BANK FOR INTERNATIONAL SETTLEMENTS

BIS Working Papers

No 799

Monetary policy surprises and employment: evidence from matched bank-firm loan data on the bank lending-channel

by Rodrigo Barbone Gonzalez

Monetary and Economic Department

July 2019

Paper produced as part of the BIS Consultative Council for the Americas (CCA) research project on "Changes in banks' business models and their impact on bank lending: an empirical analysis using credit registry data" implemented by a Working Group of the CCA Consultative Group of Directors of Financial Stability (CGDFS).

JEL classification: E52, E51, G21, G28

Keywords: employment, monetary policy, surprises, loan-level, lending channel

This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

Monetary Policy Surprises and Employment: Evidence from Matched Bank-Firm Loan Data on the Bank Lending-Channel

By RODRIGO BARBONE GONZALEZ*

This paper investigates the bank lending-channel of monetary policy (MP) surprises. To identify the effects of MP surprises on credit supply, I take the changes in interest rate derivatives immediately after each MP announcement and bring this high-frequency identification strategy to comprehensive and matched bank-firm data from Brazil. The results are robust and stronger than those obtained with Taylor residuals or the reference rate. Consistently with theory, heterogeneities across financial intermediaries, e.g. bank capital, are relevant. Firms connected to stronger banks mitigate about one third of the effects of contractionary MP on credit and about two thirds on employment. (JEL: E52, E51, G21, G28)

Banks are fundamental to the proper functioning of the economy including the transmission of monetary policy (Bernanke and Blinder, 1988, Bernanke and Gertler, 1995, Coimbra and Rey, 2019). However, the identification of these channels on credit is challenging. On the theoretical front, monetary policy (MP) simultaneously affects credit supply and demand, because bank heterogeneities or constrains (capital, share of insured deposits, Value-at-Risk (VaR)) matter for

---

* Central Bank of Brazil (BCB) and Bank of International Settlements (BIS), Rubén Darío 281 – 1703, Ciudad de Mexico, Mexico DF 11580 (e-mail: rodrigobarbone.gonzalez@bis.org). This paper should not be reported as representing the views of these two institutions. The views expressed in the paper are those of the author and not necessarily reflect those of the BCB or the BIS. I am grateful to Leonardo Gambacorta, Fernando Sotelino, José-Luis Peydró, Dmitry Khametshin, Joshua Aizerman, Ricardo Correa, Rafael Repullo, Lamont Black, Johanna Francis, Lars Norden, Fernando Córdova, Hyun Song Shin, Stijn Claessens, Benoit Mojon, Boris Hoffman, Carlos Cantú, Bryan Hardy, Sergio Lago, Bernardus Van Doornik, Eduardo Vieira dos Santos Paiva, and seminar participants at the BIS Workshop in Mexico, at the BIS MED Seminars in Switzerland, and at the XXIII Annual LACEA Meeting (Equator) for many helpful comments and suggestions.

bank's portfolio decisions (Holmstrom and Tirole, 1997, Stein, 1998, Adrian and Shin, 2014) as much as firm's net-worth (Bernanke, Gertler, and Gilchrist, 1996).

In light of overlapping channels, the empirical literature relies on loan-level data, interactions with bank controls, and focuses on compositional effects (using firm*time fixed effects - FEs) for better identification of the bank lending-channel (e.g. Jimenez et al., 2012, 2014). While this strategy is precise to estimate credit supply responses of differently constrained financial intermediaries, it leaves open questions that are relevant for policy-makers. Does the bank lending-channel of MP matter for the average firm? Or, is the average small and medium enterprise directly affected by related changes in credit supply, which in turn stimulates employment? Do heterogeneities across financial intermediaries affect the transmission of MP with real effects for firms? Or, can a firm connected to less constrained (e.g. better capitalized) banks insulate from a MP tightening and partially prevent a contraction in its total credit intake, productivity, and labor demand?

To address these questions, I estimate the bank lending-channel, i.e. the interaction of unexpected MP variation with bank controls that proxy for their strength, and related real effects on employment and wages. I find that labor demand responds to MP innovations via credit supply and that weaker (stronger) banks amplify (mitigate) this channel. The identification of unexpected MP variation (MP surprises) is crucial. Bringing MP surprises identified around MP announcements to the loan-level data, I find a potent bank lending-channel with real effects for small and medium enterprises. Consistent with an errors-in-variable problem, no (or weak) instrumentation of MP innovations leads to the underestimation of these effects even when powerful strategies to identify credit supply are implemented in exhaustive loan-level data.

For identification, I turn to Brazil, a country whose banking sector responds for 73% of total credit[1], where variation in MP has been intense, and where comprehensive high-quality data on loans and formal employment is available. Using the credit registry of the Central Bank of Brazil (BCB), I build a loan-level panel with over 70 million observations where bank-firm relationships are identified and matched by tax id. The panel spans all calendar quarters from 2004 to 2016. These credit data is matched with a dataset from the Ministry of Labor and Employment containing all formal employment relationships in Brazil[2] and augmented with bank and macro controls.

I must meet three identification challenges to answer the initial questions. The first is controlling for credit demand shifts consistently. Since credit demand and supply shocks are correlated, this typically requires focusing on bank interactions with loan-level data and firm or firm*time FEs (e.g. Khwaja and Mian, 2008, Paravisi, 2008, Schnabl, 2012, Jimenez et al., 2014, Iannidou, Ongena and Peydro, 2015, Ono et al., 2016, Barroso, Gonzalez, Van Doornik, 2017, Morais et al., 2019). While the use of firm*time FEs leads to sharp identification of credit supply shocks[3], the interpretation of these compositional results is not straightforward. Since the fixed effects absorb all the average effects on the firms, what is left after all?[4] Focusing on the relative effects certainly grants superior identification of bank

[1] Figures from December 2018, excluding the public sector, financial firms, and the largest corporations (with over BRL 100M in credit exposure). See BCB (2018)

[2] The data is truly comprehensive because banks must report all credit exposures with amounts exceding BRL 5000 (USD 1200 in April, 2019) to the credit registry of the Central Bank of Brazil (BCB) identifying each counterparty. This threshold is low enough to account for firms capital needs. Moreover, by law, all firms report all their activities in the formal labor market to the Ministry of Labor and Employment at each year-end, including each individual hired and fired across the year, wages, and the time when each of these "job transactions" happened. The resulting database is known as "RAIS transacional". After merging the BCB credit registry and "RAIS transacional", I end-up with all firms that have at least one employee in Brazil. The average firm in the data has 8 employees. This sample is more representative than the Survey of Small Business Finances or the syndicated loans databases typically used in the US.

[3] All these papers rely on the assumption that firms can perfectly substitute credit across their related banks (Khwaja and Mian, 2008). This assumption would not hold if firm demand is bank-specific as in the case of trade sector credit (e.g. Paravisini et al., 2017).

[4] The estimated compositional effects on bank interactions relate to the change in banks' "market-share" relatively to the same firm*time pair. For example, estimated with firm*time FEs, a positive parameter in the bank capital and MP interaction term means that the more capitalized bank increases its *relative* (not absolute) participation in firm credit by 1 pp more than the less capitalized ex-ante bank relationships of the same firm in light of a contemporaneous MP innovation. Notice that (1)

interactions on bank supply, but could this be myopic? What if a large chunk of credit supply (or its average effect) is also removed in the process? Or, what if the absolute (not relative) strength of financial intermediaries matter for firms? To address these questions, I must transit from the relative to the absolute effects of MP and assess the average effects on the firms while still controlling for credit demand.

Relatedly, the second challenge is assessing the real effects, or how does the lending-channel affects employment? Firms can fully (Jimenez et al., 2010) or partially (Iyer et al., 2014) insulate from negative bank supply shocks (including contractionary MP) resorting to less constrained intermediaries. In other words, I must first turn to firm-level credit to account for this equilibrium and, then, assess the employment outcomes of the firms exposed to more conflicted banks.

The third challenge is identifying the MP innovations in a country following a Taylor rule and measuring unexpected MP variation or MP surprises. Jimenez et al. (2012) uses loan-level data to estimate the bank lending-channel in Spain, a country where the monetary policy is arguably exogenous to local economic conditions due to the relative size of the country in the Eurozone. Brazil, on the other hand, is a large emerging economy following a Taylor rule. Therefore, focusing on interactions between bank controls and changes in the overnight reference rate is not enough to identify the related effects on credit supply, because the markets, including the banks, largely anticipate MP movements. Put differently, identification must focus on MP unexpected changes.

---

all the average effects on the firm are absorbed. As a consequence, one firm could be increasing its credit exposure with its more capitalized bank and still end-up with less credit overall. In other words, is there any effect beyond substitution? Moreover, (2) the same firm may even end-up with less credit in *absolute* terms from banks that are well capitalized on average. In other words, does the strength of financial intermediaries matter in *absolute* or just *relative* terms? Differences between compositional (*relative*) and *absolute* results can be expressive if bank-firm relationships are not orthogonal (e.g. Kwhaja and Mian, 2008). Importantly, the interpretation of the effects changes. Despite the neat credit supply identification, if the capital*MP interaction is significant only in the presence of firm*time FEs, it is unlikely that one could observe real outcomes, because the average firm is unaffected substituting or mitigating the effects of MP.

I follow Kuttner (2001) and use the (one-day) changes in interest rate derivatives immediately after each of the 122 MP announcements in my sample to disentangle expected from unexpected changes in MP. Importantly, as opposed to Taylor residuals, this approach avoids "model selection" or "generated-regressor" concerns.

As in the prevailing literature, I find the following robust results: bigger and more capitalized banks mitigate the effects of MP surprises on credit supply, and expected (or anticipated) changes in MP have no such effects. Using the changes in the overnight reference rate or Taylor residuals leads to results that go in the same direction, but are weaker and poorly statistically significant in relative and absolute terms consistent with an errors-in-variable problem[5].

Bank capital is the strongest of the core bank characteristics, and the only to impact firm-level outcomes. These results are not only compositional: MP surprises strongly affect average firms' credit and employment in absolute terms. I find that a one-standard positive deviation on MP surprises decreases average quarterly credit by 1.10 percentage points (pp)[6] and employment by 0.21 pp. Firms connected to stronger banks (with 4 per cent higher average capital-to-assets ratio) partially insulate from this MP surprise and contract credit by 0.73 pp and employment by 0.07 pp. I find no significant effects on wages.

I contribute to three strands of the literature. First, the identification of MP surprises using high-frequency data around key monetary policy announcements. "Central bank announcements … provide an opportunity to isolate unexpected variation in policy and, hence, can be used to assess the impact of monetary policy (Jarociński and Karadi, 2018)" on asset prices (Kuttner, 2001, Gurkaynak, Sack,

[5] In the words of Kuttner (2001): "(using the overnight reference rate leads to an) errors-in-variables problem: the surprise target rate change belonging to the regression is contaminated by the expected rate change, and this 'noise' leads to an attenuated estimate of interest rates' response to policy surprises".

[6] One-standard deviation in the one-year change of the overnight reference rate in Brazil is 3.16 pp in my sample, and one standard deviation in the one-year accumulated surprises is about 0.37 pp. In other words, while a 1 pp MP tightening over a year would be common, a 0.12 pp accumulated MP surprises would be just as common, or "equivalent".

and Swanson, 2005, Bernanke and Kuttner, 2005) and on the real economy (e.g. Gertler and Karadi, 2015). However, none of these papers bring this identification to the loan-level data to directly estimate credit supply responses, tracing the related effects on employment, and simultaneously assessing the amplifying role of financial intermediaries.

Second, I contribute to the bank lending-channel empirical literature. Tight MP aggravates a problem of asymmetric information between banks and their financiers, but bank balance-sheet strength[7] reduces monitoring costs ameliorating this problem via insured deposits (Stein, 1998), bank capital (Holmstrom and Tirole, 2007), and liquidity[8] (Diamon and Rajan, 2011). Kashyap and Stein (2000) and Kishan and Opiela (2000) are the first to identify this channel with bank-level data from the US highlighting the importance of bank size, liquidity and capital. However, firm-bank relationships are not orthogonal (e.g. Kwhaja and Mian, 2008) leading to a possible omitted variables problem and correlation between credit demand and supply shocks. Jimenez et al. (2012, 2014) address this issue estimating the bank lending-channel with loan-level data and firm*time FEs.

Nevertheless, Jimenez et al. (2012, 2014) do not instrument MP innovations. Other studies focusing on bank and loan-level data have addressed the issue of

[7] Bank balance-sheet strength proxies for bank's exposure to a principal-agent conflict with its investors or uninsured depositors (e.g. Stein, 1998). For instance, (1) the more capital constrained is the bank, the more agency conflicted it is. More agency conflicted financial intermediaries are more sensitive to changes in money aggregates, because their pool of investors (principals) are more concerned about their agents portfolio allocation. A similar mechanism operates between firms and financial intermediaries: the (2) weaker is the firm balance sheet (or the more capital constrained is the firm), the more sensitive to money tightening transmitted by its financial intermediaries as monitoring capital becomes more expensive for this firm's investments (Holmstrom and Tirole, 1997). Notice that this mechanism is both embedded in the supply and demand of credit, i.e. a money tightening contracts bank supply (and demand) on average, and more for "more agency conflicted" banks (and firms). The Bernanke, Gertler and Gilchrist (1996) financial accelerator depicts a similar mechanism, where "more conflicted" firms face a dual conundrum after a monetary tightening: first, (4) their implicit collateral or net-worth is smaller driving financial intermediaries either away from credit or towards safer lending to safer firms, i.e. "fly to quality", which in turn reduces their ability to invest in new projects. Second, (5) "more conflicted firms" cut even more investment, because they are simply more dependent on external finance and less likely to substitute funding with internal finance (Bernanke and Gertler, 1989). Again, the extent to which responses are "supply" or "demand" driven is not clear at the firm level supporting the use of loan-level data for identification.

