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Monetary Policy Surprises and Employment: evidence from matched bank-firm loan data on the bank lending-channel

Rodrigo Barbone Gonzalez

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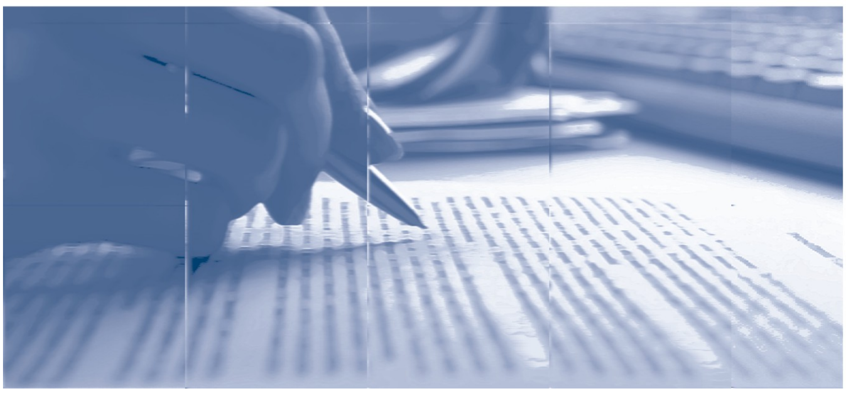

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Non-technical Summary

This paper evaluates the impacts of monetary policy surprises on credit supply and employment using comprehensive loan and firm level data from Brazil. The role of financial intermediaries in the transmission of monetary policy is still a major research topic with implications for academics and policy-makers. Theoretical models introducing heterogeneous agents seek to improve our understanding of the related transmission channels and real effects, but estimating and properly disentangling these channels requires, to a large extent, loan level data. Whereas empirical papers have identified how financially constrained banks amplify monetary policy stimulus increasing credit supply, evidence of the related real effects remains elusive. In this paper, I use a unique panel of loans and firms, mostly "mom and pop shops", and identify a strong credit supply channel with real effects. Firms more reliant on constrained banks for funding not only increase (decrease) their credit intake but also labour demand in response to unexpected monetary stimulus (tightening).

Several empirical papers have estimated the bank lending-channel of monetary policy using loan and firm level data, but the typical identification of unexpected monetary shocks entails Taylor residuals, a narrative approach, or simply the reference rate. Instead, I explore changes in interest rate derivatives immediately after each monetary policy committee announcement for sharper identification. Bringing the high-frequency identification strategy to microdata, I find strong effects of MP surprises on credit supply and evidence that financial intermediaries amplify this transmission channel with second order effects on firms' labour demand. The use of Taylor residuals or the reference rate lead to results of lower magnitude, consistent with an errors-in-variable problem. Firms connected to weaker banks observe 0.26 pp higher credit intake and 0.10 pp higher employment levels following MP stimulus.

Sumário Não-Técnico

Este paper estima o impacto dos choques inesperados (surpresas) de política monetária na oferta de crédito e emprego usando dados de empréstimos e de firmas brasileiras. O papel dos agentes financeiros na transmissão da política monetária ainda representa um tópico de pesquisa importante. Modelos teóricos introduzindo agentes heterogêneos buscam aprimorar o entendimento sobre os canais de transmissão e os efeitos da política monetária, mas estimá-los e identificá-los adequadamente requer, em grande parte, dados de empréstimos. Certos estudos empíricos identificaram como bancos mais reprimidos ("constrained") amplificam o estimulo monetário aumentando a oferta de crédito. No entanto, os efeitos adjacentes na economia real seguem desconhecidos. Neste estudo, emprega-se um painel de empréstimos e de firmas, principalmente de pequeno porte, e identifica-se um canal forte e com efeitos reais da oferta de crédito. As firmas que mais dependem de bancos frágeis para seu financiamento, não apenas aumentam (diminuem) sua exposição a credito, mas também sua demanda por mão-de-obra em resposta a um estímulo monetário.

Diversos estudos estimaram o canal de crédito bancário de política monetária usando dados de empréstimos, mas a estratégica de identificação usual para os choques inesperados de política monetária envolve resíduos da regra de Taylor, abordagem narrativa, ou o uso da taxa de referência. Por outro lado, este paper utiliza variações nos derivativos de taxa de juros imediatamente após os anúncios do Comitê de Política Monetária (COPOM) para uma identificação mais precisa. Conclui-se que os choques inesperados de política monetária identificados com dados de alta- frequência têm efeitos na oferta de crédito e no emprego e que os agentes financeiros com menos capital amplificam o canal de transmissão. Os resíduos de Taylor e o uso da taxa de levam a uma atenuação desses efeitos, em linha com o conceito de erro na variável de medida. Firmas mais dependentes de bancos frágeis para financiamento observam um aumento de 0.26 pontos percentuais na sua exposição a credito e 0.10 pontos percentuais na sua força de trabalho após um estímulo monetário.

Monetary Policy Surprises and Employment: evidence from matched bank-firm loan data on the bank lending-channel

Rodrigo Barbone Gonzalez*

Abstract

This paper investigates the effects of the bank lending-channel of monetary policy (MP) surprises on credit supply and employment. To identify the effects of MP surprises, I bring the high-frequency identification strategy of Kuttner (2001) to comprehensive and matched bank-firm data from Brazil. The results are robust and stronger than the ones obtained with Taylor residuals or the reference rate. Consistent with theory, financial intermediaries' constraints are relevant in the transmission of MP (beyond credit) to the real economy. Firms connected to weaker banks not only observe 0.26 pp higher credit intake, but also employ 0.10 pp more following MP stimulus.

Keywords: monetary policy, surprises, employment, lending-channel, banks
JEL Classification: E52, E51, G21, G28

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1. Introduction

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, 2017). However, the identification of this channel on the supply of credit is challenging, as well as the related effects on employment. On the theoretical front, monetary policy (MP) simultaneously affects credit supply and demand, because bank heterogeneities or financial constraints (capital, share of insured deposits, Value-at-Risk (VaR)) matter for 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), with implications for firms' outcomes.

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 to the literature and to policy-makers. Does the bank lending-channel of MP matter for the average firm? Or, are small and medium enterprises directly affected by the 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 and labour demand?

To address these questions, I estimate the bank lending-channel interacting bank controls that proxy for their strength with MP surprises and estimating the related effects on credit supply, employment, and wages. Importantly, I find that labour demand responds to MP surprises via credit supply and that weaker (stronger) banks amplify (mitigate) this channel. The identification of MP surprises is crucial. Bringing MP surprises identified around MP announcements to 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] and where comprehensive high-quality data on loans and formal employment is available for a period long enough to encompass several monetary policy cycles. 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 Labour 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, Paravisini, 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

[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 greater than 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 labour market to the Ministry of Labour and Employment at each year-end, including each individual hired and fired across the year, their 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 database 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 relationship of the same firm following a MP innovation. Notice that (1) all the average effect on the firm is 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. Khwaja and Mian, 2008). Importantly, the interpretation changes. Despite the neat credit supply identification, if the capital*MP interaction is significant only in the presence

identification of banks' financial constraints on credit supply following MP cycles, 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 and labour supply.

