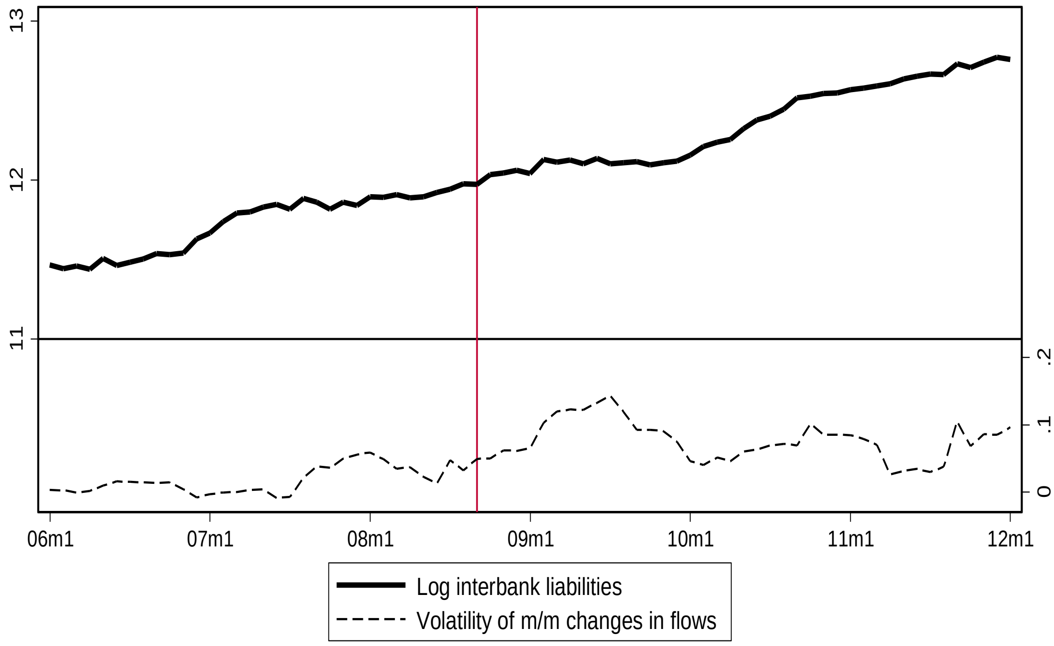
Finally, in line with our within municipality estimation approach, we only use those municipalities for our analysis that contain at least one affected and at least one non-affected bank branch. This final adjustment ensures consistency of our estimates and allows us to implement our preferred fixed effects structure. Eventually, our final sample contains 4514 bank branches that are active in 1628 municipalities. On the headquarter level, our final sample consists of 46 banks that account on average for 52 percent of total assets and 92 percent of credit outstanding of Brazil's entire banking system.

[14] The Cavallo et al. (2015) algorithm requires a continuous time-series in order to be applied, see: Section 2.3.

2.3 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 all local and unsecured interbank lending operations with a maturity of more than 90 days.[15]

Figure 1: The local and unsecured interbank market in Brazil



Notes: This figure depicts the evolution of the log amounts outstanding (in million US-Dollar) of the aggregate local and unsecured interbank funding market over time. The dashed line below the upper Panel displays the underlying volatility within this market. This volatility is calculated as the standard deviation of monthly changes in flows over the past 12-month on a rolling window. The vertical red line marks the date at with Lehman Brothers collapsed (September 2008).

Figure 1 displays the dynamics of this particular segment of the interbank market.[16] 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

[15] A more detailed description of this particular market segment can be found in Appendix A.2.
[16] Appendix A.5 displays the relative importance of this market segment over time.

liquid and well-functioning in the aggregate. The dashed line in the bottom panel shows, however, that the volatility of flows in this market did increase during the financial crisis with a peak a in the middle of 2009. This finding indicates that even though the market did not suffer from an aggregate disruption, uncertainty about counterparty risk in terms credit worthiness might have restricted access of certain banks to this market.[17] Henceforth, we refer to this market segment as interbank borrowing.

We exploit these dynamics of interbank borrowing and the data on the individual liability position of each bank vis-à-vis this market segment to apply an algorithm to identify and pin-down the moment in time when a bank is hit by an idiosyncratic interbank funding shock. It is important to note that the shock we identify is a severe shock that is similar to a partial dry-up of the 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 where the algorithm should detect potential idiosyncratic shocks. Second, we calculate the bank-specific funding growth rate in this market segment $\Delta\widetilde{IB}_{i,t}$ by subtracting the average growth rate of all other banks in this market from bank i's own interbank funding growth rate in this market. In a robustness test, we also calculate these idiosyncratic growth rates $\Delta\widetilde{IB}_{i,t}$ using a multifactor residual model (see, e.g., Pesaran, 2006 or Buch et al., 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.

$$\Delta\widetilde{IB}_{i,t} \leq \frac{\sum_{k=t-12}^{t} \widetilde{IB}_{i,k}}{12} - 2\sigma_{i,t} \qquad (3)$$

According to this condition, a bank is classified as being affected by a serious disruption in its interbank funding, if its idiosyncratic growth rate $\Delta\widetilde{IB}_{i,t}$ falls below the second standard deviation of

[17] To this regard, empirical and theoretical literature has focused on the interbank market and its evolvement during the global financial crisis - for a theoretical discussion see, e.g., Acharya et al. (2011). Relevant drivers for interbank distress have been analyzed empirically by Acharya and Merrouche (2013). They find that banks' uncertainty about their asset evaluation has led to a reduction in interbank lending in the UK due to adverse selection. Others (see, e.g., Brunnermeier, 2009, or Stiglitz, 2010) have argued that uncertainty reflected in counterparty risk was the main explanation for disruptions in global interbank markets.

its 12-month historical mean in the period from January 2008 to December 2009. If this condition is met, the start of the shock is set at the month when $\Delta\widetilde{IB}_{i,t}$ plunges below the first standard deviation of its historical mean.[18] Analogously, the end of the shock is defined when the idiosyncratic growth rate returns to the first standard deviation afterwards. Based on 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.[19] In order to analyze the effect of this shock on liquidity adjustments of bank branches over an event-timeline, we assign a pseudo shock to the non-affected banks at the particular month where the distance between $\Delta\widetilde{IB}_{i,t}$ and the threshold is minimized.[20]

2.4 Descriptive statistics and identification assumptions

The main descriptive statistics of our working sample are reported in Table 1. While 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 remaining three 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 column, we also report whether this difference is also statistically significant by employing the test of normalized differences of Imbens and Wooldridge (2009).

To this regard, we find that branches which are classified as shock-affected had on average a larger internal funding and lower deposit to total asset ratio. At the headquarter level, affected banks were on average more liquid – i.e. reported a higher liquid asset ratio – and reported on average a larger non-performing loan to total loan ratio. As shocks in our setting occur at the headquarter level, the results concerning structural differences between headquarters are more important for our analysis. To 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 loan ratio indicates the opposite. To reduce the concern that these ex-ante structural differences drive our results,

[18] Appendix A.2 discusses this procedure in greater detail.

[19] Appendix A.6 displays two graphical examples for a shock-affected and a non-shock affected bank.

[20] Appendix A.7 provides evidence that the idiosyncratic shocks and the corresponding pseudo-shocks of the control group are well distributed within the period from January 2008 to December 2009. Appendix A.8 reports further information regarding the affected banks in terms of their names, the shock duration and relative shock size. Appendix A.9 describes the amount of affected to non-affected banks and their corresponding branches and provides additional information on whether these banks are local or foreign owned.

we implement robustness tests in which these bank features compete against the shock-affected dummy in driving the difference-in-differences estimation.

When focusing on the descriptive statistics of the explanatory variables within the entire sample, we see that the difference in the deposit base between branches (36 percent) and headquarters (20 percent) points to the fact that local bank branches rely much more on local deposits as an important funding source.

Table 1: Summary statistics and the parallel trend assumption

	Entire sample Period:				Shock affected:		
	mean	**sd.**	**min**	**max**	**Yes**	**No**	**Difference in means**
Dependent variables:							
Δ Log Liquidity	-0.023	0.727	-1.971	2.055	-0.105	-0.129	-0.024
Δ Log Credit	0.010	0.972	-2.761	2.869	0.055	-0.284	-0.339
Δ Log Liquidity – Δ Log Liquidity	-0.026	1.376	-3.625	3.831	-0.101	-0.135	-0.035
Δ Log Credit – Δ Log Credit	0.007	1.844	-4.996	5.361	0.056	-0.290	-0.346
Headquarter-level control variables:							
Size (log Assets)	12.195	1.173	8.763	13.369	12.260	11.859	-0.401
Capital / Assets	0.074	0.040	0.036	0.253	0.075	0.073	-0.002
NPL / Credit	0.171	0.074	0.038	0.287	0.203	0.126	-0.077*
Adm. Cost / Income	0.004	0.002	0.001	0.011	0.004	0.004	0.000
Liquidity / Total Assets	0.012	0.005	0.002	0.022	0.014	0.010	-0.004*
Branch-level control variables:							
Size (log Assets)	3.534	1.355	1.073	8.746	3.528	3.308	-0.220
Deposits / Total Assets	0.750	0.266	0.058	0.998	0.691	0.812	0.121*
Income / Assets	0.020	0.011	0.005	0.056	0.020	0.021	0.002
Internal Liquidity / Total Assets	0.173	0.262	0.000	0.874	0.233	0.108	-0.125*

Notes: This table reports the summary statistics for our working sample. While the first four columns report the mean, the standard deviation (sd.), the minimum and the maximum value for each variable of the entire sample period, the last three columns report the mean of each variable for the group of affected and non-affected branches separately in the pre-shock period. The final column reports the difference in means between the control group (non-affected) and affected branches. Employing the normalized difference in means method of Imbens and Wooldridge (2009), * denotes whether the respective difference is statistically significant according to this method. In particular, this test also does not find any statistically significant difference in means for the first difference of our dependent variables in the pre-period (see third and fourth row). Hence, we do not detect any violation of the parallel trend assumption.