[8] The empirical literature confirms these channels. For instance, bank balance-sheet strength proxied by capital (e.g. Gambacorta and Shin, 2018, Jimenez et al., 2014, Black and Rosen, 2016), size and liquidity (e.g. Kashyap and Stein, 2000), and share of non-performing loans (Jimenez et al., 2017) are found core to the transmition of MP.

instrumenting MP in different ways[9], but the alternative I implement connects to recent and sound developments in the macro-finance literature (e.g. Gertler and Karadi, 2015), is model-free, and perhaps more elusive and straightforward to a broader number of countries following a Taylor rule. This alternative is also relevant for countries in the "peryphery". While economic conditions in the peryphery may not influence MP decisions of the "core economies", banks in perypheral countries are arguably capable of anticipating MP decisions of the core economies. Thus, the errors-in-variables problem documented by Kuttner (2001) and confirmed in this paper is likely to also affect prior empirical studies "attenuating" their estimated MP impacts on credit supply.

Third, I contribute to the literature on the real effects of credit supply shocks, i.e. firm-level outcomes such as investment, employment, and total exports across firms differently affected by a credit supply shock (e.g., Gan, 2007, Amiti and Weinstein, 2011, Chodorow-Reich, 2014, Paravini et al., 2015). However, my identification strategy does not rely on a quasi-natural experiment or any exogenous disruptive event. Instead, I track several positive and negative unexpected MP shocks in a long panel[10] in both "normal" and crisis times.

To the best of my knowledge, I am the first to identify the effects of MP surprises via credit supply on employment, or the real effects of the lending channel on the average firm using comprehensive loan, bank, and firm-level data. In line with Coimbra and Rey (2019), these results confirm that heterogeneities across financial intermediaries matter for MP transmission.

[9] The Taylor residuals are the most common choice for instrumenting monetary policy in the studies that rely on loan- and bank-level data (e.g. Maddaloni and Peydro, 2011, Altumbas, Gambacorta and Marques-Ibanes, 2014, Black and Rosen, 2016, Delis, Hasan and Mylonidis, 2017). The very influencial Kashyap and Stein (2000) amend their core analysis with the "narrative approach" of Boschen and Mills (1995). Delis, Hasan and Mylonidis (2017) implement the Romer and Romer (2004) narrative approach.

[10] Several recent papers instrument bank supply shocks at large using bank*time fixed effects (e.g. Greenstone, Mas and Nguyen, 2014, Berton et al., 2018, Degryse et al., 2019) to study the related effects on consumption, employment, and investment in long panels. In this strategy, both system-wide and bank idiosyncratic shocks are absorbed thus not supporting the identification of MP channels (see Amiti and Weinstein, 2018).

The remaining of this paper is organized as follows: session (I) presents the economic background in Brazil, session (II) discusses the identification of MP surprises, session (III) presents data and the identification strategy, session (IV) the results, and session (V), the final remarks.

I. Inflation targeting, the banking sector, and monetary policy

Brazil adopted a floating exchange rate (and an inflation target) regime in 18 January 1999, after several decades of managed exchange rates.

> Under managed exchange rates Brazil suffered recurrent balance of payments difficulties in the 1950s and 1960s, the 1980s debt crisis, which contributed to a dramatic deterioration in macroeconomic performance in the following years, and the slowdown and crisis of the 1990s, before its final collapse in January 1999 (Meirelles, 2009)

The first four years from the inception of the floating exchange rate regime coincided with several episodes of turmoil, including the High Tech buble burst, the Argentinian crisis, the September 11th attacks, and the Brazilian presidential election of 2002. Throughout these years, the BCB relied on tight monetary policy, capital controls, and FX Interventions to prevent overshooting of the local currency, the Brazilian real (BRL), to support the trade sector, and the rollover of firms' foreign debt.

Between 2003 and 2008, Brazil experienced relative bonanza and the Central Bank of Brazil (BCB) mostly met its inflation target (4.5 per cent) despite strong economic and credit growth (see Figure I).

Insert Figure I about here

Since the bankruptcy of Lehman Brothers, both developed and emerging economies faced real economy and financial sector challenges. In Brazil, the global financial crisis (GFC) first affected FX and the stock exchange negatively but only after September, 2008. Between September and October, export finance contracts fell by 30 pp and rollover ratio of foreign debt decreased from over a 100 to 22 per cent in November (Mesquita and Toros, 2010). The USD liquidity shortage triggered several BCB interventions, including derivatives' sales, spot USD sales, and direct lending to the trade sector. Monetary policy was initially contractionary in response to large capital outflows, but later relaxed to stimulate both credit and consumption in 2009 (Pereira da Silva and Harris, 2012).

In the banking sector, during the GFC, a large public bank (Banco do Brasil) capitalized a medium-sized one (Votorantim) without taking control of its operations. Liquidity issues with the large bank Unibanco motivated its merger with Itau resulting in the largest bank in Latin America. However, the smaller banks bore the highest costs of the GFC as a crunch in the repo market and a "fly-to-quality" movement (from small banks' depositors to the larger banks) deeply impacted those banks health (Oliveira, Schiozer, and Barros, 2015). The BCB responded with many alleviating macroprudential policies, including a massive release of reserve requirements (Barroso, Gonzalez, and Van Doornik, 2017). Moreover, the deposit insurance organization, ("Fundo Garantidor de Crédito" - FGC) created a successful program increasing the protection extended to depositors of the small banks.

Immediately after the GFC (2010-2011), in light of credit and aggregate demand recovery, Brazil and several other EMEs started a monetary policy tightening cycle. Unconventional monetary policy, particularly QE2, supported this recovery as large (short-term) capital inflows contributed the appreciation of many EMEs currencies including the Brazilian real (BRL).

After these two years of quick recovery, investment contraction and excessive public expenditure aggravated by political scandals put the country into inflation decontrol, credit and consumption slowdown. A local monetary policy tightening cycle started (arguably late) in 2013 to tackle inflation, but it is largely ineffective amidst "stagflation" (Figure I). Other corruption scandals have increased political uncertainty contributing to a production, credit, and aggregate demand steep decline since the re-election of president Dilma Rouseff in 2014. In particular, an investigation carried by the Federal Policy denominated "Car Wash" unfolds into several other scandals leading to the impeachment of president Rouseff in August of 2016.

It is worth noticing that monetary policy, credit, inflation, and aggregate demand have fluctuated intensively in this period (Figure I). MP is mostly responding to inflation in line with the Taylor rule implemented in 1999.

II. Identification of MP surprises in Brazil

Following Kuttner (2001), I decompose the change in the overnight target reference rate into two additive components: an unexpected component or MP surprise (Δi^s) proxied by the one-day change in interest rate derivatives immediately after each MP announcement; and the expected component (Δi^e), the difference between Δi^s and the announced change in MP (Δi). See equation (1)

$$\Delta i = \Delta i^s + \Delta i^e \tag{1}$$

The immediate reaction of the interest rate derivatives, or the one-day adjustment in the price of these contracts, captures the extent of market "surprise" to the announcement made in the previous day. Conversely, the difference between the surprise and the announcement change is already incorporated in the derivative price of the previous day, i.e. it is “expected” or anticipated (see more on Kuttner, 2001).

In Brazil, all the announcements of the monetary policy committee (COPOM) meeting have been made when the markets were already closed There are no ad hoc announcements in the sample, i.e. all announcements of the new overnight reference rate (Selic, i) rate followed COPOM meetings.

Differently from Kuttner (2001), I use the changes in the 30 days interest-rate swap and not 30-days futures as the proxy for MP surprises. Both derivatives are liquid in Brazil. The choice is for convenience since future contracts must be adjusted by the remaining days to maturity whereas the swaps represent at each day a reference (fixed) risk-free rate for the following 30-days naturally eliminating this issue. In Appendix A.1, I present the monetary policy stance before and after each COPOM meeting and the related announcement in Brazil between 2003 and 2016 as well as the expected and unexpected component.

In Figure II, I present the changes in the overnight reference rate (SELIC, Δi) and the unexpected component (Δi^s).

Insert Figure II about here

To illustrate equation (1) decomposition, I refer to the triangle in Figure II representing the MP announcement of 20 January 2016 and the related extract from the Financial Times at the same day.

> The central bank’s Monetary Policy Committee on wednesday kept the benchmark Selic rate at 14.25 per cent, disappointing most economists who had expected either a 25 or 50 basis point increase (Pearson, Samantha, “Brazil keeps interest rates on hold,” *Financial Times*, January 20, 2016)

Notice in Figure II, a 0 pp change in the announcement date (X-axis) and -0.19 pp unexpected change or MP surprise (Y-axis). In other words, between January 21 and 20, the interest rate derivative reacted to the announcement decreasing the fixed to floating interest rate swap contract for the following 30 days in almost 0.25 pp. Indeed, the COPOM decision came mostly as a surprise; in this case, reflecting an easing, as the Selic target (reference) rate turned out below expected.

The MP surprises revolve around zero in the sample and are relatively balanced between easing and tightening shocks (Figure II). MP surprises are also abundant across all my sample albeit their magnitude tend to be much lower than the related expected component. In Figure III, I present the MP surprises quarterly aggregated altogether with the change in Selic. The difference between the hollowed and the colored area is the expected change in MP.

Insert Figure III about here

As most of the empirical loan-level literature, I estimate the impacts of yearly changes in the overnight reference rate in the following quarter credit growth in log terms. For consistency, to assess the MP surprises, I accumulate one year of surprises to build the treatment variable and run comparable regressions. Since 2006, there are 8 COPOM meetings per year and before that 12. Hence, I accumulate between 8 and 12 one-day changes in these derivatives to build Δi^s_{t-1}. The average value of this variable is -0.09 pp with yearly shocks from -0.81 pp to 0.91 pp and a standard deviation of 0.37 pp (Appendix A.2).

At each announcement, I also compute the expected change in monetary policy (Δi^e) as the difference between the effective announced change in the overnight target interest rate (Δi) and each monetary policy surprise (Δi^s). Similarly, I accumulate those expected changes across one year of announcements. The average value of Δi_{t-1}^{e} is -0.27 pp with minimum and maximum of -9.94 pp and 3.29 pp, and a standard deviation of 2.92 pp.

MP surprises have lower magnitude, but they are highly informative. In Figure IV, a correlation between the average quarterly credit growth and lagged one-year changes in Selic (LHS) and MP surprises (Δi_{t-1}^{s}, RHS) clearly shows negative correlations but much stronger for the latter (Figure IV).

Insert Figure IV about here

III. Data and Identification Strategy

In this paper, I use two datasets matched by firms' tax id number: (1) the credit register of the BCB (``Nova Central de Risco") and (2) the formal employment registry from the Brazilian Ministry of Labor and Employment ("Relação Anual de Informações Sociais (RAIS)". I augment these data with (3) bank and macroeconomic controls. The final sample spans all calendar quarters from 2004Q1 to 2016Q4.

A. *Data Description*

The credit registry of the BCB (1) contains detailed and comprehensive information of the underlying credit contracts, including credit amounts, ex-ante risk classification (which connects to each loan provision for non-performing loans), and monthly information on each loan performance, i.e. delinquency. I further aggregate these credit contracts into the bank-firm level to calculate total committed credit provided by each bank[11] to each firm. I follow the quarterly dynamics of each bank-firm pair throughout the sample. The main dependent

[11] The aggregation is at the bank holding company level in order to mitigate any concerns about credit supply dependence of banks with common management.

variable is the real growth rate[12] of the bank-firm total credit exposure (in log terms) winsorized at the 2 and 98 percentiles[13].

I exclude from the sample financial firms, as well as loans that are not originated by commercial banks (8 per cent). Moreover, I focus on credit in local currency, and drop observations with at least one loan indexed to currencies other than the Brazilian Real (BRL). In the original sample, they represent less than 0.5 per cent of the loans. After this, I end-up with over 70 million observations.

However, I focus on multiple bank relationship firms in most of this paper (about 40M observations) for identification of credit supply using the firm*time FEs estimator (e.g. Jimenez et al., 2014). This step restricts the original sample to the 86 per cent more representative firms in terms of total credit extended by all financial institutions[14].

For computational reasons, I sample the data from the original database by firm, i.e. I first collect a 10 per cent random sample of firms ever present in the credit registry and then withdrawn their complete credit histories from all banks that ever lent to these firms. I exclude firms with less than two quarters of data. After this process, I end-up with a working sample of 4,061,322 observations encompassing 117,561 firms, 94 commercial banks, across 52 quarters.

The RAIS database (2) collects information on each formal job relationship including the start and end dates of each contract matched by employer-employee tax id numbers. RAIS is comprehensive[15] because all firms with at least one

---

[12] Total firm-bank credit exposure is first presented in constant BRL of December, 2016. Then, put in log format and quarterly differenced.

[13] Apart from the dummies all other controls and dependent variables in this paper are winsorized.

[14] Identification of bank supply is superior with firm*time fixed effects, but a possible concern is that multiple bank relationship (MBR) firms are fundamentally different from single bank relationship (SBR) firms leading to misrepresentative results. Degryse et al. (2019) shows that MBR firms are much smaller than SBR in Belgium and this translates into a different dynamics in loan outcomes. The average number of employees in my firm-level MBR sample is 9.35 (Table A.3) and in the complete sample about 8 with a standard deviation of 3.6 employees. Moreover, in Belgium only 46 per cent of credit is extended to MBR firms. Thus, I do not find substantial differences between these two samples and I focus on MBR. In this respect, my sample is closer to the one in Spain, where MBR is just as representative and banks provide most credit in the economy (Jimenez et al., 2014).

[15] Although comprehensive, my sample contains only information related to employment, e.g. wages, location, and sector of firms. I have no access to these firms' balance-sheets, most of which are "mom-and-pop" shops. I use all available data

employee must send information related to their labor force to the Ministry of Labor and Employment in Brazil at each year-end[16]. I use RAIS to build firm control variables and two dependent variables: the quarterly change in firm employment, and the quarterly change in average wages, which are used to estimate the real effects.