Relatedly, the second challenge is assessing real effects, or how does the bank lending-channel of MP affects labour demand? 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 in the transmission of MP.

The third challenge is properly identifying and measuring unexpected MP changes in a country where monetary policy follows the principles of the Taylor rule. 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 whose monetary policy follows the principles of the 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 cycles. Put differently, identification must focus on unexpected MP changes.

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

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.

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 affect firm level outcomes. These results are not only compositional: MP surprises strongly affect average firms' credit intake and employment decisions in absolute terms. I find that a one-standard positive deviation on MP surprises decreases average quarterly credit by 1.24 percentage points (pp)[6] and employment by 0.20 pp. Firms connected to stronger banks (with one standard deviation higher average capital-to-assets ratio) partially insulate from this MP surprise and contract credit by 0.98 pp and employment by 0.10 pp. Conversely, firms connected to weaker banks observe higher credit intake (1.50 pp) and employment (0.30 pp) following unexpected MP stimulus. I find no statistically 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, and Swanson, 2005, Bernanke and Kuttner, 2005, Chava and Hsu, forthcoming) and on the real economy (e.g. Gertler and Karadi, 2015, Paul, forthcoming). However, none of these papers brings this identification to the loan level data nor directly estimates credit supply responses[7], 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[8] reduces monitoring costs ameliorating this problem via

[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, 0.12 pp accumulated MP surprises would be just as common or "equivalent".

[7] Recent empirical papers bring this high-frequency identification strategy to the firm level data and explore credit demand responses, i.e. the firm borrowing channel (eg. Cloyde, Ferreira, Froemel, and Surico, 2018). However, we bring the identification strategy to the loan level data to explore credit supply responses, i.e. the bank lending-channel. Using loan-level data is imperative to disentangle the bank lending-channel from the firm borrowing channel (see more on Jimenez et al., 2014).

[8] 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

insured deposits (Stein, 1998), bank capital (Holmstrom and Tirole, 2007), and liquidity[9] (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. Khwaja 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. Similarly, I find evidence of a strong channel with bank capital playing the central role.

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 instrumenting MP in different ways[10], but the alternative I implement connects to recent and sound developments in the macro-finance literature (e.g. Gertler and Karadi, 2015, Chava and Hsu, forthcoming), is model-free, and is perhaps more elusive and straightforward to a broader number of countries following a Taylor rule. This alternative is also relevant for countries in the "periphery". While economic conditions in the periphery may not influence MP decisions of the "core economies", banks in peripheral countries are arguably capable of anticipating MP decisions of the core economies. Thus, the errors-

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 financially 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.

[9] 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 transmission of MP.

[10] 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, Altunbas, Gambacorta and Marques-Ibanes, 2014, Black and Rosen, 2016, Delis, Hasan and Mylonidis, 2017). Coelho et al. (2010) uses differences between MP relatively to MP expectations embedded in the most recent survey with market participants. The very influential 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.

in-variables problem documented by Kuttner (2001) and confirmed in this paper is likely to 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, 2017, Amiti and Weinstein, 2011, Chodorow-Reich, 2014, Paravisini et al., 2015).

With respect to unconventional MP, Chakraborty, Goldstein and Mackinlay (forthcoming) find that Treasury purchases in the U.S. had marginal and mostly insignificant effects on investment. MBS purchases, on the other hand, supported the supply of mortgages crowding out corporate credit with negative implications for investment. Acharya et al. (2019) find that unconventional monetary policy from the ECB led weakly capitalized banks to extend credit to zombie firms without broader effects on credit, investment, or employment.

However, my identification strategy does not rely on a quasi-natural experiment or any particular unconventional policy. Instead, I track unexpected MP innovations in long panels[11] of loans and firms and, in both, "normal" and crisis times. To the best of my knowledge, I am the first to identify the effects of (conventional) MP surprises via credit supply on employment, or the real effects of the bank lending-channel using comprehensive microdata. In line with Coimbra and Rey (2017), the results confirm that heterogeneities across financial intermediaries' strength matter for MP transmission to the real economy[12,13].

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

[12] Coimbra and Rey (2017) build a theoretical framework with heterogeneous financial intermediaries and show how their strength affect monetary policy transmission. The implications are qualitatively similar to those of the standard financial accelerator (e.g. Holmstrom and Tirole, 1997), with weaker banks amplifying the MP response and affecting firms' outcomes. In these papers, there are implications for firms' investment (rather than employment) decisions. Greenwald and Stiglitz (1983) build a financial accelerator with more implications for labour demand but a less sophisticated financial sector. Throughout this paper, I take labour demand simply as a proxy for firms' outcome. Considering how small are the firms in my sample, it is impossible to relate to any other outcome.

[13] Ottonelo and Winburry (2019) build a financial accelerator with heterogeneous firms, but the implications differ from those of the standard financial accelerator. In their model, weaker (more financially constrained) firms are less sensitive to MP (via credit demand). Notice that my identification strategy, with multiple bank relationship firms, abstracts from the firm balance sheet problem to focus on the supply of credit from banks.

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

2. 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):

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

The immediate reaction of the interest rate derivatives, or the one-day adjustment in the closing-day 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 and all announcements of the new overnight reference rate (Selic, i) followed COPOM meetings.

Differently from Kuttner (2001), I use the one-day changes in the 30-day interest rate swaps as the main the proxy for MP surprises. 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 to floating) risk-free rate for the following 30 days naturally eliminating this issue. I also replicate this analysis using the 90-day swaps14. In Appendix A.1, I present the monetary policy stance before and after each

[14] The 30-day swap is ideal though, because it will not reflect possible effects related to future COPOM decisions.

COPOM meeting and the related announcement in Brazil between 2003 and 2016 as well as the expected and unexpected component.

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

Insert Figure I about here

To illustrate equation (1) decomposition, I refer to the triangle in Figure I 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 I, a 0 pp change in the announcement date (X-axis) and -0.22 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 rate turned out below expected.

The MP surprises revolve around zero in the sample and are relatively balanced between easing and tightening episodes (Figure I). MP surprises are also abundant across all the sample albeit their magnitude tend to be much lower than the related expected component. In Figure II, 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 II about here

As most of the empirical literature, I estimate the impacts of year-over-year (yoy) changes in the overnight reference rate on credit growth (in log terms) in the following quarter. For consistency, to assess the impacts of 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_{t-1}^{s}. The average value of this variable is -0.09 pp with MP surprises spanning from -0.84 pp to 0.94 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 these expected changes across one year of announcements. The average value of Δi_{t-1}^{e} is -0.27 pp with minimum and maximum of -9.98 pp and 3.26 pp, and a standard deviation of 2.91 pp.

