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AVOIDING FINANCIAL INSTABILITY: ESSAYS ON BANK PERFORMANCE AND RISKINESS

EVITANDO A INSTABILIDADE FINANCEIRA: ENSAIOS SOBRE RISCO E PERFORMANCE EM *BANKING*

São Paulo
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Avoiding financial instability: Essays on bank performance and riskiness

Dissertation presented to the Dept. of Accountancy and Actuarial Science of the College of Economics, Business, Accounting and Actuarial Science (FEA/USP) of the University of São Paulo as a partial requirement for obtaining the title of Doctor of Science.

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To my family.
To God, who guides and provides me with all the opportunities and blessings in my life.

RESUMO

Sousa, A. P. (2022). *Avoiding financial instability: Essays on bank performance and riskiness* (Tese de Doutorado, Universidade de São Paulo, São Paulo)

A estabilidade financeira é a capacidade do mercado de capitais de desempenhar sua função principal de canalizar recursos a entidades deficitárias que possuem investimento produtivo. Questões relacionadas ao desempenho e risco dos bancos afetam a intermediação financeira, aumentando a chance de crises financeiras. Como a manutenção de um sistema financeiro sólido é importante para o desenvolvimento econômico, desenvolvemos três ensaios abordando lacunas na literatura sobre o risco bancário e avaliação de desempenho, cujo correto entendimento é importante para um sistema financeiro sólido. Em primeiro lugar, focamos na opacidade dos bancos e avaliamos se as variáveis macroeconômicas podem melhorar a previsão do desempenho financeiro dos bancos, usando medidas de desempenho baseadas em *accrual* (resultado de juros, receita de serviços e provisão para perdas com empréstimos) e as novas medidas baseadas em fluxo de caixa, que podem ser usadas como *proxies* da intermediação financeira (fluxo de caixa do crédito e de captação). Os resultados indicam que as variáveis macro podem ser usadas para prever o desempenho financeiro apenas quando variáveis de fluxo de caixa são utilizadas como medida de desempenho bancário, o que reforça a importância das métricas de fluxo de caixa para bancos, assunto que tem sido negligenciado pela literatura *de banking*. O segundo ensaio analisa o que está em jogo com o sistema bancário, pois os bancos podem perder receitas de serviços, devido ao aumento da concorrência das *fintechs*. Mostramos a relevância das receitas de serviço para a lucratividade e se há efeito compensatório entre receita de serviços e de intermediação financeira em relação à lucratividade, suavizando os efeitos do ciclo econômico, auxiliando, assim, na estabilidade financeira. Nossos resultados sugerem que as receitas de serviço impactam positivamente a lucratividade, diminuem o risco e apresentam efeito compensatório aos resultados de intermediação financeira em relação à lucratividade dos bancos. Por fim, verificamos que as receitas de serviço são mais relevantes para a lucratividade do que o resultado de intermediação financeira para grandes bancos. Para os bancos pequenos, a intermediação financeira é mais relevante, o que mostra que os bancos maiores serão, em um primeiro momento, os mais afetados pela perda potencial de receitas de serviços. O terceiro ensaio avalia se os bancos agem de forma prospectiva, aumentando a provisão para perdas esperadas logo na concessão do empréstimo. É crucial avaliar se o aumento do risco bancário com novos empréstimos é atenuado por um aumento concomitante da provisão para perdas esperadas. Os resultados indicam que o crescimento do crédito aumenta o risco dos bancos, mas também ocorre um aumento concomitante das provisões de perda esperada, o que beneficia a estabilidade financeira. Além disso, verificou-se que quando o crescimento dos empréstimos ocorre em períodos de maior incerteza financeira, os bancos alocam mais provisões para perdas esperadas para compensar um aumento no risco de crédito. Por fim, devido ao grau elevado de heterogeneidade do sistema bancário brasileiro, verificamos que bancos grandes e pequenos diferem na constituição de provisões adicionais para perdas esperadas quando a carteira de crédito aumenta, com os bancos menores provendo maior provisionamento.

Palavras-chave: Intermediação financeira, fluxos de caixa, risco de crédito, receitas de serviços, provisão incorrida, provisão esperada, crescimento de carteira, estabilidade financeira e risco bancário.

ABSTRACT

Sousa, A. P. (2022). *Avoiding financial instability: Essays on bank performance and riskiness* (Ph.D. Dissertation, University of São Paulo, São Paulo)

Financial stability is the ability of capital markets to perform their essential function, which is to channel funds to entities that have productive investments. Different issues regarding bank performance and riskiness cause friction in the financial intermediation process, shattering financial stability and increasing the chance of a financial crisis. As the maintenance of a sound financial system is important for economic development, we developed three essays covering gaps in the literature on bank riskiness and performance evaluation, whose correct understanding is important for a sound financial system. Firstly, we focus on bank opacity and evaluate whether macroeconomic variables can improve the forecast of the financial performance of banks by *using accruals-based* measures of banking performance (net-interest income, non-interest income, and loan loss provision) and the novel *cash flow-based* measures that act as a *proxy* of financial intermediation (*credit* and *liability cash flow*). The results from out-of-sample forecasts indicate that the macro variables can be used to forecast financial performance only when the cash flow-based measures are used to measure banking performance, reinforcing the importance of cash flow, which has been neglected by the banking literature for bank evaluation. The second essay analyses what is at stake with the banking system as banks are on the brink of losing non-interest income due to an increase in competition from *fintechs*. We show the relevance of non-interest income for banking profitability and if there is a compensatory effect to financial intermediation earnings in relation to bank profitability, which smooths earnings in economic downside, helping, thus, financial stability. Our findings suggest that non-interest income positively impacts bank profitability, decreases bank riskiness, and presents a compensatory effect to financial intermediation earnings in relation to bank profitability. Lastly, we find that non-interest income is more relevant to profitability than financial intermediation earnings for large banks. For the small banks, financial intermediation earnings are more relevant, which shows that larger banks shall be, at first, the most affected by the potential loss of non-interest income. The third essay evaluates whether banks act in a forward-looking way by increasing expected loss provision when there is contemporaneous loan growth. As accounting regulations around the world changed in later years to account for foreseeable credit risk; thus, it is crucial to assess whether the increase in bank riskiness with new loans is softened by a concomitant increase in expected loss provision. The results indicate that contemporaneous loan growth increases bank riskiness, but banks increase expected loss provisions respectively, which shows they act prudently regarding provisioning, benefiting, thus, financial stability. In addition, it was found that when loan growth occurs during higher financial uncertainty times, banks allocate more expected loss provisions to account for an increase in credit risk. Lastly, as the Brazilian banking industry is heterogeneous, we find that small banks set higher expected loss provisions than larger banks for a given increase in the loan portfolio.

Keywords: Banking, forecast, cash flows, credit risk, non-interest income, profitability, loan loss provision, expected loss provision, loan growth, ECL, financial stability, and bank riskiness.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACRONYM

ARIMA	Autoregressive integrated moving average
C_CAP	Credit gap
CAR	Capital adequacy ratio
CCAR	Comprehensive capital analysis and review
CCF	Credit cash flow
EBTP	Earning before taxes and provision
ECL	Expected credit loss
EMBI	Emerging markets bond index
EXL	Expected loss provision
FED	Federal reserve bank
GAAP	Generally accepted accounting principles
IASB	The international accounting standards board
IFRS	International financial reporting standards
INL	Incurred loss provision
LCF	Liability cash flow
LEV	Leverage
LGRW	Loan growth
LIQ	Liquid asset ratio
LLA	Loan loss allowance
LLP	Loan loss provision
LLPT	Total loan loss provision
NII	Non-interest income
NIM	Net-interest income
NINC	Net-interest income after provision
NPL	Non-performing loans
O_GAP	Output gap
P-VAR	Panel vector autoregressive
RMSE	Root mean square error
ROA	Return on assets
RWA	Risk-weighed assets
S-GMM	System generalized methods of moments
SIB	Systemically important banks
US	The United States
VAR	Vector autoregressive

1. INTRODUCTION

After the crisis of 2008, academics and practitioners had an immense focus on how to prevent a financial crisis by maintaining financial stability. According to Mishkin (1992), financial stability is the ability of capital markets to perform their essential function, which is to channel funds to entities that have productive investments. If there is a factor preventing the flow of these funds, then we have a situation of financial instability, which can cause a severe interruption, triggering a financial crisis. This research intends to evaluate important gaps in the literature regarding bank performance and riskiness that impact financial stability at the macro and micro levels.

This work presents three essays with research problems that may cause financial instability and that are relevant in the literature. The first essay raises the issue of bank opacity and how it is difficult for external agents and regulators to forecast the future performance of banks based on macroeconomic shocks. This opacity was a major obstacle to the needed external financing to restore bank confidence after the crisis of 2008. To reduce this opacity and restore bank financing, forward-looking supervision, such as stress test exercises, was demanded so that investors could make an accurate risk assessment of the institutions (Schuermann, 2014). However, the literature (Alfaro & Drehmann, 2009; Guerrieri & Welch, 2012; Borio, Drehmann, & Tsatsaronis, 2014) is inconclusive on the effectiveness of this approach, given that many studies (Alfaro & Drehmann, 2009; Borio *et al*., 2014) show that macroeconomic variables are a not a good predictor of measures of banking performance. Therefore, in this first essay, we analyze whether the macroeconomic variables can increase the forecasting capability of the measures of banking conditions. Different from previous work on banking forecasting, we use an extra measure of banking condition that has been neglected in the literature to forecast future bank financial performance: the *cash flow* variables (*credit* and *liability cash flow*). According to Antunes, De Moraes e Rodrigues. (2018) and De Moraes, Antunes, & Rodrigues (2019), who created these variables based on a previous theoretical framework (Minsky, 1975; and De Moraes & De Mendonça; 2017), they can be used as *proxies* for the level of financial intermediation that a bank performs, and this data should be fully impacted by economic conditions that affect banking liquidity (Tirole, 2011; Goodhart, 2008).