From (1) and (2), I build the following **firm controls** ($firm_{f,t-1}$): the ex-ante (quarterly lagged): (log of) the number of formal employees (n $employees_{t-1}$), the (log of) their average wages (avg $wage_{t-1}$), ln of total firm credit (firm $credit_{t-1}$) and a dummy variable in case the firm is in default, i.e. if it has at least one loan in arrears for more than 90 days against any financial system player in *t-1* (firm $default_{t-1}$). These controls are augmented with time invariant firm FEs (α_f). From (1), I also build $risk_{b,f,t-1}$, the weighted average provision for non-performing loans assigned by each bank to all its loans against the same firm in *t-1*. This is the only control available at the bank-firm-time dimension. Refer to the Appendix for detailed summary tables at loan, firm, bank, and macro-level data (Tables A.2, A.3, A.4, and A.5 respectively).

From (3), I build the **bank controls** ($bank_{b,t-1}$) common to the bank lending channel literature to assess bank's strength: the core capital-to-assets ratio ($capital_{t-1}$), the natural logarithm (ln) of bank's assets ($size_{t-1}$), the liquid-to-total assets ratio ($liquidity_{t-1}$), the share of non-performing loans to total credit (npl_{t-1}), and two dummy variables for banks with foreign control ($foreign_{t-1}$) and government control (gov_{t-1}). The main variable that proxy for bank balance-sheet strength, $capital_{t-1}$, averages 9.6 per cent with a standard deviation of 4 per cent at the loan-level sample (Table A.2).

and rely on the credit registry to derive additional information related to firms' risk such as total debt outstanding, delinquency, and average credit opinions provided by financial intermediaries.

[16] Because each job relationship has start and end dates, I can rebuild the RAIS end-of-the-year data into quarters, calculating at each end-of-quarter the number of active employees, their average wages, and related quarterly dynamics.

The **macro-controls** ($macro_{t-1}$) are the consumer price index (IPCA, ΔCPI_{t-1}) and yearly GDP growth (ΔGDP_{t-1}). These variables average zero as the sample is very much balanced in episodes of upswing and downswing of economic activity (Table A.2).

B. Identification Strategy

The baseline and most saturated regression to identify the bank lending channel is (2):

$$\begin{aligned}\Delta\ln(\text{credit})_{b,f,t+1:t} \\ &= \text{risk}_{b,f,t-1} + \text{bank}_{b,t-1} * \Delta i^{s}_{t-1} + \text{bank}_{b,t-1} \\ &+ \text{bank}_{b,t-1} * [\Delta\text{CPI}_{t-1}, \Delta\text{GDP}_{t-1}] \\ &+ \alpha_{f,t} \qquad (2)\end{aligned}$$

where Δi^{s}_{t-1} are MP surprises, $bank_{b,t-1}$ are bank controls, $risk_{b,f,t-1}$ is the risk control, and $\alpha_{f,t}$ are firm*time fixed effects (one for each firm*quarter pair). The interactions between bank controls and both ΔCPI_{t-1} and ΔGDP_{t-1} alleviate any further concerns that MP surprises are still correlated with Taylor fundamentals. I also replicate equation (2) using the one-year changes in the Selic rate (Δi_{t-1}) for comparison.

I run several regressions with firm and macro-controls to assess the average (absolute) effects of credit supply. In these cases, these two sets of observables control for credit demand shifts.

I account for the interaction between bank controls and the expected component (Δi^{e}_{t-1}) in equation (3), which replicates Kuttner (2001) at the loan-level.

$$
\begin{aligned}
&\Delta\ln(\text{credit})_{b,f,t+1:t} \\
&\qquad = \text{risk}_{b,f,t-1} + \text{bank}_{b,t-1} * \Delta i^{s}_{t-1} + \text{bank}_{b,t-1} \\
&\qquad + \text{bank}_{b,t-1} * [\Delta\text{CPI}_{t-1}, \Delta\text{GDP}_{t-1}] \\
&\qquad + \text{bank}_{b,t-1} * \Delta i^{e}_{t-1} \\
&\qquad + \alpha_{f,t} \qquad (3)
\end{aligned}
$$

I also run equation (3) using Taylor residuals Δi^{T}_{t-1} and the forecasted value of the Taylor equations ($\Delta i^{e,T}_{t-1}$).

To assess the real-effects of MP surprises on credit, employment and wages, I estimate equation (4) at the firm level. The most saturated firm-level equation is:

$$
\begin{aligned}
&\Delta\ln(\text{credit})_{f,t+1:t} \\
&\qquad = \text{risk}_{f,t-1} + \text{bank}_{f,t-1} * \Delta i^{s}_{,t-1} + \text{bank}_{f,t-1} \\
&\qquad + \text{bank}_{f,t-1} * [\Delta\text{CPI}_{t-1}, \Delta\text{GDP}_{t-1}] + \text{firm}_{f,t-1} \\
&\qquad + \text{bank}_{f,t-1} * [\text{firm}_{t-1}, \text{risk}_{f,t-1}] + \alpha_{t} + \alpha_{\bar{b}} \qquad (4)
\end{aligned}
$$

where all bank controls ($\text{bank}_{f,t-1}$) and $\text{risk}_{f,t-1}$are weighted averaged using the ex-ante bank-firm total credit exposure, α_t are time FEs, and $\alpha_{\bar{b}}$ are main bank FEs. The main bank ($\alpha_{\bar{b}}$) is the ex-ante most representative credit provider of firm *f* and $\alpha_{\bar{b}}$ prevent that the results are driven by few (large and overly represented) banks. In the absence of firm*time FEs, the interactions between $\text{bank}_{f,t-1}$, $\text{risk}_{f,t-1}$ and

$\text{firm}_{f,t-1}$ control for observed correlations in bank-firm association that can possibly co-move with MP surprises. I also run regressions with macro-controls and seasonal dummies to assess the effects of Δi_{t-1}^{s} on the average firm. Finally, I take the quarterly changes in firm employment, $\Delta\ln(\text{n employees})_{f,t+1:t}$, and average wages, $\Delta\ln(\text{wages})_{f,t+1:t}$, as dependent variables in equation (4).

To alleviate concerns that yearly accumulated MP surprises are not indeed exogenous, I horserace the interactions between MP surprises and bank controls with several possibly correlated global and local macro-variables that could have influenced market-players response to certain announcements of the BCB (5):

$$\begin{aligned}
&\Delta\ln(\text{credit})_{b,f,t+1:t} \\
&\qquad = \text{risk}_{b,f,t-1} + \text{bank}_{b,t-1} * \Delta i_{t-1}^{s} + \text{bank}_{b,t-1} \\
&\qquad + \text{bank}_{b,t-1} * [\Delta\text{CPI}_{t-1}, \Delta\text{GDP}_{t-1}] \\
&\qquad + \text{bank}_{b,t-1} * X_{t-1} \\
&\qquad + \alpha_{f,t} \qquad\qquad (5)
\end{aligned}$$

where X_{t-1} can be the one-year changes in the US overnight interest rates (Δi^{US}_{t-1}), the US short shadow rate (Δi^{SSR}_{t-1}. Wu and Xia, 2016), the US equity volatility index (VIX), the one-year changes in commodity prices ($\Delta\text{commodity prices}_{t-1}$), the one-year changes in the debt-to-gdp ratio ($\Delta\text{Debt/GDP}_{t-1}$), the economic policy uncertainty index for Brazil ($\text{Policy Uncertainty}_{t-1}$ from Baker, Bloom, and Davis, 2016), the total capacity utilization index (TCU_{t-1}), and the one-year percentage changes in the Brazilian long-term interest rates (Δi^{LT}_{t-1}).

IV. Results

I start by estimating the bank lending-channel of MP surprises using the core variables that are common to the empirical literature and relate to bank strength: size, capital, liquidity and share of non-performing loans - NPL, but I am mostly interested in the bank capital interaction (e.g. Jimenez et al., 2012, 2014). I hence refer to the bank whose capital-to-assets ratio is one-standard deviation (4 per cent) below (above) the mean as the weaker (stronger) bank.

Table I represents the estimates related to equation (1) and reports the effects of the bank lending-channel interactions. I also add interactions with government and foreign bank dummies to account for possibly different dynamics.

Insert Table I about here

In column (1), I present estimates of MP surprises (Δi^{s}_{t-1}) and the main interaction with bank capital. MP surprises have average strong negative effects on credit which are alleviated by ex-ante exposure to banks with higher core capital-to-assets ratio. Higher capital and bank size are on average associated with higher credit growth. A 1 pp higher GDP growth in the past year is also associated with 0.34 pp more credit in the following quarter. Riskier firm-bank relationships (with a 1 one-standard deviation higher ex-ante provisions) are associated with -3.29 pp less credit.

Introducing interactions with the remaining, and partially correlated, bank controls renders similar results for the bank capital interaction term in column (2).

In columns (3) and (5), I horserace all bank controls against the macro-controls that are typically endogenous to the monetary policy stance in a Taylor rule (ΔGDP_{t-1} and ΔCPI_{t-1}). I find that a one-standard positive deviation in MP surprises is associated with a 0.70 pp (1.889*0.37) decline in quarterly credit. The weaker bank contracts credit by 0.59 pp more, i.e. 1.29 pp in total (0.37*(1.889 + 0.397*4)).

In columns (4) and (5), I introduce firm*time FEs to control for observable and unobservable time-varying firm heterogeneity associated with firm credit growth or credit demand. The parameters of the bank control interactions are still similar, and both the compositional (or relative – column 5) and average (or absolute - column 3) effects of the bank capital interaction are comparable. This is important. As discussed before, most of the empirical literature focus on compositional (or relative) results alone for identification of credit supply. However, if average (absolute) estimates are not significant the channel may not matter for the average firm. According to Oster (2019), observing modest changes in coefficients and a large increase in R^2 (about 35%) between columns (3 and (5) suggests that (unobserved) credit demand is indeed orthogonal to these bank interactions.

Notice that the loan-level risk proxy decreases by more than half in columns (4) and (5). Naturally, the riskiness of a loan has a firm dimension and a bank dimension, associated to the each bank differential perception about the riskiness of a bank-firm relationship.

Since the differences are modest, I take model (5), the most saturated, as the baseline model in this paper. Relatively to the same firm*time pair, the weaker bank contracts credit by 0.68 pp more following a one-standard deviation positive MP surprise. The less liquid and smaller banks (one-standard deviation below the mean of these variables) also contract credit more 0.53 pp and 0.61 pp following the same MP surprise respectively. All results are in line with Kashyap and Stein (2000) and Kishan and Opiela (2000) among many others.

In Table II, I replicate Kuttner (2001) and introduce the expected component of MP directly in the regressions as well as in the related lending-channel interactions. For comparison, I bring the estimates of Table I (column 3) again in Table II column (1). Neither the expected component or its' interactions with bank controls are significant in absolute or relative terms. In other words, introducing this layer of controls weakens statistical significance, but does not materially change any of the previous estimates (columns 2 and 3).

Insert Table II about here

In columns (4) and (5), I use the one-year changes in the reference rate (Selic) as MP proxy. The results are qualitatively similar but statistically and economically weaker. This is fully consistent with the errors-in-variable problem described in Kuttner (2001), which leads to an attenuation of the effects of an unexpected MP shock. A one-standard deviation in the one-year changes in the Selic rate would contract credit on average by 0.34 pp (0.107*3.16), about half of the estimate presented on Table I and statistically non-significant at the standard levels. The weaker, the less liquid, and the smaller banks would contract credit by an additional 0.44 pp (0.035*4*3.16), 0.68 pp (0.026*8.32*3.16) and 0.52 pp (0.124*1.32*3.16) respectively. These two latter results are significant but only in relative (column 5) not absolute (column 4) terms.

In Appendix (A.6), I reproduce the same approach of Table II using Taylor residuals. A one-standard deviation on these residuals is associated with a significant average contraction of 0.66 pp (0.431*1.52) on credit, but the bank capital interaction is not statistically significant and would translate into a non-significant additional 0.12 pp (0.02*4*1.52) contraction for the weaker bank in relative and absolute terms.

Finally, I turn to the real effects of MP surprises on the firms. I first collapse the panel to the firm-time dimension using the ex-ante share of the bank credit exposure to weight risk and bank observables and test the effects on total firm credit exposure, employment, and average wages (Table III).

Since firms are arguably capable of insulating from bank shocks, firm-level elasticities are more appealing to policy-makers as they account for this final equilibrium in credit markets (Iyer et al., 2014).

Insert Table III about here

In columns (1) to (3), I use as a dependent variable the quarterly log change in firm credit. The results at the firm-level are consistent with the loan-level ones, suggesting that on average firms do not fully insulate from the lending channel of MP. The effect of a one standard deviation positive MP surprise on the average firm is a 1.10 pp (2.989*0.37) (column 1) credit contraction. More importantly, heterogeneities across financial intermediaries' strength, i.e. capital, matter for the average firm. A firm connected to a weaker bank receives a substantially higher MP shock, and face a 0.3 pp (0.202*4*0.37) to 0.39 pp (0.265*4*0.37) higher credit contraction (columns 2 and 3). Notice that I add time FEs to column (2) and main bank FEs and interactions between firm and bank controls to column (3). In the absence of firm*time FEs, this alleviates concerns that certain bank-firm associations and few influential banks are driving the results[17].

The real effects on quarterly employment of the same MP shock are also statistically and economically significant. The average firm faces an employment contraction of 0.21 pp (0.567*0.37) (column 4). Within the same quarter, a firm connected to a weaker bank receives a substantially higher MP shock, and face up to a 0.14 pp (0.093*4*0.37) (column 5) higher quarterly contraction. Conversely, a firm connected to a stronger bank mitigate about one third of the negative impacts

[17] For instance, if "better" firms are on average connected to "better" banks as in Kwhaja and Mian (2008), interactions between firms' risk and size (number of employees) and bank controls can partially absorb these effects.

of a MP positive surprise on its credit intake and about two thirds on employment. I find no statistically significant results on wages (columns 7, 8 and 9).