MP surprises have lower magnitude, but are highly informative. In Figure III, I present the correlation between the dependent variable average, quarterly credit growth, and lagged yoy changes in Selic (LHS); and between this dependent variable and MP surprises (Δi_{t-1}^{s}, RHS). Figure III clearly shows negative correlations but much stronger for MP surprises, the main treatment variable in this paper.

Insert Figure III about here

3. 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 de Crédito") 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[15] to each firm. I follow the quarterly dynamics of each bank-firm pair throughout the sample. The main dependent variable is the real growth rate[16] of the bank-firm total credit exposure (in log terms) winsorized.

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 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[17].

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 4,061,265 observations encompassing 117,559 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[18] because all firms with at least one employee must send information related to their labor force to the Ministry of Labor and Employment in

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

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

[17] 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) show 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 9.39 (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).

[18] 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 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.

Brazil at each year-end19. 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** ($\text{firm}_{f,t-1}$): 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 $\text{risk}_{b,f,t-1}$, 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 with loan, firm, bank, and macro-level data (Tables A.2, A.3, A.4, and A.5, respectively).

From (3), I build **bank controls** ($\text{bank}_{b,t-1}$) 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 that identify banks with foreign (foreign_{t-1}) and government control (gov_{t-1}). The main variable that proxies 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).

The **macro-controls** (macro_{t-1}) are the consumer price index (ΔCPI_{t-1}) and GDP growth (ΔGDP_{t-1}). These variables average zero as the sample is 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):

[19] 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.

$$\begin{aligned}\Delta\ln(\text{credit})_{b,f,t+1:t} &= \beta_1 \text{risk}_{b,f,t-1} + \beta_2 \text{bank}_{b,t-1} * \Delta i^{s}_{t-1} + \beta_3\, \text{bank}_{b,t-1} \\ &+ \beta_4 \text{bank}_{b,t-1} * [\Delta\text{CPI}_{t-1}, \Delta\text{DP}\ \ _{t-1}] \\ &+ \alpha_{f,t}, \qquad (2)\end{aligned}$$

where Δi^{s}_{t-1} are MP surprises, $\text{bank}_{b,t-1}$ are bank controls, $\text{risk}_{b,f,t-1}$ is the risk control, β_n are vectors of parameters, 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 high-frequency strategy on the 90-day interest rate swap ($\Delta i^{s,90}_{t-1}$), aggregating MP surprises quarterly (instead of yearly), ($\Delta i^{s,3m}_{t-1}$), and simply using the yoy change in the reference (Selic) rate (Δi_{t-1}) for comparison (e.g. Jimenez et al., 2012, 2014).

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.

$$\begin{aligned}\Delta\ln(\text{credit})_{b,f,t+1:t} &= \beta_1 \text{risk}_{b,f,t-1} + \beta_2 \text{bank}_{b,t-1} * \Delta i^{s}_{t-1} + \beta_3 \text{bank}_{b,t-1} \\ &+ \beta_4\, \text{bank}_{b,t-1} * [\Delta\text{CPI}_{t-1}, \Delta\text{DP}\ \ _{t-1}] \\ &+ \beta_5 \text{bank}_{b,t-1} * \Delta i^{e}_{t-1} \\ &+ \alpha_{f,t}, \qquad (3)\end{aligned}$$

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

$$\begin{aligned}\Delta\ln(\text{credit})_{f,t+1:t} \\ &= \beta_1 \text{risk}_{f,t-1} + \beta_2 \text{bank}_{f,t-1} * \Delta i^s_{,t-1} + \beta_3 \text{bank}_{f,t-1} \\ &+ \beta_4 \text{bank}_{f,t-1} * [\Delta\text{CPI}_{t-1}, \Delta\text{DP}\ _{t-1}] + \beta_5\ \text{firm}_{f,t-1} \\ &+ \alpha_{r,t} + \alpha_{s,t} + \alpha_{\bar{b}}\ , \qquad (4)\end{aligned}$$

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. The main bank ($\alpha_{\bar{b}}$) is the *ex-ante* most representative credit provider of firm *f*; thus, introducing $\alpha_{\bar{b}}$ prevent the results from being driven by few (large and overly represented) banks. In the absence firm*time FEs($\alpha_{f,t}$), 2-digit sector*time ($\alpha_{s,t}$), region*time ($\alpha_{r,t}$) FEs, and $\text{firm}_{f,t-1}$ control (altogether) for firm demand shifts. I also run regressions with macro-controls and seasonal dummies to assess the effects of Δi^s_{t-1} on the average firm. Finally, I take the quarterly logarithmic changes in firm employment, Δln(n employees)$_{f,t+1:t}$, and average wages, Δln(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):

$$\begin{aligned}\Delta\ln(\text{credit})_{b,f,t+1:t} \\ &= \beta_1 \text{risk}_{b,f,t-1} + \beta_2 \text{bank}_{b,t-1} * \Delta i^s_{t-1} + \beta_3 \text{bank}_{b,t-1} \\ &+ \beta_4 \text{bank}_{b,t-1} * [\Delta\text{CPI}_{t-1}, \Delta\text{DP}\ _{t-1}] \\ &+ \beta_5 \text{bank}_{b,t-1} * X_{t-1} \\ &+ \alpha_{f,t}, \qquad (5)\end{aligned}$$

where X_{t-1} can be the yoy change in the US overnight interest rates (Δi^{US}_{t-1}), the US short shadow rate (i^{SSR}_{t-1}. See Wu and Xia (2016)), the US equity volatility index (VIX), the yoy change in commodity prices (Δcommodity prices$_{t-1}$), the yoy change in the debt-to-gdp ratio (ΔDebt/GDP$_{t-1}$), the economic policy uncertainty index for Brazil (Policy Uncertainty$_{t-1}$ from

Baker, Bloom, and Davis, 2016), the total capacity utilization index (TCU_{t-1}), and the yoy change in the Brazilian long-term interest rates[20] (Δi^{LT}_{t-1}).

4. 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 below (above) the mean as the weaker (stronger) bank.

Table I represents the estimates related to equation (2) 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

I present estimates of MP surprises (Δi^{s}_{t-1}) altogether with the bank capital interaction and related effects on credit. MP surprises have average strong negative effects on credit, but banks with higher core capital-to-assets ratio alleviate these effects. Other controls are also worth mentioning. A 1 pp higher GDP growth in the past year is associated with 0.42 pp more credit in the following quarter (column 1). Riskier firm-bank relationships (with a one-standard deviation higher *ex-ante* provisions, $risk_{b,f,t-1}$) are associated with -3.29 pp less credit. Higher bank capital and size are on average associated with higher credit growth.