We also use the traditional *accruals-based* banking condition measures (net-interest income, non-interest income, and loan loss provision) to test the forecasting capability of the macroeconomic variables. Our sample consists of one full sample of aggregated time series data with 213 Brazilian banks, with four subsamples to account for banks of different sizes and importance to the banking system, which helps us account for bank heterogeneity. The data has a quarterly frequency, ranging from September 2000 to September 2019. We test *pseudo*-out-of-sample forecasting of banking condition measures with the *macro variables* models, comparing it to two benchmarks: the lower bound *random walk* and the upper bound *autoregressive integrated moving average* (ARIMA) model. The results show that the *macro variables* model is superior to the *random walk* model for all banking condition measures. However, when the benchmark model is changed to the ARIMA model, the *macro variable* model can only consistently beat the benchmark when predicting the *cash flow* variables, indicating that cash flows are a good measure of banking conditions to evaluate future bank performance. This study is an innovation to the literature, as it adds to bank performance the *cash flow* variables that are proxies of financial intermediation and try to fill the gap of whether macro variables are relevant to forecast.

The second essay deals with another threat to financial stability: the risk of the current players in the banking system losing an important source of revenue diversification, the non-interest income (NII). This potential loss may occur due to the rise of *fintechs* and the increase in financial innovation, which decreases entry barriers to new players and causes pressure on non-interest revenues of the banking system. This loss of income may put banks under pressure to maintain profitability, making them less risk-averse and bringing additional risk to the financial system. This second essay explores the relationship between NII and financial intermediation earnings to investigate whether NII (1) has a positive impact on overall profitability, (2) reduces bank riskiness; (3) compensates for changes in financial intermediation earnings; thus, smoothing bank's profitability; and (4) “compete” with financial intermediation earnings, reducing its relevance in banks' profitability for large banks; thus, curbing financial intermediation appetite. Using a system generalized method of moments (S-GMM) dynamic panel approach on a sample of quarterly data, from 2003 to 2019, from 95 Brazilian banks, this second essay shows that NII adds to the overall bank profitability and reduces bank riskiness. In addition, we find that NII and financial intermediation earnings have a compensating effect on each other, indicating that as one increases (decreases), the other decreases (increases) concerning their impact on overall bank profitability. As NII can act to soften the procyclicality of the banking system cycle (Albertazzi & Gambacorta, 2009; Shim, 2013), the loss of this income can deepen the credit cycle and generate financial instability. Therefore, this result shows what is at stake with the potential loss of this source of income. Finally, comparing the large and small banks in Brazil to how NII and financial intermediation earning were relevant for each group, we see that NII is more relevant for the large banks than for small ones. This result corroborates with the literature that says that larger banks can capture the benefits of NII in a better way than small institutions (Abedifar, Molyneux & Tarazi, 2018). This second essay added to the literature by revealing how the NII impacts overall profitability and reduces bank riskiness, compensating or moderating the reduction in financial intermediation. As NII is different around the world, the literature has different results in respect of the importance of NII on bank profitability and risk (Stiroh, 2004; Stiroh, 2006; Murphy, 2009; Lee, Yang, & Chang, 2014; Williams, 2016; Chen, Huang, & Zhang, 2017). Also, we revealed how NII could "compete" with financial intermediation earnings, reducing the relevance of the latter in banks' profitability. As technology changes the banking industry by lowering the barrier of entry to new entrants, banks are at risk of losing non-interest revenues.

Lastly, the third essay focuses on how the new accounting regulations that reinforce expected loss provisioning may help balance risks when banks have loan growth. As the literature (Minsky, 1992; Borio, Furfine & Lowe, 2001, Berger & Udell, 2004; and Messai & Jouini, 2013) points out that banks do not account for the increase in the credit risk when they grow financial intermediation and don't start provisioning until is too late (Laeven & Majnoni, 2003; Beatty & Liao, 2009), we show that banks use forward-looking provisions to counterbalance these risks. For this assertion, we use the Brazilian market as a model, as the country has adopted the mixed model provisioning since 1998, using non-discretionary (incurred loss) and discretionary (expected loss) provisioning. In this third essay, 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 the systemically important banks (SIBs) and small banks have different allocations of expected provision as their loan portfolio grows. We used 34 bi-annual time observations with 95 banks. Data analysis was conducted under a dynamic panel 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. However, banks increase expected loss provisions, respectively, which is the desired result for prudential and account standard reasons. It shows that banks act prudently regarding provisioning, which benefits financial stability. Other findings point out that when loan growth occurs during higher financial uncertainty times, banks allocate more expected loss provisions to account for increased credit risk. In addition, the results show that larger and small banks differ in setting additional expected loss provisions given a loan growth, with the smaller banks setting additional expected loss provisions, indicating a difference in credit risk between these two segments.

These three essays provide us with a further understanding of the banking system, using the Brazilian market as an example. It is an important emerging market country with a developed financial system. We start analyzing the banking system at the macro or aggregated level, showing how exogenous macroeconomic shocks impact aggregated banking data. Then, we advance into the micro-level, explore the nature of banks' revenue, and show what is at stake with the change in competitive forces due to financial innovation. Lastly, we use Brazil as an example of how the new accounting regulation, such as IFRS 9, may soften the credit cycle. We show how banks act prudentially by increasing expected loss provision when loan growth occurs, counterbalancing the increase in credit risk that an increase in financial intermediation brings.

1.1.References

Abedifar, P., Molyneux, P., & Tarazi, A. (2018). Non-interest income and bank lending. *Journal of Banking & Finance*, *87*, 411-426.

Albertazzi, U., & Gambacorta, L. (2009). Bank profitability and the business cycle. *Journal of Financial Stability*, *5*(4), 393-409.

Alfaro, R. A., & Drehmann, M. (2009). Macro stress tests and crises: what can we learn?. *BIS Quarterly Review December*.

Antunes, J. A. P., De Moraes, C. O., & Rodrigues, A. (2018). How financial intermediation impacts on financial stability? *Applied Economics Letters*, 1–5.

Beatty, A., & Liao, S. (2009). Regulatory capital ratios, loan loss provisioning and procyclicality. *Columbus, United States: Ohio State University. Mimeographed document*.

Berger A. N., & Udell, G. F. (2004). The institutional memory hypothesis and the procyclicality of bank lending behavior. *Journal of financial intermediation*, *13*(4), 458-495.

Borio, C., Drehmann, M., & Tsatsaronis, K. (2014). Stress-testing macro stress testing: Does it live up to expectations? *Journal of Financial Stability*, *12*(1), 3–15. https://doi.org/10.1016/j.jfs.2013.06.001

Borio, C., Furfine, C., & Lowe, P. (2001). Procyclicality of the financial system and financial stability: issues and policy options. *BIS papers*, *1*(March), 1-57.

Chen, C. R., Huang, Y. S., & Zhang, T. (2017). Non-interest income, trading, and bank risk. *Journal of Financial Services Research*, *51*(1), 19-53.

De Moraes, C. O., Antunes, J. A. P, Rodrigues, A., (2019). Financial intermediation analysis from financial flows. *Journal of Economic Studies*, *46*(3), 727-747.

De Moraes, C. O., & de Mendonça, H. F. (2017). The bridge between macro and micro banking regulation: A framework from the model of financial flows. *Journal of Economic Studies*, 44(2), 214-225.

Goodhart, C. A. (2008). The regulatory response to the financial crisis. *Journal of Financial Stability*, *4*(4), 351-358.

Guerrieri, L., & Welch, M. (2012). Can macro variables used in stress testing forecast the performance of banks? *Finance and Economics Discussion Series-FEDs*, 49.

Laeven, L., & Majnoni, G. (2003). Loan loss provisioning and economic slowdowns: too much, too late?. *Journal of financial intermediation*, *12*(2), 178-197.

Lee, C. C., Yang, S. J., & Chang, C. H. (2014). Non-interest income, profitability, and risk in banking industry: A cross-country analysis. *The North American Journal of Economics and Finance*, *27*, 48-67.

Messai, A. S., & Jouini, F. (2013). Micro and macro determinants of nonperforming loans. *International journal of economics and financial issues*, *3*(4), 852.

Minsky, H. P. (1992). The financial instability hypothesis. *The Jerome Levy Economics Institute Working Paper*, (74).

Minsky, H. P. (1975). Suggestions for a cash flow-oriented bank examination.

Mishkin, F. S. (1992) Anatomy of a financial crisis. *Journal of Evolutionary Economics*, n. 2, p. 115-130.

Murphy KJ (2009) Compensation structure and systematic risk. *Marshall Research Paper series Working Paper PBE-34-09*, University of Southern California

Schuermann, T. (2014). Stress testing banks. *International Journal of Forecasting*, *30*(3), 717-728.

Shim, J. (2013). Bank capital buffer and portfolio risk: The influence of business cycle and revenue diversification. *Journal of Banking & Finance*, *37*(3), 761-772.

Stiroh, Kevin, (2004), "Diversification in Banking: Is Non-interest Income the Answer?" *Journal of Money, Credit and Banking* 36, 853-882.

Stiroh, Kevin, (2006), "A Portfolio View of Banking with Interest and Non-interest Activities," *Journal of Money, Credit and Banking* 38, 2131-2161.

Tirole, J. (2011). Illiquidity and all its friends. *Journal of Economic Literature*, 49(2), 287–325.

Williams, B. (2016). The impact of non-interest income on bank risk in Australia. *Journal of Banking and Finance*. https://doi.org/10.1016/j.jbankfin.2016.07.019

2. MACRO VARIABLES AND THE PREDICTION OF OUT-OF-SAMPLE BANK FINANCIAL PERFORMANCE[2]

Abstract

As the literature diverges on whether macro variables are useful in forecasting future bank performance in forward-looking assessment, this paper evaluates whether macroeconomic variables can improve the forecast of financial performance of banks, assessing if the predictability power varies when the choice of bank financial performance are *accruals-based* (net-interest income, non-interest income, and loan loss provision) or *cash flow-based* measures (credit and liability cash flow). Our sample consists of aggregated time series data for the entire Brazilian banking system, and its sub-segments, from September 2000 to September 2019. The results from out-of-sample forecasts indicate that the macro variable with ARIMA errors model offers a clear gain in predictivity when compared to a lower bound benchmark *random walk* model. Still, these gains are severely reduced when the benchmark model is replaced by a pure ARIMA model. The cash flows performance measures (*credit* and *liability cash flow*) have the most significant gain in forecastability by including macro variables, which corroborates the importance of cash flow information for evaluating bank performance. These results are essential for forward-looking banking supervision, as preemptive actions that prevail in financial crises can be taken. It is also innovative to the literature, as it offers an extra tool for evaluating bank performance based on macroeconomic events.