To alleviate concerns that the lending channel of MP surprises reflect other possibly correlated global variables, I horserace the baseline model with a number of global shocks (Table IV). Because MP stances in emerging countries can respond to the global financial cycle (e.g. Rey, 2015), I horserace all bank controls against: the one-year change in the overnight Fed funds rate (column 2), global liquidity (proxied by the US short shadow rate - column 3), and global uncertainty or risk aversion (proxied by VIX - column 4). I also control for the changes in commodity prices (column 5). Because of space limitations, I present only the bank capital interactions, but I simultaneously horserace all bank controls and global shocks against the MP interactions of the baseline model in all regressions. In column (6), global shocks are considered altogether. Although I find a positive and significant correlation between global liquidity and bank capital, controlling for this dimension does not seem to affect the baseline lending-channel estimates.

Insert Table IV about here

In Table V, I follow the same steps and horserace the baseline model with possibly correlated local macro-variables. The weakening of the country fiscal position as well as political uncertainty have been associated with low investment and economic activity particularly since 2013. To account for possible correlations between these effects and MP surprises, I horserace the baseline model with interactions between all bank controls and one-year changes in the debt-to-GDP ratio (column 2) and the Political Uncertainty index of Baker, Bloom, and Dale (2016) for Brazil (column 3). I also account for Total Capacity Usage (TCU – columns 4) and the one-year changes in the long-term interest rates (TJLP – column

5). In column (6), all these shocks are considered altogether. None of these variables affect the baseline interactions.

Insert Table V about here

Importantly, this sample is balanced in terms of episodes of easing and tightening of MP, GDP, and credit growth. However, to alleviate concerns that the results are driven by influential quarters, I regress the baseline model excluding the GFC quarters (column 2). I also exclude first the foreign banks (column 3) and then government banks (column 4) without any material change in the bank capital and MP interaction.

Insert Table VI about here

V. Final Remarks

This paper evaluates the bank lending-channel of MP surprises in Brazil and its real effects using exhaustive bank, firm, and loan-level data. To disentangle MP surprises from expected changes in the overnight reference rate, I rely on high-frequency data from interest rate derivatives. This identification strategy leads to sharp and strong results. On the other hand, using directly the overnight reference rate leads to statistically and economically weaker estimates consistent with an errors-in-variable problem (Kuttner, 2001). A common choice in the empirical literature, the Taylor residuals, also leads to weaker estimates. These results help to qualify a number of prior empirical studies focusing on the bank lending-channel and that similarly rely on loan-level data and firm*time FEs for superior identification of credit supply. While recent empirical papers examining MP effects on macro-financial aggregates rely heavily on high-frequency identification to isolate the unexpected component of MP (e.g., Gertler and Karadi, 2015, Jarociński and Karadi, 2018), researches empowered with exhaustive databases not always share the same concerns. Thus, even papers drawing on loan-level data could have underestimated the impacts of MP on credit supply.

MP surprises extracted from the derivatives market are indeed exogenous to, or not systematically associated with, a number of global and local macroeconomic variables likely to have influenced market-players response to certain announcements of the Central Bank of Brazil, including economic policy uncertainty or the state of the global financial cycle.

I find a strong bank lending-channel operating mostly through capital and consistent with the theoretical and empirical literature. This channel has important real effects for the average firm credit and employment outcomes. Importantly, I find that the absolute strength of financial intermediaries (Coimbra and Rey, 2019) matter for firms. Firms connected to weaker banks face stronger positive MP shocks that translate into deeper decline on credit intakes and employment outcomes. Conversely, firms connected to stronger banks alleviate about one third of these effects on credit and two thirds on employment.

REFERENCES

Adrian, Tobias and Hyun Song Shin. 2014. "Procyclical Leverage and Value-at-Risk." *Review of Financial Studies*, 27(2): 373-403.

Amiti, Mary and David Weistein. 2011 "Exports and Financial Shocks."*Quarterly Journal of Economics*, 126: 1841-1877.

Amiti, Mary and David Weistein. 2018. "How Much Do Idosyncratic Bank Shocks Affect Invesdtment? Evidence From Matched Bank-Firm Loan Data." *Journal of Political Economy*, 126(2): 525-587.

Baker, Scott, Nicholas Bloom, and Steven Davis. 2016. "Measuring Economic Policy Uncertainty." *Quarterly Journal Economics*, 131(4):1593-1636.

Banco Central do Brasil. 2018. "Relatorio de Economia Bancaria". Available at: https://www.bcb.gov.br/content/publicacoes/relatorioeconomiabancaria/reb_2018.pdf

Barroso, Joao Barata, Rodrigo Gonzalez, and Bernardus Van Doornik. 2017. "Credit Supply Responses to Reserve Requirement: loan-level evidence from macroprudential policy." BIS Working Paper Series 674.

Bernanke, Ben and Alan Blinder. 1988. "Credit, Money, and Aggregate Demand." *American Economic Review*, 78(2): 435-439 Papers and Proceedings of the One-Hundredth Annual Meeting of the American Economic Association

Bernanke, Ben and Mark Gertler. 1989. "Agency Costs, Net Worth, and Business Fluctuations." *American Economic Review*, 79(1): 14–31.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist. 1996. "The Financial Accelerator and the Flight to Quality." *Review of Economics and Statistics*, 78(1): 1–15.

Bernanke, Ben and Mark Gertler. 1995. "Inside the Black Box: The Credit Channel of Monetary Policy Transmission." *The Journal of Economic Perspectives*, 9(4): 27-34.

Bernanke, Ben and Kenneth Kuttner. 2005. "What Explains the Stock Market's Reaction to Federal Reserve Policy?" *The Journal of Finance*, 60: 1221-1257.

Berton, Fabio, Sauro Mocetti, Andrea Presbitero, and Matteo Richiardi. 2018. "Banks, Firms, and Jobs." *The Review of Financial Studies*, 31(6).

Black, Lamont and Richard Rosen. 2016. "Monetary Policy, Loan Maturity, and Credit Availability." *International Journal of Central Banking*," March: 199-230.

Boschen, John and Leonard Mills. 1995 “The Effects of Countercyclical Policy on Money and Interest Rates: An Evaluation of Evidence from FOMC Documents.” Federal Reserve Bank of Philadelphia Working Paper 91-20

Chodorow-Reich, Gabriel. 2014. “The employment effects of credit market disruptions: firm-level evidence from the 2008–9 financial crisis.” *Quarterly Journal of Economics*, 129(1): 1-59.

Coimbra, Nuno and Hélène Rey. 2019. “Financial Cycles with Heterogeneous Intermediaries.” NBER Working Paper 23245.

Delis, Manthos, Ifthekar Hasan, and Nikolaos Mylonidis. 2017. “The Risk-Taking Channel of Monetary Policy: Evidence from Corporate Loan Data.” *Journal of Money, Credit and Banking*, 49(1): 187-213.

Diamond, Douglas and Raghuram Rajan. 2011. “Fear of Fire Sales, Illiquidity Seeking, and Credit Freezes.” *Quarterly Journal of Economics*, 126 (2): 557–91.

Gambacorta, Leonardo and Hyun Song Shin. 2018. “Why bank capital matters for monetary policy.” *Journal of Financial Intermediation*, 35 (2018), 17-29

Gan, Jie. 2017 “The Real Effects of Asset Market Bubles: Loan-and Firm-level Evidence of a Lending Channel.” *Review of Financial Studies*, 20: 1941-1973.

Gertler, Mark and Simon Gilchrist. 1994. “Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms.” *Quarterly Journal of Economics*, 109(2): 309–40.

Gertler, Mark and Peter Karadi. 2015. “Monetary Policy Surprises, Credit Costs, and Economic Activity.” *American Economic Journal: Macroeconomics*, 7: 44-76.

Greenstone, Michael, Alexandre Mas, and Hoai-Luu Nguyen. 2014. “Do credit market shocks affect the real economy? Quasi-experimental evidence from the great recession and `normal’ economic times.” NBER Working Paper 20704.

Greenwald, Bruce and Joseph Stiglitz. 1983. “Financial Market Imperfections and Business Cycles.” *Quarterly Journal of Economics*, 108: 77-114.

Gurkaynak, Refet, Brian Sack, and Eric Swanson. 2005. "The Sensitivity of Long-Term Interest Rates to Economic News: Evidence and Implications for Macroeconomic Models." *American Economic Review*, 95(1): 425–436.

Holmstrom, Bengt and Jean Tirole. 1997. "Financial Intermediation, Loanable Funds, and the Real Sector." *The Quarterly Journal of Economics*, 112(3): 663-691

Iannidou, Vasso, Steven Ongena, and José-Luis Peydró. 2015. "Monetary Policy, Risk-Taking and Pricing: Evidence From a Quasi-Natural Experiment." *Review of Finance*, 19(1): 95-144.

Iyer, Rajkamal, José-Luis Peydró, Samuel da-Rocha-Lopes, and Antoinette Schoar. 2014. "Interbank Liquidity Crunch and the Firm Credit Crunch: Evidence from the 2007-2009 Crisis." *Review of Financial Studies*, 27: 347-372.

Jarociński, Marek and Peter Karadi. 2018. "Deconstructing monetary policy surprises: The role of information shocks." ECB Working Paper 2133.

Jiménez, Gabriel, Atif Mian, José-Luis Peydró, and Jesús Saurina. 2010. "Local versus Aggregate Lending Channels: The Effects of Securitization on Corporate Credit Supply in Spain." NBER Working Paper 16595.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina. 2012. "Credit Supply and Monetary Poliy: Indentifying the Bank Balance-Sheet with Loan Applications." *American Economic Review*, 102(5): 2301-2326.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina. 2014. "Hazardous Times for Monetary Policy: What do Twenty-Three Million Bank Loans Say About the Effects of Monetary Policy on Credit Risk-Taking." *Econometrica*, 82(2): 463-505.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina. 2017. "Do Demand or Supply Factors Drive Bank Credit, In Good and Crisis times?" Universitat Pompeu Fabra, Economic Working Paper 1567.

Kashyap, Anil and Jeremy Stein. 2000. “What Do a Million Observations on Banks Say about the Transmission of Monetary Policy?” *American Economic Review*, 90(3): 407-428.

Kishan, Ruby and Timothy Opiela. 2000. “Bank size, bank capital and the bank lending channel.” *Journal of Money, Credit and Banking*, 32: 121-141.

Kuttner, Kenneth 2001. “Monetary policy surprises and interest rates: Evidence from the Fed funds futures market.” *Journal of Monetary Economics*, 47:523–544.

Maddaloni, Angela and José-Luis Peydró. 2013. “Monetary Policy, Macroprudential Policy, and Banking Stability: Evidence from the Euro Area.” *International Journal of Central Banking*, 9(1): 122-68

Meirelles, Henrique. 2009. “Ten years of floating exchange rates in Brazil”, Speech by Mr Henrique Meirelles, Governor of the Central Bank of Brazil, to celebrate 10 years of floating exchange rates in Brazil, Central Bank of Brazil, Brasília, January 19.

Mesquita, Mário and Mário Toros. 2010. “Brazil and the 2008 panic.” BIS Papers 54.

Morais, Bernardo, José-Luis Peydró, Jessica Roldán-Peña, and Claudia Ruiz-Ortega. 2019. “The international bank-lending channel of monetary policy rates and QE: credit supply, reach-for-yield, and real effects.” *Journal of Finance,* 74(1): 55-90.

Oliveira, Rachel, Rafael Schiozer, and Lucas Barros. 2015. “Depositors' Perception of 'Too-Big-to-Fail'.” *Review of Finance*, 19: 191-227.

Ono, Arito, Kosuke Aoki, Shinichi Nishioka, Kohei Shintani, and Yosuke Yasui. 2016. “Long-term interest rates and bank loan supply: evidence from firm-bank loan-level data.” Institute of Economic Research , Hitotsubashi University, Working Paper 43.

Oster, Emily. 2019. “Unobservable Selection and Coefficient Stability: Theory and Evidence”. *Journal of Business, Economics and Statistics,* 37(2): 187-204.

Paravisini, Daniel. 2008. “Local Bank Financing Constraints and Firm Access to External Finance.” *Journal of Finance*, 63: 2161-2193.

Paravisini, Daniel, Veronica Rappoport, Philipp Schnabl, and Daniel Wolfenzon. 2015. “Dissecting the effect of credit supply on trade: evindence from matched credit-exporter data.” *Review of Economic Studies*, 82: 333-359.

Paravisini, Daniel, Rappoport, Veronica and Schnabl, Philipp. 2017. “Specialization in bank lending: evidence from exporting firms.” Centre for Economic Performance, London School of Economics and Political Science, CEP Discussion Papers 1492.

Pearson, Samantha. 2016. “Brazil keeps interest rates on hold.” *Financial Times,* January 20.

Pereira da Silva, Luiz. Awazu and Ricardo Harris. 2012. “Sailing through the Global Financial Storm: Brazil's recent experience with monetary and macroprudential policies to lean against the financial cycle and deal with systemic risks.” Central Bank of Brazil, Working Paper 290.

Romer, Christina and David Romer. 2004. “A New Measure of Monetary Shocks: Derivation and Implications.” *American Economic Review*, 94: 1055–84

Schnabl, Philipp. 2012. “The International Transmission of Bank Liquidity Shocks: Evidence From an Emerging Market.” *Journal of Finance*, 67: 897-932.

Stein, Jeremy. 1998. “An Adverse Selection Model of Bank Asset and Liability Management with Implications for the Transmission of Monetary Policy.” *Rand Journal of Economics*, 29(3): 466–86.