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. Such violation could severely bias the results of our difference-in-differences estimation. To this regard, we first test whether growth rates are on a similar level. The final column of the first two rows in Table 1 shows that there is no statistically significant difference in the average liquidity and credit growth rates between both groups (affected vs. non-affected branches). This provides evidence that there is no underlying systematic sorting of banks in terms of our dependent variables which might also bias our results. The third and fourth row of the last column of Table 1 provide an explicit test for the violation of the parallel trend assumption. This test focuses on the first difference of the group specific dependent variables in the pre-shock period. Thereby, a statistically significant difference of the first difference between both groups would indicate a violation of the parallel trend assumption. Again, we do not find any statistically significant difference between affected and not-affected branches.[21]

Finally, apart from these descriptive statistics presented in Table 1, we also test another assumption that is important for our identification approach. To rule out that the shocks identified by the Cavallo et al. (2015) algorithm in interbank borrowing are not driven by bank's own demand and indeed reflect interbank loan supply, we test whether the interest rates of interbank borrowing changes in the 12 month run-up to the shock. As bank-specific interest rates in the interbank market are not publically available, we use a standard proxy for this variable. For this procedure, we take the amount of interest paid relative to the loan amount outstanding in the interbank market for each individual bank. As this interest rate proxy increases for affected relative to non-affected banks immediately one month in advance to the idiosyncratic shock, we provide evidence that our funding shock is indeed driven by supply and not by bank funding preferences – this would imply that affected banks would report a smaller interest rate relative to non-affected banks. This test is discussed in greater detail in Appendix A.3 and the corresponding results are reported in Appendix A.11.

[21] Appendix A.10 also depict the average liquidity and lending growth rates of affected and non-affected branches over the event-timeline.

3 Results

3.1 Baseline estimation

Table 2 reports the baseline results for the estimation equations Eqs. (1) and (2) in columns I to III and IV to VI, respectively. Columns I and IV estimate the specifications without neither control variables nor any fixed effects structure and columns II and V include headquarter and branch controls as well as branch and actual time fixed effects. Finally, columns III and VI report the results for our preferred specification, i.e. we include control variables of both levels of the organizational structure of the banking conglomerate and saturate our model with municipality-time fixed effects which are based on a monthly basis to account for global as well as regional specific factors such as credit demand.[22]

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 a 13 p.p. higher liquidity growth rate than non-affected branches in the post-shock period when accounting for differences in the pre-shock period. As this effect captures 18.6% of the within variation of the liquidity growth rate (70 p.p.), this effect is sizeable for the perspective of economic significance. Furthermore, the idiosyncratic interbank funding shock decreases the credit growth rate by around 27.3 p.p. on average (i.e. the difference-in-differences effect). This effect accounts for 29% of the within variation of the lending growth rate (94 p.p.). Taken together, these results depict an economically significant liquidity hoarding reaction with relevant spillovers in branches' credit supply as they account for a large share of the within variation.

[22] In Appendix A.12, we provide evidence that these baseline results are also robust to the inclusion of the loan to asset ratio and the mortgage to asset ratio on the branch level and the interbank funding to total funding ratio, a foreign currency exposure measure and the mortgage to asset ratio at the headquarter level.

Table 2: Results - Baseline Estimation

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***	-0.090	-0.087	0.591***	0.118	0.106
	(0.004)	(0.058)	(0.054)	(0.006)	(0.096)	(0.090)
Affected	0.001			0.374***		
	(0.004)			(0.006)		
Headquarter controls:						
Size (log total assets)		0.214	0.277**		0.343	0.382
		(0.181)	(0.135)		(0.369)	(0.303)
Capital / Total 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
		(22.190)	(15.999)		(40.937)	(32.371)
Liquidity / Assets		4.442*	3.719*		5.319	5.147
		(2.211)	(2.057)		(4.290)	(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 / Total 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)	(1.470)		(2.045)	(2.038)
Internal funding / Total Assets		-0.080	-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 Time 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 baseline estimation (see: Eq. (1) and Eq. (2)). Columns I to III report the results of the liquidity growth and columns IV to VI of the credit growth equation. For growth rates, we use log changes of the respective variables. The variable of interest in these equations is difference-in-differences variable Affected X Shock which displays the difference between affected versus non-affected branches in the respective dependent variable in the post-shock period when accounting for differences of the pre-shock period between both groups. Columns I and IV contain neither control variables at the headquarter nor at the branch level nor any type of fixed effects structure. Columns II and V include headquarter and branch controls as well as branch and as well as 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-time fixed effects. Given that ordinary time fixed effects are nested in the municipality-time fixed effects, the time fixed effects are not additional included in the model, and thus, are stated as (.) in this table. For all equations, we use standard errors that are clustered at the headquarter-time level and ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

In line with previous literature that has found that interbank market disruptions can have severe consequences over the long-run in the case of aggregate market disruptions (see, e.g., Ananda et al., 2011), using a 24 month post-shock window in our baseline setting suggests that liquidity and lending adjustments of regional bank branches exert similar properties. The parallel effect of the interbank shock on liquidity and lending suggests that affected bank branches reallocate from illiquid assets to liquid assets in order to satisfy their liquidity preferences. Since these shocks are idiosyncratic by its very own nature and complete dry-ups are excluded from our analysis, we can infer that our results are unlikely to be driven by the speculative movie of banks hoarding liquidity but rather by the precautionary motive – i.e. banks fearing market exclusion increase their liquid asset positions.

3.2 Robustness analysis

We run a number of robustness tests aimed at exploring the validity and stability of our baseline results. First, we show in Table 3 whether we find similar results when we use a 12 month pre- and 12 month post-shock period to gauge the short-term effect of the idiosyncratic shock on the liquidity and lending adjustments. To test whether these results still prevail in the long run, we exclude the period between $\tau = -12$ and $\tau = +12$ from our sample. While the results of the former analysis are depicted in columns I and II of Table 3, the results of the latter procedure are depicted in columns III and IV of the same table. Overall, we find for both procedures that our baseline result remains qualitatively unaltered. Results further suggest that the short-term effect is smaller compared to the long-term effect which might reflect that banks are more restricted reallocating assets in the short-run. In Table 4, we provide an number of 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 based on panel data are potentially suffering from serial correlation of the error terms (see Bertrand et al. (2004)), we transform our data to two cross-sections – one for the pre – and one for the post-shock period. For this more conservative approach, we compute the average of each variable for the pre- and post-shock period per bank branch.[23] Columns I and II of Table 4 depict the corresponding results of this approach for liquidity and credit growth respectively. Overall, we find similar results compared to our

[23] This time-collapse procedure also has the drawback that the municipality-time fixed effects are less powerful in capturing common demand effects. Therefore, these results are only represented as a robustness test.

baseline estimation, however, the statistical significance improves to the 1 percent level for both dependent variables.

Table 3: Robustness – Short- versus long-term impact

Specification:	**Short-term impact [only τ-12 to τ +12]**		**Long-term impact [drop τ-12 to τ+12]**	
Dep. Var.:	**Δ Liquidity**	**Δ Credit**	**Δ Liquidity**	**Δ Credit**
	I	**II**	**III**	**IV**
Affected X Shock	0.088*	-0.070*	0.189***	-0.494***
	(0.050)	(0.041)	(0.064)	(0.139)
Controls included	YES	YES	YES	YES
Branch FE	YES	YES	YES	YES
Municipality x Time FE	YES	YES	YES	YES
Observations	147,307	147,944	142,792	142,792
R-squared	0.389	0.445	0.422	0.468

Notes: This table reports additional robustness tests of our baseline results when restricting our sample to the 12 month around the shock occurrence (see columns I and II) and when excluding this period around the shock (columns III and IV). While the first specification gauges the short-term impact, 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 columns III and VI from Table 2. Standard errors that are clustered at the headquarter-time level and ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

In order to ensure that our results are not driven by Brazil's financial centers – i.e. Sao Paulo and Rio de Janeiro – we exclude these from our analysis. Overall, this procedure does not alter our baseline results qualitatively or quantitatively (see columns III and IV of Table 4).

Finally, we perform a placebo test by randomly selecting the groups of affected and non-affected banks (columns V and VI of Table 4). As we find no statistically significant results, this test strengthens the case that our results are not driven by any random selection.[24]

In addition to these robustness checks, Table 5 reports that our results are robust to alternative clustering of standard errors and when using the change in liquidity to lagged total assets and the

[24] In an additional robustness test, we employ a dynamic parameter approach where we evaluate the difference-in-differences effect at a monthly frequency at each point in time. Appendix A.13 depicts the corresponding results. It shows a positive "on impact" effect of the shock on liquidity growth, which holds over the time window of the estimation. The effect on credit growth is consistently negative throughout the shock period, emerging around three months after the shock. This lagged effect of shocks on credit as compared to liquidity supports our interpretation of the credit adjustment being driven by an asset reallocation reaction leading branches to hold larger liquid assets balances.

change in loans to lagged total assets as an alternative dependent variable definition.[25] Our baseline results remain unaltered to these additional tests.

Table 4: Robustness – Collapsed Time Approach, Financial Centers, and Placebo Test

Specification:	**Collapsed Pre- and Post-Shock Periods**		**Excluding Financial Centers**		**Placebo Test**	
Dep. Var.:	**ΔLiquidity**	**ΔCredit**	**ΔLiquidity**	**ΔCredit**	**ΔLiquidity**	**ΔCredit**
	I	**II**	**III**	**IV**	**V**	**VI**
Affected X Shock	0.066***	-0.217***	0.163***	-0.245**	-0.101	0.144
	(0.024)	(0.044)	(0.053)	(0.123)	(0.086)	(0.106)
Controls included	YES	YES	YES	YES	YES	YES
Branch FE	YES	YES	YES	YES	YES	YES
Municipality x Time FE	YES	YES	YES	YES	YES	YES
Observations	8,366	8,366	147,385	147,385	196,667	196,667
R-squared	0.749	0.765	0.405	0.445	0.396	0.432

Notes: This table reports the results of three additional robustness tests. First, columns I and II report the results for both dependent respective variables when collapsing the pre- and post-shock period in two single time periods to address potential concerns about autocorrelated error terms (see: Bertrand et al. (2004)). Second, columns III and IV report the baseline results when excluding the financial centers of Sao Paulo and Rio de Janeiro. Finally, columns V and VI perform a Placebo test where we randomly select the groups of affected and unaffected banks. 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 are clustered at the headquarter-time level and ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

[25] We have also employed clustered standard errors at the headquarter and the headquarter-timeline level, our results remain also statistically significant for this procedure. These results are available upon request.