JEL Classification: C53, G17, G28, and E44

Keywords: Forecast, banking, financial intermediation, stress test, supervision, cash flows, and credit risk,

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Title: Macro variable and the Prediction of Out-of-Sample Financial Performance
Author: Sousa, Alan P.
Co-authors: Pimentel, Renê C., Flores, Eduardo S.

2.1.Introduction

Bank opacity is a relevant problem for bank stability as it increases bank insolvency risks (Fosu, Ntim, Coffie, & Murinde, 2017) and is also associated with inefficient market discipline (Boot & Schmeits, 2000). According to Flannery e Nikolova (2004), bank opacity means external agents fail to value bank assets efficiently. In the crisis of 2008, to reduce this opacity and restore bank financing, a different approach to risk assessment was demanded, so investors could have a sense of what to expect under different scenarios in the future. This new approach was demanded as investors were reluctant to contribute capital to the bank´s balance sheets due to a lack of confidence in these institutions' assets (Schuermann, 2014). Until that point, banking supervision, which aims to guarantee financial stability and to protect the depositors from information asymmetry, had a backward-looking approach, focused on past financial performance, such as incurred losses or problems that occurred in the past that were not captured by the supervisor (Bouvatier & Lepetit, 2012). Therefore, forward-looking based supervision, such as stress test exercises, gained relevance (Quagliariello, 2009; Alfaro & Drehmann, 2009; Tirole, 2011; Covas, Rump, & Zakrajšek, 2014).

According to Guerrieri & Welch (2012), a premise of stress tests that uses macroeconomic scenarios is that macro variables should be a valuable source of forecasting the performance of banks. However, previous studies say that macro variables lose to more straightforward forecasts, i.e., the *random walk* model, in predicting bank performance (Alfaro & Drehmann, 2009; Borio *et al.*, 2014). Others say that macro variables, in some cases, can outperform the benchmark *random walk* model, indicating that macroeconomic variables can be used for future bank performance prediction (Guerrieri & Welch, 2012). This divergence leads us to the research problem: the need to forecast future banking performance based on macroeconomic conditions.

Additionally, an extra tool that can be used for assessments of future financial performance and that is neglected in the literature as a way of forecasting future bank financial performance is the level of financial intermediation, which is fully affected by economic conditions and that affects banking liquidity (Tirole, 2011; Goodhart, 2008). In this regard, based on the previous hypothesis and theoretical framework of Minsk (1975, 1992) and De Moraes & De Mendonça (2017) on bank cash flows, propose a *proxy* for financial intermediation based on cash flow from *credit* and *liability*. Specifically, Antunes *et al.* (2018) and De Moraes *et al.* (2019) show that analysis of cash flow metrics can help to reduce the bank opacity that is present in the financial sector since *earning* variables, commonly used as a measure of banking condition in stress test exercises, contains *accruals*, which can affect how macroeconomic shocks impact these metrics. Hence, using *cash flow* variables may offer more significant insights into whether macro variables are suitable for future bank performance prediction.

Therefore, in this paper, we analyze whether the macroeconomic variables can increase the forecasting capability of measures of banking conditions and if the predicability power varies according to the choice of these measures, either using *cash flow* or *earning* variables. Using a sample of quarterly data from 213 Brazilian banks, ranging from September 2000 to September 2019, we construct aggregated time series of measures of banking condition, which includes *cash flow* variables -*credit* (CCF) and *liability* (LCF)- used by Antunes *et al.* (2018) and De Moraes *et al.* (2019), and the *earnings' variables - net interest income* (NII)*, non-interest income* (MIM), and *loan loss provision* (LLPT) - commonly used as a measure of bank performance and that contain accruals. To account for heterogeneity in the banking system, we use five aggregate series in our analysis: one full sample aggregated data with all banks and the other four subsamples according to bank size and importance to the banking system. We use a macro variable regression model with ARIMA errors and compare it to a benchmark model to determine forecast accuracy. As the *random walk* is a standard benchmark for forecast assessment and it beats pure autoregressive models, as per Guerrieri & Welch (2012), we use the *random walk* model as the lower bound; and the pure ARIMA model as the upper bound benchmark for our study, as Afero & Drehmann (2009) suggests that autoregressive models perform well as benchmark models.

The results show that the *macro variables* model with ARIMA errors is clearly superior to the *random walk* model for almost all variables and subsamples. However, when we used the pure restricted ARIMA model as a benchmark, the forecast capability of the macro variables is diminished, and the superiority of macro variables in predicting future performance only remains for CCF in large and medium banks subsamples and LCF for all samples.

This study is an innovation to the literature, as it adds to bank performance evaluation of the *cash flow* variables that are *proxies* of financial intermediation. It tries to fill the gap of whether macro variables are relevant to forecast performance and shows that autoregressive models are essential tools for forecasting. Also, this work connects financial intermediation to the banking accounting literature. In addition, it uses an out-of-sample forecast, which is not a commonly used methodology to evaluate the Brazilian banking system, using data from a well-developed financial system in a relevant emerging market economy. It is a step towards a better understanding of the microeconomics of banking and how accounting can help with it.

2.2.Literature review and hypothesis development

2.2.1. The need for a forward-looking tool for banks

"You know it when you stress it."
(Tirole, 2011)

An important characteristic of the banking industry is the opacity of the assets, which occurs when investors cannot determine their intrinsic value through the information disclosed in the balance sheet. Stress tests, after the crisis of 2008, became the primary tool for forward-looking supervision by Central Banks around the world. According to Petrella e Resti (2013), stress tests play an essential role in reducing banks' opacity since the prices of bank assets react positively to stress tests conducted by supervisors.

After the crisis of 2008, the Federal Reserve Bank (FED) adopted the stress test-based supervision, which simulated how banks reacted under different macroeconomic scenarios. However, using accruals-based earnings data, Guerrieri e Welch (2012) point out that the *macro variable* model was a good predictor for net-chargeoffs. Still, the *random walk* model is a better predictor for the remaining variables. Alfaro e Drehmann (2009) showed that stress tests had poor predictive performance when the macroeconomics variables were used as explanatory variables. On the other hand, Borio *et al.* (2014) concluded that stress tests are quite effective in predicting the behavior of banks during crises. However, they cannot unveil these banks' vulnerabilities during periods of stability. These findings indicate that it is important to use data that can be adequately forecasted and affected by macroeconomic variables.

The banking supervisors seek continuously to find any methodology that can produce early warning systems that can capture signs that banks are having troubles (Aldasoro, Borio, & Drehmann 2018). According to Quagliariello (2008), studies that show the relationship between the business cycle and bank distress are divided into macro-oriented models, which forecast systemic banking crises using aggregated micro-data, macroeconomic, and financial variables; and micro-oriented models, which discriminate between sound and fragile banks, and uses bank-specific variables and prudential information.

Still, according to Quagliariello (2008), macroeconomic and financial factors are causes of bank distress, and crises are often associated with macroeconomic shocks. Specifically, he points out that macroeconomic variables show inferior performance when used for out-of-sample forecasts. According to Mishkin e Barton (1999), exogenous shocks in the financial system interfere with the flow of information, causing financial intermediation to be overly sensitive to these exogenous events. On the other hand, Barrell, Davis., Karim e Liadze (2010) say that for an early warning system for bank crises, macroeconomic variables shocks don´t play a significant role in sensing a major crisis, being outperformed by other variables, such as property prices and capital adequacy.

Many studies about the predictability of macroeconomic variables for financial data were performed in the past. It is widespread in the literature that the term structure of interest rates has predictive power ability (Estrella & Mishkin, 1997). Dynan e Maki (2001) find that the stock market affects the cost of capital and current consumption due to the *wealth effect*. Regarding the impact of the macroeconomic variables on financial markets, Chen (2009) says that macro variables cannot predict stock returns but are important to predict bear markets.

Regarding other important variables, interest rates measure the cost of capital and have a substantial role in models of consumption and investment spending (Tsatsaronis, 2005). Smets (2014) says that a restrictive monetary policy is a friction factor in the intermediation process and that interest rates are a factor that affects financial intermediation. He argues that monetary policy should be concerned not only with price stability but also with financial stability, as changes in interest rates can affect banks' risk propensity and affect lending. Concerning methodologies that have been used to investigate the effect of macroeconomic shocks on banks in forward-looking exercises, such as stress tests, including regression and vector autoregressive (VAR) time series models investigating the bank dynamics of the bank as a function of macroeconomic variables (Kalirai & Scheicher, 2002; Cihák, 2007; Foglia, 2009).

Acknowledging the importance of macro variables, the Federal Reserve (FED) uses several macroeconomic and financial measures for its annual stress test exercise. It uses six measures of economic activity and prices, such as GDP, unemployment, consumer price index, and other measures of national income. Four financial conditions measures, such as price house index, equity prices, and stock market volatility. Six measures of interest rates containing short- and long-term interest rates and variables describing international economic activities, such as exchange rates and foreign output and income data (FED System Board of Governors, 2020).

2.2.2. Cash flow importance for banks

Tirole (2011), Goodhart (2008), De Moraes e De Mendonça (2017), and Mishkin & Barton (1999) praise the importance of cash flow data for the banking system, as they represent the system's liquidity and the volume of financial intermediation. Frictions in the intermediation process lead to financial instability, which can cause a severe interruption in the flow of funds to people and business activities, causing a financial crisis.

Current measures of banking conditions mainly focus on loans' stocks and do not measure their flows: new credit, amortization, and paid interest. As an example, in case a bank receives an exogenous economic shock, the cash flow of the bank will be the first to react, as loans may be prepaid/defaulted, new money will be granted to customers, or loans might be forborne, depending on the type of the economic event. This change in flows will only be noticed in financial statements over time when the net-interest income changes due to the interest added (lost) due to the variation of the bank's assets or the accurate change in loss provision due to shifts in risk parameters. Hence, *cash flow* variables may be more sensitive to stressed events than other financial statement variables currently used to predict future earnings and should be used to measure banking conditions.

Minsky (1975) suggests that bank examinations should be performed by analyzing cash flows because it assesses the quality of financial soundness of a bank based not only on the quality of loans but also on the liability that funds them. Also, it establishes the quality of banking assets according to their cash-generating capability. Finally, it enables the regulator to assess how the cash flow activities from an individual bank affect the aggregated financial system, as the cash flow from one bank impacts the supply/demand of cash flow of the entire system. De Moraes & De Mendonça (2017), based on Minsk´s literature, built a theoretical framework of the importance of cash flows in the financial system that led to the work of Antunes *et al.* (2018) and De Moraes *et al.* (2019), who created *cash flow* metrics, showing that they can be used as *proxies* of financial intermediation, both at the financial system and the financial institution levels. Specifically, they use the cash flows from existing loans and the granting of new loans, CCF, and the new funding cash flow and the redemption of existing funding, LCF, as measures of financial intermediation.