FIGURES

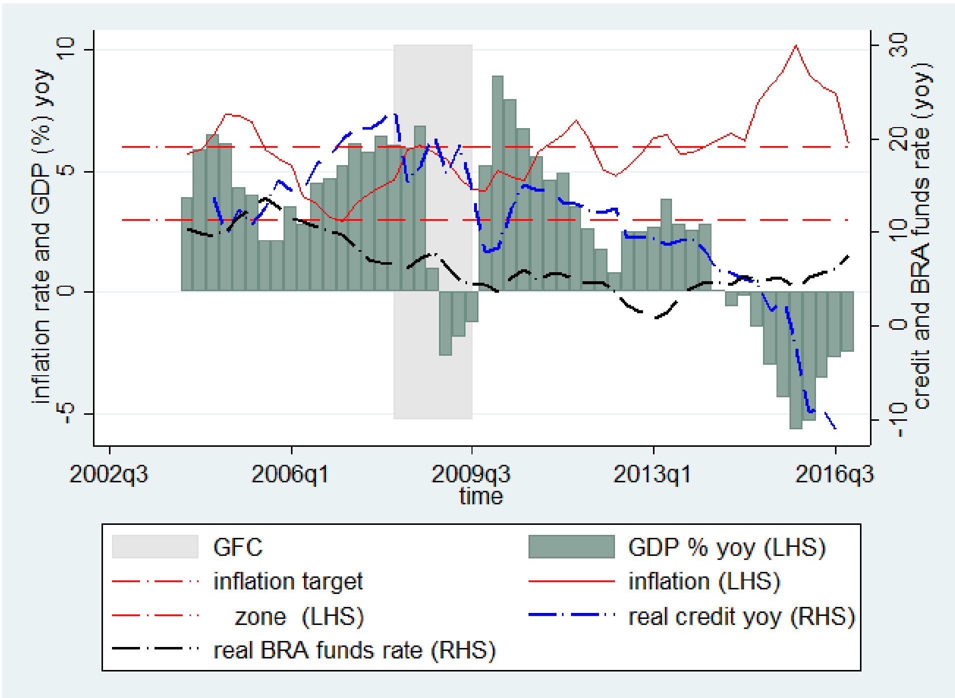

FIGURE I

MONETARY POLICY, GDP, AND CREDIT GROWTH IN BRAZIL

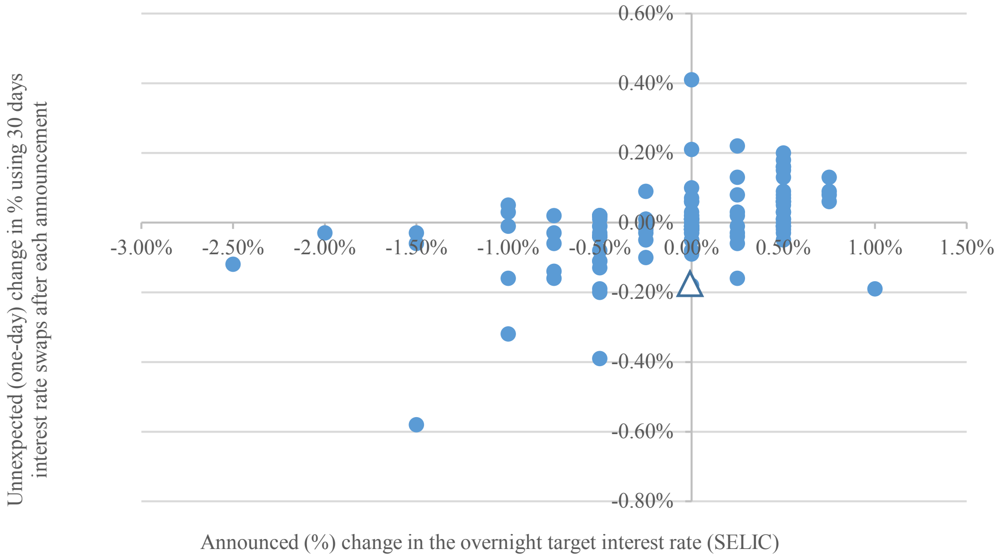

FIGURE II.

MP SURPRISES AND ANNOUNCED CHANGES IN SELIC (%)

Notes: Dots correspond to each of 122 COPOM announcement per cent change in SELIC and MP surprise (2003Q1 to 2016Q3)

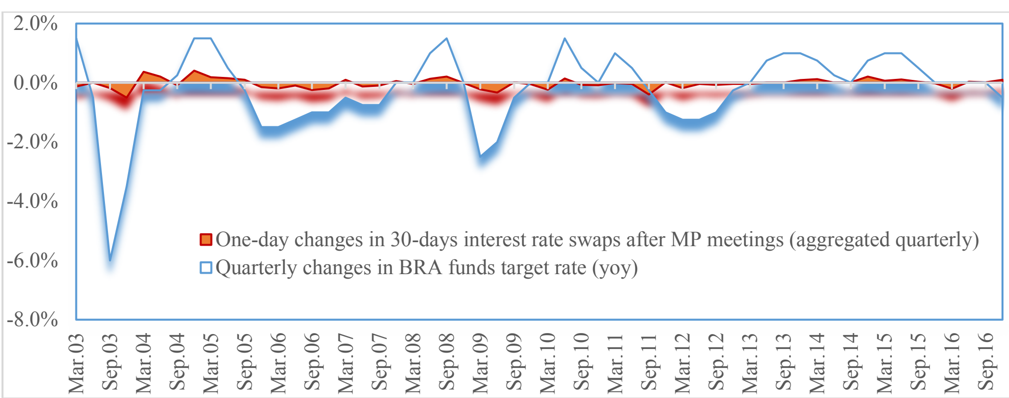

FIGURE III.

MP SURPRISES ACROSS TIME

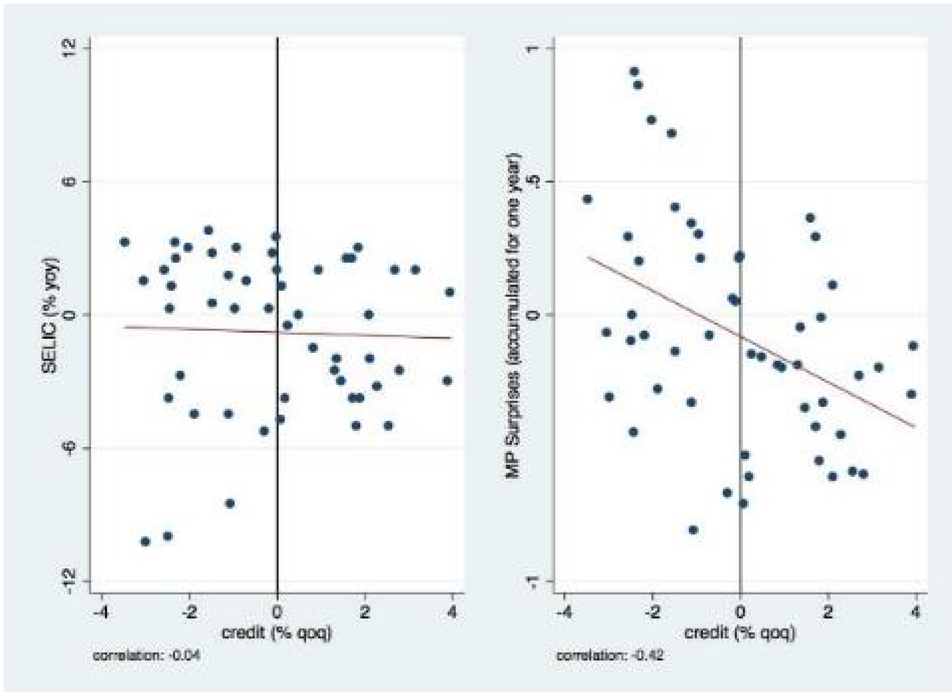

FIGURE IV

MP SURPRISES, SELIC, AND CREDIT GROWTH

Notes: Time correlation between average quarterly credit growth in log-terms (this paper main dependent variable) and lagged one year changes in SELIC (LHS) and MP surprises (RHS) based on 52 quarters. Credit growth is in real terms and it has been detrended and deseasoned in these two graphs.

Table I - The Bank Lending-Channel of Monetary Policy at Loan-Level

Dependent: $\Delta\ln(\text{credit})_{b,f,t+1:t}$	(1)	(2)	(3)	(4)	(5)
Δi^s_{t-1} * capital_{t-1}	0.288*	0.443**	0.397**	0.432**	0.445**
	(0.144)	(0.187)	(0.184)	(0.188)	(0.213)
Δi^s_{t-1} * size_{t-1}		1.041**	0.951***	1.290***	1.249***
		(0.442)	(0.352)	(0.447)	(0.450)
Δi^s_{t-1} * liquidity_{t-1}		0.164	0.079	0.208**	0.173**
		(0.133)	(0.123)	(0.090)	(0.075)
Δi^s_{t-1} * npl_{t-1}		-0.397	-0.256	-0.385**	-0.257
		(0.247)	(0.279)	(0.167)	(0.175)
Δi^s_{t-1} * gov_{t-1}		-0.071	-0.551	-1.340	-1.453
		(1.789)	(1.611)	(1.937)	(1.957)
Δi^s_{t-1} * foreign_{t-1}		0.149	1.019	-0.879	-0.121
		(1.248)	(1.003)	(1.343)	(1.233)
risk_{t-1}	-3.294***	-3.292***	-3.263***	-1.386***	-1.378***
	(0.312)	(0.322)	(0.326)	(0.147)	(0.153)
capital_{t-1}	0.285***	0.286***	0.271***	0.226***	0.220**
	(0.074)	(0.083)	(0.086)	(0.083)	(0.090)
size_{t-1}	1.584***	1.554***	1.628***	0.933***	0.969***
	(0.319)	(0.330)	(0.324)	(0.286)	(0.261)
liquidity_{t-1}	0.017	0.011	0.015	-0.055	-0.053
	(0.052)	(0.055)	(0.062)	(0.038)	(0.042)
npl_{t-1}	-0.194	-0.165	-0.086	-0.034	-0.035
	(0.262)	(0.305)	(0.281)	(0.172)	(0.180)
gov_{t-1}	1.820*	1.906*	1.864*	2.595***	2.495***
	(0.936)	(0.966)	(0.972)	(0.890)	(0.898)
foreign_{t-1}	-1.658**	-1.650**	-1.789**	-1.106	-1.216*
	(0.775)	(0.797)	(0.687)	(0.677)	(0.619)
firm credit_{t-1}	-7.612***	-7.609***	-7.660***		
	(0.440)	(0.447)	(0.448)		
n employees_{t-1}	3.944***	3.944***	3.936***		
	(0.214)	(0.221)	(0.217)		
avg payroll_{t-1}	-0.468***	-0.468***	-0.464***		
	(0.084)	(0.086)	(0.092)		
firm default_{t-1}	-4.807***	-4.810***	-4.811***		
	(0.535)	(0.552)	(0.547)		
Δi^s_{t-1}	-2.259***	-2.298*	-1.889*		
	(0.529)	(1.303)	(1.094)		
ΔGDP_{t-1}	0.420***	0.416***	0.424***		
	(0.098)	(0.106)	(0.141)		
ΔCPI_{t-1}	0.110	0.143	0.341		
	(0.338)	(0.327)	(0.499)		

continued

Observations	4,061,322	4,061,322	4,061,322	4,061,322	4,061,322
R-squared	0.055	0.055	0.056	0.408	0.408
Seasonal effects & Macro controls$_{t-1}$	Yes	Yes	Yes	<>	<>
Bank Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes
Risk Control$_{t-1}$	Yes	Yes	Yes	Yes	Yes
Firm Controls$_{t-1}$	Yes	Yes	Yes	<>	<>
Firm*Time FE	No	No	No	Yes	Yes
{Δi^{s}_{t-1}} * Bank Controls$_{t-1}$	No	Yes	Yes	Yes	Yes
{ΔCPI_{t-1} , ΔGDP_{t-1}} * Bank Controls$_{t-1}$	No	No	Yes	No	Yes
N firms	117561	117561	117561	117561	117561
N banks	94	94	94	94	94
N quarters	52	52	52	52	52
Cluster			bank & time		

Notes: This table presents the bank lending channel estimates. I compute monetary policy surprises taking the 30-days interest rate swap one day after each announcement of the Monetary Policy Committe Meeting (COPOM) in Brazil. Because the announcements are always made after the markets are closed, I take the following (closing day) rate relatively to the announcement day rate (Kuttner, 2001). Monetary policy (MP) surprises (Δi^{s}_{t-1}) represent one year of these accumulated surprises. Since 2006, there are 8 meetings per year (and 12 before). The macro-controls are changes in the consumer price index (IPCA, ΔCPI_{t-1}) and GDP growth (ΔGDP_{t-1}). The bank controls are the core capital-to-assets ratio (capital$_{t-1}$), the natural logarithm (ln) of bank's assets (size$_{t-1}$), the liquid-to-total assets ratio (liquidity$_{t-1}$), the share of non-performing loans to total credit (npl$_{t-1}$), a dummy variable for banks with foreign control (foreign$_{t-1}$), and a dummy variable for banks with government control (gov$_{t-1}$). The firm controls are the ln of total firm credit (firm credit$_{t-1}$), the ln of the number of its employees (n employees$_{t-1}$), and the ln of the average monthly wage of its employees (avg wage$_{t-1}$). I also use a dummy variable in case the firm is in default, i.e. if it has at least one loan in arrears for more than 90 days against any financial system player in *t-1* (firm default$_{t-1}$). This information is promptly available to all banks in the credit registry. I use an additional risk control, risk$_{t-1}$, which is the weighted average provision assigned by each bank to all its loans against the same firm in *t-1* . This is the only control available at the firm-bank-time dimension. In model (1), I take the capital and MP surprise interaction alone. In model (2), all bank control are introduced. In models (1) to (3), I estimate seasonal dummies, macro-controls, and MP surprises while relying on firm observables and (time invariant) firm FEs for demand control. In models (4) and (5), I use firm*time fixed effects (FEs) to control for credit demand shifts. I horserace the bank controls against the macro controls in models (3) and (5). Model (5) is the most saturated model and the baseline result throughout this paper. All standard errors are two-way clustered at the bank and time (year:quarter) dimension. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