Introducing interactions with the remaining bank controls renders similar results 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, 0.37 pp at the loan-level, is associated with a 0.83 (2.258*0.37 – column 3) pp decline in quarterly credit. The weaker bank[21] contracts credit by 0.54 pp more, i.e. 1.37 pp in total (0.37*(2.258 + 0.362*4.05)).

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

[20] "Taxa de Juros de Longo-Prazo (TLJP) ".

[21] The standard deviation of the capital ratio is 4.05% at the loan level (See Table A.2).

compositional (or relative – column 5) and average (or absolute - column 3) effects of the bank capital interaction are comparable[22]. This is important because most of the empirical literature focuses on compositional (or relative) results alone for identification of credit supply. However, the channel may not matter for the average firm if average (absolute) estimates are not significant.

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 0.63 (0.426*4.05*0.37) pp more following a one-standard deviation positive MP surprise, i.e. tightening. The less liquid and smaller banks (one-standard deviation below the mean of these variables) contract credit more, 0.50 (0.164*8.32*0.37) pp and 0.54 (1.107*1.32*0.37) pp respectively, following the same MP surprise. All these 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 bank 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 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 yoy change 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 yoy change in the Selic rate (3.16 pp) would contract credit on average by 0.34 (0.107*3.16) pp, about half of the estimate presented in 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 (0.035*4.05*3.16), 0.68 (0.026*8.32*3.16), and 0.52 (0.124*1.32*3.16) pp 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 of these residuals (1.52 pp) is associated with a statistically significant average contraction of 0.67 (0.441*1.52 – column 8) pp on credit, but the bank capital interaction 0.12 (0.02*1.52*4 – column 6) pp is not significant.

[22] According to Oster (2019), observing (altogether) modest changes in coefficients and a large increase in R^2 (about 35%), such as in columns (3) and (5), suggests that (unobserved) credit demand is indeed orthogonal to these bank interactions.

Finally, I turn to the real effects of MP surprises on the firms. I first collapse the panel (from the bank-firm-time) 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 estimates 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 effects of a one-standard deviation positive MP surprise on the average firm is a 1.24 (3.359*0.37 - column 1) pp credit contraction. More importantly, heterogeneities across financial intermediaries' strength, i.e. capital, matter for the average firm. A firm connected to stronger banks[23] receives a substantially lower MP surprise and faces a 0.20 (0.185*2.88*0.37) to 0.26 (0.246*2.88*0.37) pp lower credit contraction (columns 1 and 3, respectively). I add sector*time and region*time FEs to column (2) and main bank FEs to column (3). In the absence of firm*time FEs, these controls alleviate concerns that credit demand shifts and few influential banks drive the results.

The real effects on quarterly employment of the same MP surprise are also statistically and economically significant. The average firm faces an employment contraction of 0.20 (0.537*0.37 - column 4) pp. Within the same sector, region and quarter, a firm connected to stronger banks receives a substantially lower MP surprise and faces up to a 0.10 (0.092*2.88*0.37 - column 6) pp lower quarterly contraction, i.e. 0.10 pp in total. Conversely, firms connected to weaker banks observe higher credit intake (1.50 pp) and employment outcome (0.30 pp) following unexpected MP stimulus. I find no statistically significant effects on wages (columns 7, 8 and 9).

To alleviate concerns that the lending channel of MP surprises reflect other possibly correlated global macro-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 yoy 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

[23] The standard deviation of the capital ratio is 2.88% at the firm level. The bank controls are weighted using the *ex-ante* firm-bank credit exposure.

interactions, but I simultaneously horserace the bank controls and global shocks against all 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 bank 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 variables are considered altogether but none is significant nor affects 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 influential quarters drive the results, I regress the baseline model excluding the GFC quarters (column 2) in Table VI. I also exclude the government banks (column 3) and foreign banks (column 4) without any material change in the bank capital and MP interaction.

Insert Table VI about here

I use the 90-day interest rate swaps (instead of the 30-day) in Appendix A.7 and find similar results (columns 1 and 2). Although my preference is regressing one year of accumulated MP surprises on quarterly credit growth mimicking the typical alternative of using the yoy change on the reference rate as an MP proxy (e.g. Jimenez et al., 2012, 2014), I accumulate MP surprises quarterly in columns (3) and (4). With this latter alternative proxy, I find that the average response to a positive one-standard deviation MP surprise (0.15 pp) is -1.12 (7.438*0.15) pp. The weaker bank responds with -1.62 (0.15*(7.438+0.841*4.05)) pp.

5. Final Remarks

The theoretical literature highlights the amplifying role of financial intermediaries' strength in the transmission of monetary policy from credit to the real economy (e.g. Holmstrom and Tirole, 1997, Coimbra and Rey, 2017). Whereas the empirical literature has neatly identified the "first order" effects of the bank lending-channel, i.e. the amplifying role of bank capital on credit supply (e.g. Kashyap and Stein, 2000, Jimenez et al., 2012), it had not yet presented evidence of the "second order" effects into the real economy. Put differently, are firms more (less) reliant on weaker banks for funding also more (less) exposed to monetary policy? Beyond credit allocation, what are the real effects to the economy?

In this paper, I present evidence that the bank lending-channel of MP surprises have strong effects, not only on credit supply, but also on labour demand of Brazilian firms. For identification, I rely on matched, comprehensive, and exhaustive loan and firm level data from mostly small and medium enterprises, and I find that this channel is operative on the average Brazilian firm. MP surprises have stronger effects on firms connected to weaker banks, leading to a deeper decline (increase) on their credit intake and employment outcomes following tightening (loosening) episodes.

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, while 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. 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, Chava and Hsu, forthcoming, Paul, forthcoming), researchers empowered with exhaustive databases not always share the same concerns. The results presented in this paper help to qualify a number of influential 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.

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FIGURES

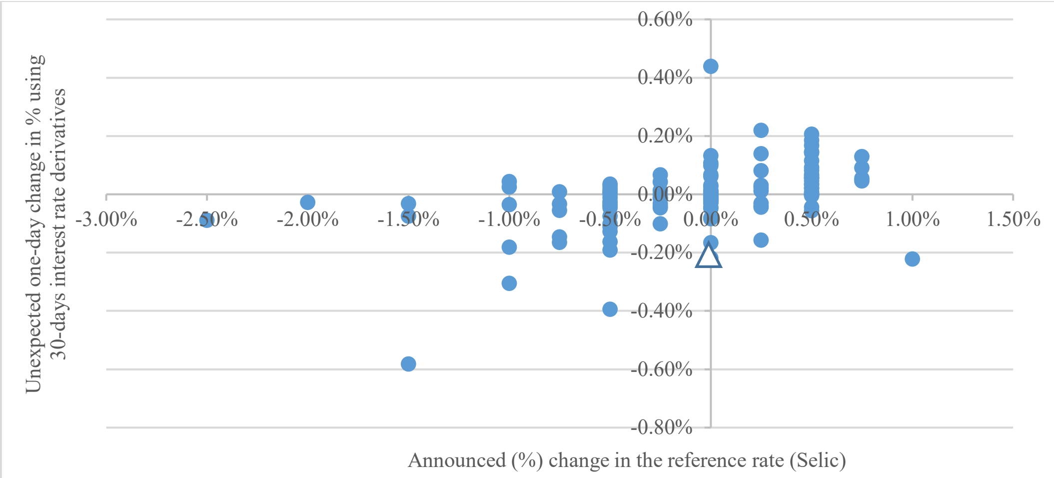

FIGURE I.