According to Antunes *et al.* (2018), "the cash flow metrics rationale assumes that changes in the book balance of any account between two subsequent periods are the result of accounting events (revenues and expenses) and cash flow events (cash flows)." Therefore, the bank is in financial disintermediation when CCF is positive and LCF is negative, as the cash outflow from loans is used to redeem funding from liability. At the same time, the bank is in financial intermediation when CCF is negative and LCF is positive. As the bank grants more loans, it increases the liability funding to perform this task.

According to the banking literature shown above, financial intermediation will occur depending on economic conditions. Therefore, any changes in the economy or risk environment will immediately reflect on these metrics. Thus, it would be important to research how the macroeconomic variables impact the *cash flow* variables of the bank. If we have a good reflection of the economic scenario, then *cash flow* metrics translate into earning persistence, quality, and prediction. An excellent way to measure how exogenous economic shocks affect bank variables is with a stress test methodology.

This leads us to the first two hypotheses, which will test the predictivity gain of the macroeconomic variables model compared to its benchmark model. Hypotheses 1 and 2 test whether macroeconomic variables can predict the measure of banking condition, hence represented by the *cash flow* variables. Suppose the macroeconomic model outperforms a more parsimonious benchmark model. In that case, it signals that future values of these variables are impacted by current and past macroeconomic events, as according to IASB (2015), a fundamental qualitative characteristic of accounting information is relevance. To be relevant, the information should provide predictive power regarding possible future events or/and have confirmatory value about past evaluations.

Regarding benchmark models, many authors use the naïve *random walk* model to evaluate forecast accuracy (Foster, 1977; Clark & West, 2007; Guerrieri & Welch, 2012). Others (Foster, 1977; Alfaro & Drehhmann, 2009) point out that autoregressive models are good predictors of future performance. Based on that, we use two benchmarks: the lower bound naïve *random walk* model and the upper bound ARIMA[3] model. We nest the upper bound benchmark for our alternative model by adding the macroeconomic variables, resulting in the macro variables with ARIMA error model. As autocorrelation of series is a common problem in time series, our results would become less reliable if these were not considered when testing the gain in predictivity of the macroeconomic variables for future bank performance forecasts. A similar test with a nested ARIMA benchmark was conducted by Ravazzollo & Rothman (2013) to assess whether a model of macroeconomic variables with ARIMA errors could better forecast future oil prices than a pure ARIMA model. For our hypotheses 1 through 5, we will use the variation “a” for the *random walk* benchmark and “b” for the pure restricted ARIMA model benchmark.

[3] ARIMA order of p, q, and d will be determined by an automatic ARIMA forecasting by Hyndman & Khandakar (2008).

Hypothesis 1: Macroeconomic variables with ARIMA errors model can better predict future *Cash Flow from Credit*-CCF, compared to the benchmark model, for one period ahead forecast.

$$H_0: Ee_{1t} - \ Ee_{2t} \leq 0$$

$$H_1: Ee_{1t} - \ Ee_{2t} > 0$$

*where e_{1t} represents the benchmark model root mean squared error (RMSE) and e_{2t} represents macro variables model RMSE for CCF.

Hypothesis 2: Macroeconomic variables with ARIMA errors model can better predict future *Liability Cash Flow* -LCF, compared to the benchmark model, for one period ahead forecast.

$$H_0: Ee_{1t} - \ Ee_{2t} \leq 0$$

$$H_1: Ee_{1t} - \ Ee_{2t} > 0$$

*where e_{1t} represents the benchmark model RMSE, and e_{2t} represents macro variables model RMSE for LCF.

2.2.3. Accrual for banks

Dechow (1994) claims that the primary purpose of accruals is to overcome problems with measuring firm performance when firms are in continuous operation. The purpose of accruals is to mitigate the timing and matching properties of cash flows by offsetting cash-flow components unrelated to performance. Barth, Clinch, & Israeli (2016) also indicate that earnings are designed to reflect current period economics, not current period cash flow. Therefore, accruals should align a firm’s cash flows and the economic generating of the cash flows. In the same sense, Ohlson (2014) states that “accrual accounting counterdemands the deficiencies inherent in cash accounting when there are costly strategic activities that serve as the foundation for potentially creating value in subsequent periods.”

Many studies were performed to analyze how accruals define future earning prediction. A line of study attests the greatest the accrual in relation to cash in current *earnings*, the less persistent this *earning* is. Other studies mention that the quality of accruals depends on their discretionary because these are not susceptible to many kinds of earning management. In a seminal paper, Sloan (1996) finds that the accrual component of current profitability is less persistent than the cash flow component. He notes that investors don´t fully price the differing implications of the accrual and cash flow components of current profitability for one-year-ahead profitability. Ohlson (2014) reinforces that the literature indicates that an accurate accrual should be a leading indicator or produce forecasts of subsequent cash flows. However, this assumption has a problem, as future cash flows interact with future accruals.

An essential attribute of the quality of accounting information is the extent to which accruals are mapped to cash flows. A poor mapping of the accruals in cash flows reduces the content of reported earnings information and results in lower quality gains. Specifically, Bhattacharya, Desai, & Venkataraman (2013) show that a company with a lower-earning quality has more significant information asymmetry and suffers greater from adverse selection, thereby decreasing the liquidity of its assets. Flores & Braunbeck (2017) explain that the accrual will turn into cash at some point in time. The harshness is to estimate when this transformation occurs and what is the value of this conversion. This misalignment of expectations can be a significant cause of reversals and reduce the persistence of *earnings*.

But where does the banking industry stand in all of this? The dynamic of the financial sector is different from what the authors above say, mainly because of the nature of banking and operating assets. According to Damodaran (2013), the dynamics on banks’ balance sheets are different than in other industries. Debt, for example, can be considered a raw material rather than a source of capital. The discussion of accruals, cash flows, *earnings* persistence, and *earnings* quality is challenged by this distinct nature. In addition, in the well-known *forbearance* mechanism, accruals that were once considered non-discretionary can quickly become discretionary through renegotiations or prepayments.

Why are the accruals in the banking industry considered to be the cause of so much noise in banks´ financial statements? As previously mentioned, discretionary accruals are quite relevant to banks’ *earnings*. The largest discretionary accruals on banks’ financial statements are loan loss provision, which is in significant portion discretionary.

According to Beatty e Liao (2014), between 2005 and 2012, the ratio of the mean of the absolute value of the provision of the total accruals was about 56%, which was almost twice the value of the next most significant accrual. Loan loss provisioning directly influences the volatility and cyclicality of bank *earnings*, as reflects its loan portfolios’ risk attributes (Bushman & Williams, 2012).

As per Borio *et al.* (2001) and Laeven & Majnoni (2013), incurred loss accounting rules contribute to backward-looking provisioning, as they are based on past events, not on expectations. On the other hand, empirical evidence shows that forward-looking provisioning mitigates procyclicality in lending (Beatty & Liao, 2011; Bouvatier & Lepetit, 2012). Also, accounting rules may allow for loan renegotiations, which is done to avoid loss recognition, the so-called *forbearance,* which increases opacity (Brown & Dinç, 2011; Flannery & Nikolova, 2004).

The challenges that accruals bring to evaluating a bank´s performance lead us to the third, fourth, and fifth hypotheses that test the predictivity gain of the macroeconomic variables model compared to its benchmark model for the *earnings* variables. Specifically, the three variables are tested: *net-interest income* (NIM), *non-interest income* (NII), and *loan loss provisions* (LLPT). These variables are commonly used in stress tests exercise and are widely used in the banking literature.

Hence, Hypothesis 3 to 5 test whether macroeconomic variables can predict the *earnings* variables. Suppose the macroeconomic model outperforms a more parsimonious benchmark model. In that case, it is a sign that the future values of these measures of banking conditions are impacted and can be forecasted by macroeconomic events**.**

Hypothesis 3: Macroeconomic variables with ARIMA errors model can better predict future *net-interest income* (NIM), compared to a benchmark model, for one period ahead forecast.

$$H_0: Ee_{1t} - \ Ee_{2t} \leq 0$$

$$H_1: Ee_{1t} - \ Ee_{2t} > 0$$

*where e_{1t} represents the benchmark model RMSE, and e_{2t} represents macro variables model RMSE for NIM

Hypothesis 4: Macroeconomic variables with ARIMA errors model can better predict future *non-interest income* (NII), compared to a benchmark model, for one period ahead forecast.

$$H_0: Ee_{1t} - \ Ee_{2t} \leq 0$$

$$H_1: Ee_{1t} - \ Ee_{2t} > 0$$

*where e_{1t} represents the benchmark model RMSE, and e_{2t} represents macro variables model RMSE for NII

Hypothesis 5: Macroeconomic variables with ARIMA errors model can better predict future *loan loss provision* (LLPT), compared to a benchmark model, for one period ahead forecast.

$$H_0: Ee_{1t} - \ Ee_{2t} \leq 0$$

$$H_1: Ee_{1t} - \ Ee_{2t} > 0$$

*where e_{1t} represents the benchmark model RMSE and e_{2t} represents macro variables model RMSE for LLPT.

2.3. Data and methodology

This study will use times series forecasts, using the *Combination of Forecasts* model of Bates & Granger (1969), with a *pseudo-out-of-sample* approach, dividing the dataset into training and testing data. The training set will be used to model the data tested for forecast accuracy in the *pseudo*-out-of-sample, also called testing data or holdout data. The prevalence of out-of-sample tests in regression model has been defended since Watts & Leftwich (1977) mentioned the "Regression Fallacy" when performing predictions with in-sample data. It is noted that many in-sample positive results are not able to perform well in out-of-sample data. This is pointed out by Kim e Kross (2005) that in-sample, descriptive goodness of fit does not imply an accurate out-of-sample forecast due to the overfitting of the model.

