LOAN GROWTH AND FORWARD-LOOKING LOSS RECOGNITION: HOW BANKS REACT FROM AN INCREASE IN CREDIT RISK

ABSTRACT

This paper evaluates whether banks increase expected loss recognition when there is contemporaneous loan growth, counterbalancing a potential increase in credit risk by acting in a forward-looking way. Using a sample of semi-annual data from 2003 to 2019 from 95 Brazilian banks, the results indicate that contemporaneous loan growth increases bank riskiness, but banks increase expected loss provisions respectively, which shows that they act prudently, benefiting financial stability. Lastly, we find that larger and small banks differ in setting additional expected loss provisions when the credit portfolio increases, by setting additional expected loss provisions. As a country with a mixed model of incurred and expected loss recognition, Brazil is a uniquely suited environment to analyze this subject, especially after the recent change in accounting regulations worldwide.

JEL Classification: G01, G18, G21, G32, G33

Keywords: Loan loss provision, expected loss provision, loan growth, ECL, bank riskiness

1. INTRODUCTION

This paper investigates the forward-looking behavior of banks, particularly with expected loss provisions counterbalancing the likely increase in credit risk caused by loan growth. As expected losses models are incipient in the world (Lopez-Espinola, Ormazabal, & Sakasai., 2021), Brazil offers a unique, 20-year longitudinal benchmark. Since 1999, the Brazilian banking system has operated under a hybrid model that mandates both incurred and forward-looking loss recognition. This provides a rare 'natural laboratory' to assess the long-term effectiveness and procyclicality of such a model, a perspective that is currently absent in studies focused on the more recent global transitions.

The literature on financial intermediation (Minsky, 1992; Borio *et al.*, 2001, Berger & Udell, 2004; Messai & Jouini, 2013) points out that banks increase lending when risk aversion is low, and as a consequence, risks start to be built up as a result of loan growth in this expansionary phase of the credit cycle. Therefore, when new loans are originated, the risk perception of banks should be low; otherwise, they would not have engaged in financial intermediation at that moment. As time passes, banks do not account for the increase in the credit risk of their operations until the point that those risks are materialized, and banks see themselves with no cushion to absorb losses and flatten this cycle. The literature also evolved to show that excessive loan growth causes an increase in credit risk and that it may take time to materialize (Keeton, 1999; Foos *et al.,* 2010).

After the crisis of 2008, regulators around the world acknowledged that the financial system operated in a procyclical way (Edwards, 2014; Cohen & Edwards, 2017). The two main measures taken to soften the credit cycle and reduce procyclicality were the Basel III requirements introducing the countercyclical capital buffer (BCBS, 2011) and the introduction of expected loss provisioning with the IFRS 9. The first one required banks to hold additional capital when the credit gap was widened. The second measure required banks to account for risks not only when they materialized but when expected risks changed. That included the provision of loan loss provisioning for newly originated loans.

The literature has deeply studied whether banks act in a procyclical or in a countercyclical way, examining different tools used by banks to smooth the credit cycle, such as income smoothing (Bikker & Hu, 2002; Laeven & Majnoni, 2003; Bikker & Metzemakers, 2005; Bouvatier & Lepetit, 2008). However, regulators should not put prudential regulatory objectives over accounting objectives, as this may increase information asymmetry (Gaston & Song, 2014). In this regard, Brazil adopted a mixed model of expected/incurred loss provisioning in 1998 and has a high provision coverage ratio, defined by the ratio of loan loss allowance (LLA) to nonperforming loans (NPL). According to data provided by the World Bank from the Global Financial Development dataset in 2017, Brazil has the highest provision coverage ratio in a list of 77 countries covered. This fact, along with the adoption of expected loss provisioning by the IFRS 9, put the Brazilian system in a uniquely suited position to respond to whether banks use expected loss provisioning to account for credit risks that are risen from the growth of the credit portfolio from newly originated loans.

Therefore, as Brazil has adopted this mixed model since 1998, we can study whether banks use expected loss provisions to account for increased credit risk from new loans. As the literature focuses on the impact of loan growth on an increase in solvency risk, risk perception, and credit risk, we show how banks use forward-looking provisions to counterbalance these risks. Despite the recent IFRS 9 adoption in many jurisdictions, it may be too early to evaluate the long-term effect of loan growth on the forward-looking provision. In contrast, the Brazilian case provides a unique and robust environment to analyze the proposed relations.

Our dataset provides 34 semi-annual time observations with 95 banks (2,459 semi-annual-bank observations). This period is strategically capped at December 2019 to preserve the integrity of the econometric signals. The 2020–2022 interval represents a structural break characterized by unprecedented government liquidity injections and regulatory relief measures that decoupled loan growth from traditional risk recognition and the subsequent accounting transition to Resolution CMN 4,966 (Central Bank of Brazil, 2021), which implements the expected credit loss model in Brazil (aligning local standards with IFRS 9).. Data analysis was conducted under a dynamic panel framework with S-GMM estimation, and additional analyses to reinforce our conclusions were performed with a Panel-VAR approach. The results show that contemporaneous loan growth increases bank riskiness, which is expected. However, banks increase expected loss provisions, respectively, which is the desired result for prudential and accounting standard reasons. It shows that banks act prudently regarding provisioning, benefiting, thus, financial stability. Finally, the results show that larger and small banks differ in setting additional expected loss provisions when the credit portfolio increases, with smaller banks exhibiting a more pronounced increase in additional provisions compared to larger peers.

There are several contributions offered in this paper. First, we segregate the impact of loan growth on banks' risk indicators by showing: (i) whether risk measures increase with loan growth. Secondly, we show the behavior of expected loan loss provision by showing; (ii) how expected loss provision is impacted by loan growth; (iii) how expected provision is affected by economic uncertainty; (iv) and whether different banks have different allocations of expected provision as their loan portfolio grows. These results are important to give evidence that the accounting standard's intention of loan loss provisioning is to provision when risks appear, not when they are materialized.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

According to Keeton (1999), loan growth tends to occur during the expansionary phase of the credit cycle, while losses materialize during the contractions. Based on this assertion, several authors tested whether an increase in loan growth leads to an increase in credit risk. Using loan loss provision (LLP) under the incurred loss model, Foos *et al.* (2010) analyzed annual data from 9.000 banks from OCDE and found that abnormal loan growth led to an increase in asset risk, bank profitability, and bank solvency risk. They also document that additional credit risk appears in the occurrence of abnormal loan growth from the third year on.

Using data from 200 banks in 30 European countries, Tölö & Virén (2021) show that loan growth is endogenous, as an increase in NPL can also affect credit growth in subsequent periods, indicating that post-crisis accumulation of NPLs has affected bank lending. Similarly, using data from listed and unlisted banks in 15 European countries, Köhler (2015) found that banks with high loan growth rates are riskier than those with low growth. In this sense, Fahlenbrach, Prilmeier, & Stulz (2012) shows that banks with faster growth and high leverage were more likely to have performed poorly during the financial crisis of 2008.

Concerning loan growth in developing countries, Amador, Gómez-González, & Pabón (2013), using data from the Colombian financial system, show that abnormal credit growth during a prolonged period leads to an increase in banks' riskiness, accompanied by a reduction in solvency and an increase in the ratio of NPL to total loans. Further evidence of a decrease in solvency was provided by Foos *et al*. 2010, which found a reduction in Z-Score and Equity to Assets ratio to loan growth.

According to Stolz & Wedow (2011), there is a conflicting view regarding well and low-capitalized banks' cyclical behavior regarding capital buffer. A study performed with German local banks from 1993 to 2004 found that well-capitalized banks act countercyclically. According to the author, a low capital buffer would reflect banks' lower risk aversion. On the opposite, low-capitalized banks increase their exposure to credit risk by increasing risk-weighted assets in boom times and do not increase capital accordingly. This last behavior supports Ayuso *et al*. (2004), concluding that banks that do not build up capital in booms provide higher exposure to credit risk, thus amplifying the cycle by increasing the risk of financial instability events (De Moraes & De Mendonça, 2019).