Table 5: Additional Robustness – alternative clusters and relative growth equation

Specification:	**SE Cluster: UF x time**		**SE Cluster: municipality x time**		**Relative Growth**	
Dep. Var.:	**ΔLiquidity**	**ΔCredit**	**ΔLiquidity**	**ΔCredit**	**ΔLiquidity**	**ΔCredit**
	I	**II**	**III**	**IV**	**V**	**VI**
Affected X Shock	0.130***	-0.273***	0.130***	-0.273***	0.001*	-0.112***
	(0.037)	(0.060)	(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 Time 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	0.410	0.462

Notes: This table reports the results of further robustness analysis of our baseline results. The first two columns provide evidence that our results remain robust when the standard errors are clustered by the federal unit-time level (UF stands for federal unit), or when clustered at the municipality-time level (columns III and IV). Columns V and VI report the results when using the change in liquid assets to total assets lagged by one month and the change in commercial loans outstanding relative to total assets lagged by one month. 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 headquarter-time level and ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively

Another concern is that the differences-in-differences effect can be driven by another bank characteristic which could be, for example, related to bank risk and would lead to omitted variable bias. This would be the case, for example, if affected banks report ex-ante a weaker capitalization that makes their branches sensible to balance-sheet fluctuations at the parent-bank level during a period of financial distress. Hence, we also address ex-ante sorting of banks, by running multiple so called "horse-races", that is, we include competing interaction terms between the shock and bank characteristics that could be related to banks' exposure to liquidity risk. Table 6 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 6) are included in the model.

Table 6: Summary Table - Horse Race with Bank Traits

Dep. Var.	**ΔLiquidity**	**ΔCredit**
Reported Parameter:	Affected X Shock	Affected X Shock
	I	**II**
Included competing non-linearity:		
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**
	(0.060)	(0.109)
NPL Ratio X Shock	0.150***	-0.247***
	(0.034)	(0.089)
Foreign Ownership X Shock	0.208***	-0.100**
	(0.045)	(0.050)
Foreign Funding X Shock	0.157***	-0.238**
	(0.054)	(0.106)
State Owned X Shock	0.109***	-0.293**
	(0.027)	(0.110)

Notes: This table summarizes the results of the "horse race" between the difference-in-differences parameter of the variable [Affected X Shock] and other competing non-linearities. Column I reports the parameters of the difference-in-differences effect for the liquidity growth equation and column II reports these results for the credit growth equation, analogously. Each row, thus, reports the difference-in-differences parameter of the variable [Affected X Shock] when including the non-linearity that is stated by the first column in the respective row in this table. 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 Owned is also a dummy variable that equals one if it is at least partially owned by a government entity. 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 headquarter-time level and ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

We test if our results hold when including interaction variables between the shock and bank size (log of total assets), the capital to assets ratio, the parent banks' liquid assets ratio, the administrative cost to income ratio, and the NPL ratio. Across these different specifications our baseline results are confirmed. Of particular interest is that we also find robust results when we include foreign ownership or parent banks' ratio of foreign interbank liabilities to total assets as competing non-linearities to our interaction of interest. This result suggests that the effects found are not driven by direct-cross border contagion during the global financial crisis. Another concern is that in Brazil state-owned banks in our sample might drive our results. To address this issue, we also include a competing interaction between a state owned dummy variable and the shock variable in our model. Overall, we find that confirming evidence that our difference-differences effect is not driven by a competing non-linearity.[26]

Since we have specified in section 2.3 the idiosyncratic interbank funding growth rate as the difference between the individual interbank funding growth rate of bank i and the average growth rate of the market excluding bank i, we also test whether the results of the model remain robust to an alternative parametric estimation of these idiosyncratic growth rates. For this purpose, we compute the interbank funding growth rate $\Delta\widetilde{IB}_{i,t}$ 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 it enables us to filter out observed as well as 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 and banking system variables in bank-specific time series regressions. These latter controls include aggregated variables describing the dynamics in the local banking system computed from our bank-level data. This time-series approach filters out aggregate variation such that the residual term of this (bank-specific) model captures the idiosyncratic growth rate of bank i. Finally, this (parametrically estimated) growth rate is then employed within the Cavallo et al. (2015) algorithm.[27] Table 7 reports the results when calculating the idiosyncratic growth rates based on a MFR model. While column I and III report results with time fixed effects, columns II and IV report the results for the saturated model that includes municipality-time fixed effects on a monthly basis. These results confirm our main findings.

[26] Appendix A.14 provides additional evidence that the difference-in-differences effect of our baseline estimation also survives additional horse races against non-linearities that are based on the remaining branch control variables.

[27] The multifactor residual model includes the following monthly variables whereby the corresponding data source is depicted in parenthesis. As macroeconomic variables we include: 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). As a proxy for unobserved macroeconomic variables we use 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. This variable choice is similar to Pesaran (2006) and Buch et al. (2009).

Table 7: Robustness – MFR-model based idiosyncratic growth rates

Dep. Var.:	ΔLiquidity		ΔCredit	
	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 Time FE	NO	YES	NO	YES
Observations	162,512	155,982	162,512	155,982
R-squared	0.129	0.387	0.200	0.441

Notes: This table reports further robustness results when calculating the idiosyncratic funding growth rate using a multifactor residual (MFR) model (see, e.g., Pesaran, 2006 or Buch et al., 2009). Column I and II report these results for the liquidity growth rate and column III and IV for the credit growth rate. 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 extend this setting by including municipality-time fixed effects (baseline specification Table 2 columns III and VI. Standard errors that are clustered at the headquarter-time level and ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

In a further robustness test, we try to shed additional light on the internal capital market funding risk channel on bank branches' liquidity and lending adjustments. As bank branches rely predominantly on a mix that consists of local deposits and internal funding, we conjecture that bank branches which rely more heavily on internal funding are more prone to the interbank funding shock that occurs at the headquarter level. In contrast, we expect that branches that have a larger deposit base are less exposed to this shock as their funding risk will be affected to a lesser extend. Exploring the role internal capital markets is central to our research question as it allows us to retrieve evidence on whether market frictions related to the geographically fragmented structure of branches' funding markets are indeed driving the results.

To gauge this potential difference in risk transmission, we split our branch sample into two groups. In a first stage, we calculate the internal funding to total funding ratio as well as the deposit to total funding ratio for each individual bank branch for the pre-shock period. We then assign all branches to the high funding risk group that report larger values than the sample median. Analogously, we measure the sensitivity for the risk transmission in terms of local deposit reliance. If branches report values above the sample median in the pre-shock period, they are assigned to the group of high deposit reliance. We then use this assignment to enhance our difference-in-differences approach by introducing a triple interaction model to gauge how these differences in the exposure to this funding risk affects our results.

The additional conditional variable included in our baseline model is a dummy variable that either measures the exposure of an individual branch to internal funding or its reliance on local deposits. All constitutive terms of the triple interaction are included in the specification as long as these are not accounted for by our fixed effects structure. Table 8 reports the corresponding results.

Table 8: Internal capital market risk transmission

Funding Risk Group Def.:	**FRisk-Group defined by internal funding dependence**		**FRisk-Group defined by local deposit reliance**	
Dependent variable:	**ΔLiquidity**	**ΔCredit**	**ΔLiquidity**	**ΔCredit**
	I	**II**	**III**	**IV**
Affected X Shock X FRisk-Group	0.185***	0.140	-0.211***	-0.049
	(0.063)	(0.085)	(0.040)	(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 Time FE	YES	YES	YES	YES
Observations	196,667	196,667	196,667	196,667
R-squared	0.398	0.431	0.400	0.435

Notes: This table reports the results of the triple-interaction model when using a dummy variable for different funding risks groups as additional modifying variables of the difference-in-differences effect. Columns I and III report the results for the liquidity growth and columns II and IV for the credit growth equation. In columns I and II, bank branches are classified as belonging to the funding risk group (high risk group) if their internal funding to total funding ratio is above the sample median for the pre-shock period. Analogously, in columns III and IV bank branches are assigned to the funding risk group (low risk group) by their local deposit to total funding ratio. 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 headquarter-time level and ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

In line with our conjecture, we find that our liquidity hoarding effect is driven by internal funding risk group – that is by those branches that have a higher ex-ante share in internal funding to total funding. Using the alternative funding risk group definition – i.e. the funding risk group is defined by the local deposit reliance – we find that the liquidity hoarding effect disappears for this low funding risk group. Interestingly, these non-linarites only affect the liquidity growth equations, while the decision whether to cut lending as a response to the shock seems to be driven by other (probably local) factors. Overall, this provides additional evidence that the liquidity hoarding effect is driven by branches' internal capital market dependence and thus by a limited capacity to compensate for the loss of one funding channel by taping alternative liquidity sources. This finding further suggests that the fragmented structure of branches' funding markets drives the transmission of funding shocks within the banking conglomerates in the sample.

4 Emergency liquidity facilities and liquidity hoarding

As we identify idiosyncratic shocks over the period around the global financial crisis from January 2008 to December 2009, banks in Brazil also got access to emergency liquidity facilities activated by the Banco Central do Brasil (BCB). These facilities, which were similarly designed in comparison to other measures undertaken by central banks worldwide, were activated soon after the collapse of Lehman Brothers (September 2008) and provided additional funding for banks to stabilize their funding structure.[28] Hence, also from the perspective of the monetary policy maker it is important to understand, whether these measures were able to alter bank branches' inclination to hoard liquid assets. Furthermore, tracing the role of emergency liquidity for our analysis sheds additional light on the underlying liquidity reallocation process and the trade-off between lending and liquidity. We therefore exploit our setting to explore whether a larger bank-level access to emergency liquidity offsets the transmission of the interbank funding shocks to branches' liquidity and lending growth.

For this purpose, we use individual bank balances vis-à-vis the emergency liquidity facilities of the BCB. Using this data is not without limitations as potential endogeneity can affect such an analysis. In this regard, the main problem is that banks which were more dramatically hit by interbank funding shocks might have had received preferential access to this facility. To account for this drawback, we weight the 6-month post-shock balances vis-à-vis BCB facilities by the size of the shock that each bank experienced.[29] As this bank-specific shock weighted measure is hard to interpret economically, we normalize the final measure to a continuous variable $\widetilde{CBI}_i$ between 0 and 1.[30]

[28] A more detailed description of these policy interventions is provided by Appendix A.4, while Appendix A.15 displays the aggregated (not the individual) balances vis-à-vis this emergency liquidity facilities over time.