TABLE II: EXPECTED CHANGES IN MONETARY POLICY AND MONETARY POLICY SURPRISES

Dependent: $\Delta\ln(\text{credit})_{b,f,t+1:t}$	(1)	(2)	(3)		(4)	(5)
Δi^{s}_{t-1} * capital_{t-1}	0.397**	0.419*	0.443*	Δi_{t-1} * capital_{t-1}	0.021	0.035
	(0.184)	(0.229)	(0.255)		(0.029)	(0.024)
Δi^{s}_{t-1} * size_{t-1}	0.951***	0.820*	1.095**	Δi_{t-1} * size_{t-1}	0.070	0.124**
	(0.352)	(0.461)	(0.527)		(0.073)	(0.055)
Δi^{s}_{t-1} * liquidity_{t-1}	0.079	-0.046	0.076	Δi_{t-1} * liquidity_{t-1}	0.019	0.026**
	(0.123)	(0.154)	(0.137)		(0.014)	(0.012)
Δi^{s}_{t-1} * npl_{t-1}	-0.256	-0.198	-0.250	Δi_{t-1} * npl_{t-1}	-0.025	0.043
	(0.279)	(0.329)	(0.213)		(0.268)	(0.264)
Δi^{s}_{t-1} * gov_{t-1}	-0.551	-1.137	-2.673	Δi_{t-1} * gov_{t-1}	-0.013	0.024
	(1.611)	(2.100)	(2.511)		(0.208)	(0.176)
Δi^{s}_{t-1} * foreign_{t-1}	1.019	1.279	-0.669	Δi_{t-1} * foreign_{t-1}	-0.032	-0.024
	(1.003)	(1.712)	(1.961)		(0.030)	(0.024)
Δi^{e}_{t-1} * capital_{t-1}		-0.007	0.001			
		(0.038)	(0.034)			
Δi^{e}_{t-1} * size_{t-1}		0.027	0.049			
		(0.105)	(0.079)			
Δi^{e}_{t-1} * liquidity_{t-1}		0.028	0.024			
		(0.021)	(0.021)			
Δi^{e}_{t-1} * npl_{t-1}		-0.009	0.003			
		(0.033)	(0.027)			
Δi^{e}_{t-1} * gov_{t-1}		0.111	0.272			
		(0.375)	(0.376)			
Δi^{e}_{t-1} * foreign_{t-1}		-0.085	0.111			
		(0.334)	(0.315)			

continued

Δi^{s}_{t-1}	-1.889*	-2.359**		Δi_{t-1}	-0.107	
	(1.094)	(1.019)			(0.182)	
Δi^{e}_{t-1}		0.102				
		(0.208)				
ΔGDP_{t-1}	0.424***	0.425***		ΔGDP_{t-1}	0.468***	
	(0.141)	(0.141)			(0.145)	
CPI_{t-1}	0.341	0.297		CPI_{t-1}	0.157	
	(0.499)	(0.475)			(0.503)	
Observations	4,061,322	4,061,322	4,061,322	Observations	4,061,322	4,061,322
R-squared	0.056	0.056	0.408	R-squared	0.055	0.408
Seasonal effects & Macro controls$_{t-1}$	Yes	Yes	<>	Seasonal effects & Macro controls$_{t-1}$	Yes	<>
Bank Controls$_{t-1}$	Yes	Yes	Yes	Bank Controls$_{t-1}$	Yes	Yes
Risk Control$_{t-1}$	Yes	Yes	Yes	Risk Control$_{t-1}$	Yes	Yes
Firm Controls$_{t-1}$	Yes	Yes	<>	Firm Controls$_{t-1}$	Yes	<>
Firm*Time FE	No	No	Yes	Firm*Time FE	No	Yes
$\{\Delta CPI_{t-1}, \Delta GDP_{t-1}\}$ * Bank Controls$_{t-1}$	Yes	Yes	Yes	$\{\Delta CPI_{t-1}, \Delta GDP_{t-1}\}$ * Bank Controls$_{t-1}$	Yes	Yes
$\{\Delta i^{s}_{t-1}\}$ * Bank Controls$_{t-1}$	Yes	Yes	Yes	$\{\Delta i_{t-1}\}$ * Bank Controls$_{t-1}$	Yes	Yes
$\{\Delta i^{e}_{t-1}\}$ * Bank Controls$_{t-1}$	No	Yes	Yes			

Notes: In this table, I horserace monetary policy surprises against the expected changes in monetary policy. Monetary policy surprises (Δi^{s}_{t-1}) represent one year of accumulated (one-day) changes in the 30-days interest rate swap immediately after each announcement of the Monetary Policy Committe Meeting (COPOM) in Brazil (8 after 2006 and 12 before). At each announcement, I compute the expected change in monetary policy (Δi^{e}_{t-1}) as the difference between the effective announced change in the overnight target reference rate (Selic, Δi_{t-1}) and each monetary policy surprise (Kuttner, 2001). Similarly, I accumulate expected changes (Δi^{e}_{t-1}) across one year of announcements. In model (1), I reintroduce the model, with absolute estimates of Table 1 (column 3). In models (2) and (3), I horserace all bank controls with the expected monetary policy changes (Δi^{e}_{t-1}). In models (4) and (5), I interact the changes in Selic with the bank controls. I use firm*time fixed effects (FEs) to control for credit demand shifts in models (3) and (5). In models (1), (2) and (4), seasonal dummies, macroeconomic variables as well as firm controls are estimated. All standard errors are two-way clustered at the bank and time (year:quarter) dimension. Robust standard errors in parentheses : *** p<0.01, ** p<0.05, * p<0.1.

Table III: The Bank Lending-Channel of Monetary Policy and Real Effects at Firm-Level

	$\Delta\ln(\text{credit})_{f,t+1:t}$			$\Delta\ln(\text{n employees})_{f,t+1:t}$			$\Delta\ln(\text{wages})_{f,t+1:t}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δi^{s}_{t-1} * capital_{t-1}	0.202*	0.251**	0.265**	0.009	0.093**	0.091*	0.006	0.006	0.005
	(0.115)	(0.096)	(0.124)	(0.056)	(0.041)	(0.047)	(0.037)	(0.017)	(0.021)
Δi^{s}_{t-1} * size_{t-1}	-0.168	0.049	0.181	-0.488**	-0.058	-0.047	0.092	0.111	0.098
	(0.413)	(0.391)	(0.387)	(0.209)	(0.120)	(0.129)	(0.128)	(0.070)	(0.071)
Δi^{s}_{t-1} * liquidity_{t-1}	-0.101	0.007	0.007	-0.037	0.026	0.023	0.026	0.015**	0.013
	(0.103)	(0.073)	(0.072)	(0.041)	(0.025)	(0.031)	(0.031)	(0.007)	(0.012)
Δi^{s}_{t-1} * npl_{t-1}	-0.139	-0.285*	-0.242*	-0.009	-0.087*	-0.075	-0.016	-0.057**	-0.044
	(0.204)	(0.152)	(0.143)	(0.085)	(0.046)	(0.057)	(0.042)	(0.026)	(0.030)
Δi^{s}_{t-1} * gov_{t-1}	1.055	1.047	1.273	0.156	0.077	0.162	-0.043	0.016	-0.004
	(1.336)	(1.362)	(1.329)	(0.169)	(0.269)	(0.309)	(0.070)	(0.122)	(0.140)
Δi^{s}_{t-1} * foreign_{t-1}	1.280	1.172	0.930	-0.052	-0.054	-0.043	0.093	0.043	0.012
	(1.008)	(1.061)	(1.054)	(0.252)	(0.175)	(0.211)	(0.158)	(0.133)	(0.130)
Δi^{s}_{t-1}	-2.989***			-0.567**			-0.179		
	(1.033)			(0.273)			(0.267)		
ΔGDP_{t-1}	0.538***			0.212***			-0.045		
	(0.138)			(0.046)			(0.028)		
CPI_{t-1}	0.369			-0.072			-0.132		
	(0.469)			(0.082)			(0.121)		
Observations	1,607,303	1,607,303	1,607,303	1,607,303	1,607,303	1,607,303	1,607,303	1,607,303	1,607,303
R-squared	0.187	0.189	0.191	0.174	0.175	0.176	0.274	0.276	0.277
Bank, Firm Controls_{t-1} & Risk Control_{t-1}	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\{\Delta i^{s}_{t-1}\}$ * Bank Controls_{t-1}	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\{\Delta CPI_{t-1}, \Delta GDP_{t-1}\}$ * Bank Controls_{t-1}	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal effects & Macro controls_{t-1}	Yes	<>	<>	Yes	<>	<>	Yes	<>	<>
Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Bank*{Firm & Risk Controls_{t-1}}	No	No	Yes	No	No	Yes	No	No	Yes
Main Bank FE	No	No	Yes	No	No	Yes	No	No	Yes

continued

Notes: This table presents firm-level estimates of the bank lending channel on credit, employment, and wages. All bank controls and the risk control are weighted averaged using the ex-ante firm-bank credit exposure. The bank controls are core capital-to-assets ratio (capital$_{t-1}$), the natural logarithm of banks' assets (size$_{t-1}$), the liquid-to-total assets ratio (liquidity$_{t-1}$), the share of non-performing loans to total credit (npl$_{t-1}$), a dummy variable for banks with foreign control (foreign$_{t-1}$), and a dummy variable for banks with government control (gov$_{t-1}$). The risk control, risk$_{t-1}$, is the weighted average provision assigned by each bank to all its loans against the same firm in *t-1*. The firm controls are the natural logarithm (ln) of total firm credit (firm credit$_{t-1}$), the ln of the number of its employees (n employees$_{t-1}$), and the ln of the average monthly wage of these firms' employees (avg wage$_{t-1}$). I also use a dummy variable in case the firm is in default, i.e. if it has at least one loan in arrears for more than 90 days against any financial system player in *t-1* (firm default$_{t-1}$). This information is promptly available to all banks in the credit registry. I use firm controls and (time invariant) firm FEs to control for credit demand shifts augmented with macro-controls and seasonal dummies in models (1), (4) and (7); and, time FEs in all other models. In models (3), (6) and (9), I introduce interactions between all bank controls, firm and risk controls augmented with the main bank FE. The main bank is the one to which the firm has the largest credit exposure. All standard errors are two-way clustered at the main bank and time dimension. Robust standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE IV - MONETARY POLICY AND POSSIBLY CORRELATED GLOBAL VARIABLES

Dependent: $\Delta\ln(\text{credit})_{b,f,t+1:t}$	(1)	(2)	(3)	(4)	(5)	(6)
Δi^{s}_{t-1} * capital_{t-1}	0.445**	0.444*	0.422**	0.440**	0.470**	0.462**
	(0.213)	(0.221)	(0.201)	(0.214)	(0.204)	(0.184)
Δi^{US}_{t-1} * capital_{t-1}		0.019				-0.113
		(0.081)				(0.127)
$i^{US}_{SSR,t-1}$ * capital_{t-1}			0.075**			0.079**
			(0.031)			(0.036)
VIX_{t-1} * capital_{t-1}				-0.002		-0.006
				(0.008)		(0.015)
Δcommodity prices_{t-1} * capital_{t-1}					0.007	0.008
					(0.005)	(0.008)
Observations	4,061,322	4,061,322	4,061,322	4,061,322	4,061,322	4,061,322
R-squared	0.408	0.408	0.408	0.408	0.408	0.409
Bank Controls_{t-1} & Risk Control_{t-1}	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Time FE	Yes	Yes	Yes	Yes	Yes	Yes
{ΔCPI_{t-1} , ΔGDP_{t-1} } * Bank Controls_{t-1}	Yes	Yes	Yes	Yes	Yes	Yes
{Δi^{s}_{t-1} } * Bank Controls_{t-1}	Yes	Yes	Yes	Yes	Yes	Yes
{Δi^{US}_{t-1} } * Bank Controls_{t-1}	No	Yes	No	No	No	Yes
{$i^{US}_{SSR,t-1}$ } * Bank Controls_{t-2}	No	No	Yes	No	No	Yes
{VIX_{t-1} } * Bank Controls_{t-1}	No	No	No	Yes	No	Yes
{Δcommodity prices_{t-1} } * Bank Controls_{t-1}	No	No	No	No	Yes	Yes

Notes: This table controls for possibly correlated global variables. Model (1) is the baseline model. In models (2) to (5), I interact all bank controls against a global variable. Because of space limitations, I only present the bank capital interactions. In model (2), I interact the one-year changes in the US overnight interest rates (Δi^{US}_{t-1}) with all bank controls, and horserace those againt all interactions between MP surprises and bank controls; in model (3), I do the same with the US short shadow rate ($\Delta i^{US}_{SSR,t-1}$. See Wu and Xia, 2016); in model (4), with the US equity volatility index (VIX); in model (5), with the one-year changes in commodity prices. In model (6), all those interactions are horseraced alltogeter. All standard errors are two-way clustered at the bank and time dimension. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

TABLE V - MONETARY POLICY AND POSSIBLY CORRELATED LOCAL VARIABLES

Dependent: $\Delta\ln(\text{credit})_{b,f,t+1:t}$	(1)	(2)	(3)	(4)	(5)	(6)
Δi^{s}_{t-1} * capital_{t-1}	0.445**	0.502**	0.392**	0.425*	0.474**	0.482**
	(0.213)	(0.215)	(0.190)	(0.215)	(0.219)	(0.198)
$\Delta\text{Debt/GDP}_{t-1}$ * capital_{t-1}		-0.000				0.014
		(0.016)				(0.018)
Policy Uncertainty_{t-1} * capital_{t-1}			0.001			0.001
			(0.002)			(0.002)
TCU_{t-1} * capital_{t-1}				0.024		0.035
				(0.034)		(0.043)
Δi^{LT}_{t-1} * capital_{t-1}					0.005	-0.080
					(0.086)	(0.102)
Observations	4,061,322	4,061,322	4,061,322	4,061,322	4,061,322	4,061,322
R-squared	0.408	0.409	0.408	0.409	0.408	0.409
Bank Controls_{t-1} & Risk Control_{t-1}	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Time FE	Yes	Yes	Yes	Yes	Yes	Yes
{ΔCPI_{t-1} , ΔGDP_{t-1} } * Bank Controls_{t-1}	Yes	Yes	Yes	Yes	Yes	Yes
{Δi^{s}_{t-1} } * Bank Controls_{t-1}	Yes	Yes	Yes	Yes	Yes	Yes
{$\Delta\text{Debt/GDP}_{t-1}$ } * Bank Controls_{t-1}	No	Yes	No	No	No	Yes
{Political Uncertainty_{t-1} } * Bank Controls_{t-1}	No	No	Yes	No	No	Yes
{IUC_{t-1} } * Bank Controls_{t-1}	No	No	No	Yes	No	Yes
{Δi^{LT}_{t-1} } * Bank Controls_{t-1}	No	No	No	No	Yes	Yes

Notes: This table controls for possibly correlated local variables. Model (1) is the baseline model. In models (2) to (5), I interact all bank controls against a local variable. Because of space limitations, I only present the capital interactions in this table. In model (2), I interact the one-year changes in the debt-to-gdp ratio ($\Delta\text{Debt/GDP}_{t-1}$) with all bank controls, and horserace those againt all interactions between monetary policy surprises and bank controls; in model (3), I do the same with the Economic Policy Uncertainty index for Brazil (Policy Uncertainty_{t-1} . See Baker, Bloom and Davis, 2015); in model (4), with the total capacity utilization index (TCU_{t-1}): in model (5), with the one-year changes in the long-term interest rates (TJLP). In model (6), all those interactions are horseraced alltogeter. All standard errors are two-way clustered at the bank and time dimension. Robust standard errors in parentheses : *** p<0.01, ** p<0.05, * p<0.1.