Therefore, in hypothesis 1, we will test whether loan growth increases the riskiness of banks. As loan growth exposes banks to greater credit risk and magnifies earnings volatility (Köhler, 2015), it is important to know if banks are prepared to cushion the increased risks, which brings us to our first hypothesis.

Hypothesis 1: Bank solvency risk increases with positive loan growth.

The view that credit risk is endogenous to the system was raised by Minsky (1992) in the *financial instability hypothesis*. He showed that financial instability is endogenous and derives from the risk-taking behavior of agents. According to this theory, the cycle of financial instability is caused by the financial system, reducing the agents' risk aversion in a proportion of profit expectation from assets in the economy. In this sense, Berger & Udell (2004) examined the procyclicality of bank lending in the US during 1980–2000. They find that credit standards are relaxed, and more loans are granted as time passes since a bank's last peak in loan losses. They introduce the hypothesis of *loan seasoning*, saying that the banks' soft monitoring ability is forgotten until the next crisis comes up. The institutional memory problem may have several adverse consequences, one of them is to exacerbate the procyclical lending behavior that increases systemic risk. The *financial instability* and the *loan seasoning* hypothesis show that the financial system itself sharpens the credit cycle, which prudential regulations of capital buffers and expected loss provisions are designed to avoid.

Other lines of research show that a high amount of credit growth itself might not be the reason for an *ex-post* failure of loans. According to Messai & Jouini (2013), macroeconomics plays a vital role in determining NPL, as banks will incur loan growth in the economic expansion phase, characterized by a small number of bad loans. The author mentions that if the expansion phases continue, more credit will be awarded without considering the quality of the receivables. The recession will indeed cause an increase in bad debts due to a faster deterioration of the loans conceded with no proper screening.

One important aspect of loan growth is how it impacts the credit risk of financial institutions in the near future, as they engage in financial intermediation when the economy's prospects are high, and risk aversion is low. Therefore, it is not expected that credit risk will materialize when a new loan is granted. However, acknowledging credit risk only when a loss occurs can harm a bank's financial stability and represents backward-looking provisioning or "driving looking at the mirror." This type of provisioning is one of the responsible factors for the buildup of risks that caused the financial crisis of 2008 (Cohen & Edwards, 2017).

According to Jesus & Gabriel (2006), LLP has three components: (i) specific provisioning, which would be addressed to cover incurred losses, (ii) latent provision, which is the LLP added when a new loan is granted, (iii) additional or forward-looking provision, which is an additional countercyclical provision for when new loan growth is above the historical trend of loan growth. This idea of additional provisioning was later incorporated in Basel III with the concept of a countercyclical buffer when banks are required to add capital in boom times. This proposal was adopted in Spain as a dynamic provisioning system. Still, many other banks and jurisdictions indirectly use the possibility of additional provision to flatten the credit cycle over time with the use of income smoothing.

The literature on loan provisioning focuses on income smoothing and the impact of macroeconomic factors on loan provisioning. Several studies assess whether banks act cyclically or procyclically by using accounting discretion to flatten the business cycle. They mainly tested the income smoothing hypothesis by focusing on the relation between LLPs and pre-provision and pre-tax earnings (Laeven & Majnoni, 2003; Bikker & Metzemakers, 2005; Fonseca & Gonzalez, 2008; Skała, 2015). In these studies, the authors try to discover whether banks increase provisions when earnings are high in anticipation of loan losses during bad years. In addition, some empirical works test whether macroeconomic variables determine the cyclicality of LLP. Managers act countercyclically when they increase LLP during economic expansion and decrease in an economic recession. (Bikker & Hu, 2002; Laeven & Majnoni, 2003; Bikker & Metzemakers, 2005; Bouvatier & Lepetit, 2008). These studies find that banks act mainly in a backward-looking manner, concluding that the banking system is highly procyclical. Regarding macroeconomic determinants, Bikker & Metzemakers (2005) found a negative relationship between GDP growth and provisioning for 29 OECD countries, indicating backward-looking practices. This procyclicality is lessened partly by the positive relation between banks' earnings and provisions. Laeven & Majnoni (2003) and Beatty & Liao (2009) conclude that banks don't start provisioning until it is too late when a less favorable scenario for loans starts to appear. Bouvatier & Lepetit (2008) find that backward-looking provisioning amplifies credit fluctuations, while forward-looking provisioning or income smoothing does not. Bouvatier & Lepetit (2012) show that forward-looking provisions can eliminate procyclicality in lending standards induced by backward-looking provisions.

The procyclicality of the financial system brought attention to a new way of provisioning. The need for countercyclical measures led regulators to search for a new provisioning system, such as the dynamic model, which is mainly utilized in Spain (Jiménez, Ongena, Peydró, & Saurina*,* 2017). Similarly, Fillat & Montoriol-Garriga (2010) conclude that if US banks had used dynamic provisioning models, they would have been better positioned to absorb losses during economic declines.

The change from incurred loss to expected loss has evolved with the Basel accord. Basel I allowed the use of LLP as a tier 2 capital. However, this was criticized as banks artificially increased capital by changing LLP estimates (Ahmed, Takeda, & Thomas, 1999). Under Basel II, banks were required to have expected losses covered in LLP. The differences between incurred and expected losses within LLP would then be added/subtracted from the capital calculation. Basel III introduces the LLP system that requires banks to set aside specific provisions on newly originated loans based on individual borrower characteristics that drive the performance of the loan (Wezel, Chan-Lau, & Columba., 2012). Thus, LLPs will be based on bank-specific and borrower-specific criteria even though the loan impairment has not occurred yet or is unlikely to happen shortly (Wezel *et al.*, 2012). An important concept reminded by Ozilli (2017) is that provisions are intended for expected losses, not for abnormal/unexpected shocks. He mentions that although some authors argue that capital and provisions should be used simultaneously as countercyclical measures, there is no evidence supporting this hypothesis.

Sometimes, the forward-looking behavior that the regulators intend can cause conflict with current accounting standards. According to Gaston & Song (2014), there is a conflict between prudential regulatory objectives and accounting standards objectives. The same is observed by Zeff (2012) and Rochet (2005), who state that the bank regulation goals are macroprudential ones, where the focus is to maintain financial stability. So, the accounting rules that the regulator will define are the ones that are more aligned to this objective, even if it is conflicting with the Conceptual Framework (IASB, 2015). In this perspective, income smoothing or other types of countercyclical provision unrelated to current or expected credit loss may have conflictive objectives, as it achieves prudential objectives at the expense of accounting transparency.

To adapt accounting rules and objectives to a need for a countercyclical behavior that accounted for expected credit risks, the IASB introduced IFRS 9, which stipulated a three-stage model of recognition of expected losses. Therefore, following the IASB principles, what will drive additional provisioning is the expected credit risk of loans granted. Thus, macroeconomic events should only affect provisioning levels of granted loans if it changes the riskiness of the portfolio. Therefore, the countercyclical measures of banks can be achieved through two channels: the creation of the expected loss provision, which accounts only for changes in the credit risk; and the countercyclical buffer, whose main driver is the flattening of the credit cycle, with the use of more/less capital depending on the stage of the cycle.