[29] The size of the shock is defined by the percentage change in interbank funding (in logs) from the peak value prior to the shock to the lowest value during the shock occurance.

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

Estimating a multiplicative interaction model within a difference-in-differences approach, we investigate whether the impact of $[Affected_i \times Shock_{i,\tau}]$ is moderated by banks access to unconventional monetary policy $\widetilde{CBI}_i$. Analyzing this non-linearity within a difference-in differences-framework means to extend Eqs. (1) and (2) to a triple interaction model where the triple interaction term determines the dependence of the difference-in-differences effect on the additional funding source. Table 9 reports the corresponding results and Figure 2 displays the corresponding overall marginal effect of the difference-in-differences effect on the liquidity (Panel A) and lending growth rates (Panel B), conditional on our measure for the relative access to unconventional monetary policy $\widetilde{CBI}_i$.

Interestingly, Figure 2 shows that access to this emergency liquidity facility altered the asset reallocation affect. First, the marginal effect of the idiosyncratic shock on liquidity growth is more pronounced for branches whose corresponding headquarter had better access to this facility relative to the shock size (Panel A) while the contrary situation occurs in case of credit growth (Panel B). These results suggest that branches whose corresponding headquarter had better access to this facility cut lending to a lesser extent. On the contrary, bank branches that cannot rely on this funding source can only cut lending in order to retain some of their liquid assets. As this does not come without limits, these branches are not able to build up liquidity buffers in response to the shock. Hence, we conclude that even though in some cases branches did not have to cut lending, monetary policy interventions did not change banks' preferences to hoard liquidity. Columns III and IV of Table 9 also confirm these results when $\widetilde{CBI}_i$ is computed as a dummy variable equal to 1 if a branch's headquarter reports a $\widetilde{CBI}_i$ measure above the sample median and 0 otherwise. Overall, these results provide additional evidence that our model reveals a liquidity hoarding reaction driven by precautionary motives.

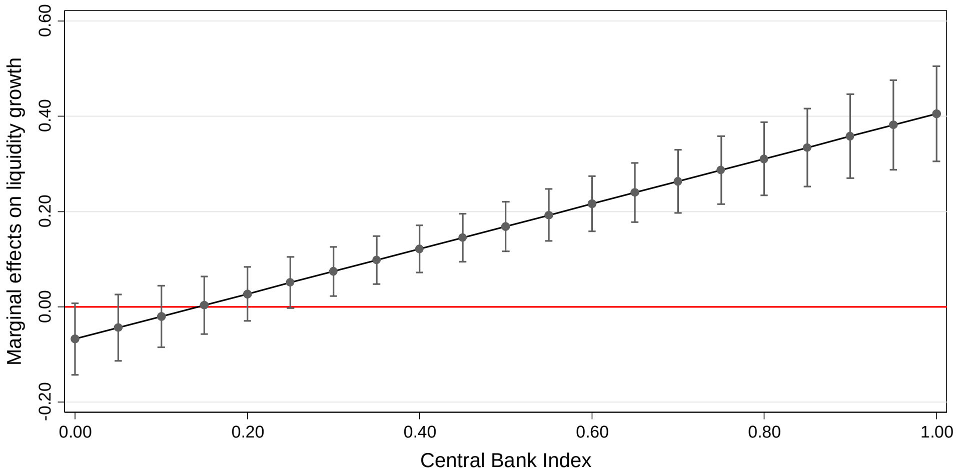
Table 9: Liquidity Hoarding and Emergency Liquidity Facilities

Intervention measure:	**Continuous variable**		**Categorical variable**	
Dep. Var.:	**ΔLiquidity**	**ΔCredit**	**ΔLiquidity**	**ΔCredit**
	I	**II**	**III**	**IV**
Affected X Shock X CBI	0.473***	0.609***	0.496***	0.512***
	(0.087)	(0.149)	(0.080)	(0.151)
Affected X Shock	-0.068	-0.607***	-0.156***	-0.583***
	(0.046)	(0.130)	(0.039)	(0.138)
All constitutional terms included	YES	YES	YES	YES
Controls included	YES	YES	YES	YES
Branch FE	YES	YES	YES	YES
Municipality x Time FE	YES	YES	YES	YES
Observations	196,667	196,667	196,667	196,667
R-squared	0.400	0.439	0.401	0.437

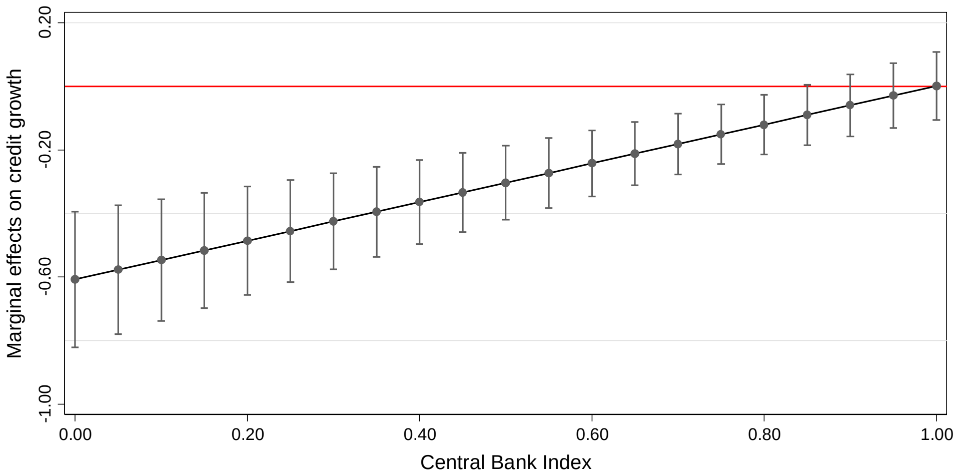
Notes: This table reports the results of the triple interaction model that evaluates the effect of the idiosyncratic interbank funding shock on liquidity growth (columns I and III) and on credit growth (columns II and IV) conditional on the bank-specific access to the emergency liquidity facilities activated by the BCB. All specifications are based on the baseline estimation (Table 2 columns III and VI). While equations I and II report the results when including the shock weighted unconventional monetary policy variable $\widetilde{CBI}_i$ as a contiguous modifying variable, columns III and IV employ a categorical variable that equals one for banks where $\widetilde{CBI}_i$ is above its median value and zero otherwise. All constitutive terms of the interaction terms are included. Standard errors that are clustered at the headquarter-time level and ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

Figure 2: Marginal Effect of the idiosyncratic interbank funding shock on liquidity growth and credit growth conditional on of BCB intervention

Panel A: Liquid Asset Growth



Panel B: Credit Growth



Notes: This figure illustrates the overall marginal effects of the idiosyncratic interbank funding shock on liquid asset growth (Panel A) and on credit growth (Panel B) conditional on the bank-specific shock-weighted access to the emergency liquidity facilities activated by the BCB. The solid line presents the marginal effect of the difference-in-differences for particular levels of the $\widetilde{CBI}_i$ variable. The whiskers represent the corresponding 95% confidence interval. These marginal effects are based on columns I and II of Table 9.

5 Concluding remarks and policy evaluation

Our study explores how idiosyncratic, i.e. bank headquarter-specific, shocks in interbank funding can prompt banks' corresponding branches to rapidly increase their liquid asset positions. These disruptions do not only lead to long-term effects on liquid assets growth but also prompt branches to cut lending. Overall, we find compelling empirical evidence for this market-to-market spillover effect via internal capital markets. Hence, we provide evidence on how shocks that occur in a market segment where only the headquarter can obtain funds leads to liquidity and lending adjustments at the municipality branch market which is directly excluded from this funding source. In contrast to previous studies that focus on aggregate disruptions in the interbank market or on the interbank market as a channel of financial contagion itself, we highlight the effect of granular shocks channeled via internal capital markets to local concentrated bank branch markets with potential real effects via reductions in credit supply. By exploiting the idiosyncrasy of these events, we further are able to infer that liquidity hoarding in our context does arise from precautionary instead of speculative motives.

Our empirical analysis exploits a unique balance-sheet data set on the Brazilian banking system to track the consequences of sudden disruptions in interbank funding between 2008 and 2009. We first use an adjusted methodology proposed by Cavallo et al. (2015) to identify banks in Brazil affected by interbank funding shocks as well as the specific date at which each shock occurs. We avoid endogeneity concerns by merging to this data set information on all individual branches that belong to their respective headquarter in the country. This enables us to distinguish the headquarter level – at which funding disruptions occur – from their corresponding regional branch level where liquidity and lending adjustments are analyzed. We rely on an event-timeline to compare liquidity and credit growth by shock-affected branches with the outcomes of branches whose headquarters were not affected by a funding shock within a difference-in-differences estimation. Municipality-date fixed effects on a monthly frequency are used to isolate the effect of shocks from country- and municipality-specific confounding factors.

Our key finding is that branches tend to hoard liquid assets and to reduce credit after their headquarter experienced a shock. These findings are robust to a large battery of sensitivity analysis. Furthermore, we find that emergency liquidity facilities implemented in Brazil since September 2008 were partially effective in supporting branch lending operations while liquidity hoarding as a phenomenon did not disappear. Thus, these results suggest that liquidity hoarding caused by a change in bank branches' preferences could not be altered by broad unconventional monetary policy measures.

Our results show that a combination of banks' changing preferences towards liquid assets and institutionally constrained regional funding markets can explain the transmission of idiosyncratic funding shocks to lending. This market-to-market spillover effect is also relevant from the perspective of the policy maker as idiosyncratic shocks transmitted to concentrated regional bank branch markets can have severe implications for local economies. Hence, our approach highlights particular frictions which might be relevant for future regulatory innovations. Concerning frictions on the interbank market, policy initiatives such as Basel III which place greater weight on bank-specific characteristics might be helpful to reduce bank-specific vulnerabilities, and thus, can potentially mitigate risks of market exclusion of individual banks. Other policy initiatives that aim at reducing regional bank branch market concentration and/or establish alternative funding opportunities for the real economy can address or reduce the spillover effect to the local economy.