TABLE VI - Influential quarters, foreign and private domestic banks

Dependent: $\Delta\ln(\text{credit})_{b,f,t+1:t}$	(1) All quarters	(2) No GFC quarters	(3) No foreign banks	(4) Only private domestic
Δi^{s}_{t-1} * capital$_{t-1}$	0.445**	0.306**	0.468**	0.315*
	(0.213)	(0.148)	(0.232)	(0.174)
Δi^{s}_{t-1} * size$_{t-1}$	1.249***	0.729***	1.091***	1.731***
	(0.450)	(0.217)	(0.308)	(0.465)
Δi^{s}_{t-1} * liquidity$_{t-1}$	0.173**	0.181**	0.116	-0.097
	(0.076)	(0.078)	(0.075)	(0.173)
Δi^{s}_{t-1} * npl$_{t-1}$	-0.257	-0.313*	-0.012	-0.720**
	(0.175)	(0.161)	(0.189)	(0.291)
Δi^{s}_{t-1} * gov$_{t-1}$	-1.453	-2.256		
	(1.957)	(1.739)		
Δi^{s}_{t-1} * foreign$_{t-1}$	-0.121	-0.812		
	(1.233)	(0.909)		
Observations	4,061,322	3,579,591	3,122,530	952,948
R-squared	0.408	0.409	0.434	0.466
Bank Controls$_{t-1}$ & Risk Control$_{t-1}$	Yes	Yes	Yes	Yes
Firm*Time FE	Yes	Yes	Yes	Yes
$\{\Delta CPI_{t-1}, \Delta GDP_{t-1}\}$ * Bank Controls$_{t-1}$	Yes	Yes	Yes	Yes
$\{\Delta i^{s}_{t-1}\}$ * Bank Controls$_{t-1}$	Yes	Yes	Yes	Yes
N firms	117561	115590	98522	38889
N banks	94	94	68	56
N quarters	52	45	52	52

Notes: This table controls for influential quarters, foreign, and government banks. All standard errors are two-way clustered at the bank and the time dimension. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

TABLE A.1- MONETARY POLICY SURPRISES AND COPOM ANNOUNCEMENT DATES

Date	New target (per cent)	Prior Target (per cent)	MP announced change (pp)	Unantecipated MP change (pp)	Antecipated MP change (pp)
22 January 2003	25.50%	25.00%	0.50%	0.07%	0.43%
19 February 2003	26.50%	25.50%	1.00%	-0.19%	1.19%
19 March 2003	26.50%	26.50%	0.00%	-0.01%	0.01%
23 April 2003	26.50%	26.50%	0.00%	-0.02%	0.02%
21 May 2003	26.50%	26.50%	0.00%	0.01%	-0.01%
18 June 2003	26.00%	26.50%	-0.50%	0.01%	-0.51%
23 July 2003	24.50%	26.00%	-1.50%	-0.03%	-1.47%
20 August 2003	22.00%	24.50%	-2.50%	-0.12%	-2.38%
17 September 2003	20.00%	22.00%	-2.00%	-0.03%	-1.97%
22 October 2003	19.00%	20.00%	-1.00%	0.05%	-1.05%
19 November 2003	17.50%	19.00%	-1.50%	-0.58%	-0.92%
17 December 2003	16.50%	17.50%	-1.00%	0.03%	-1.03%
21 January 2004	16.50%	16.50%	0.00%	0.41%	-0.41%
18 February 2004	16.50%	16.50%	0.00%	0.06%	-0.06%
17 March 2004	16.25%	16.50%	-0.25%	-0.10%	-0.15%
14 April 2004	16.00%	16.25%	-0.25%	-0.02%	-0.23%
19 May 2004	16.00%	16.00%	0.00%	0.21%	-0.21%
16 June 2004	16.00%	16.00%	0.00%	0.02%	-0.02%
21 July 2004	16.00%	16.00%	0.00%	-0.02%	0.02%
18 August 2004	16.00%	16.00%	0.00%	-0.02%	0.02%
15 September 2004	16.25%	16.00%	0.25%	-0.04%	0.29%
20 October 2004	16.75%	16.25%	0.50%	0.20%	0.30%
17 November 2004	17.25%	16.75%	0.50%	0.08%	0.42%
15 December 2004	17.75%	17.25%	0.50%	0.13%	0.37%
19 January 2005	18.25%	17.75%	0.50%	0.03%	0.47%
16 February 2005	18.75%	18.25%	0.50%	-0.02%	0.52%
16 March 2005	19.25%	18.75%	0.50%	0.18%	0.32%
20 April 2005	19.50%	19.25%	0.25%	0.08%	0.17%
18 May 2005	19.75%	19.50%	0.25%	0.13%	0.12%
15 June 2005	19.75%	19.75%	0.00%	-0.05%	0.05%
20 July 2005	19.75%	19.75%	0.00%	0.01%	-0.01%
17 August 2005	19.75%	19.75%	0.00%	0.10%	-0.10%
14 September 2005	19.50%	19.75%	-0.25%	-0.01%	-0.24%
19 October 2005	19.00%	19.50%	-0.50%	-0.19%	-0.31%
23 November 2005	18.50%	19.00%	-0.50%	0.02%	-0.52%
14 December 2005	18.00%	18.50%	-0.50%	0.02%	-0.52%
18 January 2006	17.25%	18.00%	-0.75%	-0.16%	-0.59%
08 March 2006	16.50%	17.25%	-0.75%	-0.03%	-0.72%
19 April 2006	15.75%	16.50%	-0.75%	0.02%	-0.77%
31 May 2006	15.25%	15.75%	-0.50%	-0.11%	-0.39%
19 July 2006	14.75%	15.25%	-0.50%	-0.04%	-0.46%
30 August 2006	14.25%	14.75%	-0.50%	-0.20%	-0.30%
18 October 2006	13.75%	14.25%	-0.50%	-0.08%	-0.42%
29 November 2006	13.25%	13.75%	-0.50%	-0.11%	-0.39%

continued

24 January 2007	13.00%	13.25%	-0.25%	0.09%	-0.34%
07 March 2007	12.75%	13.00%	-0.25%	0.01%	-0.26%
18 April 2007	12.50%	12.75%	-0.25%	0.01%	-0.26%
06 June 2007	12.00%	12.50%	-0.50%	-0.13%	-0.37%
18 July 2007	11.50%	12.00%	-0.50%	-0.04%	-0.46%
05 September 2007	11.25%	11.50%	-0.25%	-0.05%	-0.20%
17 October 2007	11.25%	11.25%	0.00%	0.06%	-0.06%
05 December 2007	11.25%	11.25%	0.00%	0.00%	0.00%
23 January 2008	11.25%	11.25%	0.00%	-0.02%	0.02%
05 March 2008	11.25%	11.25%	0.00%	-0.02%	0.02%
16 April 2008	11.75%	11.25%	0.50%	0.16%	0.34%
04 June 2008	12.25%	11.75%	0.50%	-0.03%	0.53%
23 July 2008	13.00%	12.25%	0.75%	0.13%	0.62%
10 September 2008	13.75%	13.00%	0.75%	0.08%	0.67%
29 October 2008	13.75%	13.75%	0.00%	-0.08%	0.08%
10 December 2008	13.75%	13.75%	0.00%	0.07%	-0.07%
21 January 2009	12.75%	13.75%	-1.00%	-0.16%	-0.84%
11 March 2009	11.25%	12.75%	-1.50%	-0.06%	-1.44%
29 April 2009	10.25%	11.25%	-1.00%	-0.01%	-0.99%
10 June 2009	9.25%	10.25%	-1.00%	-0.32%	-0.68%
22 July 2009	8.75%	9.25%	-0.50%	-0.01%	-0.49%
02 September 2009	8.75%	8.75%	0.00%	0.02%	-0.02%
21 October 2009	8.75%	8.75%	0.00%	-0.03%	0.03%
09 December 2009	8.75%	8.75%	0.00%	-0.02%	0.02%
27 January 2010	8.75%	8.75%	0.00%	-0.05%	0.05%
17 March 2010	8.75%	8.75%	0.00%	-0.18%	0.18%
28 April 2010	9.50%	8.75%	0.75%	0.09%	0.66%
09 June 2010	10.25%	9.50%	0.75%	0.06%	0.69%
21 July 2010	10.75%	10.25%	0.50%	-0.05%	0.55%
01 September 2010	10.75%	10.75%	0.00%	-0.02%	0.02%
20 October 2010	10.75%	10.75%	0.00%	0.01%	-0.01%
08 December 2010	10.75%	10.75%	0.00%	-0.09%	0.09%
19 January 2011	11.25%	10.75%	0.50%	-0.01%	0.51%
02 March 2011	11.75%	11.25%	0.50%	0.00%	0.50%
20 April 2011	12.00%	11.75%	0.25%	-0.06%	0.31%
08 June 2011	12.25%	12.00%	0.25%	0.02%	0.23%
20 July 2011	12.50%	12.25%	0.25%	-0.01%	0.26%
31 August 2011	12.00%	12.50%	-0.50%	-0.39%	-0.11%
19 October 2011	11.50%	12.00%	-0.50%	-0.01%	-0.49%
30 November 2011	11.00%	11.50%	-0.50%	0.02%	-0.52%
18 January 2012	10.50%	11.00%	-0.50%	-0.04%	-0.46%
07 March 2012	9.75%	10.50%	-0.75%	-0.14%	-0.61%
18 April 2012	9.00%	9.75%	-0.75%	-0.06%	-0.69%
30 May 2012	8.50%	9.00%	-0.50%	0.02%	-0.52%
11 July 2012	8.00%	8.50%	-0.50%	-0.03%	-0.47%
29 August 2012	7.50%	8.00%	-0.50%	-0.04%	-0.46%
10 October 2012	7.25%	7.50%	-0.25%	-0.03%	-0.22%
28 November 2012	7.25%	7.25%	0.00%	-0.01%	0.01%

continued

16 January 2013	7.25%	7.25%	0.00%	-0.02%	0.02%
06 March 2013	7.25%	7.25%	0.00%	-0.02%	0.02%
17 April 2013	7.50%	7.25%	0.25%	-0.16%	0.41%
29 May 2013	8.00%	7.50%	0.50%	0.16%	0.34%
10 July 2013	8.50%	8.00%	0.50%	-0.01%	0.51%
28 August 2013	9.00%	8.50%	0.50%	0.01%	0.49%
09 October 2013	9.50%	9.00%	0.50%	0.06%	0.44%
27 November 2013	10.00%	9.50%	0.50%	0.03%	0.47%
15 January 2014	10.50%	10.00%	0.50%	0.15%	0.35%
26 February 2014	10.75%	10.50%	0.25%	-0.03%	0.28%
02 April 2014	11.00%	10.75%	0.25%	0.03%	0.22%
28 May 2014	11.00%	11.00%	0.00%	-0.03%	0.03%
16 July 2014	11.00%	11.00%	0.00%	0.00%	0.00%
03 September 2014	11.00%	11.00%	0.00%	0.01%	-0.01%
29 October 2014	11.25%	11.00%	0.25%	0.22%	0.03%
03 December 2014	11.75%	11.25%	0.50%	-0.01%	0.51%
21 January 2015	12.25%	11.75%	0.50%	0.06%	0.44%
04 March 2015	12.75%	12.25%	0.50%	0.01%	0.49%
29 April 2015	13.25%	12.75%	0.50%	0.06%	0.44%
03 June 2015	13.75%	13.25%	0.50%	0.05%	0.45%
29 July 2015	14.25%	13.75%	0.50%	0.09%	0.41%
02 September 2015	14.25%	14.25%	0.00%	-0.05%	0.05%
21 October 2015	14.25%	14.25%	0.00%	-0.01%	0.01%
25 November 2015	14.25%	14.25%	0.00%	-0.01%	0.01%
20 January 2016	14.25%	14.25%	0.00%	-0.19%	0.19%
02 March 2016	14.25%	14.25%	0.00%	-0.01%	0.01%
27 April 2016	14.25%	14.25%	0.00%	0.01%	-0.01%
08 June 2016	14.25%	14.25%	0.00%	0.03%	-0.03%
20 July 2016	14.25%	14.25%	0.00%	0.01%	-0.01%
31 August 2016	14.25%	14.25%	0.00%	0.01%	-0.01%
19 October 2016	14.00%	14.25%	-0.25%	0.07%	-0.32%
30 November 2016	13.75%	14.00%	-0.25%	0.03%	-0.28%

Notes: Data from BM&F Bovespa and Central Bank of Brazil. The strategy of decomposing monetary policy overnight target reference rate changes into two additive components (expected and unexpected) using derivatives' data one-day after each Monetary Policy Committee Announcement replicates Kuttner (2001).