There are many studies in the literature attempt to separate the discretionary to non-discretionary part of LLP. The inception of IFRS 9 only occurred in 2018, and yet, many banking jurisdictions still have not fully adopted it. Therefore, researchers use econometrics, more specifically, two-stage regression, to analyze the behavior of discretionary LLP (Bouvatier & Lepetit, 2008, 2012) to capture some forward-looking behavior of banks. In this sense, Brazil offers an interesting perspective for this type of analysis, as the country adopted the expected loss model back in 1999 from Resolution 2.682 (Central Bank of Brazil, 1999). According to the regulation, banks are obligated to classify loans from AA to H depending on the period a loan is in arrears. Depending on which letter the loan is classified, banks must apply a provisioned amount predetermined by the regulation. In addition, banks need to evaluate the credit risk of granted loans targeting their expected losses. Based on that, banks will allocate the loans in the categories from AA (best) to H (worst) and apply the minimum predetermined provision required for that specific classification. Brazil hasn't adopted IFRS 9 for banking supervision purposes, but the transition is currently underway under Resolution 4,966 (Central Bank of Brazil, 2021).. So, as Brazil offers a good opportunity to study expected loss provisions, we test in hypothesis 2 how banks protect themselves from credit risk that arises from the increment of the loan portfolio, counterbalancing the increase of solvency risks that new loans bring.

Hypothesis 2: Expected loss provision is positively associated with loan growth to account for an increase in credit risks from new loans.

The last important aspect analyzed in this paper is how banks in different segments differ in their forward-looking LLP behavior among themselves. More specifically, how systemically important banks (SIBs) differ their LLPs from non-SIBs. The importance of differentiating SIBs and non-SIBs is the shift in focus from micro to macro-prudential regulation, especially after the bank crisis of 2008. The focus on systemic risk converted to more strict supervisory requirements for SIBs because they pose the greatest risk to the global financial system's stability from a macro-prudential regulation perspective (Galati & Moessner, 2013). Peterson & Arun (2018) found that SIBs engage in the forward-looking provision and exhibit greater income smoothing via LLP during recessionary times. These findings probably respond to the great scrutiny that SIBs are under; thus, the need to demonstrate financial stability through LLP can be exacerbated.

According to Abedifar *et al.*(2017), larger banks have a more significant diversification benefit than small ones. According to Shim (2013), this diversification benefit decreases insolvency risk. Therefore, less diversified institutions should have a higher profitability risk. As small banks are less diversified, they are expected to offer greater profitability risk for the financial system, which may impair their ability to create additional provisioning. At the same time, these small institutions suffer from adverse selection, which makes their loan growth riskier than other segments, demanding more expected loss provisions to counterbalance this increase in credit risk

In opposite, larger institutions are systemically more important and suffer more scrutiny from regulators. This situation may impose an extra burden and pressure to account for any foreseeable risk, as they may be "too big to fail." At the same time, they are more diversified and do not suffer from adverse selection, carrying a lower credit risk when their portfolio grows. Therefore, hypothesis 3 will test whether there are differences in the allocation of expected loss provision between SIBs and SMALL banks when they increase their loan portfolio.

Hypothesis 3: Systemically important banks-SIBs and Small banks allocate different expected loss provisions for new loans.

Regarding studies of LLP in Brazil, Araújo, Lustosa, & Dantas (2018) find a procyclical behavior in the Brazilian banking system. Concerning the impact of loan growth on provisions, the author said that it is not safe to attest that the behavior of provisions is associated with the variation in loan growth. Dantas, de Medeiros, & Lustosa (2013), comparing nine models of LLP determinants, find that macroeconomic variables and characteristics of the quality of the loan portfolio improved the measure of LLP measures in Brazil. In a recent study, Galdi, De Moura, & França (2021) conclude that the Brazilian GAAP for financial institutions, a mixed model, presents higher quality in terms of predictability than the IAS 39. However, they find no evidence of earnings management in these two systems.

As expected loss accounting models are recent, and there is not enough data to provide consistent evidence on the effect of the new model on banking risk performance. As time passes, some studies are starting to appear, such as the work of Lopez-Espinola *et al.* (2021), which compares and finds that expected loss provision is a better indicator than incurred loss provision to predict future bank performance risk. The lack of work on expected loss provision is a motivation to analyze the system in Brazil. As mentioned above, it provides banks with LLP capability for both incurred losses and expected losses.

3. DATA AND METHODOLOGY

3.1. Sample

This paper performs a longitudinal analysis of the Brazilian banking system through a sample of 95 Brazilian banks comprising semi-annual data ranging from June 2003 to December 2019, yielding 2,459 semi-annual observations. The period concludes in 2019 to ensure data homogeneity, avoiding the structural breaks triggered by the COVID-19 pandemic and the subsequent accounting transition to Resolution 4,966 (Central Bank of Brazil, 2021), the IFRS 9 equivalent in Brazil. The data is from Financial Institutions/Conglomerates Balance Sheets and IF.data from the Central Bank of Brazil. The sample is representative of the

Brazilian banking system, as it consists of over 90% of the system's total assets (only banks with large gaps in loan data and public development banks were excluded from our analysis).

3.2.Empirical model

The analyses were conducted by using dynamic panel models, which mitigate non-observed effects on regressions, provide a low-bias estimator, and the estimates are robust even in the presence of omitted variables (Arellano & Bond, 1991). Since lagged levels can generate weak instruments and the first difference GMM may be low in precision estimates (Blundell & Bond, 1998; Arellano & Bover, 1995), we follow Blundell & Bond (1998), by using the System GMM (S-GMM), which provides a more consistent estimator and eliminates the problems of omitted variables present in the equation. In addition, we used the forward mean-differencing procedure, known as the "Helmert procedure" (Arellano & Bover, 1995).

Hence, to account for endogeneity bias, a common factor in banking research, we use the S-GMM and perform two diagnostic tests to justify it: the Hansen test for over-identifying restrictions, which validates the appropriateness of instruments; and the Arellano–Bond test for the autocorrelation in residuals, in which the absence of the second-order autocorrelation is required. In addition, we keep the number of cross-sections greater than the number of instrumental variables to avoid biased results (De Mendonça & Barcelos, 2015; De Moraes & De Mendonça, 2019), and we use the Windmeijer (2005) finite-sample correction to the standard errors in the two-step estimations, so we make our results robust to heteroskedasticity.

The empirical model, vastly used in the literature on LLP determinants, follows Nicoletti (2019) and Nichols, Wahlen, & Wieland (2008). According to Beatty & Liao (2014), this model has a high predictive power regarding future LLP. We use this model for both the RISK and LLP variables: Therefore, Equations 1 and 2 are used to test hypotheses 1 and 2, respectively.

$$RISK_{i,t} = \beta_0 + \beta_1 RISK_{i,t-1} + \beta_2 LGRW_{i,t} + \beta_3 \Delta NPL_{i,t-2} + \beta_4 \Delta NPL_{i,t-1} + \beta_5 \Delta NPL_{i,t+} \beta_6 \Delta NPL_{i,t+1} + \sum_{k=7}^{10} \beta_k BANK_{i,t} + \varepsilon_{i,t} \quad (1)$$

Where subscript i is the cross-section number of banks; t is the time (semi-annual) period, and ε is the disturbance. For Equation 1, the dependent variable is RISK, which corresponds to four measures: bank's perceived risk, measured as Capital Adequacy Ratio (CAR), or banks' stability (solvency risk), measured by the ZSCORE. In addition, we use two derivations of ZSCORE: the risk-adjusted ROA (ROASTD) and risk-adjusted leverage

(LEVSTD). The other variables are LGRW stands for Loan Growth. It is calculated by the change of the loan portfolio of a given bank i from period *t-1* to t ($loan\ portfolio_t/$ $loan\ portfolio_{t-1}$ - 1). NPL is the ratio of nonperforming credit divided by the $loan\ portfolio_t$. *BANK* variables are controls that correspond to bank-specific characteristics that are Earnings Before Provision and Taxes scaled by $total\ assets_{t-1}$ (EBTP), Liquid assets to $total\ assets_t$ ratio (LIQ), and the bank's natural logarithm of $total\ assets_t$ (SIZE).