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Appendix

A.1 Data construction

We combine different sources of publicly-available regulatory data to investigate how interbank funding shocks in a market in which banks’ headquarters participate affects the liquid assets and lending growth rates of municipal bank branches in Brazil. We downloaded the balance sheets and income statements of banks' headquarters and their individual branches from the website of the BCB. This information is reported in two distinct datasets. First, the data on banks’ headquarters comes from the data base “Balancetes e Balanos Patrimoniais” (Bank Balances and Equity) published by the BCB. Second, the data on bank branches was retrieved from the data base “Estadistica Bancaria Mensal por Municipio” (Monthly Banking Statistics by Municipality). This latter data reports the balance sheet of banks aggregated at the municipal level, so that all branches operating within a municipality are reported as a joint entity. We obtained the definition of the balance sheet positions from the “Manual de Normas do Sistema Financeiro” (Manual of Financial System’s Norms or COSIF). We checked the definition of each variable and translated them to English to facilitate the empirical analysis. A name and internal code assigned by the BCB to each financial institution in Brazil was used to match the headquarter with the branches’ data.

Besides of reporting a large set of balance-sheet and income-statements variables, these data include both the name and an internal code assigned by the BCB to each financial institution. These information allow us to merge the municipal level data on bank branches with the balance-sheet information on banks' headquarters. The definitions of the balance-sheet items were retrieved from the Manual of Financial System's Norms or COSIF (Manual de Normas do Sistema Financeiro).

The bank level data consists of banks' mandatory call reports, collected by the BCB. These data set is reported on a monthly basis in local currency (Brazilian Reais, BRL). This data were downloaded somewhere between the years of 2014 and 2015. Further adjustments, translation and labeling were conducted to achieve consistency. As this data is based on mandatory reports from banks to the BCB, the data set includes all institutions in Brazil that have a banking license. Hence, the data set provides the comprehensive account on all banks operating within Brazil. Thus, other financial institutions that do not have an official banking license are not recorded in this dataset. To facilitate the analysis, we converted the original currency denomination to millions of BRL. While banks in the final sample are active throughout the sample period, some merges and acquisitions took place generating discrete changes in banks’ balance sheets. We control for these changes by winsorizing data at the 1 and 99 percentiles for each variable. In addition to this regulatory data, additional information on the ownership structure was merged to this data set. This information is based on the Claessens and Van Horen's (2014) Banks Ownership Database and on information disseminated on banks' own homepages.[31]

A.2 Pinning Down Idiosyncratic Interbank Funding Shocks

This part of the Appendix explains the procedure used to pin down the idiosyncratic interbank funding shocks in the unsecured interbank market in Brazil. The general idea of the applied procedure stems from Cavallo et al. (2015) which is originally supposed to detect at the country level the occurrence and the timing of sudden stops in capital flows. Before we discuss this procedure in greater detail and how it is adjusted for our purposes, this section of the Appendix starts with the definition of the particular segment of the interbank market.

The data for this segment of the interbank market and the bank specific exposure to this segment is taken from the Call Reports of the Banco Central do Brasil (BCB). The liability position we use captures loans outstanding in the unsecured domestic interbank market in Brazil with a relatively long maturity of more than 90 days. Hence, this market segment excludes interbank funding of banks that are located outside of Brazil. All operations within this market are executed on an OTC (over-the-counter) basis. This segment is henceforth called interbank borrowing.

Overall, this segment accounts for approximately 25 percent of the Brazilian interbank market and 16 percent of total bank liabilities. Relative to other segments of the interbank market, it is the second largest market for interbank funding. Only interbank deposits which amounts for approximately 50 percent has a larger share than interbank borrowing. The other segments in this market account for the remaining 25 percent of the market which includes, for example, the foreign interbank market. Apart

[31] A similar, however, less detailed description can also be found in Noth and Ossandon Busch (2017).

from these other segments, it is important to note that our interbank borrowing market excludes also borrowing from the Brazilian central bank. Another important feature of this market segment is that it did not experience a complete dry-up during the period of the global financial crisis. Nevertheless, the underlying volatility in this market increased rapidly with the outbreak of the financial crisis in 2008. Interestingly, Pérignon et al. (2018) documents similar dynamics for a comparative segment of the European interbank market.

We exploit these dynamics of interbank borrowing in order to apply the following algorithm to identify and pin-down the moment in time when a bank is hit by a bank-specific, i.e. idiosyncratic, funding shock. It is important to note that the shock we identify is a severe shock that is similar to a partial dry-up of the bank specific funding source. The algorithm we employ further enables us to specify the size and the duration of this shock.

In a first step, we have to define a time window where our algorithm is supposed to detect these bank specific shocks. Based on the market dynamics described above, we determine the period from January 2008 to December 2009 as the relevant period to apply this algorithm.

Second, we compute the bank-specific monthly change in log interbank borrowing $\Delta IB_{i,t}$ on a year-over-year basis to adjust for potential seasonal effects. Subsequently, we subtract the sample mean in interbank borrowing $\Delta\overline{IB}_{i,t\,\forall j\neq i}$ which includes all banks j but not bank i from the individual growth rate of bank i ($\Delta IB_{i,t}$). This gives us the idiosyncratic growth rate $\Delta\widetilde{IB}_{i,t} = \Delta IB_{i,t} - \Delta\overline{IB}_{j,t\,\forall\, j\neq i}$ of bank i at date t. For robustness, we additionally calculate these idiosyncratic growth rates employing a MFR (multifactor residual) model (see, e.g., Pesaran, 2006 or Buch et al., 2009).

Next, we employ the Cavallo et al. (2015) algorithm to determine whether and when a bank has experienced an idiosyncratic shock in interbank funding. According to this procedure, a bank is affected by an idiosyncratic shock in interbank funding if the following condition is met at least at one point in time during the period from January 2008 to December 2009:

$$\Delta\widetilde{IB}_{i,t} \leq \frac{\sum_{k=t-12}^{t}\widetilde{IB}_{i,k}}{12} - 2\sigma_{i,t} \qquad \text{(A1)}$$

Eq. (A1) defines the occurrence of a shock if the idiosyncratic growth rate $\Delta\widetilde{IB}_{i,t}$ falls below the second standard deviation of its 12-month historical mean – which is calculated on a rolling window.[32] If this condition is met, the start of the shock is set at the month when $\Delta\widetilde{IB}_{i,t}$ plunges below the first standard deviation of the historical mean around the time of the identified event. The end is defined analogously at that point in time when the idiosyncratic growth rate has returned back to the first standard deviation after the shock was identified.

A.3 Do shocks reflect banks' changing preferences towards interbank funding?

As discussed in the main article, the identified interbank funding shocks may reflect a change in banks' preferences regarding their funding mix. For example, banks suffering from negative credit demand shocks may decide to restrict their exposure to interbank funding and weather the storm represented by the weak demand by relying on more stable (deposit based) funding sources. In such situation, our estimation could be biased due to a reserve-causality problem between liquidity and credit growth affecting the assignment of bank headquarters into the groups of affected and non-affected banks. Considering the importance of this identification challenge, we perform a preliminary econometric test aimed at visualizing whether the identified shocks can be related to banks' own demand for interbank funding.

In this test, which is briefly discussed in Section 2.4 in this paper, we explore whether the interest rates paid by banks for borrowing in the interbank market increase immediately before the shock occurs. To evaluate this we use the run-up period of 12 months before the shock. A tightening of lending conditions of a particular bank would lead to an increase in the interest rate while a negative reaction would indicate a demand driven effect. To test this assumption, we specify the following empirical model:

$$IBBRate_{i,\tau} = \mu_i + \beta_\tau \left(Affected_i \times PreShock_\tau\right) + \epsilon_{i,\tau} \qquad \text{(A2)}$$

[32] The standard deviation is calculated on the same sample as the historical mean – i.e. the previous twelve month.

In Eq. (A2) the variable $IBBRate_{i,\tau}$ represents a proxy for banks' interest rate of interbank borrowing. We define this proxy as the ratio of the monthly interest rate payments in interbank market to interbank balances outstanding for each individual bank. In Eq. (A2), the time-varying parameter β_τ of the interaction $(Affected_i \times PreShock_\tau)$ measures the difference in the interbank borrowing rate between affected and non-affected headquarters for the pre-shock period. The variable ($Affected_i$) follows the same definition as in the baseline model. However, the variable $PreShock_\tau$ is a dummy variable that equals one for each individual event-time prior to the shock. Overall, we use the period from $\tau = -13$ to $\tau = -1$, whereas the parameters are estimated for the twelve month in the run-up to the individual shock. We further control for the same set of headquarter characteristics as in our baseline estimation specification and we also control bank fixed-effects. One detail of our event-timeline approach is that we also have to define the beginning of the pseudo shock for the control group of non-affected banks. As the Cavallo et al. (2015) algorithm does not provide a definition for the control group post-shock assignment within our difference-in-differences methodology, we use the average period from the starting date of the shock (first standard deviation below the historical mean) to the moment that identifies the occurrence of the shock (second standard deviation) of the affected banks and use this value to determine the starting month of the pseudo shock.[33] It is important to note that we do not have information on the amount of interest rate expenses paid for the specific segments of the interbank market. Nevertheless, as interest payments are based on interbank loans (not interbank deposits), our market segments accounts for the largest share of these loans. Perignon et al. (2018) use a similar approach to provide evidence that the idiosyncratic funding shocks in the certificates of deposits market are not driven by demand but by the supply-side of the market.

Using our approach, we find that only $\beta_{\tau=-1}$ is statistically significant and positive (see Appendix A.11). At $\tau = -1$, affected banks have to pay a 2.9 percentage point larger interest rate on average than relative to the control group. Hence, we conclude that the shocks identified by the Cavallo et al. (2015) algorithm are unlikely to be driven by bank's changes in funding preferences, but evidence suggests that banks are hit by supply shocks.

[33] The average time between the beginning of the shock and the moment that determines the occurrence of the shock is on average two month.

A.4 BCB’s emergency liquidity facilities and liquidity hoarding

This section in the Appendix describes in greater detail the data for unconventional monetary policy and the measure employed to study how banks’ access to this additional source of funding alters the liquid hoarding process observed at the corresponding branch level.