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)

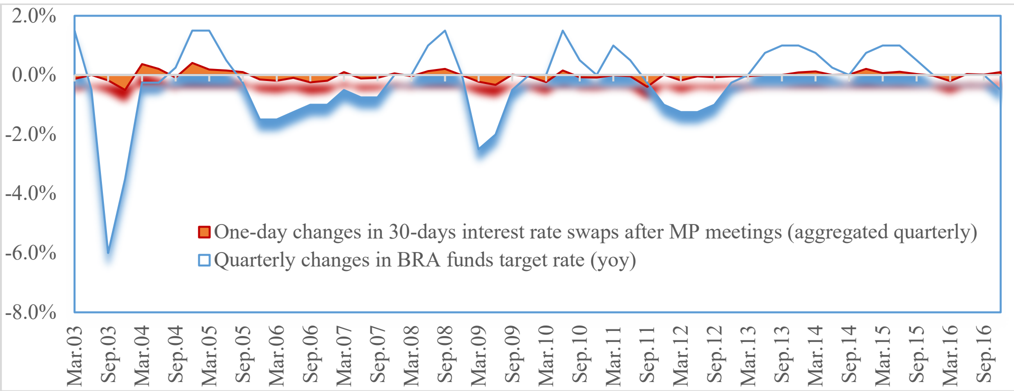

FIGURE II.

MP SURPRISES ACROSS TIME

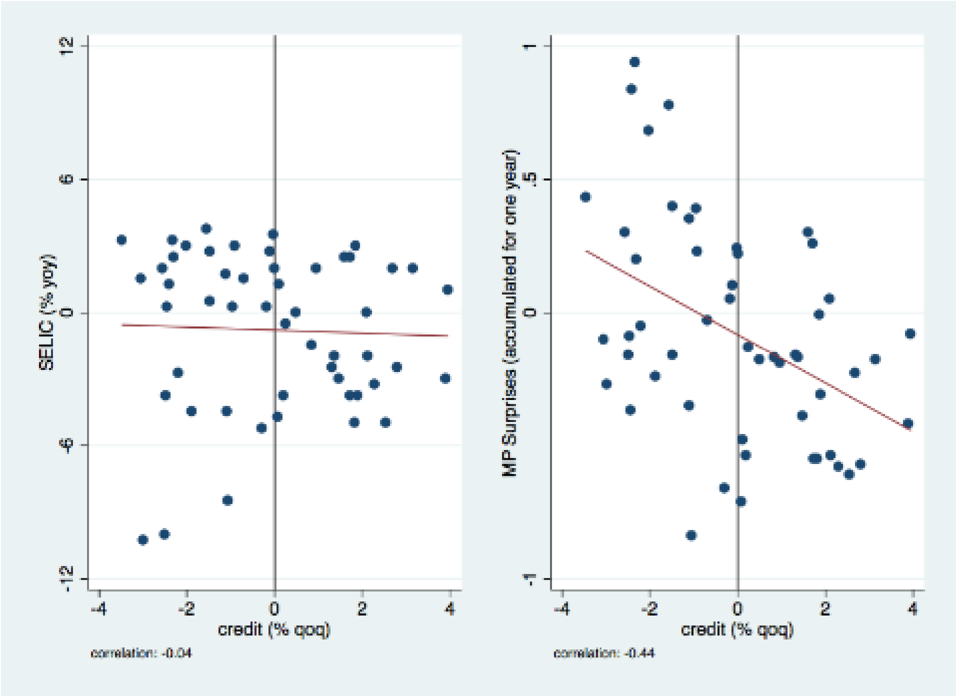

FIGURE III

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}	0.246*	0.418**	0.362**	0.419**	0.426**
	(0.131)	(0.166)	(0.172)	(0.177)	(0.202)
Δi^{s}_{t-1} * size_{t-1}		0.853*	0.747*	1.155**	1.107**
		(0.455)	(0.376)	(0.432)	(0.424)
Δi^{s}_{t-1} * liquidity_{t-1}		0.151	0.064	0.197**	0.164**
		(0.132)	(0.117)	(0.088)	(0.073)
Δi^{s}_{t-1} * npl_{t-1}		-0.402	-0.259	-0.390**	-0.265
		(0.245)	(0.275)	(0.166)	(0.167)
Δi^{s}_{t-1} * gov_{t-1}		0.511	0.154	-0.677	-0.643
		(1.659)	(1.544)	(1.781)	(1.845)
Δi^{s}_{t-1} * foreign_{t-1}		0.293	1.165	-0.611	0.197
		(1.178)	(0.950)	(1.190)	(1.082)
risk_{t-1}	-3.289***	-3.287***	-3.258***	-1.386***	-1.377***
	(0.314)	(0.321)	(0.327)	(0.147)	(0.153)
capital_{t-1}	0.282***	0.287***	0.272***	0.232***	0.225**
	(0.073)	(0.080)	(0.086)	(0.081)	(0.089)
size_{t-1}	1.579***	1.563***	1.631***	0.945***	0.976***
	(0.318)	(0.327)	(0.321)	(0.285)	(0.260)
liquidity_{t-1}	0.014	0.011	0.016	-0.052	-0.050
	(0.052)	(0.054)	(0.063)	(0.037)	(0.041)
npl_{t-1}	-0.201	-0.181	-0.112	-0.049	-0.057
	(0.258)	(0.300)	(0.277)	(0.173)	(0.182)
gov_{t-1}	1.798*	1.898*	1.862*	2.607***	2.514***
	(0.933)	(0.958)	(0.971)	(0.887)	(0.899)
foreign_{t-1}	-1.679**	-1.656**	-1.789**	-1.116	-1.228*
	(0.771)	(0.785)	(0.685)	(0.669)	(0.614)
firm credit_{t-1}	-7.601***	-7.597***	-7.650***		
	(0.439)	(0.443)	(0.448)		
n employees_{t-1}	3.945***	3.944***	3.935***		
	(0.214)	(0.222)	(0.218)		
avg payroll_{t-1}	-0.466***	-0.465***	-0.461***		
	(0.084)	(0.085)	(0.091)		
firm default_{t-1}	-4.806***	-4.810***	-4.809***		
	(0.536)	(0.548)	(0.534)		
Δi^{s}_{t-1}	-2.255***	-2.592**	-2.258**		
	(0.502)	(1.283)	(1.107)		
ΔGDP_{t-1}	0.423***	0.417***	0.414***		
	(0.097)	(0.104)	(0.141)		
ΔCPI_{t-1}	0.081	0.114	0.366		
	(0.350)	(0.334)	(0.503)		