According to De Moraes & De Mendonça (2019), CAR increases when banks perceive an increase in risk in the business activity. Thus, banks increase CAR when their views of the business cycle are negative, as it gives them an extra cushion to absorb future losses. Foos *et al.* (2010) pointed out that a negative relationship between loan growth and equity to capital ratio indicates a higher solvency risk by being less prepared to absorb unexpected losses. Therefore, an increase/decrease in CAR corresponds to a decrease/increase in solvency risk. As per Stolz & Wedow (2011), a low capital buffer would reflect banks' lower risk aversion, and according to Ayuso *et al*. (2004), banks do not build up capital in booms to provide for the higher exposure to credit risk.

We also analyze ZSCORE, which assesses bank stability as a measure of bank risk, and it is a well-known metric in the banking literature to reflect a bank's probability of insolvency (Roy, 1952; Boyd *et al*., 1993, Foos *et al*., 2010, Bouvatier & Nicolas, 2017). It is calculated by the return on assets (ROA) plus the equity to asset ratio divided by a rolling window of four semesters of the standard deviation of ROA. As banks increase loan growth, they become riskier and tend to become less stable. An increase/decrease in this variable corresponds to a decrease/increase in solvency risk. As ZSCORE is both affected by earnings and capital, to segregate the driver of bank riskiness, if it is caused by the rise in the volatility of earnings or by the usage of capital, we will use additional two variables that compose ZSCORE, as per, as per Köhler (2015), which are ROASTD and LEVSTD. The former is calculated with the ROA in the numerator and the four-semester rolling window standard deviation of ROA in the denominator. It measures how much earning is being conquered by each unit of the standard deviation of the earnings.

Similarly, LEVSTD is the capital-to-asset ratio in the numerator and the four-semester rolling window standard deviation of ROA in the denominator. It measures how much capital a bank holds for a unit of earning standard deviation. The summation of ROASTD and LEVSTD is equivalent to the variable ZSCORE.

$$LLP_{i,t} = \beta_0 + \beta_1 LLP_{i,t-1} + \beta_2 LGRW_{i,t} + \beta_3 \Delta NPL_{i,t-2} + \beta_4 \Delta NPL_{i,t-1} + \beta_5 \Delta NPL_{i,t+} \beta_6 \Delta NPL_{i,t+1} + \sum_{k=7}^{10} \beta_k BANK_{i,t} + \varepsilon_{i,t} \quad (2)$$

For Equations 2, 6, and 7, LLP dependent variables correspond to provisions variables which are expected loss (EXL), incurred loss (INL), or total loan loss provision (LLPT), which is the sum of EXL and INL. These variables are scaled by $loan\ portfolio_{t-1}$.The Brazilian system is a mixed model, where banks conjugate EXL and INL. In this system, banks must rate loans according to the delinquency period, covering the incurred loss provision. They may apply discretionary provisioning for the remaining loans, covering EXL. Therefore, to calculate EXL, we split LLPT between the one aimed to cover INL, which is not discretionary, and the one intended for EXL, which is discretionary. A similar calculation was performed by Schechtman & Takeda (2018) to separate discretionary from the non-discretionary provision.

We calculate the incurred loan loss allowance ($LLA_{incurred}$)[1], a stock variable of the balance sheet, which is the minimum regulatory allowance of *i* at *t*, and subtract it from the total LLA_{total} from the given period. This separation provides us with the additional or expected $LLA_{expected}$, which is a stock variable. To transform this into a flow variable, we need to calculate the variation of the expected loss LLA from period *t* to *t-1* and make the proper M&A adjustments[2]. This variation will give us the amount of the LLP, an income statement flow variable. As LLPT is given, we can find INL, as well.

$LLA\ {total}_{it}$= Total loan loss allowance of *i* at *t*

$LLA\ {incurred}_{it}$ = minimum regulatory allowance of *i* at *t*

$$LLA_{expected_{it}} = LLA_{total_{it}} - LLA_{incurred_{it}}, \quad (3)$$

$$EXL_{it} = (LLA_{expected_{it}} - LLA_{expected_{it-1}}) - M\&A\ adjustments \quad (4)$$

$$INL = LLPT_{it} - EXL_{it} \quad (5)$$

[1] Resolution 2.682 (Central Bank of Brazil, 1999) demands mandatory provisioning for credit depending on rating classification, which is based on delinquency period. Loans can be classified from AA to H; which imposes a minimum mandatory allowance percentage according to the classification. Banks should disclose this information in their financial statements, as requested by the Brazilian banking accounting rule (COSIF), Resolution 2.697 (Central Bank of Brazil, 2000).

[2] As EXL is a flow variable, it is important to deduct any amount that was added in this variable that was due to mergers and acquisitions done by the acquirer bank.

BANK variables are controls that correspond to bank-specific characteristics that are Earnings Before Provision and Taxes scaled by $total\,assets_{t-1}$ (EBTP), Liquid assets to $total\,assets_t$ ratio (LIQ), bank capital to $total\,assets_t$ ratio (LEV), which is the total equity divided by total assets, and bank's natural logarithm of $total\,assets_t$ (SIZE).

EBTP measures whether banks increase/decrease provisions when earnings are better or worsen. Many authors (Laeven & Majnoni, 2003; Bikker & Metzemakers, 2005; Bouvatier & Lepetit, 2008) describe this as an income smoothing variable, whereas a positive relation to LLP indicates additional evidence of income smoothing for a given bank. Banks increase the amount of liquid assets in their portfolios to prepare for an adverse economic condition when risk is high. Riskier banks tend to have a higher LIQ. Although this ratio increases when banks are riskier, it is costly to maintain, as these are assets that yield low returns. The same occurs with LEV, where banks will maintain higher/lower leverage depending on whether they have a higher/low-risk aversion.

LGRW[3] *– Loan growth* – This variable will be our primary independent variable of the study. It is calculated by the change of the loan portfolio of a given bank *i* from period *t-1* to *t* ($loan\,portfolio_t/loan\,portfolio_{t-1}$ - 1). Some studies use abnormal loan growth as the variable of interest but subtract aggregated loan growth of the financial system from loan growth of an individual bank. According to Laidroo & Männasoo (2014) analysis, the use of abnormal growth has some disadvantages as it ignores the bank-specific differences in loan growth problems, and long-term growth trends in the banking market are difficult to determine. In addition, loan growth among Brazilian banks varies consistently, and it has a wide amplitude, making the variability of loan growth data similar to the variability of abnormal loan growth. Thus, abnormal loan growth would not provide extra useful information.