During the global financial crisis, various central banks were forced to introduce measures of unconventional monetary policy programs to stabilize their domestic financial markets, i.e. to support funding structures of banks in this market. These measures often aimed at providing liquidity support for a prolonged maturity and/or by lowered collateral standards to receive central bank funds. In similar vein, the BCB also implemented such policies. With the bankruptcy of multiple U.S. investment banks in September 2008, the BCB activated these measures, and hence, provided an additional funding source for banks with potential implications for bank branches tendencies to hoard liquid assets. In the specific case of Brazil and other emerging markets, these measures were also supported by currency swap arrangements between the BCB and the FED.[34] While this swap arrangement line provided up to USD 30 bn in liquidity, additional foreign currency reserves used for this intervention amounted to USD 2000 bn (end of August 2008 value). One primary reason for this foreign currency based intervention was also to facilitate banks’ hedging operations. The mechanism through which these resources were inserted to the banking system were either via open market operations or by selling foreign currency directly in the spot market. The former mechanism which is more important for our analysis amounted for about USD 12 bn up to the middle of 2009 (BCB, 2010).

To measure the access to central bank intervention at the bank headquarter level, we exploit the granularity of our data set. Specifically, we use the liability side position that captures lending from local public institutions which captures predominantly the specific assistance programs activated by the central bank during the crisis period. Appendix A.15 depicts the aggregate liability position over time. Overall, this measure increases rapidly around the Lehman Brother bankruptcy event in September 2008.

[34] See Federal Reserve news release on October 29, 2008: https://www.federalreserve.gov/newsevents//press/monetary//20081029b.htm.

We construct the corresponding bank-specific measure in the following way: As shock-affected banks might have had a more preferential access to this funding source, endogeneity is a concern for our analysis. Hence, we first calculate a bank-specific index that captures the access to the liquidity source. This index CBI_i is computed according to Eq. (A3):

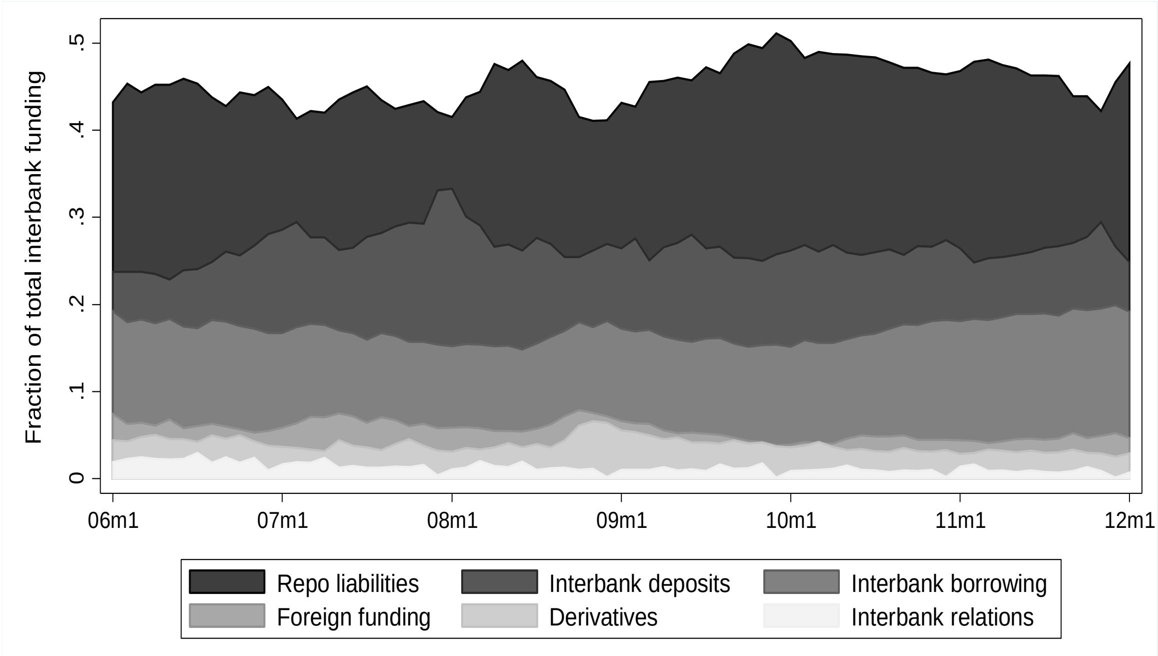
$$CBI_i = \frac{CBL_i}{\Delta Shock_i}, \tag{A3}$$

where CBL_i denotes the post-shock ratio of the individual liability position of this emergency liquidity facility to total liabilities. For this ratio, we the average values of the first 6 months in the post-shock period. This adjustment is needed in order to evaluate the contemporaneous effect of the liquidity facility. To avoid the above mentioned endogeneity concerns, we weight this ratio by the individual shock size. In this context, the size of the shock is defined by the percentage change in interbank funding (defined in logs) from the peak value prior to the shock to the lowest value during the shock occurrence ($\Delta Shock_i$).

As this measure CBI_i is difficult to interpret, we normalize it to values between 0 and 1, where 1 is the maximum value of the shock weighted access to this funding source and 0 is the minimum value in our sample. This normalized index is denoted as $\widetilde{CBI}_i$. The emergency liquidity facility in the immediate 6 month period after the shock amounted for 6.3 percent relative to total liabilities on average. Overall, shock-weighted access was relatively heterogeneous for bank in our sample, which is also plausible as banks experienced interbank funding shocks at different points in time which includes also the period prior to activation of these emergency liquidity measures.

Further Tables and Figures

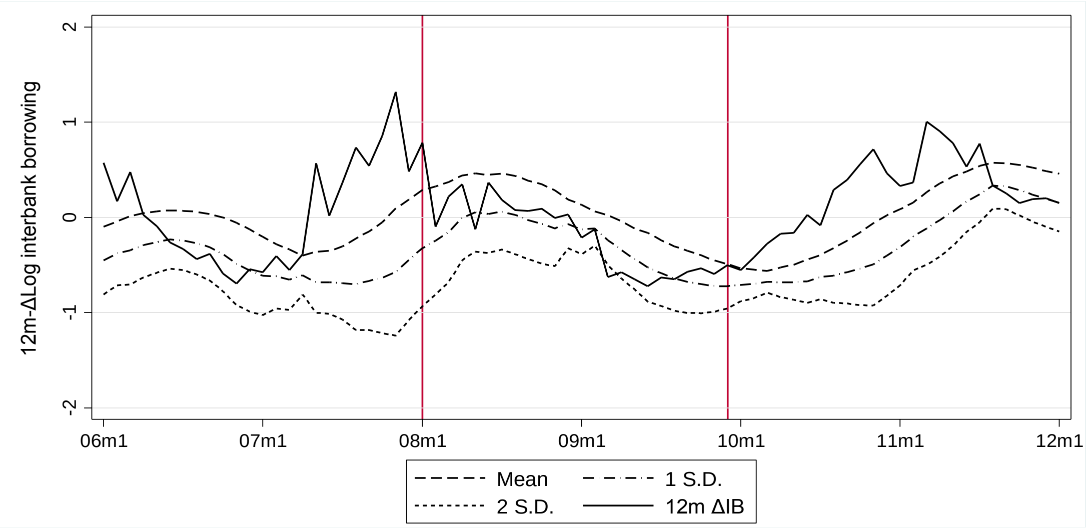
A.5 The relative size of different interbank market segments



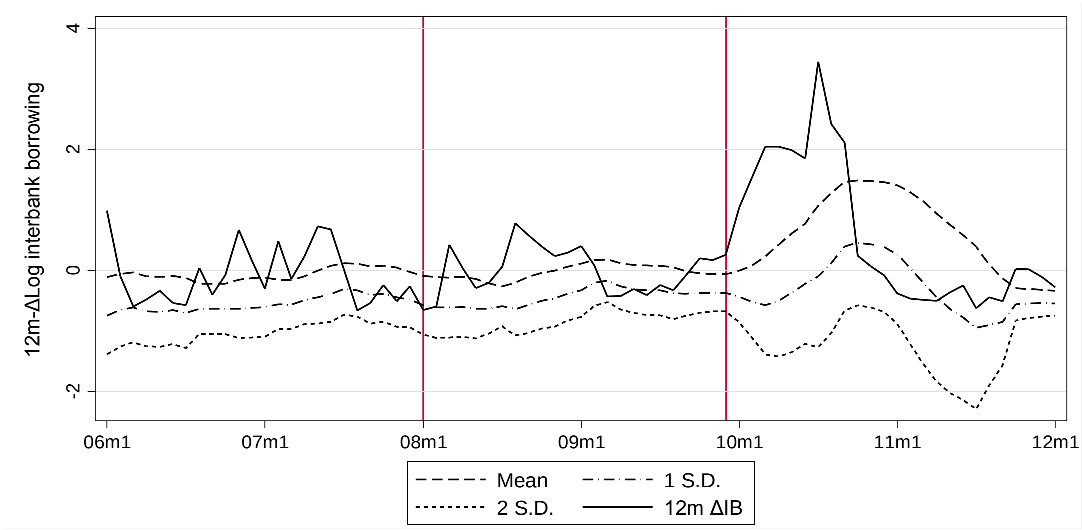
Notes: This figure displays the size of each interbank market segment relative to the entire Brazilian interbank market over time. Interbank borrowing denotes the local unsecured interbank market with a maturity of more than 90 days. This segment is the second most important funding source in this market as it accounts for approximately 25 percent of the entire market and is the segment our analysis is based on. Notably, these market segments remain relatively stable in their relative size over time.