More recent work from Lorek e Willingner (2010, 2010b) uses out-of-sample data not used in the model to test quarterly cash flow from operations forecast. The authors mentioned that they avoided problems encountered in previous work, such as Barth, Cram, & Nelson (2001), which relied on fit measures of in-sample data to assess predictive performance. Other authors in the accounting literature also use regression models to generate out-of-sample cash flow and EPS forecasts, such as Krishnan & Largay (2000), Lev & Sougiannis (2010), Francis & Eason (2012), and Francis & Olsen (2015).

2.3.1. Data and Sample

This paper uses data for bank conglomerates in Brazil, from Financial Institutions/Conglomerates Balance Sheets and IF.data from the Central Bank of Brazil. The reason for using Brazilian data is the good data granularity, and the fact that the financial intermediation in Brazil is historically done mainly by financial institutions in a distinctive economic scenario with high-interest rates makes this type of market unique for analysis of the behavior of this banking system.

The analysis is based on quarterly data from 213[4] financial institutions from September 2000 to September 2009, accounting for 77 periods. Development banks are not included in this study, as they have special incentives and operate differently from other commercial banks.

[4] Including the entire period studied. Many institutions were no longer active or merged, so the number as of 2019 is lower, with 132 banks.

The entire financial system and four distinctive bank segments – systemically important banks (SIB), large, medium, and small banks – are investigated to test whether there is a variation in forecasting capability between different segments of the banking system. For macroprudential regulatory reasons, these segments are set by the Central Bank of Brazil, Resolution 4.553 (Central Bank of Brazil, 2017), grouping banks according to their relevance to the financial system. This approach is also consistent with the Basel Framework segmentation to identify Global Systemically Important Banks – GSIBs in BCBS (2011), as they require higher capital requirements due to their importance to the financial system. Comparing these four distinctive groups makes it possible to compare forecast accuracy considering the heterogeneity of these segments and see how the cash and accrual data are effective when used in forecasting models for stress testing.

- **SIB** – It contains the largest Brazilian banks, which hold 80% of the banking system's total assets. It is comprised of seven financial institutions. These banks are considered domestically systemically important banks (D-SIBs).
- **Large banks (LARGE)** – It is composed of six institutions, representing 6% of the total assets of the financial system. It consists of banks that, for the most part, also have a strong presence in the wholesale segment; they have high participation in corporate credit but are not as active in retail as SIB banks.
- **Medium banks (MEDIUM),** with 33 institutions representing 10% of the banking system's total assets, are institutions that focus on small and medium-sized companies or the so-called middle market. Their funding comprises short-maturity financing, such as CDB (Bank Deposits Certificate) and short notes, among other types of funding. It is primarily a wholesale segment for higher-risk clients than the large banks.
- **Small Banks- (SMALL)** – With 3% of total assets and 87 banks, it is composed of niche institutions, which often assist an industrial group in financing their customers. These banks operate in particular markets.

2.3.1.1. Mergers and acquisitions adjustments

For mergers and acquisitions (M&A), we will work with the current institutions and adjust the data for M&A backward, back to September 2000. So, this work created a unique time series by segregating the banks into these four segments as of September 2019. Then, we adjusted the time series by aggregating the data of the acquiree to the acquirer back to

September 2000. Also, as the classification of the segments was only done for 2017 forward 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 September 2000.

2.3.1.2. *Cash flow* variables as a measure of banking condition

This study will use two *cash flow* variables, created by Antunes *et al.* (2018) and De Moraes *et al.* (2019), which are CCF, and LCF described below.

***CCF*[5] $_t$: Credit Cash Flow**

***CCF*: -**(*credit asset $_t$ – credit asset $_{t-1}$) + interest revenue – net provisions – net write-offs*

***LCF*[6]: Liabilities Cash Flow**

***LCF*:** *(funding $_t$ – funding $_{t-1}$) – interest expenses*

** Calculations provided by Antunes *et al.* (2018) and De Moraes *et al.* (2019)

2.3.1.3. *Earnings´* variables as a measure of banking condition

The variables that make up most of the earnings for a bank balance sheet are NIM, NII, and LLPT, which are the variables used by CCAR (FED System Board of Governors, 2020) and by the Brazilian Financial Stability Report (Central Bank of Brazil, 2018) for their stress exercise. These variables will be scaled by total asset $_{t-1}$[7].

2.3.1.4. Exogenous macroeconomic variables

The macroeconomic variables that will be used to forecast the *cash flows* and the *earnings*

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[5] Scaled by total assets at *t-1*.
[6] Scaled by total assets at *t-1*.
[7] As per Guerrieri & Welch (2012).

variables are proposed by the stress test scenarios built by the Central Bank of Brazil in the Financial Stability Report (Central Bank of Brazil, 2018). These variables are aligned to what is used in the *Comprehensive Capital Analysis and Review* (CCAR) (FED System Board of Governors, 2020) in stress scenarios for the US. This data is composed of the leading indicators of economic and financial market activity, and they are used in stress tests due to their impact on the financial industry. This study is focused on how exogenous macroeconomic events impact bank variables; therefore, we will not use bank-specific variables as explanatory variables in the forecasting model.

- ***GDP*** – Quarterly (YoY) GDP % variation, provided by the Brazilian Bureau of Statistics (IBGE) and IPEA data.
- ***FOREX*** – Quarterly Exchange rate USD/BRL % variation, quarterly, provided by the Central Bank of Brazil
- ***IR***- Repo rate for government bonds. Provided by the Central Bank of Brazil
- ***EMBI*** – Risk premium of Dollar-denominated Brazilian Bonds in basis points. Calculated by JP Morgan Chase.
- **TNX**- Rate for the 10 yr. US government bond. It shows the long-term rate for risk-free assets in Dollar.
- ***UNEMP*** – Brazilian unemployment rate measured by the PNAD data. Before 2012, the index used to measure Brazilian unemployment was the unemployment rate for the main metropolitan regions of Brazil. Data is provided by IBGE.
- ***DI360*** – Term spread of Brazilian rates measured by swap D1 X Pre 360, a float vs. fixed-rate Brazilian government bond swap. Data provided by the Central Bank of Brazil.
- ***BVSP*** – Stock market index for Brazil. It measures the variation of equity risk in Brazil. Data is provided by B3.

2.3.1.5. Data treatment

All bank variables were divided by the previous period's total assets ($total\ assets_{t-1}$). The reason for it is to make the data comparable and diminish time effects on data.

Summaries of the bank variables and the macro variables are presented in Tables 2.1 to 2.3. The number of banks shown in the descriptive statistics reflects the ones operating as of September 2019.

Table 2.1*:* Descriptive statistics for Credit Cash Flow -CCF and Liability Cash Flow -LCF

	SIB CCF	*Large CCF*	*Medium CCF*	*Small CCF*	*All banks CCF*	*SIB LCF*	*Large LCF*	*Medium LCF*	*Small LCF*	*All banks LCF*
Mean	0.29	0.55	0.56	0.89	0.36	0.42	-0.11	0.39	-0.54	0.32
Std. Error	0.14	0.18	0.20	0.26	0.13	0.24	0.38	0.41	0.46	0.22
Std. Deviation	1.26	1.55	1.75	2.32	1.18	2.08	3.35	3.59	4.02	1.92
Min	-2.24	-3.20	-5.77	-5.58	-2.13	-4.34	-9.07	-8.85	-14.01	-4.00
Max	3.90	4.86	5.25	10.18	3.82	6.17	7.72	13.33	8.66	5.60
Time series period	77	77	77	77	77	77	77	77	77	77
Dickey-fuller test* p-value	0.02	0.01	0.01	0.06	0.03	0.02	0.01	0.01	0.01	0.02
Number of banks	6	6	33	87	132	6	6	33	87	132
% of total assets	80%	7%	10%	3%		80%	7%	10%	3%	

*Null hypothesis denotes non-stationarity for Adf test up to lag three.

Table 2.2: Descriptive statistics for Net Interest Income -NIM and Non-Interest Income -NII

	SIB NIM	*Large NIM*	*Medium NIM*	*Small NIM*	*All banks NIM*	*SIB NII*	*Large NII*	*Medium NII*	*Small NII*	*All banks NII*
Mean	1.62	1.56	1.75	1.81	1.62	0.68	0.50	0.39	0.38	0.63
Std. Error	0.06	0.05	0.06	0.06	0.05	0.02	0.01	0.01	0.01	0.01
Std. Deviation	0.53	0.40	0.50	0.56	0.47	0.15	0.12	0.06	0.09	0.12
Min	-0.39	0.15	0.19	0.14	-0.10	0.49	0.28	0.30	0.18	0.47
Max	2.53	3.06	3.17	3.27	2.58	0.97	0.89	0.58	0.68	0.88
Time series period	77	77	77	77	77	77	77	77	77	77
Dickey-fuller test* p-value	0.38	0.41	0.21	0.25	0.36	0.02	0.59	0.28	0.51	0.41
Number of banks	6	6	33	87	132	6	6	33	87	132
% of total assets	80%	7%	10%	3%		80%	7%	10%	3%	

*Null hypothesis denotes non-stationarity for Adf test up to lag three.

Table 2.3:Descriptive statistics for Loan Loss Provision -LLPT

	SIB LLPT	*Large LLPT*	*Medium LLPT*	*Small LLPT*	*All banks LLPT*
Mean	0.52	0.33	0.40	0.38	0.49
Std. Error	0.01	0.02	0.02	0.02	0.01
Std. Deviation	0.12	0.17	0.14	0.14	0.11
Min	0.26	0.00	0.00	0.06	0.26
Max	1.09	0.71	0.76	0.75	0.97
Time series period	77	77	77	77	77
Dickey-fuller test* p-value	0.49	0.44	0.55	0.45	0.50
Number of banks	6	6	33	87	132
% of total assets	80%	7%	10%	3%	

*Null hypothesis denotes non-stationarity for Adf test up to lag three.