NPL – Non-Performing Loans-. It is calculated with the ratio of nonperforming loans divided by the contemporaneous loan portfolio. This metric is vastly used in the literature to measure the credit quality of a bank institution and how risky it is. (Laeven & Majnoni, 2003; Bikker & Metzemakers, 2005; Bouvatier & Lepetit, 2008; Nichols *et al.*, 2008; & Nicholetti , 2019). The model used in this work is based on past and future first differences of NPL, the

[3] A problem with this metric is that can get considerably large if the denominator is small, creating outliers that are not representative of bank behavior regarding loan growth. To avoid this, we excluded these outliers that were created due to a small denominator bias.

same as adopted by Bouvatier & Lepetit (2008); Nichols *et al.*. (2008); and Nicoletti (2019), so we can control for the timeliness of the incurred loss.

$$EXL_{i,t} = \beta_0 + \beta_1 EXL_{i,t-1} + \beta_2 LGRW_{i,t} + \beta_3 d.SEGMENT_{i,t} + \beta_4 LGRW * d.SEGMENT_{i,t} + \beta_5 \Delta NPL_{i,t-2} + \beta_6 \Delta NPL_{i,t-1} + \beta_7 \Delta NPL_{i,t+} \beta_8 \Delta NPL_{i,t+1} + \sum_{k=9}^{12} \beta_k BANK_{i,t} + \varepsilon_{i,t} \quad (6)$$

For hypothesis 3, Equation 6 will test whether LGRW for different bank segments yields further changes in EXL. The novelty in this equation is the inclusion of the dummy *SEGMENT*, which will test two distinct segments of banks in Brazil according to their relevance to systemic risk. These are dummies that divide the banks into two segments. The BCBS (2011), for macroprudential regulatory reasons, encouraged regulators to segment institutions accordingly to their relevance to the financial system. Based on that, the Central Bank of Brazil, through Resolution 4.553 (Central Bank of Brazil, 2017), classified banks into four groups according to the importance of the systemic risk. In this work, we will use the SIBs and SMALL segments. SIBs contain the largest Brazilian banks, with 80% of the total assets of the banking system. SMALL banks hold 3% of total assets and are the majority of banks in the financial system. It is composed of niche institutions, which often have the function of assisting an industrial group in financing their customers, or these banks operate in specific markets.

As the classification of the segments was only done in 2017 by the Central Bank of Brazil for macroprudential reasons, we manually classified the institutions before this period according to the same criteria in case they didn't have a classification. With these treatments, we could replicate the segmentation of banks in Brazil to the initial point of observation, which was June 2003. As per this classification, in our sample, the segmentation is divided into SIB with eight banks and SMALL with 58 banks.

This study included time-fixed effects to account for all the unobservable macroeconomic events that might affect our dependent variables. Also, to provide robustness to the results, as this paper does not focus on macroeconomic determinants of expected loss provision, we included in an alternative model two well-recognized macro variables in the literature. The first is the Credit Gap (C_GAP), which is recognized by the BCBS (2011) and Drehmann & Yetman (2018) as a guide for setting the countercyclical capital buffers. Borio *et al.* (2001) suggested the credit gap as the best early warning indicator for banking crises. It measures the deviations of the credit-to-GDP ratio from a one-sided Hodrick-Prescott (HP) filter with a significant smoothing parameter. The Central Bank of Brazil provides this calculated C_CAP.

In addition, we include a measure of the output gap (O_GAP) that reflects how much the economy is deviating from its long-term trend by using the Hamilton filter (Hamilton, 2018). Specifically, Hamilton (2018) argues that the HP Filter suffers from endpoint problems due to its high sensitivity to the addition of new data, which may create spurious relations for macroeconomic data. Therefore, for the O_GAP, this paper also uses the natural logarithm of the Hamilton filter.

4. EMPIRICAL RESULTS

The first empirical analysis answer hypothesis 1, assessing whether bank solvency risk increases with positive loan growth. For this proposition, we will use four variables: CAR, ZSCORE, ROASTD, and LEVSTD. As ZSCORE is impacted by the change in bank leverage and change in earnings' volatility, we will further unravel the source of ZSCORE variation, by splitting it into ROASTD and LEVSTD, following Kohler (2015).

Each equation has a variation of "a" and "b" with the first using time effects in the equation and the second using macroeconomic variables C_GAP and O_GAP. As macro variables are fixed effects for all cross-sections, they are multicollinear with the time dummies, justifying, thus, the use of both variations.

For the results in Table 1, we expect that LGRW increases solvency risk, as previous literature (Foos *et al.* 2010, Köhler, 2015) points out. In addition, we expect that CAR is reduced as LGRW reduces bank capital as a sign of banks being comfortable with the future economic prospect (De Moraes & De Mendonça, 2019).

Table 1: Effect of CAR, Z-Score, ROASTD, and LEVSTD on EXL

VARIABLES	(1a) CAR	(1b) CAR	(1c) ZSCORE	(1d) ZSCORE	(1e) ROASTD	(1f) ROASTD	(1g) LEVSTD	(1h) LEVSTD
CAR (-1)	0.711***	0.683***						
	(0.068)	(0.073)						
ZSCORE (-1)			0.651***	0.670***				
			(0.067)	(0.059)				
ROASTD (-1)					0.566***	0.572***		
					(0.037)	(0.039)		
LEVSTD (-1)							0.734***	0.708***
							(0.064)	(0.071)
LGRW	-0.043***	-0.042***	-4.947**	-5.521**	0.339	0.647	-4.270**	-3.477
	(0.014)	(0.014)	(2.433)	(2.795)	(0.358)	(0.417)	(2.097)	(2.540)
ΔNPL (-2)	0.067	0.015	-14.157	-16.072	0.518	-0.271	-13.516*	-8.101
	(0.131)	(0.113)	(9.494)	(9.840)	(1.000)	(1.128)	(7.196)	(9.197)
ΔNPL (-1)	0.246	0.160	-23.825*	-27.910	0.514	-0.492	-23.128**	-14.775
	(0.220)	(0.185)	(14.094)	(17.403)	(1.806)	(1.806)	(10.416)	(15.087)
ΔNPL	0.450	0.379	-41.376**	-58.198**	-4.770**	-5.643***	-30.526***	-38.550*
	(0.343)	(0.290)	(17.849)	(23.318)	(2.140)	(2.071)	(10.839)	(22.079)
ΔNPL (+1)	0.858	0.696	-62.394*	-92.854**	1.547	0.999	-46.517**	-53.958
	(0.552)	(0.494)	(34.257)	(46.744)	(1.905)	(1.718)	(20.396)	(42.520)
LIQ	0.174***	0.163***	-2.937	-2.911	0.870	0.894	1.827	0.802
	(0.062)	(0.051)	(7.183)	(6.671)	(1.218)	(1.267)	(5.832)	(6.719)
EBTP	0.381**	0.393***	33.446	38.663**	8.822	8.101	3.319	17.283
	(0.171)	(0.146)	(20.760)	(16.066)	(13.620)	(16.722)	(13.395)	(15.775)
SIZE	-0.006**	-0.007***	1.089***	1.158***	0.294***	0.290***	0.869***	0.897***
	(0.003)	(0.002)	(0.342)	(0.316)	(0.049)	(0.057)	(0.264)	(0.273)
C_GAP		-0.001**		-0.136*		-0.010		-0.156**
		(0.000)		(0.080)		(0.018)		(0.068)
O_GAP		0.005		3.389**		-0.174		3.539**
		(0.006)		(1.500)		(0.496)		(1.651)
Constant	0.1552**	0.1061	-13.932*	-60.931***	-5.059***	-3.055	-13.990**	-59.379**
	(0.064)	(0.085)	(7.659)	(20.544)	(1.373)	(7.669)	(6.134)	(24.569)
Observations	2,357	2,357	2,447	2,447	2,445	2,445	2,458	2,458
Number of banks	92	92	95	95	95	95	95	95
Instr./CrossSec.	0.54	0.28	0.67	0.33	0.60	0.32	0.64	0.27
Time effect	Yes	No	Yes	No	Yes	No	Yes	No
Macro variables	No	Yes	No	Yes	No	Yes	No	Yes
J-statistic	15.79	17.75	28.19	22.47	23.88	25.98	19.36	18.17
p-value	*0.15*	*0.22*	*0.30*	*0.26*	*0.16*	*0.10*	*0.62*	*0.20*
AR(1)	-3.69	-3.75	-3.95	-4.08	-5.00	-4.99	-3.94	-3.82
p-value	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
AR(2)	1.63	1.58	0.05	0.05	-0.08	0.03	0.20	0.15
p-value	*0.10*	*0.11*	*0.96*	*0.96*	*0.94*	*0.98*	*0.84*	*0.88*

Note: Levels of significance (***) represents 0.01, (**) represents 0.05, and (*) represents 0.1.Standard errors between parentheses. N.Inst / N. Cross sec. should be at most equal to 1 in each regression to avoid excessive use of instruments. The J-test (Hansen) indicates that the models are correctly identified. The autocorrelation tests AR (1) and AR (2) reject the hypothesis of the presence of first and second order autocorrelation. Time effects are included to account for unobserved macroeconomic effects that might affect the relation of our variables. Macro variables controls and time effects cannot be in the same equation due to the multicollinearity of S-GMM.