continued

Observations	4,061,265	4,061,265	4,061,265	4,061,265	4,061,265
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	117559	117559	117559	117559	117559
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)
	(0.172)	(0.188)	(0.239)		(0.029)	(0.024)
Δi^{s}_{t-1} * size_{t-1}	0.747*	0.491	0.891*	Δi_{t-1} * size_{t-1}	0.070	0.124**
	(0.376)	(0.384)	(0.466)		(0.073)	(0.055)
Δi^{s}_{t-1} * liquidity_{t-1}	0.064	-0.083	0.062	Δi_{t-1} * liquidity_{t-1}	0.019	0.026**
	(0.117)	(0.144)	(0.130)		(0.014)	(0.012)
Δi^{s}_{t-1} * npl_{t-1}	-0.259	-0.197	-0.265	Δi_{t-1} * npl_{t-1}	-0.025	0.043
	(0.275)	(0.331)	(0.201)		(0.268)	(0.264)
Δi^{s}_{t-1} * gov_{t-1}	0.154	0.001	-1.544	Δi_{t-1} * gov_{t-1}	-0.013	0.024
	(1.544)	(1.725)	(2.395)		(0.209)	(0.176)
Δi^{s}_{t-1} * foreign_{t-1}	1.165	1.616	-0.199	Δi_{t-1} * foreign_{t-1}	-0.032	-0.024
	(0.950)	(1.439)	(1.727)		(0.030)	(0.024)
Δi^{e}_{t-1} * capital_{t-1}		-0.003	0.002			
		(0.036)	(0.033)			
Δi^{e}_{t-1} * size_{t-1}		0.052	0.063			
		(0.100)	(0.077)			
Δi^{e}_{t-1} * liquidity_{t-1}		0.033	0.024			
		(0.020)	(0.021)			
Δi^{e}_{t-1} * npl_{t-1}		-0.009	0.005			
		(0.034)	(0.027)			
Δi^{e}_{t-1} * gov_{t-1}		0.027	0.194			
		(0.352)	(0.379)			
Δi^{e}_{t-1} * foreign_{t-1}		-0.118	0.074			
		(0.318)	(0.305)			

continued

Δi^{s}_{t-1}	-2.258**	-3.081***		Δi_{t-1}	-0.107	
	(1.107)	(0.890)			(0.182)	
Δi^{e}_{t-1}		0.171				
		(0.196)				
ΔGDP_{t-1}	0.414***	0.414***		ΔGDP_{t-1}	0.468***	
	(0.141)	(0.141)			(0.145)	
CPI_{t-1}	0.366	0.293		CPI_{t-1}	0.157	
	(0.503)	(0.478)			(0.503)	
Observations	4,061,265	4,061,265	4,061,265	Observations	4,061,265	4,061,265
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)
	(0.102)	(0.089)	(0.101)	(0.057)	(0.039)	(0.039)	(0.035)	(0.013)	(0.012)
Δi^{s}_{t-1} * size_{t-1}	-0.373	0.041	0.115	-0.473**	-0.042	-0.041	0.086	0.099	0.110
	(0.416)	(0.378)	(0.377)	(0.209)	(0.110)	(0.113)	(0.120)	(0.071)	(0.070)
Δi^{s}_{t-1} * liquidity_{t-1}	-0.092	0.013	0.009	-0.042	0.008	0.006	0.023	0.007	0.007
	(0.097)	(0.075)	(0.065)	(0.040)	(0.021)	(0.021)	(0.029)	(0.005)	(0.006)
Δi^{s}_{t-1} * npl_{t-1}	-0.183	-0.254*	-0.214*	0.006	-0.058	-0.048	-0.014	-0.058***	-0.055***
	(0.200)	(0.127)	(0.119)	(0.083)	(0.051)	(0.052)	(0.042)	(0.017)	(0.017)
Δi^{s}_{t-1} * gov_{t-1}	1.553	1.732	1.670	0.166	0.079	0.135	-0.034	-0.098	-0.075
	(1.353)	(1.373)	(1.387)	(0.201)	(0.249)	(0.233)	(0.070)	(0.111)	(0.107)
Δi^{s}_{t-1} * foreign_{t-1}	1.296	1.246	0.921	0.042	-0.041	-0.027	0.115	0.080	0.085
	(0.963)	(0.921)	(0.872)	(0.254)	(0.124)	(0.148)	(0.157)	(0.129)	(0.125)
Δi^{s}_{t-1}	-3.359***			-0.537*			-0.165		
	(1.039)			(0.280)			(0.267)		
ΔGDP_{t-1}	0.528***			0.215***			-0.045		
	(0.139)			(0.045)			(0.028)		
CPI_{t-1}	0.387			-0.080			-0.136		
	(0.474)			(0.082)			(0.120)		
Observations	1,607,278	1,607,278	1,607,278	1,607,278	1,607,278	1,607,278	1,607,278	1,607,278	1,607,278
R-squared	0.187	0.197	0.197	0.174	0.184	0.184	0.274	0.282	0.282
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
$\{\Delta \text{CPI}_{t-1}, \Delta \text{GDP}_{t-1}\}$ * Bank Controls_{t-1}	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal effects & Macro controls_{t-1}	Yes	<>	<>	Yes	<>	<>	Yes	<>	<>
Sector*Time FE & Region*Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Main Bank FE	No	No	Yes	No	No	Yes	No	No	Yes
Cluster					main bank & time				