Table 2.4: Descriptive statistics for macro variables

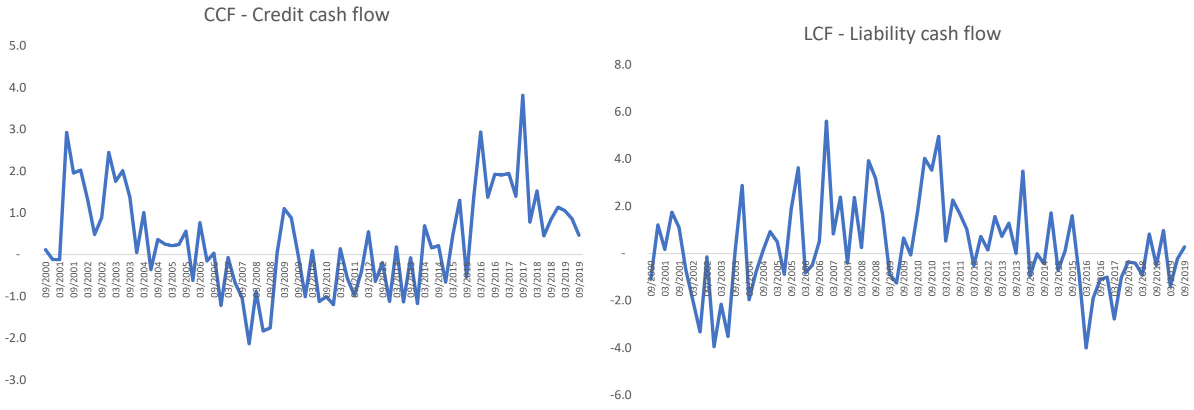
	EMBI	*FOREX*	*PIB*	*DI 360*	*BVSP*	*TNX*	*IR*	*UNEMP*
Mean	415	1.1	2.4	13.5	2.4	3.3	13.0	9.0
Std. Error	41	1.0	0.4	0.6	1.5	0.1	0.5	0.3
Std. Deviation	363	9.2	3.1	5.5	13.0	1.2	4.7	2.4
Min	142	-17.1	-5.5	4.9	-31.4	1.5	5.7	4.8
Max	2,397	31.4	9.2	29.9	32.8	5.8	26.3	13.7
Time series period	77	77	77	77	77	77	77	77
Dickey-fuller test* p-value	0.2	0.0	0.0	0.2	0.0	0.0	0.2	0.7

*Null hypothesis denotes non-stationarity for Adf test up to lag three.

In Figures 2.1, 2.2, and 2.3, we can see the behavior of the *cash flow* variables and the *earning* variables aggregated for the entire banking system. In Figure 2.1, we see that CCF and LCF are very volatile. It is interesting to note the behavior of these variables during specific periods in the Brazilian economy. During 2002, when the country went through financial turmoil due to presidential elections, the banking system was cashing in, meaning that it was taking cash out of the loan portfolio. During the same period, the LCF was negative, meaning that the banking system was returning cash to the depositors. A negative LCF with a positive CCF implies that the bank is in the process of disintermediation, as we can recall from Figure 2.1, which is a typical process during the economic downturn. This process of disintermediation inverts as the economy recovers. From 2006 to 2008, the CCF is negative, which indicates that banks are putting cash into the loan portfolio. At the same time, the LCF is positive, meaning that new deposits finance this investment in the loan portfolio during this process of financial intermediation.

During the financial crisis of 2008, we see that CCF and LCF quickly reverts, showing the effects of the financial turmoil. Soon later, the intermediation process recovers, showing a quick reaction to the financial crises. The process of financial intermediation continued until 2016, when an intense process of financial disintermediation occurred due to the economic crises of 2016 and 2017.

Figure 2.1: CCF and LCF from Sep. 2000 to Sep. 2019 – all banks



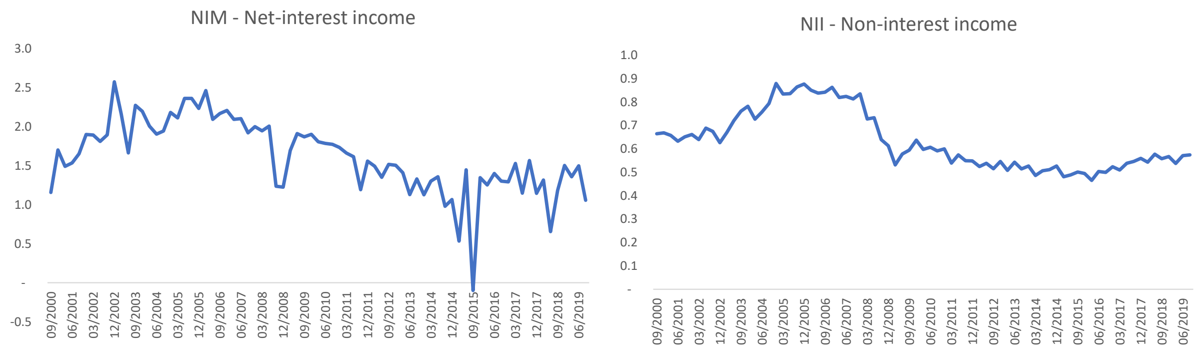
Source: Author and Central Bank of Brazil

The behavior of the *earning* variables in the same period is much more stable than the *cash flow* variables, as we can see in Figures 2.1, 2.2, and 2.3 and the descriptive statistics in Tables 2.1, 2.2, and 2.3. Regarding the behavior of these variables, we can see that they follow a similar pattern during the studied period.

It is also important to note the difference in standard deviation among the segments for different variables. For instance, the standard deviation of CCF and LCF increases substantially as the size of bank segments diminishes. When we analyze the *earnings* variables, we see steady data volatility among all segments. In this sense, the *cash flow* variables may reflect more the risk differences among these banks than the *earning* variables. Another interesting fact about the *earning* variables is the behavior of NIM and LLPT during the crises of 2016 and 2017. During this time, NIM suffered a sharp decline. At the same time, LLPT also decreased, which is unexpected in economic downturns.

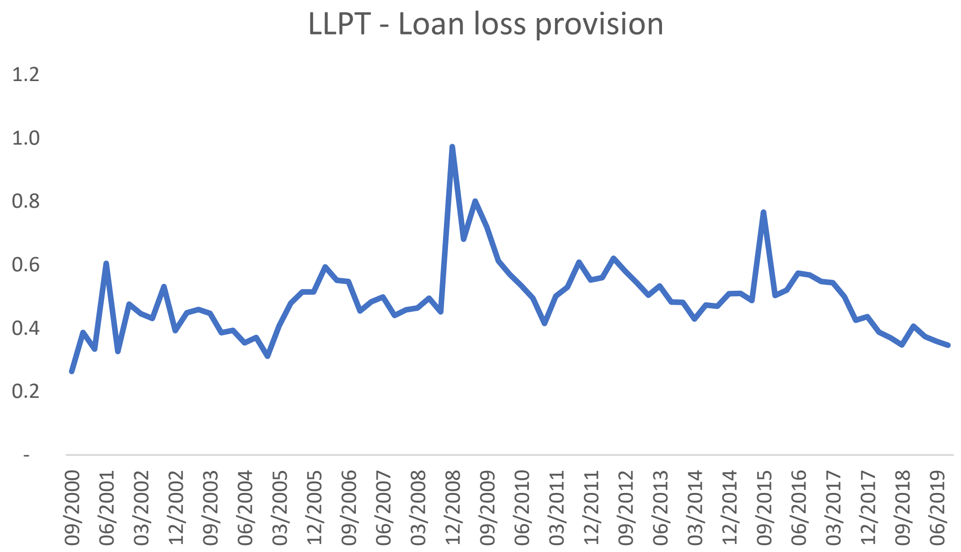
Table 2.5 shows the matrix correlation of all variables, exogenous macro variables, and measures of banking conditions for the entire banking system. It is important to note the high negative correlation of GDP and CCF, meaning that the higher the GDP, the more the banks will have a cash outflow by investing money in the loan portfolio. At the same time, the higher the GDP, the higher the LCF will be, as families and businesses will be keener to fund banks, and banks will increase funding to increase financial intermediation. The same process happens with unemployment and the *cash flow* variables. It is important to be cautious with correlation in time series, as not all variables are stationary, leading to a spurious correlation. However, this matrix can give some important first clues to the behavior of our data.

Figure 2.2: Net-interest income and non-interest income interest from Sep. 2000 to Sep. 2019 - all banks



Source: Author and Central Bank of Brazil

Figure 2.3: Loan loss provision from Sept. 2000 to Sep. 2019 - all banks



Source: Author and Central Bank of Brazil

Table 2.5: Correlation matrix - Bank variables and macro variables - all banks

	EMBI	*FOREX*	*GDP*	*DI360*	*BVSP*	*TNX*	*IR*	*UNEMP*	*CCF*	*LCF*	*NII*	*NIM*	*LLPT*
EMBI	1.00												
FOREX	0.33	1.00											
GDP	-0.02	-0.04	1.00										
DI 360	0.84	0.11	0.09	1.00									
BVSP	-0.23	-0.73	-0.11	-0.13	1.00								
TNX	0.36	-0.13	0.46	0.58	0.09	1.00							
IR	0.63	-0.10	0.01	0.90	0.05	0.56	1.00						
UNEMP	-0.13	-0.17	-0.24	-0.20	0.29	-0.12	-0.00	1.00					
CCF	0.36	-0.19	-0.54	0.25	0.26	-0.08	0.29	0.40	1.00				
LCF	-0.35	0.18	0.42	-0.21	-0.14	0.09	-0.26	-0.32	-0.68	1.00			
NII	0.15	-0.20	0.52	0.41	0.18	0.78	0.51	0.16	-0.25	0.22	1.00		
NIM	0.20	-0.53	0.47	0.41	0.41	0.62	0.48	0.03	-0.02	0.04	0.76	1.00	
LLPT	-0.18	0.08	-0.29	-0.17	-0.10	-0.30	-0.12	-0.22	-0.09	0.09	-0.22	-0.13	1.00

2.3.2. Forecast model

The model to be used is the *Combination of Forecasts* of Bates & Granger (1969). This model is chosen because it is not overly complex, and, according to Guerrieri & Welch (2012), this technique has yielded results near the frontier of best performance. Therefore, it can be considered a benchmark for forecasting.

The combination of forecasts works with several regression models chosen by the researcher. Each model will produce errors in the training data. The combination of forecasts will choose a combination of models that minimizes the variance of these errors over time. Models that have a high variance of errors throughout the entire training period are considered not to be the best model. Therefore, the combination of forecasts will choose the weights of each model to minimize the overall variance. So, the higher the model's variance, the lower weight it will have in the combination of forecasts.