According to Table 1, results show that the main variables that impact ZSCORE are LGRW, ΔNPL, and SIZE. Higher ZSCORE means a decrease in solvency risk. We see that LGRW increases bank riskiness, which means that growth in the loan portfolio increases bank riskiness. Interestingly, the greater the bank SIZE, the lower the risk. As larger banks have lower volatility of returns due to diversification benefits (Abedifar *et al.*, 2017), this may be a possible explanation for this result. As we further extricate ZSCORE to analyze the drivers of bank riskiness, with the variables ROASTD and LEVSTD, as per Köhler (2015), we see that the main driver for an increase in bank riskiness is the drop in bank capital to cover each unit of earnings volatility, as LEVSTD is negative and statistically significant, and ROASTD is not statistically significant. This result corroborates with the result of LGRW on CAR, showing that when banks further engage in financial intermediation, they decrease regulatory capital.

As for CAR dependent variables, we find that LGRW also decreases CAR, which means that banks reduce regulatory capital as they increase the loan portfolio, becoming procyclical. As for the other independent variables, LIQ positively affects CAR. According to the literature (De Moraes & De Mendonça, 2019), a higher LIQ shows that banks are more risk-averse, and it may trigger a higher CAR, so banks become more conservative. Lastly, we find that EBTP has a positive effect on CAR. As a higher EBTP indicates higher earnings, higher risk should be sought, triggering CAR increases.

With the results above, we confirm the first hypothesis that an increase in LGRW causes a reduction in ZSCORE, which means that the distance to default for Brazilian banks decreases with an increment in the loan portfolio. This finding is in accordance with prior literature (Foos *et al*. 2010, Köhler, 2015), which says that an increase in loan growth causes an increase in bank riskiness. Also, bank SIZE increases Z-Score, which corroborates Shim (2013) and Abedifar *et al.*(2017) and means that larger banks are financially more stable than small ones.

Regarding bank capital (CAR), as expected, an increase in LGRW negatively impacts bank capital. De Moraes & De Mendonça (2019) shows that when banks decide to engage in financial intermediation, they have a good economic prospect. If banks had a worse view of the future, more capital would be allocated to counterbalance an increase in the loan portfolio to account for unexpected losses. This result is also in accordance with Ayuso *et al*. (2004), concluding that banks that do not build up capital in boom times provide a cushion for higher exposure to credit risk, thus amplifying the credit cycle. This result is the main critique performed by Borio *et al.* (2001), as they mention that banks are very procyclical by increasing/decreasing capital in bad/good times. In this case, for hypothesis 1, we see that solvency risk increased with loan growth, as both CAR and ZSCORE are negatively associated with LGRW. So, as risk increases, banks act procyclically by decreasing the amount of capital when risks are building up, making them more vulnerable. This cycle led to the creation of the countercyclical buffer by the BCBS (2011) and the expected loss provision accounting as an international accounting standard. Regarding CAR, it is interesting to note that SIZE impacts CAR negatively. As shown before, larger banks have a lower solvency risk; therefore, the need to hold capital is lower.

To further investigate whether banks act prudentially regarding new loans, we tested hypothesis 2 in Table 2. We segregated the INL and EXL from the LLPT and put them as dependent variables.

Table 2: Impact of LGRW on provisions

	(2a)	(2b)	(2c)	(2d)	(2e)	(2f)
VARIABLES	INL	INL	EXL	EXL	LLPT	LLPT
INL (-1)	0.254***	0.137**				
	(0.081)	(0.058)				
EXL (-1)			-0.202***	-0.208***		
			(0.039)	(0.040)		
LLPT (-1)					0.152*	0.162**
					(0.085)	(0.071)
LGRW	0.006	0.004	0.016***	0.017***	0.014***	0.011**
	(0.006)	(0.007)	(0.005)	(0.004)	(0.005)	(0.005)
ΔNPL (-2)	0.1554***	0.1358*	-0.0042	0.0011	0.0371	0.1011**
	(0.041)	(0.069)	(0.025)	(0.025)	(0.071)	(0.045)
ΔNPL (-1)	0.116**	0.123**	0.019	0.037	0.002	0.115*
	(0.050)	(0.051)	(0.041)	(0.037)	(0.098)	(0.064)
ΔNPL	0.405***	0.382***	0.085**	0.096***	0.260***	0.369***
	(0.054)	(0.074)	(0.037)	(0.033)	(0.094)	(0.050)
ΔNPL (+1)	-0.050	-0.138	0.105**	0.119**	-0.326	-0.132
	(0.146)	(0.235)	(0.053)	(0.053)	(0.225)	(0.125)
LIQ	-0.020	-0.015	0.007	0.003	0.008	-0.008
	(0.016)	(0.018)	(0.034)	(0.017)	(0.113)	(0.010)
EBTP	0.109	0.042	0.021	0.019	0.203	0.230**
	(0.106)	(0.186)	(0.026)	(0.025)	(0.148)	(0.101)
SIZE	0.002	0.001	-0.001	-0.001	-0.000	-0.001
	(0.001)	(0.005)	(0.004)	(0.002)	(0.005)	(0.001)
LEV	0.057	0.072	-0.011	-0.011	-0.049	-0.045*
	(0.045)	(0.139)	(0.024)	(0.019)	(0.128)	(0.023)
C_GAP		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)
O_GAP		0.001		0.001		0.003
		(0.005)		(0.002)		(0.003)
Constant	-0.0314	-0.022	0.019	0.007	0.017	-0.008
	(0.039)	(0.116)	(0.098)	(0.032)	(0.115)	(0.031)
Observations	2,457	2,457	2,457	2,457	2,462	2,462
Number of banks	95	95	95	95	95	95
Instr./CrossSec.	0.67	0.31	0.47	0.20	0.55	0.46
Time effect	Yes	No	Yes	No	Yes	No
Macro variables	No	Yes	No	Yes	No	Yes

J-statistic	25.90	14.41	5.34	4.93	18.44	39.28
p-value	*0.36*	*0.57*	*0.38*	*0.55*	*0.10*	*0.15*
AR(1)	-2.85	-2.58	-2.88	-2.89	-2.68	-3.11
p-value	*0.00*	*0.01*	*0.00*	*0.00*	*0.01*	*0.00*
AR(2)	1.07	0.85	-0.83	-0.89	1.14	1.34
p-value	*0.29*	*0.39*	*0.41*	*0.38*	*0.26*	*0.18*

Note: Levels of significance (***) represents 0.01, (**) represents 0.05, and (*) represents 0.1.Standard errors between parentheses. N.Inst / N. Cross sec. should be at most equal to 1 in each regression to avoid excessive use of instruments. The J-test (Hansen) indicates that the models are correctly identified. The autocorrelation tests AR (1) and AR (2) reject the hypothesis of the presence of first and second-order autocorrelation. Time effects are included to account for unobserved macroeconomic effects that might affect the relation of our variables. macro variables controls and time effects cannot be in the same equation due to the multicollinearity of S-GMM.

The results show that LGRW influences EXL and LLPT, but not INL. In addition, lagged NPL change affects INL and LLPT, but not EXL, which reinforces the forward-looking nature of EXL.