A.6 Graphical example of affected and non-affected banks

Panel A: HSBC Bank Brazil SA – affected bank

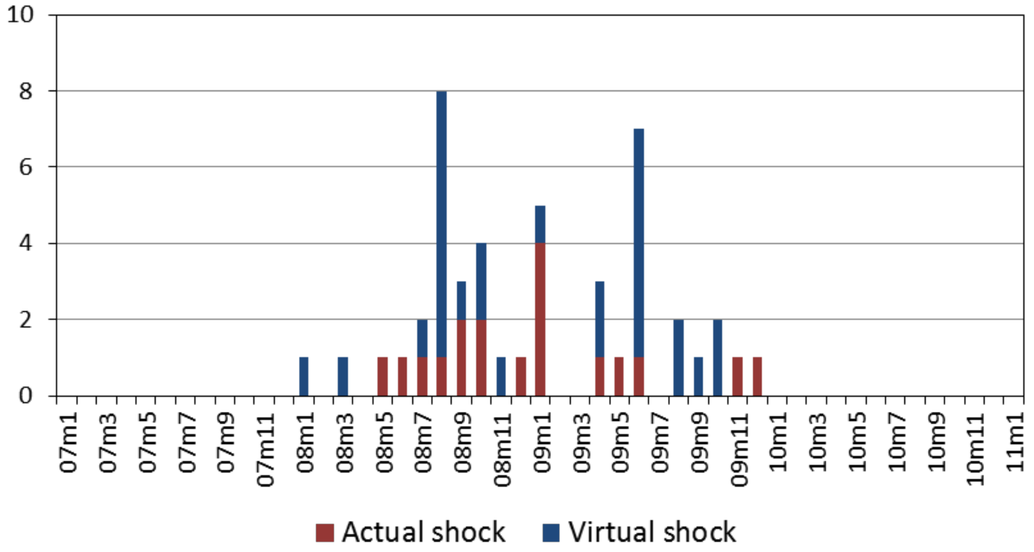


Panel B: Banco Rendimento SA – non-affected bank



Notes: This figure depicts two graphical examples of the Cavallo et al. (2015) algorithm for two banks. While Panel A displays the results for an affected bank, Panel B depicts the results of a non-affected bank. The solid line denotes the idiosyncratic growth rate, the upper dashed line the corresponding 12 month historical mean and the two dashed lines below depict the first and second standard deviation below the historical mean, respectively. In Panel A, we can see that the idiosyncratic growth rate falls below the threshold of the second standard deviation in the beginning of 2009, while in Panel B there is no such instance. Thus, the second bank does not experience a idiosyncratic funding shock. We assign to this bank a pseudo-shock at the period in the beginning of 2009, as this bank is at this point in time the closest to the threshold.

A.7 Distribution of bank-specific shocks and pseudo-shocks over time



Notes: This figure depicts the number of banks affected by idiosyncratic shocks over the period from 2007-2011. Banks that are actually affected by a shock are depicted in red, while banks only 'affected' by pseudo shocks (here denoted as Virtual Shock) are depicted in blue. The virtual shock or pseudo-shock assignment is used to implement a proper difference-in-differences setup over an event-time. The virtual shock is assigned to banks in the control group around the time where the non-affected bank is the closest to the threshold which identifies a bank as being affected.

A.8 Additional descriptive statistics for affected banks

Bank Name	Shock Date	Ex-ante Interbank funding ratio (%)	Duration (months)	Shock Size (% of total assets)
Banco ABC Brasil	09m1	24.38	6	20.31
Banco do Brasil	08m10	9.50	2	0.96
BNP Paribas	09m1	28.08	2	35.36
Banco Bancoob	08m9	14.86	3	0.66
Banestes Banco Estado	09m11	4.41	5	1.05
Banco Brascan	09m1	2.55	7	0.38
Citibank Brasil	08m9	45.19	3	21.57
Banco Fibra S.A.	09m4	14.36	7	9.74
Banco Guanabara	09m6	16.56	4	2.14
HSBC Brasil	09m1	6.52	8	6.70
Banco Industrial e Comercial	08m6	16.56	2	5.49
Banco Paulista	09m5	7.18	3	7.12
Banco Ribeirao	08m5	20.07	7	7.58
Banco Rural	09m12	11.99	4	8.42
Banco Santander Brasil	08m10	7.04	2	0.68
Banco Sumitomo	08m12	25.86	2	11.11
Banco Triangulo	08m8	4.71	6	2.87
Banco Votorantim	08m7	5.55	2	0.61

Notes: This table reports additional information on affected banks. It reports the name of the bank, the date at which the bank experienced an idiosyncratic funding shock, the ex-ante interbank funding ratio, the duration of the shock (months) and the respective shock size relative to total assets.

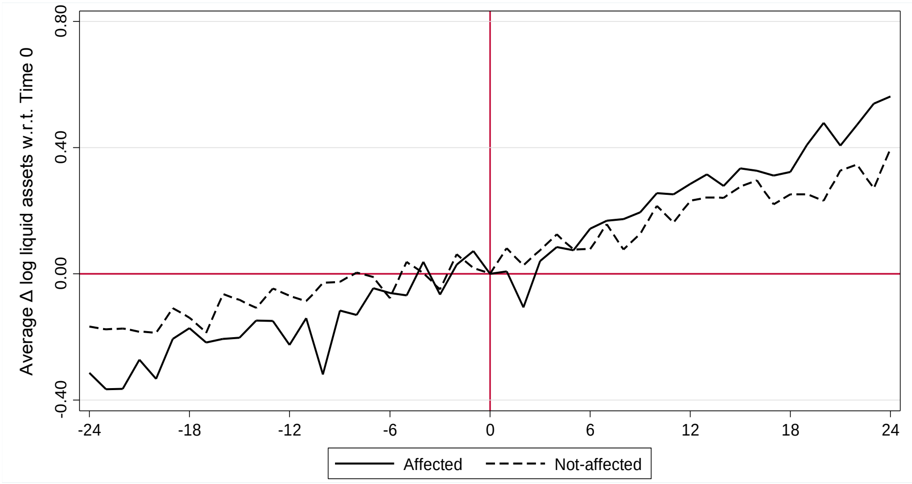
A.9 Affected and non-affected banks and branches – local vs. foreign ownership

	Parent banks sample				Branches sample		
	Affected	Not-affected	Total		Affected	Not-affected	Total
Foreign	7	9	16	Foreign	563	132	695
Local	12	19	31	Local	1683	2137	3820
Total	18	28	46	Total	2365	2149	4514

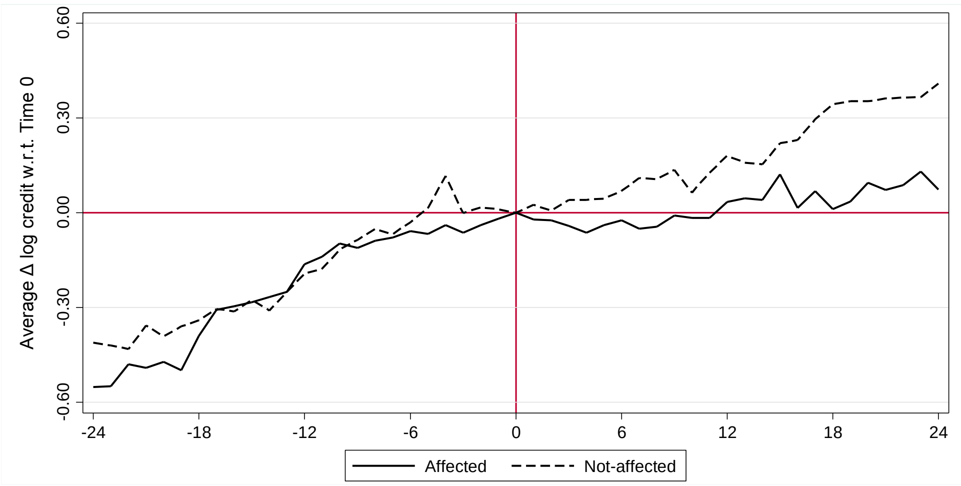
Notes: This table reports information on the number of affected versus non-affected banks and their corresponding branches as well as their ownership structure in terms of local versus foreign banks.

A.10 Liquidity and lending adjustment over the event-timeline

Panel A – Liquidity Adjustment



Panel B – Lending Adjustment



Notes: This figure depicts the average liquid asset and lending growth rate adjustment for affected (solid line) versus non-affected bank branches (dashed line) with respect to τ=0. Panel A depicts the average liquidity growth rate and Panel B the average lending growth rate of affected versus non-affected branches over the event-time.

A.11 Pre-test – supply driven funding shock

Dep. Var.:	**Interest rate expenses from interbank borrowing to total interbank borrowing**		
	I	**II**	**III**
$\boldsymbol{\beta_{\tau-1}}$	**0.030*** **	**0.029** **	**0.029** **
	(0.011)	**(0.012)**	**(0.012)**
$\boldsymbol{\beta_{\tau-2}}$	0.008	0.008	0.008
	(0.011)	(0.009)	(0.009)
$\boldsymbol{\beta_{\tau-3}}$	0.019*	0.019	0.019
	(0.011)	(0.014)	(0.014)
$\boldsymbol{\beta_{\tau-4}}$	0.020*	0.020	0.020
	(0.011)	(0.013)	(0.013)
$\boldsymbol{\beta_{\tau-5}}$	0.009	0.009	0.009
	(0.011)	(0.011)	(0.011)
$\boldsymbol{\beta_{\tau-6}}$	0.013	0.012	0.012
	(0.011)	(0.012)	(0.012)
$\boldsymbol{\beta_{\tau-7}}$	0.004	0.003	0.003
	(0.011)	(0.007)	(0.007)
$\boldsymbol{\beta_{\tau-8}}$	0.001	0.000	0.000
	(0.011)	(0.009)	(0.009)
$\boldsymbol{\beta_{\tau-9}}$	-0.000	-0.001	-0.001
	(0.011)	(0.011)	(0.011)
$\boldsymbol{\beta_{\tau-10}}$	0.002	0.000	0.000
	(0.011)	(0.011)	(0.011)
$\boldsymbol{\beta_{\tau-11}}$	0.008	0.007	0.007
	(0.011)	(0.014)	(0.014)
$\boldsymbol{\beta_{\tau-12}}$	-0.002	-0.003	-0.003
	(0.011)	(0.012)	(0.012)
Headquarter controls	NO	YES	YES
SE Cluster: HQ	NO	YES	YES
Bank FE	NO	NO	YES
Observations	598	598	598
R-squared	0.0563	0.0691	0.0691

Notes: This table reports the results of the pre-test which explores whether the shock identified by the Cavallo et al. (2015) algorithm is driven by a supply or a demand shock. The underlying empirical model is defined by Eq. (A.2) in Appendix A.3. The time-varying parameters of the interaction in the 13 month pre-shock period indicate whether there is a significant difference between affected and non-affected banks in the run-up to the idiosyncratic shock. The dependent variable is a proxy for the interest rate in the interbank funding which is the ratio between interest rate expenses from interbank funding to total interbank funding. Standard errors either not-clustered (column I) or clustered at the headquarter-level (columns II and III) and ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