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, sector*time and regin*time FEs in all other models. In models (3), (6) and (9), I introduce the main bank FE. The main bank is the one to which the firm has the largest ex-ante 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)
	(0.202)	(0.221)	(0.192)	(0.205)	(0.194)	(0.182)
Δi^{US}_{t-1} * capital$_{t-1}$		0.017				-0.120
		(0.085)				(0.129)
$i^{US}_{SSR,t-1}$ * capital$_{t-1}$			0.078**			0.084**
			(0.033)			(0.037)
VIX$_{t-1}$ * capital$_{t-1}$				-0.002		-0.007
				(0.008)		(0.015)
Δcommodity prices$_{t-1}$ * capital$_{t-1}$					0.007	0.008
					(0.005)	(0.008)
Observations	4,061,265	4,061,265	4,061,265	4,061,265	4,061,265	4,061,265
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
$\{\Delta i^{s}_{t-1}\}$ * Bank Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
$\{\Delta CPI_{t-1}, \Delta GDP_{t-1}\}$ * Bank Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
$\{\Delta i^{US}_{t-1}\}$ * 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
$\{\Delta$commodity 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 ($i^{US}_{SSR,t-1}$. 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)
	(0.202)	(0.203)	(0.177)	(0.204)	(0.208)	(0.183)
ΔDebt/GDP$_{t-1}$ * capital$_{t-1}$		-0.001				0.013
		(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		0.034
				(0.033)		(0.042)
Δi^{LT}_{t-1} * capital$_{t-1}$					-0.002	-0.082
					(0.086)	(0.101)
Observations	4,061,265	4,061,265	4,061,265	4,061,265	4,061,265	4,061,265
R-squared	0.408	0.409	0.408	0.408	0.408	0.409
Bank Controls$_{t-1}$ & Risk Control$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
{Δi^{s}_{t-1} } * Bank Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
{ΔCPI$_{t-1}$, ΔGDP$_{t-1}$ } * Bank Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
{ΔDebt/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 (ΔDebt/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 government banks

Dependent: $\Delta \ln(\text{credit})_{b,f,t+1:t}$	(1) All quarters	(2) No GFC quarters	(3) No gov banks	(4) No foreign banks
Δi^{s}_{t-1} * capital$_{t-1}$	0.426**	0.288**	0.483*	0.296*
	(0.202)	(0.140)	(0.286)	(0.169)
Δi^{s}_{t-1} * size$_{t-1}$	1.107**	0.678***	1.897***	0.986***
	(0.424)	(0.225)	(0.518)	(0.291)
Δi^{s}_{t-1} * liquidity$_{t-1}$	0.164**	0.167**	0.085	0.118
	(0.073)	(0.077)	(0.095)	(0.077)
Δi^{s}_{t-1} * npl$_{t-1}$	-0.265	-0.303*	-1.056***	-0.084
	(0.167)	(0.162)	(0.218)	(0.206)
Δi^{s}_{t-1} * gov$_{t-1}$	-0.643	-1.493		
	(1.845)	(1.686)		
Δi^{s}_{t-1} * foreign$_{t-1}$	0.197	-0.647		
	(1.082)	(0.791)		
Observations	4,061,265	3,579,536	1,745,734	3,122,488
R-squared	0.408	0.409	0.429	0.434
Firm*Time FE	Yes	Yes	Yes	Yes
{ΔCPI_{t-1} , ΔGDP_{t-1} } * Bank Controls$_{t-1}$	Yes	Yes	Yes	Yes
{Δi^{s}_{t-1} } * Bank Controls$_{t-1}$	Yes	Yes	Yes	Yes
N firms	117559	115588	61711	98520
N banks	94	94	82	68
Cluster	bank & time			

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%	-0.22%	1.22%
19 March 2003	26.50%	26.50%	0.00%	-0.02%	0.02%
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%	-0.09%	-2.41%
17 September 2003	20.00%	22.00%	-2.00%	-0.03%	-1.97%
22 October 2003	19.00%	20.00%	-1.00%	0.04%	-1.04%
19 November 2003	17.50%	19.00%	-1.50%	-0.58%	-0.92%
17 December 2003	16.50%	17.50%	-1.00%	0.02%	-1.03%
21 January 2004	16.50%	16.50%	0.00%	0.44%	-0.44%
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%	-0.01%	-0.24%
19 May 2004	16.00%	16.00%	0.00%	0.13%	-0.13%
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%	0.21%	0.29%
17 November 2004	17.25%	16.75%	0.50%	0.09%	0.41%
15 December 2004	17.75%	17.25%	0.50%	0.12%	0.38%
19 January 2005	18.25%	17.75%	0.50%	0.03%	0.47%
15 June 2005	19.75%	19.75%	0.00%	-0.02%	0.02%
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%	-0.16%	-0.34%
23 November 2005	18.50%	19.00%	-0.50%	0.01%	-0.51%
14 December 2005	18.00%	18.50%	-0.50%	0.02%	-0.52%
18 January 2006	17.25%	18.00%	-0.75%	-0.17%	-0.58%
08 March 2006	16.50%	17.25%	-0.75%	-0.03%	-0.72%
19 April 2006	15.75%	16.50%	-0.75%	0.01%	-0.76%
31 May 2006	15.25%	15.75%	-0.50%	-0.10%	-0.40%
19 July 2006	14.75%	15.25%	-0.50%	-0.04%	-0.46%
30 August 2006	14.25%	14.75%	-0.50%	-0.19%	-0.31%
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%	-0.05%	-0.20%
07 March 2007	12.75%	13.00%	-0.25%	0.00%	-0.25%
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%	-0.04%	-0.21%
17 October 2007	11.25%	11.25%	0.00%	0.07%	-0.07%
05 December 2007	11.25%	11.25%	0.00%	0.00%	0.00%
23 January 2008	11.25%	11.25%	0.00%	-0.03%	0.03%
05 March 2008	11.25%	11.25%	0.00%	-0.01%	0.01%
16 April 2008	11.75%	11.25%	0.50%	0.14%	0.36%
04 June 2008	12.25%	11.75%	0.50%	-0.04%	0.54%
23 July 2008	13.00%	12.25%	0.75%	0.13%	0.62%
10 September 2008	13.75%	13.00%	0.75%	0.05%	0.70%
29 October 2008	13.75%	13.75%	0.00%	-0.08%	0.08%
10 December 2008	13.75%	13.75%	0.00%	0.11%	-0.11%
21 January 2009	12.75%	13.75%	-1.00%	-0.18%	-0.82%
11 March 2009	11.25%	12.75%	-1.50%	-0.07%	-1.43%
29 April 2009	10.25%	11.25%	-1.00%	-0.03%	-0.97%
10 June 2009	9.25%	10.25%	-1.00%	-0.31%	-0.69%
22 July 2009	8.75%	9.25%	-0.50%	-0.01%	-0.49%
02 September 2009	8.75%	8.75%	0.00%	0.03%	-0.03%
21 October 2009	8.75%	8.75%	0.00%	-0.01%	0.01%
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%	-0.17%	0.17%
28 April 2010	9.50%	8.75%	0.75%	0.09%	0.66%
09 June 2010	10.25%	9.50%	0.75%	0.05%	0.70%
21 July 2010	10.75%	10.25%	0.50%	-0.06%	0.56%
01 September 2010	10.75%	10.75%	0.00%	-0.03%	0.03%
20 October 2010	10.75%	10.75%	0.00%	0.01%	-0.01%
08 December 2010	10.75%	10.75%	0.00%	-0.08%	0.08%
19 January 2011	11.25%	10.75%	0.50%	0.00%	0.50%
02 March 2011	11.75%	11.25%	0.50%	0.00%	0.50%
20 April 2011	12.00%	11.75%	0.25%	-0.04%	0.29%
08 June 2011	12.25%	12.00%	0.25%	0.01%	0.24%
20 July 2011	12.50%	12.25%	0.25%	0.02%	0.23%
31 August 2011	12.00%	12.50%	-0.50%	-0.39%	-0.11%
19 October 2011	11.50%	12.00%	-0.50%	0.00%	-0.50%
30 November 2011	11.00%	11.50%	-0.50%	0.03%	-0.53%
18 January 2012	10.50%	11.00%	-0.50%	-0.03%	-0.47%
07 March 2012	9.75%	10.50%	-0.75%	-0.15%	-0.60%
18 April 2012	9.00%	9.75%	-0.75%	-0.06%	-0.69%
30 May 2012	8.50%	9.00%	-0.50%	0.03%	-0.53%
11 July 2012	8.00%	8.50%	-0.50%	-0.03%	-0.47%
29 August 2012	7.50%	8.00%	-0.50%	-0.05%	-0.45%
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%	-0.01%	0.01%
17 April 2013	7.50%	7.25%	0.25%	-0.16%	0.41%
29 May 2013	8.00%	7.50%	0.50%	0.17%	0.33%
10 July 2013	8.50%	8.00%	0.50%	0.00%	0.50%
28 August 2013	9.00%	8.50%	0.50%	0.02%	0.48%
09 October 2013	9.50%	9.00%	0.50%	0.06%	0.44%
27 November 2013	10.00%	9.50%	0.50%	0.04%	0.46%
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%	0.01%	-0.01%
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%	0.00%	0.50%
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%	0.08%	0.42%
02 September 2015	14.25%	14.25%	0.00%	-0.04%	0.04%
21 October 2015	14.25%	14.25%	0.00%	0.00%	0.00%
25 November 2015	14.25%	14.25%	0.00%	-0.01%	0.01%
20 January 2016	14.25%	14.25%	0.00%	-0.22%	0.22%
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%	0.04%	-0.29%