The empirical evidence shows that LGRW positively affects EXL. This result shows that Brazilian banks act in a forward-looking prudential behavior by allocating provisions for newly originated loans. On the other hand, LGRW does not impact INL. According to Foos *et al*. (2010), credit risk takes time to be materialized from LGRW. As for the results for LLPT from an increase in LGRW, we see a dominance of EXL, as total provisioning expense rises with LGRW.

Specifically, the literature shows that an increase in LGRW causes banks to decrease LLPT. Although the results displayed in Table 2 show a positive coefficient, we cannot say that our findings oppose the literature since their LLPTs (Laeven & Majnoni, 2003; Bikker & Metzemakers, 2005; Skala, 2015, Huizinga& Laeven, 2019) are based chiefly on incurred loss, which is not the Brazilian case. This result, however, is what is expected in a forward-looking provisioning system, such as the mixed model adopted in Brazil and what is being implemented with IFRS 9, in which banks recognize credit risks when they arise, not when they materialize. It is a piece of further evidence that changes in accounting rules can stabilize a bank's financial by addressing the buildup of risks that occur in boom times and that is only recognized in unstable times.

There are other noteworthy facts from Table 2 When analyzing the NPL coefficients that account for incurred loss and timeliness of recognition, we see that INL is mainly affected by contemporaneous and lagged changes in NPL. For LLPT, the effect of NPL is significant as well. This relation indicates that the two major factors affecting LLPT are expected risk, given by the increase in LGRW, and incurred losses, presented by the change in NPL.

With hypothesis 2, EXL increases with LGRW, which tells us that banks set additional provisions for newly originated loans to account for an increase in credit risk. EXL accounts for additional provisions for coverage of expected credit risk.

The last hypothesis tested differences in new loan provisions for different bank segments according to their importance to the Brazilian financial system. As per previous literature (Galati & Moessner, 2013; Peterson & Arun, 2018), SIBs and SMALL segments may have differences in the credit risk of their portfolio. In addition, SIBs are under more severe scrutiny by investors and regulators, as they offer a more severe impact on systemic risk. Therefore, we would expect that there would be differences in the amount of EXL due to an increase in the credit portfolio for these banks.

Table 3: Bank segmentation and the impact of LGRW on EXL

VARIABLES	(3a) EXL	(3b) EXL	(3c) EXL	(3d) EXL
EXL (-1)	-0.179***	-0.192***	-0.187***	-0.157***
	(0.052)	(0.053)	(0.053)	(0.057)
LGRW	0.016***	0.015***	0.009***	0.007***
	(0.004)	(0.004)	(0.003)	(0.002)
d.SIB	-0.001	0.000		
	(0.002)	(0.001)		
LGRW*d.SIB	-0.003	-0.005		
	(0.005)	(0.004)		
d.SMALL			-0.002	0.001
			(0.008)	(0.002)
LGRW*d.SMALL			0.007*	0.008**
			(0.004)	(0.004)
ΔNPL (-2)	-0.0449	0.0037	-0.007	-0.069
	(0.063)	(0.021)	(0.026)	(0.053)
ΔNPL (-1)	0.005	0.019	0.005	-0.002
	(0.032)	(0.026)	(0.035)	(0.027)
ΔNPL	0.075**	0.100**	0.088**	0.045*
	(0.038)	(0.046)	(0.035)	(0.028)
ΔNPL (+1)	0.111	0.157**	0.147	0.095
	(0.068)	(0.069)	(0.094)	(0.119)
LIQ	0.012	0.013*	0.009	0.017
	(0.007)	(0.007)	(0.009)	(0.010)
EBTP	0.025	0.025	0.028	0.053**
	(0.023)	(0.039)	(0.021)	(0.023)
SIZE	0.000	0.000	-0.001	0.001
	(0.000)	(0.000)	(0.003)	(0.002)
LEV	-0.004	-0.009	-0.010	-0.005
	(0.011)	(0.010)	(0.023)	(0.037)
C_GAP		-0.000		0.000
		(0.000)		(0.000)
O_GAP		-0.001		-0.001
		(0.001)		(0.002)
Constant	-0.0117	0.008	0.011	-0.008

	(0.013)	(0.021)	(0.071)	(0.033)
Observations	2,457	2,457	2,457	2,457
Number of banks	95	95	95	95
Instr./CrossSec.	0.60	0.65	0.72	0.31
Time effects	Yes	No	Yes	No
Macro variables	No	Yes	No	Yes
J-statistic	13.12	54.04	25.79	9.88
p-value	*0.59*	*0.22*	*0.48*	*0.77*
AR(1)	-2.67	-2.51	-2.60	-2.68
p-value	*0.01*	*0.01*	*0.01*	*0.01*
AR(2)	-0.13	-0.26	-0.21	0.29
p-value	*0.90*	*0.79*	*0.83*	*0.78*

Note: Levels of significance (***) represents 0.01, (**) represents 0.05, and (*) represents 0.1. Standard errors between parentheses. N.Inst / N. Cross sec. should be at most equal to 1 in each regression to avoid excessive use of instruments. The J-test (Hansen) indicates that the models are correctly identified. The autocorrelation tests AR (1) and AR (2) reject the hypothesis of the presence of first and second-order autocorrelation. Time effects are included to account for unobserved macroeconomic effects that might affect the relation of our variables. Macro variables controls and time effects cannot be in the same equation due to the multicollinearity of S-GMM.

As we see in Table 3, larger banks represented the SIB segment, and Small banks set different amounts of additional provisioning for LGRW. This result can be seen by the dummy interaction of LGRW and the two bank segments. The value of the interaction of SIB is not statistically significant, indicating that the larger banks do not set a different amount of expected provision. Conversely, the interaction SMALL is statistically significant, which means that the group of small banks set higher amounts of expected loss provisions for LGRW than the rest of the financial system.

These results show that smaller banks set higher amounts of EXL aside for new loans. Peterson & Arun (2018) found that SIBs engage in the forward-looking provision and exhibit greater income smoothing via LLP during recessionary periods. Our results do not show signs of income smoothing and do not show signs of greater allocation of EXL for SIBs but show signs of greater allocation of EXL for SMALL, which is an indication that SIBs and SMALL banks set different additional provisions for LGRW. This difference can occur due to differences in credit risk, as loans of SMALL institutions may have greater credit risk due to adverse selection and to lack of diversification derived from economies of scope (Shim, 2013, Abedifar *et al.*,2017). In Figure 2 we show the predictive margins graph showing the difference in plots of SMALL and non-SMALL banks, based on hypothesis 3c from Table 3. When LGRW is positive and reaches the threshold point of 0.2, we see that SMALL banks allocate more EXL than non-SMALL banks.