TABLE A.2 - LOAN-LEVEL SUMMARY

	Unit	min	p25	p50	mean	p75	max	sd
Dependent								
$\Delta\ln(\text{credit})_{b,f,t+1:t}$	pp qoq	-144.24	-15.92	-4.97	-0.69	5.70	188.62	45.57
Loan control								
risk_{t-1}	Ln(1 + %)	0.00	0.41	0.50	0.88	1.06	4.62	1.03
Firm Controls								
firm credit_{t-1}	Ln	10.05	12.83	14.11	14.29	15.54	20.37	2.08
n employees_{t-1}	Ln	0.00	1.39	2.20	2.39	3.09	11.31	1.39
avg wage_{t-1}	Ln	0.00	6.50	6.84	6.67	7.18	10.35	1.28
firm default_{t-1}	0/1	0.00	0.00	0.00	0.09	0.00	1.00	0.28
Bank Controls								
size_{t-1}	Ln (BRL Millions)	16.94	25.96	26.86	26.42	27.32	27.76	1.32
capital_{t-1}	% of assets	1.73	6.88	9.82	9.60	11.63	87.03	4.05
liquidity_{t-1}	% of assets	0.94	12.52	18.67	19.58	23.92	86.13	8.32
npl_{t-1}	% of credit	0.00	4.97	5.74	5.95	6.76	87.86	1.89
foreign_{t-1}	0/1	0.00	0.00	0.00	0.16	0.00	1.00	0.37
gov_{t-1}	0/1	0.00	0.00	0.00	0.40	1.00	1.00	0.49
Macro Variables								
Δi^{s}_{t-1}	(accum 12m)	-0.81	-0.33	-0.14	-0.09	0.21	0.91	0.37
Δi^{e}_{t-1}	(accum 12m)	-9.94	-2.67	0.64	-0.27	2.20	3.29	2.92
Δi_{t-1}	pp yoy	-10.25	-3.00	0.50	-0.36	2.00	3.75	3.16
$\Delta i^{T(\Delta CPI)}_{t-1}$	pp yoy	-2.64	-1.35	-0.12	-0.03	1.13	4.08	1.61
$\Delta i^{e,T(\Delta CPI)}_{t-1}$	pp yoy	-10.01	-1.93	-0.02	-0.30	2.16	4.33	2.80
$\Delta i^{T(\Delta CPI,\ \Delta GDP)}_{t-1}$	pp yoy	-2.94	-1.27	-0.11	0.00	1.06	3.65	1.52
$\Delta i^{e,T(\Delta CPI,\ \Delta GDP)}_{t-1}$	pp yoy	-10.15	-2.04	-0.51	-0.33	2.04	4.14	2.84
ΔGDP_{t-1}	pp yoy	-8.00	-2.45	0.36	0.00	2.89	6.60	3.56
ΔCPI_{t-1}	pp yoy	-5.84	-0.35	0.11	0.00	0.56	1.72	0.92
$\Delta Debt/GDP_{t-1}$	pp yoy	-8.05	-3.80	-1.57	0.41	3.35	18.26	6.03
Policy Uncertainty_{t-1}	index	46.26	89.19	131.46	162.68	198.72	457.10	92.22
TCU_{t-1}	index	72.40	80.20	81.10	80.83	82.90	86.50	3.29
Δi^{LT}_{t-1}	pp yoy	-2.90	-0.50	0.00	-0.19	0.00	2.00	0.95
VIX_{t-1}	index	11.03	13.74	16.75	19.35	21.59	58.60	8.15
Δi^{US}_{t-1}	pp yoy	-2.92	-0.09	0.00	-0.13	0.08	2.12	1.10
$i^{US}_{SSR,t-1}$	pp yoy	-2.92	-1.41	-0.69	0.13	1.14	5.35	2.35
Δcommodity price_{t-1}	pp yoy	-56.62	-10.00	2.63	0.05	20.99	43.14	25.85
N observations	4,061,322							
N firms	117,561							
N banks	94							
N quarters	52							

TABLE A.3: FIRM-LEVEL SUMMARY

	Unit	min	p25	p50	mean	p75	max	sd
Dependent								
Δln(credit)$_{f,t+1:t}$	pp qoq	-611.64	-12.89	-3.92	-0.60	9.56	514.89	35.54
Δln(n employees)$_{f,t+1:t}$	pp qoq	-866.81	-6.45	0.00	-1.37	4.88	617.59	29.88
Δln(avg payroll)$_{f,t+1:t}$	pp qoq	-49.84	-0.47	0.00	1.58	4.87	36.34	11.76
Loan control								
risk$_{t-1}$	Ln(1 + %)	0.00	0.39	0.57	0.88	0.98	4.62	0.91
Firm Controls								
firm credit$_{t-1}$	Ln	9.12	12.64	13.86	14.04	15.23	29.79	2.03
n employees$_{t-1}$	Ln	0.00	1.39	2.08	2.24	2.89	11.31	1.29
avg wage$_{t-1}$	Ln	0.00	6.49	6.82	6.63	7.16	10.35	1.33
firm default$_{t-1}$	0/1	0.00	0.00	0.00	0.08	0.00	1.00	0.27
Bank Controls								
size$_{t-1}$	Ln (BRL Millions)	17.55	26.01	26.85	26.57	27.30	27.76	0.97
capital$_{t-1}$	% of assets	2.35	7.43	9.12	9.32	11.00	72.06	2.88
liquidity$_{t-1}$	% of assets	2.19	13.26	17.34	18.98	23.74	70.79	6.67
npl$_{t-1}$	% of credit	0.00	5.09	5.75	5.90	6.54	68.94	1.30
foreign$_{t-1}$	0/1	0.00	0.00	0.00	0.15	0.24	1.00	0.25
gov$_{t-1}$	0/1	0.00	0.03	0.46	0.46	0.79	1.00	0.37
Macro Variables								
Δi^s_{t-1}	(accum 12m)	-0.81	-0.33	-0.14	-0.09	0.21	0.91	0.37
ΔGDP $_{t-1}$	pp yoy	-8.00	-2.45	0.36	-0.06	2.64	6.60	3.59
ΔCPI $_{t-1}$	pp qoq	-5.84	-0.35	0.11	0.00	0.56	1.72	0.92
N observations	1,607,303							
N firms	117,561							
N main banks	91							
N quarters	52							

TABLE A.4: BANK-LEVEL SUMMARY

	Unit	min	p25	p50	mean	p75	max	sd
Bank Controls								
$size_{t-1}$	Ln (BRL Millions)	16.94	20.90	22.19	22.36	23.55	27.76	2.15
$capital_{t-1}$	% of assets	1.73	9.40	13.25	15.83	19.10	87.03	10.31
$liquidity_{t-1}$	% of assets	0.94	14.43	22.15	24.88	32.58	86.13	13.79
npl_{t-1}	% of credit	0.00	2.23	4.65	5.73	7.18	87.86	6.26
$foreign_{t-1}$	0/1	0.00	0.00	0.00	0.23	0.00	1.00	0.42
gov_{t-1}	0/1	0.00	0.00	0.00	0.16	0.00	1.00	0.36
N observations	2,938							
N banks	94							
N quarters	52							

TABLE A.5: MACRO-VARIABLES SUMMARY

	Unit	min	p25	p50	mean	p75	max	sd
Δi^{s}_{t-1}	(accum 12m)	-0.81	-0.34	-0.13	-0.08	0.21	0.91	0.41
Δi^{e}_{t-1}	(accum 12m)	-9.94	-2.97	0.18	-0.70	2.20	3.29	3.29
Δi_{t-1}	pp yoy	-10.25	-3.50	0.25	-0.78	2.00	3.75	3.55
$\Delta i^{T(\Delta CPI)}_{t-1}$	pp yoy	-2.64	-1.44	-0.13	0.00	1.31	4.08	1.69
$\Delta i^{e,T(\Delta CPI)}_{t-1}$	pp yoy	-10.01	-2.45	-0.21	-0.74	1.58	4.33	3.12
$\Delta i^{T(\Delta CPI,\ \Delta GDP)}_{t-1}$	pp yoy	-2.94	-1.29	-0.23	0.00	1.09	3.65	1.60
$\Delta i^{e,T(\Delta CPI,\ \Delta GDP)}_{t-1}$	pp yoy	-10.15	-2.28	-0.80	-0.76	1.70	4.14	3.16
ΔGDP_{t-1}	pp yoy	-8.00	-1.99	0.49	0.27	3.09	6.60	3.55
ΔCPI_{t-1}	pp qoq	-5.84	-0.37	0.01	-0.13	0.51	1.72	1.16
$\Delta Debt/GDP_{t-1}$	pp yoy	-8.05	-4.00	-2.52	-0.21	1.90	18.26	5.97
Politicy $Uncertainty_{t-1}$	index	46.26	87.74	129.41	157.11	190.09	457.10	90.72
TCU_{t-1}	index	72.40	80.15	81.25	80.91	83.10	86.50	3.28
Δi^{LT}_{t-1}	pp yoy	-2.90	-0.68	0.00	-0.30	0.00	2.00	1.04
VIX_{t-1}	index	11.03	13.69	16.61	19.16	21.13	58.60	8.49
Δi^{US}_{t-1}	pp yoy	-2.92	-0.09	0.00	-0.08	0.22	2.12	1.24
$i^{US}_{SSR,t-1}$	pp yoy	-2.92	-1.29	0.05	0.66	2.47	5.35	2.49
Δcommodity $price_{t-1}$	pp yoy	-56.62	-5.83	7.75	2.51	22.61	43.14	25.90
N quarters	52							

TABLE A.6: TAYLOR RESIDUALS

Dependent: $\Delta\ln(\text{credit})_{b,f,t+1:t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta i_{t-1}^{\ T(\Delta CPI)}$ * capital$_{t-1}$	0.036	0.026	0.027	0.020				
	(0.044)	(0.041)	(0.050)	(0.047)				
$\Delta i_{t-1}^{\ e,T(\Delta CPI)}$ * capital$_{t-1}$		0.034		0.018				
		(0.025)		(0.030)				
$\Delta i_{t-1}^{\ T(\Delta CPI)}$			-0.409	-0.438*				
			(0.277)	(0.242)				
$\Delta i_{t-1}^{\ e,T(\Delta CPI)}$				0.083				
				(0.188)				
$\Delta i_{t-1}^{\ T(\Delta CPI,\ \Delta GDP)}$ * capital$_{t-1}$					0.026	0.024	0.020	0.018
					(0.042)	(0.041)	(0.049)	(0.047)
$\Delta i_{t-1}^{\ e,T(\Delta CPI,\ \Delta GDP)}$ * capital$_{t-1}$						0.033		0.019
						(0.024)		(0.029)
$\Delta i_{t-1}^{\ T(\Delta CPI,\ \Delta GDP)}$							-0.431*	-0.440*
							(0.248)	(0.240)
$\Delta i_{t-1}^{\ e,T(\Delta CPI,\ \Delta GDP)}$								0.025
								(0.184)
Observations	4,061,322	4,061,322	4,061,322	4,061,322	4,061,322	4,061,322	4,061,322	4,061,322
R-squared	0.408	0.408	0.055	0.055	0.408	0.408	0.055	0.055
Seasonal effects & Macro controls$_{t-1}$	<>	<>	Yes	Yes	<>	<>	Yes	Yes
Firm Controls$_{t-1}$	<>	<>	Yes	Yes	<>	<>	Yes	Yes
Bank Controls$_{t-1}$ & Risk Control$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Time FE	Yes	Yes	No	No	Yes	Yes	No	No
{ΔCPI_{t-1} , ΔGDP_{t-1}} * Bank Controls$_{t-}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
{$\Delta i^{T}_{\ t-1}$} * Bank Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
{$\Delta i^{e,T}_{\ t-1}$} * Bank Controls$_{t-1}$	No	Yes	No	Yes	No	Yes	No	Yes

continued

Notes: This table presents an alternative assessment using taylor residuals instead of MP surprises. As in Table II, I interact expected and unexpected changes in monetary policy with all bank controls. I use two approches. In the first, one year changes in the overnight target reference rate (Selic) are regressed on CPI.The residuals of this macro regression ($\Delta i_{t-1}^{T(\Delta CPI)}$) are used in models (1) to (4). The predicted values of the same regression represent expected changes in the Selic rate ($\Delta i_{t-1}^{e,T(\Delta CPI)}$). In the second approach, changes in the overnight referece rate are regressed against both CPI and GDP growth and its residuals are used in models (5) to (8), $\Delta i_{t-1}^{T(\Delta CPI,\Delta GDP)}$. Similarly, the predicted values of this second regression represent expected changes in the Selic rate, $\Delta i_{t-1}^{e,T(\Delta CPI,\Delta GDP)}$. All bank controls are interacted with these two proxies. For space limitations, I present only the capital interactions. I use firm*time FEs to control for credit demand shifts in models (1), (2), (5) and (6), and rely on firm, macro-controls, and (time invariant) firm FEs for demand control in the remaining models. All standard errors are two-way clustered at the bank and time dimension. Robust standard errors in parentheses : *** p<0.01, ** p<0.05, * p<0.1. Using only seasonal dummies, the estimated macro regressions for both approaches are:

$$\Delta i_{t-1}^{e,T(\Delta CPI)} = \underset{(0.078)}{0.768\Delta i_{t-2}} + \underset{(0.197)}{1.557\,\Delta CPI_{t-2}}$$

$R^2 = 0.77$

N= 52

$$\Delta i_{t-1}^{e,T(\Delta CPI,\Delta GDP)} = \underset{(0.091)}{0.864\Delta i_{t-2}} + \underset{(0.197)}{1.506\Delta CPI_{t-2}} + \underset{(0.078)}{0.176\,\Delta GDP_{t-2}}$$

$R^2 = 0.80$

N= 52

Previous volumes in this series

All volumes are available on our website www.bis.org.