2.3.2.1. Bates & Granger Combination of Forecasts model

Let w_j be the weight of each model *j*. The values of w_j are not known at the beginning of the forecast and are based on the errors of the fitted model of each model *j* with the training data of the series. The value of w_j for the final model will be inversely proportional to its error variance $\hat{\sigma}_j^2$. In equations 2.1 and 2.2; we can see the general equation for the Bates & Granger model for j values:

$$w_j = \widehat{\sigma^{-2}}(j)/\Sigma_{j=1}^{N}\widehat{\sigma^{-2}}(j) \tag{2.1}$$

Where $\widehat{\sigma^2}(j)$ is the MSE of model *j*.

The combination of forecasts is given by the weights of each model multiplied by their fitted model f_t^j :

$$\widehat{y_t} = \left(f_t^j\right)' w_t^j \tag{2.2}$$

As we will test if the macroeconomic variables can predict cash flow and income state variables, we will use a multiple regression with ARIMA errors to determine the fitted values used for weighting the combination of forecasts in equation 2.2.

$$f_t^j = \sum_1^{i=3} \sum_1^{k=2} \beta_i x_{t-k}^i + n_t \quad (2.3)$$

where, $n_t = \phi_1 n_{t-1} + \cdots + \phi_p n_{t-p} - \theta_1 z_{t-1} - \cdots - \theta_q z_{t-q} + z_t$

$f_t = fitted\ value\ for\ cash\ flow\ and\ earning\ variables$ at time *t and model j*

x_t^i =*Macro variable i* at time t

k= lags[8] *of* x_t^i.

$n_t = ARIMA\ errors$[9], where

$z_t = white\ noise$

P=lags AR

q-= lags MA

From equations 2.1, 2.2, and 2.3, we arrive at the following forecast equation:

$$y_{t+1} = \sum_1^{j=6} \left(f_{t+1}^j\right)' w_t^j \quad (2.4)$$

where, $w_t^i = weight\ of\ modelj\ obtained\ from\ equation\ 1$

We built six models[10], each containing a different set of macroeconomic variables that could affect the bank variables and that are usually used in stress test scenarios, according to the Financial Stability Report- Stress Test Methodology (Central Bank of Brazil, 2018) and the

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[8] We used two lags. Guerrieri & Welch (2012) tested four lags, but with the limited number of time series observations, more lags would overfit the model and decrease forecast accuracy.

[9] ARIMA order of p, q, and d will be determined by an automatic ARIMA forecasting by Hyndman & Khandakar (2008). The ARIMA order will be calculated restricting the exogenous covariates to zero. Based on the defined order, we include the exogenous regressors for our alternative hypothesis. The benchmark ARIMA and the Macro variables with ARIMA errors will have the same ARIMA parameters, making the benchmark a restricted version of the alternative model.

[10] six models j with different covariates to be used in the combination of forecasts model.

$j_{1t} = GDP + IR + UNEMP$

$j_{2t} = GDP + IR + FOREX$

$j_{3t} = GDP + IR + EMBI$

$j_{4t} = FOREX + DI360 + EMBI$

$j_{5t} = DI360 + EMBI + BVSP$

$j_{6t} = FOREX + DI360 + TNX$

CCAR (FED Board of Governors, 2020). This approach was also made by Guerrieri & Welch (2012). We built these six models, so we can test different models with different covariates that are used in stress test exercises. As our time series sample is not very large, we need other models to test all the covariates.

The combination of forecasts consolidates these six models into one optimal model, according to their forecast accuracy, determined by equations 2.1 and 2.2. This is important as we are performing multiple-period forecasts, which will be influenced by different business cycles. Therefore, the macro variables' influence on the dependent variables changes over time, causing different macro models to be relevant with different *rolling forecast origins*. The combination of forecasts will choose these models dynamically, weighting them in a combination that diminishes the forecast error.

2.3.2.2. Time Series Cross-Validation

A recurring problem for regression modeling in forecasting is the error measures when forecasting different business cycles (Tashman, 2000). A multi-period test, a form of Times Series Cross-Validation, is important to obtain business cycle diversity and improve your forecast capability. According to Hydman &Athanasopoulos (2018) and Bergmeir, Hydman & Koo (2018), the *Time Series Cross-Validation* technique is a more sophisticated training/test forecast version. It allows you to better use available data by performing several forecasts with the same data. It also helps to mitigate possible overfitting in the model. In this model, no future observation is used when building the model. In this approach, you perform several rounds of training forecasts, and you increase the training data by one observation in each of them until you use all the data points available for your time series.

It is good to have the test data to at least 20% of the total data (Hydman & Athanasopoulos, 2018). When your dataset is not large, you can increase the proportion of the test set. In this study, we first train our model with data observation from 1 to 54, which is a proportion of 70%-30% train/test. As the dataset is not large, we chose 30% to generate enough forecast errors, in our case, 23 for each step forecasted.

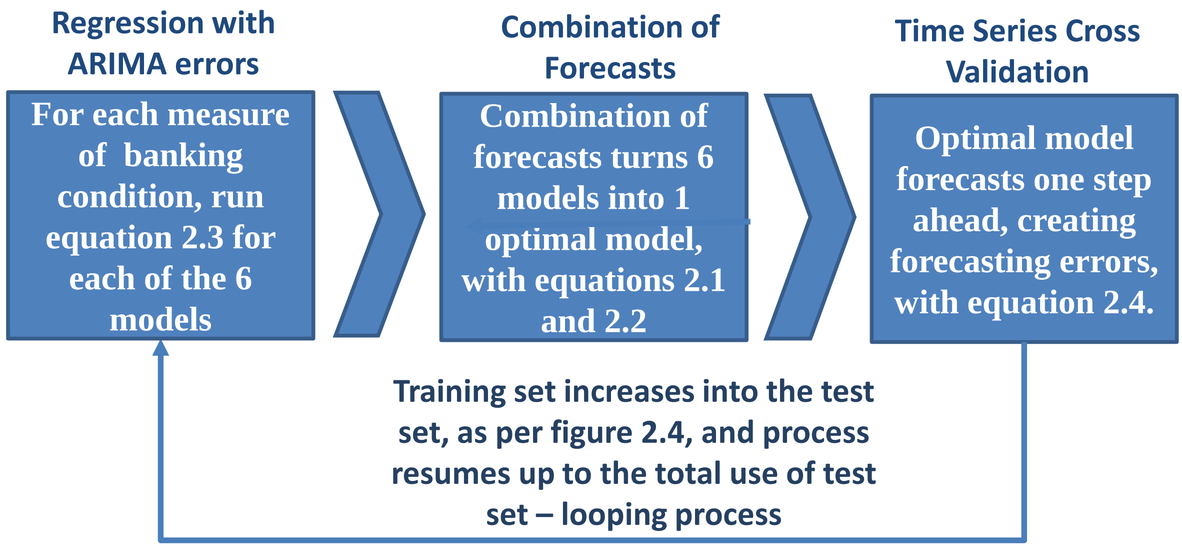
At the end of each training round, the model generated one forecast error for each predicted variable. Then, this error will be compared to a more parsimonious benchmark model to test superior forecast power for each of the steps forecasted. Figure 2.4 below shows an example of the *Time Series Cross-Validation* that will be performed. The type of *Cross-Validation* used in this work is *Rolling Origin Forecast with Constant Holdout*. This approach was also used in a study by Svetunkov & Petropoulos (2018) and defended by Tashman (2000) and Hydman & Athanasopoulos (2018) as the best type of out-of-sample technique for cross-validation forecast. According to the last author, *the Rolling Origin* offers a more efficient series splitting rule, allowing for distinct error distributions by lead time, and desensitizes the error measures to special events at any single origin. It helps to mitigate the error measurement of a single phase of business cycles (Tashman, 2000). The technique has this name because the training data is not fixed regarding the number of observations, as it increases at each round, but the out-of-sample data is constant, always having one period in the forecast range, as we are performing a one-step forecast.

Figure 2.4: Time Series Cross-Validation – Rolling Origin Forecast with Constant Holdout

Source: https://godatadriven.com/

Therefore, for each measure of banking condition – CCF, LCF, NIM, NII, and LLPT – we will have 23 different steps of time series cross-validation for our *macro variable* model with ARIMA errors, which is the model for our alternative hypothesis represented by equation 2.3. So, for each of the 23 forecast steps, we perform the combination of forecasts (Bates & Granger, 1969) to determine the best weighing of the six models and combine them into one optimal model, as presented in equations 2.1 and 2.2. For each forecast step, we run a forecast and produce forecast errors based on the combination of forecasts, which is represented by equation 2.4. Therefore, for each measure of banking condition, we will calculate six equations for each of the 23 one-step forecasts, which yields 138 equations for each measure of banking condition. As we have five hypotheses, each of them with one different measure of banking condition, the total number of equations to determine the RMSE necessary to assess forecast accuracy will be 690. As our sample consists of five segments –all banks, SIBs, LARGE, MEDIUM, and SMALL – the total number of equations for all the alternative hypotheses, provided by equation 2.3, will be 3,450.

Figure 2.5: Summary of the forecasting model process: Time series regression with ARIMA errors, Combination of Forecasts, and Time Series Cross-Validation



Source: Author

2.3.2.3. Clark and West statistic test

We use the appropriate statistical test of Clark & West (2005, 2007b) to test these hypotheses, which is considered an adequate test to compare nested and expanded models (Hubrich & West, 2010; Diebold, 2015). The test compares the RMSEs of the benchmarks against the RMSE of the alternative model. Clark & West (2006, 2007b) test that the two models have equal RMSE when parameters are set at population values. However, they found that the results are biased because the benchmark model, usually a *random walk*, has all the parameters set to zero, while the alternative, or the expanded model, introduces noise into the forecasts, resulting in an inflated RMSE. The author proposes an adjustment that will correct this bias. For this reason, because of the adjustment, we might be able to reject the null hypothesis of equal predictivity ability, even though the alternative model has a higher RMSE than the *random walk* model. For a 10% significance level, the Clark and West statistics test if the RMSE of the macroeconomic variables models has a lower RMSE than the nested *random walk* and pure ARIMA models.

$$\hat{f}_{t+1} = \hat{e}^2_{1t+1} - [\hat{e}^2_{2t+1} - (\hat{y}_{1t+1} - \hat{y}_{2t+1})^2] \tag{2.5}$$

$$\bar{f} = P^{-1} \sum_R^T \hat{f}_{t+1} \tag{2.6}$$

$$\text{Clark West test statistic} = \frac{\sqrt{P\bar{f}}}{\hat{\sigma}^2_{(\hat{f}_{t+1} - \bar{f})}} \tag{2.7}$$

$\hat{e}$ = forecast out-of-sample error to observed data

t= last observation of the training model

where P = number of forecasts $t+1$

*Clark West statistics follows a t-student distribution, with n-1 degrees of freedom.