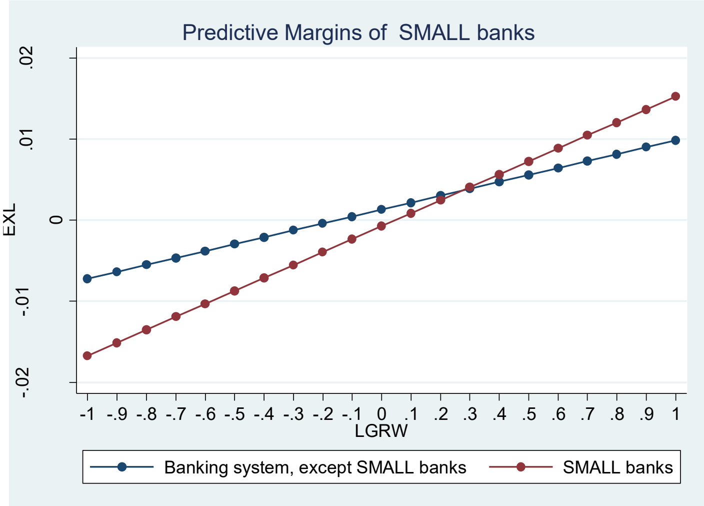

Figure 2: Predictive margins of SMALL banks and non-SMALL banks

4.1.Additional analysis

To provide additional analysis on the impact of LGRW on EXL and other risk variables, we perform an impulse and response simulation of a shock of LGRW on the bank's risk and provision measures (EXL, INL, and CAR) to test whether EXL counterbalances current risks that are being built up when a bank increases the loan portfolio. This impulse-response function describes the reaction of one variable to the innovations in another variable in the system while holding all other shocks equal to zero. The procedure, known as the Cholesky decomposition, isolates shocks to one of the variables in the system. We perform this using a panel vector auto-regressive approach (pVAR), which combines the traditional VAR approach that treats all the variables in the system as endogenous, with the panel data approach, which allows for unobserved individual heterogeneity. Another critical advantage of pVAR is that impulse response functions based on VARs can register any delayed impacts on the variables under consideration; these dynamic effects would not have been recorded by panel regressions (Grossman, Lover, & Orlov, 2014). To eliminate fixed effects, the pVAR utilizes a GMM approach with the forward mean-differencing procedure, known as the "Helmert procedure" (Arellano & Bover, 1995).

For the pVAR model, we include the variables EXL, INL, LGRW, and CAR as endogenous, and the variables $\Delta NPL_{i,t-2}$, $\Delta NPL_{i,t-1}$, $\Delta NPL_{i,t}$, $\Delta NPL_{i,t+1}$, EBTP, LIQ, LEV, and SIZE as exogenous. All variables were tested for stationary using the Fisher – Augmented Dickey-Fuller test's panel unit root test. Also, following Andrews & Lu (2001), the optimal lag for the model selection was based on the first-order pVAR. Additional robustness of the pVAR is the stability graph, which shows that pVAR satisfies the stability conditions. According to Abrigo & Love (2016), Hamilton (1994)a VAR model is stable if all the companion matrices are strictly less one and the eigenvalues lie with the unit circle.

We get similar results of pVAR to the results of Equations 1 and 2 that were applied to hypotheses 1 and 2. A one standard deviation shock in LGRW immediately impacts the EXL positively. The impact dissipates immediately, which corroborates with our hypothesis 2, that LGRW impacts EXL positively. This impact is in accordance with the literature (Jesus & Gabriel, 2006; Lopez-Espinola *et al.*, 2021), which says that EXL should increase with new loans. When we look at CAR, we see the opposite: the initial impact takes longer to dissipate than the impact of LGRW on EXL, which is similar to our previous results when testing hypothesis 1. This result showed that a reduction of capital is the main fact that elevates bank riskiness, which corroborates with Ayuso *et al*. (2004), that banks do not increase capital in booms to provide for the higher exposure to credit risk, turning the credit cycle more procyclical (Borio *et al.*, 2001). According to De Moraes & De Mendonça (2019), banks increase capital when they foresee risk. Therefore, LGRW has the opposite effect on CAR, as banks decide to lend when they have good economic prospects. However, this reduction in capital elevates bank riskiness, as banks will have a thinner "cushion" to absorb unexpected losses, which is the function of bank capital.

As for INL, according to Foos *et al*. (2010), an increase in credit growth will immediately reduce INL, as new loans will take time until risks start to materialize. This growth may impact, at first, the ratio of INL in the opposite direction, as the ratio of bad-to-good loans tends to diminish initially. What is clear and the most important in these three figures is that EXL counterbalances the increase in risk captured by the procyclical behavior of CAR and the reduction of INL. It is further evidence that an increase in LGRW positively impacts EXL in Brazil.

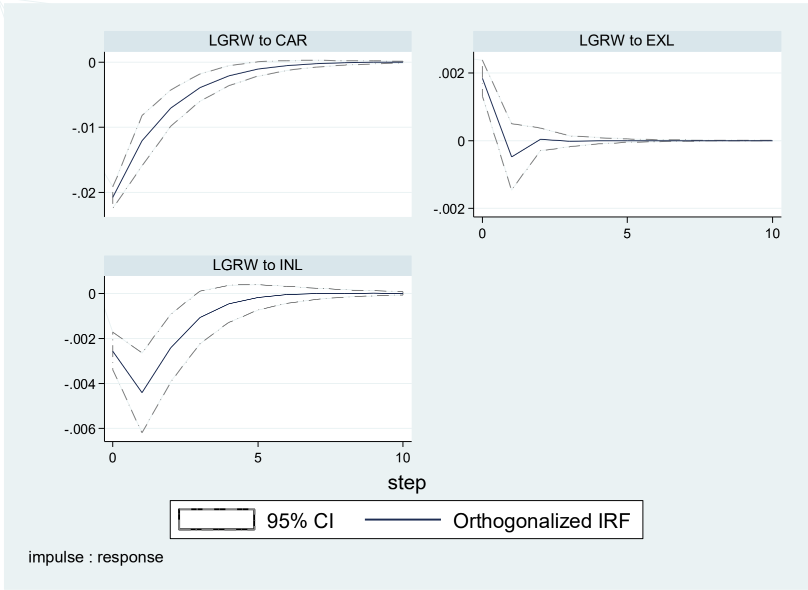

Figure 3: Impulse-response of LGRW on EXL, INL, and CAR

5. CONCLUDING REMARKS

This paper investigated the forward-looking behavior of banks, particularly with expected loss provisioning offsetting the likely increase in credit risk caused by loan growth. Using a sample of semi-annual data, adjusted for bank M&A, with 95 banks, which is over 90% of the banking system, from June 2003 to December 2019, we showed that (i) there is an increase in bank riskiness with loan growth. This finding reinforces the prior literature that said that loan growth increases the riskiness of banks (Keeton, 1999; Foos *et al*., 2010; Fahlenbrach *et al.* 2012; Amador *et al.*, 2013; Dan, 2019). We found that a positive loan growth decreases the distance to default, measured by the indicator Z-Score, and also decreases the capital ratio, showing that banks become more vulnerable at the same time that risks are building up (Ayuso *et al*., 2004; Stolz & Wedow, 2011; De Moraes & De Mendonça (2019). In addition to that, we found that (ii) as loan growth increases credit risk, expected loss provisions rise. Loan growth tends to occur during an economic expansion in a time of low-risk aversion of banks. However, as the loan portfolio grows, credit risk grows as well. The finding that there is an increase in expected loss provision concomitant to loan growth is a positive indicator that banks are being prudential with their market discipline and with their risk management, which is the opposite of what many authors in the literature found in different studies (Laeven & Majnoni, 2003; Bikker & Metzemakers, 2005; Skala, 2015; Huizinga & Laeven, 2019). This additional provisioning is what forward-looking provision aims for: risks to be recognized before materialization, specifically when new loans are made (Jesus & Gabriel, 2006; Lopez-Espinola *et al.*, 2021). These results are important findings, as they trigger the expectation that the new accounting rules for ECL may yield similar results, which is positive.

Lastly, it was important to know whether (iii) different banks have different allocations of expected provision as their loan portfolio grows. We found that SMALL banks allocate a higher amount of EXL, given an increase in the credit portfolio. This result can be explained by the higher credit risk of loans in smaller institutions caused by adverse selection in credit lending, demanding, thus, a higher expected loss provisioning when there is loan growth. In addition, SMALL banks are less diversified, which is another factor that increases credit risk (Shim, 2013, Abedifar *et al.*,2017).

Our main contribution is to segregate the impact of loan growth in bank risk indicators and, concerning future research, as the time of inception of IFRS 9 passes and a greater amount of data is available, it is essential to understand whether the ECL component was effective in reducing the procyclicality of banks. In addition, the change in accounting standards regarding expected loss provision may diminish the need for the countercyclical buffer. Further research should be performed to test this relation.

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