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
$\text{firm default}_{t-1}$	0/1	0.00	0.00	0.00	0.09	0.00	1.00	0.28
Bank Controls								
size_{t-1}	Ln (BRL Millions)	-9.50	-0.47	0.42	-0.01	0.89	1.32	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	-17.89	-6.98	-0.82	0.08	4.43	66.64	8.32
npl_{t-1}	% of credit	-5.96	-0.99	-0.22	-0.01	0.80	50.89	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)	-0.84	-0.37	-0.16	-0.09	0.22	0.94	0.37
Δi^{e}_{t-1}	(accum 12m)	-9.98	-2.61	0.62	-0.27	2.20	3.26	2.91
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
$\Delta i^{s,90}_{t-1}$	(accum 12m)	-0.90	-0.46	-0.20	-0.14	0.13	1.23	0.42
$\Delta i^{s,3m}_{t-1}$	(accum 3m)	-0.51	-0.08	0.00	-0.02	0.06	0.41	0.15
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
$\text{Policy Uncertainty}_{t-1}$	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
$\Delta \text{commodity price}_{t-1}$	pp yoy	-56.62	-10.00	2.63	0.05	20.99	43.14	25.85

N observations	4,061,265	N banks	94
N firms	117,559	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)	-0.84	-0.37	-0.16	-0.09	0.22	0.94	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	1,607,278							
N firms	117,559							
N main banks	91							
N quarters	52							
N sectors	76							
N regions	98							

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	56.45	5.90
$foreign_{t-1}$	0/1	0.00	0.00	0.00	0.21	0.00	1.00	0.41
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

	Unit	min	p25	p50	mean	p75	max	sd
Δi^{s}_{t-1}	yoy (acum)	-0.84	-0.38	-0.16	-0.08	0.23	0.94	0.41
Δi^{e}_{t-1}	yoy (acum)	-9.98	-2.95	0.19	-0.70	2.20	3.26	3.28
Δi_{t-1}	pp yoy	-10.25	-3.50	0.25	-0.78	2.00	3.75	3.55
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
$\Delta i^{T(\Delta CPI)}_{t-1}$	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
$\Delta i^{s,90}_{t-1}$	(accum 12m)	-0.90	-0.45	-0.21	-0.11	0.14	1.23	0.46
$\Delta i^{s,3m}_{t-1}$	(accum 3m)	-0.51	-0.09	-0.01	-0.02	0.07	0.41	0.17
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)
	(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)				
$\Delta i_{t-1}^{\ e,T(\Delta CPI)}$				0.084				
				(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*	-0.441*
							(0.248)	(0.240)
$\Delta i_{t-1}^{\ e,T(\Delta CPI,\ \Delta GDP)}$								0.026
								(0.184)
Observations	4,061,265	4,061,265	4,061,265	4,061,265	4,061,265	4,061,265	4,061,265	4,061,265
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

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

TABLE A.7: ALTERNATIVE INTEREST RATES

	(1)	(2)	(3)	(4)
Dependent: $\Delta\ln(\text{credit})_{b,f,t+1:t}$	$\Delta i^{s,90}_{t-1}$		$\Delta i^{s,3m}_{t-1}$	
Δi^{s}_{t-1} * capital_{t-1}	0.377***	0.397**	0.616	0.841*
	(0.137)	(0.171)	(0.525)	(0.497)
Δi^{s}_{t-1} * size_{t-1}	0.799***	1.031***	1.905	2.696*
	(0.212)	(0.305)	(1.411)	(1.441)
Δi^{s}_{t-1} * liquidity_{t-1}	0.068	0.136**	0.325	0.746***
	(0.097)	(0.067)	(0.243)	(0.210)
Δi^{s}_{t-1} * npl_{t-1}	-0.193	-0.235*	-0.815	-0.948***
	(0.212)	(0.121)	(0.537)	(0.308)
Δi^{s}_{t-1} * gov_{t-1}	0.291	-0.724	4.916	1.422
	(1.420)	(1.616)	(3.312)	(4.366)
Δi^{s}_{t-1} * foreign_{t-1}	0.690	-0.178	7.332**	5.922
	(0.947)	(1.077)	(3.002)	(3.740)
Δi^{s}_{t-1}	-1.632*		-7.438***	
	(0.906)		(1.947)	
Observations	4,061,265	4,061,265	4,061,265	4,061,265
R-squared	0.056	0.408	0.056	0.408
Seasonal effects & Macro controls_{t-1}	Yes	<>	Yes	<>
Bank Controls_{t-1} & Risk Control_{t-1}	Yes	Yes	Yes	Yes
Firm*Time FE	No	Yes	No	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
Cluster	bank & time			

Notes: In this table, I reproduce Kuttner (2001) high-frequency identification strategy using two different alternatives. In columns (1) and (2), I use the 90-day interest rate swap accumulated for one year. In columns (3) and (4), I take the same interest rate derivative as before, the 30-day interest rate swap but accumulated quarterly. 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.