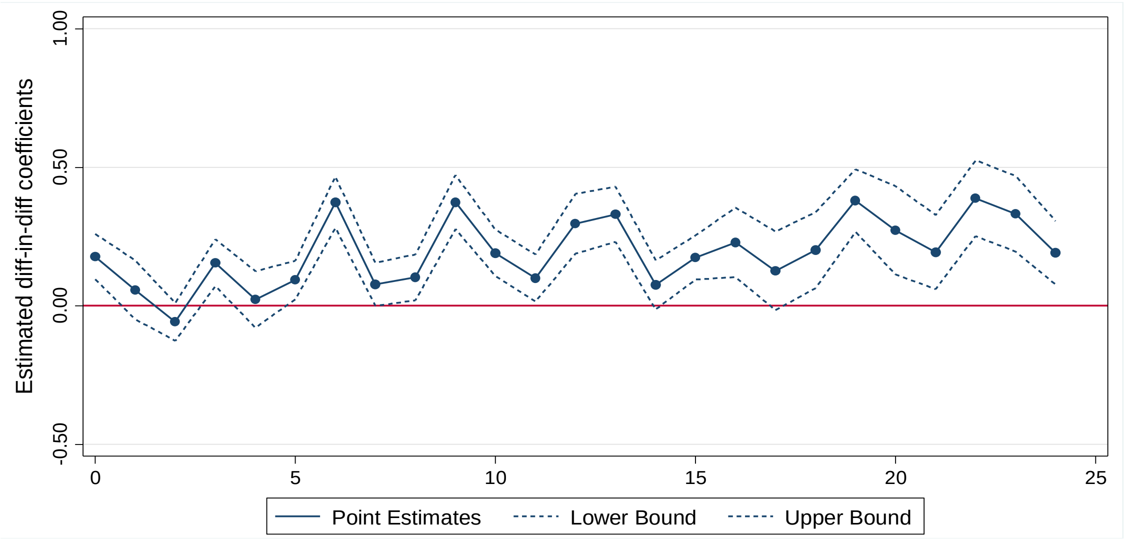
A.12 Robustness – additional control variables

Dep. Var.:	**Δ Log Liquidity**		**Δ Log Credit**	
	I	**II**	**III**	**IV**
Affected X Shock	0.143***	0.0980**	-0.249**	-0.239**
	(0.0529)	(0.0452)	(0.114)	(0.117)
Controls included	YES	YES	YES	YES
Additional Branch Controls:				
Mortgage To Asset Ratio	0.244	0.286	-0.881	-0.892
	(0.209)	(0.208)	(0.727)	(0.744)
Loan To Asset Ratio	0.209**	0.180**	1.319***	1.334***
	(0.0844)	(0.0716)	(0.317)	(0.327)
Additional Headquarter Controls:				
Interbank Deposits to Total Funding		2.53e-05*		-3.76e-05
		(1.47e-05)		(3.34e-05)
Mortgage To Asset Ratio		-0.000189		0.000142
		(0.000129)		(0.000164)
Foreign Currency Exposure		0.00135**		0.00156
		(0.000566)		(0.00108)
Branch FE	YES	YES	YES	YES
Municipality x Time FE	YES	YES	YES	YES
Observations	192,568	192,568	192,568	192,568
R-squared	0.397	0.398	0.439	0.440

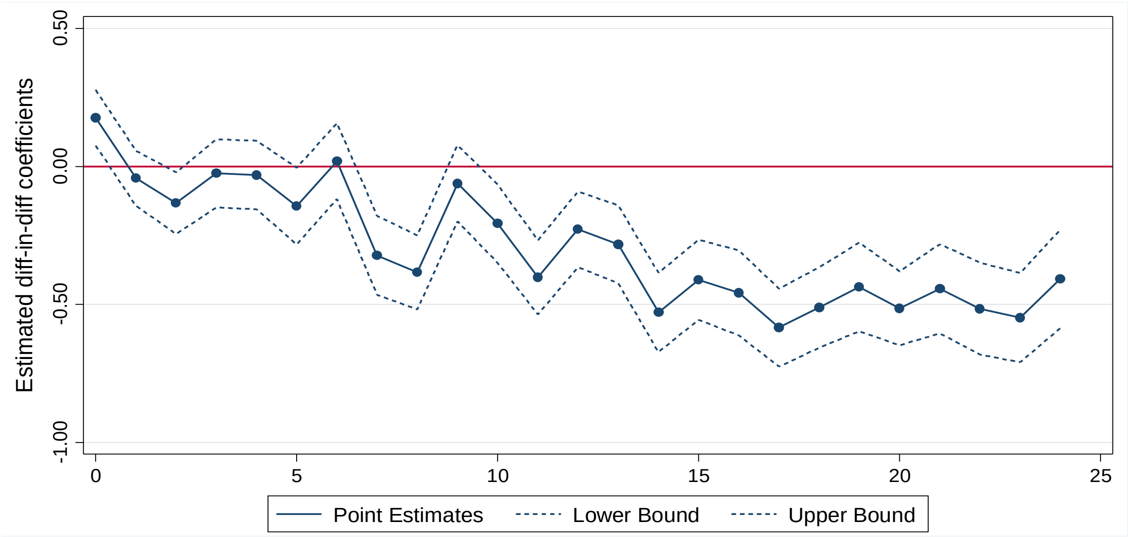
Notes: This table reports the results of a further robustness test when including additional control variables at the branch as well as the headquarter level. These inlcude the mortgage to asset ratio and the loan to asset ratio at the branch level to capture branch business model traits. At the headquarter level we control for the interbank deposit to total funding ratio to account for access to funding from the largest interbank market. The mortgage to asset ratio captures the headquarters involvement in the mortgage market during the crisis time, and finally, we include the net postion of foreign currency liquidity in assets and liabilities to total assets. This variable is called Foreign Currency Exposure. 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 are clustered at the headquarter-time level and ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

A.13 Robustness – Dynamic panel approach

Panel A – Liquidity Adjustment



Panel B – Lending Adjustment



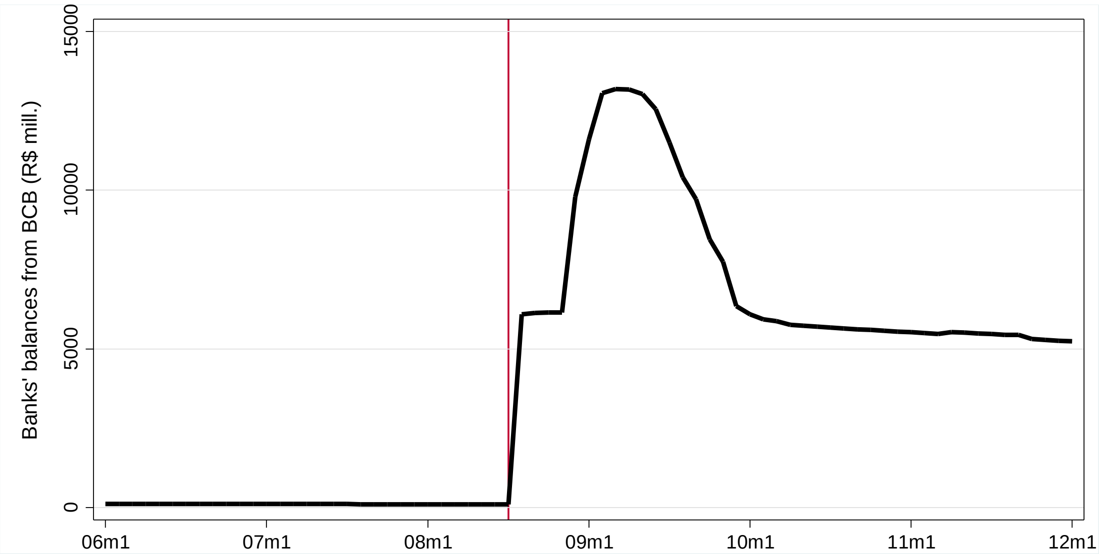
Notes: This figure displays the time-varying coefficients from the dynamic panel approach in the post-shock period. Panel A displays the difference-in-differences parameter for liquid asset growth rate and Panel B depicts these results for the lending growth rate. The dashed lines depict the the 95th confidence interval of the respective point estimates. All control variables and the fixed effects structure are based on our preferred within municipality specification of columns III and VI from Table 2.

A.14 Robustness – Horse Race with branch traits

Dep. Var. Reported Parameter	**ΔLiquidity** Affected X Shock **I**	**ΔCredit** Affected X Shock **II**
Included competing non-linearity:		
BR: Size X Shock	0.0962**	-0.302***
	(0.0365)	(0.111)
BR: (Deposits/Total Assets) X Shock	0.133**	-0.253**
	(0.0547)	(0.114)
BR: (Income/Total Assets) X Shock	0.113**	-0.288**
	(0.0514)	(0.122)
BR: (Internal Funding/Total Assets) X Shock	0.124**	-0.268**
	(0.0592)	(0.120)

Notes: This table summarizes the results of an additional "horse race" between the difference-in-differences parameter of the variable [Affected X Shock] and other competing non-linearities. Column I reports the parameters of the difference-in-differences effect for the liquidity growth equation and column II reports these results for the credit growth equation, analogously. Each row, thus, reports the difference-in-differences parameter of the variable [Affected X Shock] when including the non-linearity that is stated by the first column in the respective row in this table. For all interactions including the competing non-linearities, all constitutive terms of the interaction are included as individual variables. "BR" denotes that variables refer to the branch level. 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 headquarter-time level and ***, **, * denote the 1, 5, and 10 percent level of statistical significance, respectively.

A.15 Emergency liquidity facilities over time



Notes: This figure displays the aggregate balances connected to the emergency liquidity facilities activated by the BCB in million R$ from 2006 to 2012. The vertical line display September 2008, the month when Lehman Brothers collapsed. It self-evident that this additional funding source was activated in response to the breakout of the global financial crisis. We use the disaggregated data at the bank level to determine the bank-specific access to additional funding source.

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