For this work, we standardize the RMSE, as it is scale-dependable data. As our variables are on different scales, we should have a common ground of comparability among the RMSEs. To achieve this, we standardize the RMSE by dividing it by the interval max-min, according to equation 2.8. This will put all the RMSEs in the same unit and not alter the forecast errors' distribution.

$$nRMSE = \frac{RMSE}{X_{obs,max} - X_{obs,min}} \tag{2.8}$$

2.4.Empirical results

2.4.1. Results for the aggregated banking system

The results in Table 2.6 show that the *macro variables* model, when the information for the entire banking system in Brazil is aggregated, is better able to predict future financial performance than a *random walk* model for all CCF, LCF, NIM, and NII; meaning that hypotheses 1a to 4a are rejected, indicating that the *macro variables* model is more suited to forecast bank performance than the *random walk* model. However, when we compare the *macro variable* model to the upper bound benchmark ARIMA model for the entire banking system, the results show that only LCF and NII can be better predicted by the macroeconomic variables, with a 90% significance level. This result indicates that for the aggregated data of the entire financial system, using the ARIMA as a benchmark, only hypotheses 2b and 4b are rejected. This is an indication that for CCF, LLPT, and NIM, their own past observations are better predictors of their future performance and that macroeconomic scenarios do not offer gains in predictivity for aggregated data of the entire banking system, indicating that autoregressive models can be a good predictor of future performance.

De Moraes *et al.* (2019) mentioned that LCF could be considered a *proxy* for financial intermediation, which is very sensitive to macroeconomic conditions. Therefore, the financial system is expected to react to macroeconomic and financial scenario changes at the aggregated level. CCF, the other *cash flow* variable, does not have the same response to macro variables as the LCF for the entire banking system sample. It is natural that LCF is much more volatile than CCF, as bank liability has lower maturity than loans and may be more sensitive to external economic shocks. This higher volatility may explain the results, as LCF reflects macroeconomic scenarios, and CCF may depend more on other distinctive factors for each bank. In addition, aggregated information about the financial system is dominated by data from SIBs banks, which accounts for 80% of the system’s total assets and may skew the analysis.

According to De Moraes e De Mendonça (2017), a financial crisis occurs when there is a mismatch in bank cash flows. If LCF and CCF are not in balance, meaning that the cash used or provided by loans and liabilities do not offset each other, a bank will be forced to use (provide) cash from (to) financial buffers and use the money market in case there is a net cash outflow (inflow). Depending on the magnitude of the impact of the exogenous macroeconomic shock on LCF, banks may face liquidity constraints, as they won´t be able to use the money market, and their financial buffers may not be enough to withstand the liquidity needs, which according to Tirole (2011) and Goodhart (2008) was one of the causes of the 2008 crisis. So, the fact that macro variables can predict LCF is extremely important. If the supervisor can determine the impact of macroeconomic variables on a bank´s funding, it will evaluate possible liquidity constraints that the financial system might incur.

Guerrieri e Welch (2012) mention that autoregressive models underperform *random walk* models. This superiority is severely rejected in our results, as the ARIMA benchmark clearly presents a higher benchmark standard for our study, and it corroborates with Alfaro & Drehmann (2009). They say that autoregressive models perform better as more straightforward forecast benchmarks. These results mean that except for hypotheses 2b and 4b when we set ARIMA as the benchmark, we cannot affirm that macro variables help predict future values of the remaining measures of banking conditions. It means that autoregressive data can be very informative of future values. However, if no exogenous macro variable influences the measures of banking condition CCF, NIM, and LLPT, stress tests will be ill-suited for these variables, as pointed out by Borio *et al.* (2014). However, as the same author points out, aggregated data can uncover possible heterogeneities among banks. So, to further investigate this, we will explore the results for the subsamples of different bank segmentation.

Table 2.6: One-step forecast results for the entire banking system-nRMSE comparison

	cash flow variables		*earning variables*		
Hypothesis	*(1a)*	*(2a)*	*(3a)*	*(4a)*	*(5a)*
	CCF	*LCF*	*NIM*	*NII*	*LLPT*
Macro variables	**23.5**	**22.8**	**29.2**	**14.4**	19.7
Random walk	28.0	31.8	34.2	21.0	20.7
t-stat	2.95	3.56	1.35	4.14	0.89
p-value	**0.00*** **	**0.00*** **	**0.09***	**0.00*** **	0.19
	cash flow variables		*earning variables*		
Hypothesis	*(1b)*	*(2b)*	*(3b)*	*(4b)*	*(5b)*
	CCF	*LCF*	*NIM*	*NII*	*LLPT*
Macro variables	23.5	**22.8**	29.2	**14.4**	19.7
ARIMA	23.2	24.8	26.3	15.2	18.4
t-stat	0.87	1.47	-1.53	1.70	-1.41
p-value	0.20	**0.08***	0.93	**0.05***	0.91

Note: Bold indicates significance at 10%, one-tailed, Clark and West Statistic. Levels of significance (***) represents 0.01, (**) represents 0.05, and (*) represents 0.1. ARIMA order of p, q, and d will be determined by an automatic ARIMA forecasting by Hyndman & Khandakar (2008). The ARIMA order will be calculated, restricting the exogenous covariates to zero. Based on the defined order, we include the exogenous regressors for our alternative hypothesis. The benchmark ARIMA and the Macro variables with ARIMA errors will have the same ARIMA parameters, making the benchmark a restricted version of the alternative model. If $\beta = 0$, the Macro variables model with ARIMA errors and the benchmark ARIMA model will be the same.

2.4.2. Results for different segments of the banking system

The banking system in Brazil has a high degree of heterogeneity. Although there are approximately 132 banks in the country as of September 2019, the top six banks in total assets account for more than 80% of the system's total assets. For this reason, it is important to stack the time series according to bank segmentation, which tries to cluster banks in a more homogeneous grouping. The results from Tables 2.7 to 2.10 show us the superiority of the *macro variable* model in forecasting LCF for all segments. This result shows great robustness for this *cash flow* variable and points out that macroeconomic shocks affect banks first on the funding side. Other variables, such as CCF, also present good results, but it is not as consistent as LCF.

2.4.2.1. Results for SIBs banks

As the SIB segment makes up 80% of the banking system's total assets, we expect the results for SIB banks to be similar to the results for the aggregated banking system, as it will significantly influence the entire sample data. As shown in Table 2.7, this relation occurs partially. We see similar results showing that macroeconomic models perform better than the benchmark *random walk* model, rejecting hypotheses 1a and 2a. However, when we replace the benchmark with the restricted pure ARIMA model, we see that only hypothesis 2b is rejected, with a 90% significance level. This result means that the macroeconomic variables can only better forecast future values of LCF when we use the ARIMA benchmark. For the other measures of banking condition, the benchmark ARIMA model presents a lower nRMSE, which means that past values of these dependent variables are a better tool to predict their own future values.

The results for SIB reinforce how LCF is sensitive to exogenous macroeconomic shocks. As we test more segments of the banking system in Brazil, we are beginning to uncover that *cash flow* variables may be more sensible to exogenous shocks, more specifically, the LCF. This result means that banks will first feel the impact of macroeconomic shocks on their funding.

Table 2.7: One-step forecast results for the SIB segment-nRMSE comparison

	cash flow variables		*earning variables*		
Hypothesis	*(1a)*	*(2a)*	*(3a)*	*(4a)*	*(5a)*
	CCF	*LCF*	*NIM*	*NII*	*LLPT*
Macro variables	**23.5**	**22.5**	30.4	18.7	21.3
Random walk	28.0	31.6	34.8	19.5	21.8
t-stat	2.24	3.65	1.28	1.10	0.91
p-value	**0.02****	**0.00*****	0.11	0.14	0.19
	cash flow variables		*earning variables*		
Hypothesis	*(1b)*	*(2b)*	*(3b)*	*(4b)*	*(5b)*
	CCF	*LCF*	*NIM*	*NII*	*LLPT*
Macro variables	23.5	**22.5**	30.4	18.7	21.3
ARIMA	23.2	24.9	27.6	19.1	19.9
t-stat	0.45	1.47	-1.62	0.78	-1.24
p-value	0.33	**0.08***	0.94	0.22	0.88

Note: Bold indicates significance at 10%, one-tailed, Clark and West Statistic. Levels of significance (***) represents 0.01, (**) represents 0.05, and (*) represents 0.1. ARIMA order of p, q, and d will be determined by an automatic ARIMA forecasting by Hyndman & Khandakar (2008). The ARIMA order will be calculated, restricting the exogenous covariates to zero. Based on the defined order, we include the exogenous regressors for our alternative hypothesis. The benchmark ARIMA and the Macro variables with ARIMA errors will have the same ARIMA parameters, making the benchmark a restricted version of the alternative model. If $\beta = 0$, the Macro variables model with ARIMA errors and the benchmark ARIMA model will be the same.

2.4.2.2. Results for Large banks

The results in Table 2.8 show that, once again, the *macro variable* model has better forecast accuracy than the *random walk* model for all measures of banking conditions. However, when using the pure ARIMA model as the benchmark, we only reject hypotheses 1b, 2b, and 4b, with a 95% significance level. This result reinforces the forecastability of LCF and shows that for this segment, CCF is also well predicted by the macroeconomic variables. Suppose the regulator can predict, based on macroeconomic shocks, the cash flow from banks. In that case, it will anticipate any liquidity constraints in an institution or the financial system. Banks in this segment are large in assets and are focused on the wholesale market, and they don´t have a wide capillarity of retail customers like the SIB banks. This lack of capillarity can explain the results of NII, as the lack of diversification may make the NII more susceptible to macroeconomic shocks.

Table 2.8: One-step forecast results for the Large segment-nRMSE comparison

	cash flow variables		*earning variables*		
Hypothesis	*(1a)*	*(2a)*	*(3a)*	*(4a)*	*(5a)*
	CCF	*LCF*	*NIM*	*NII*	*LLPT*
Macro variables	**24.8**	**27.0**	**35.7**	**23.9**	**27.6**
Random walk	26.1	38.2	38.0	29.8	28.0
t-stat	3.67	3.13	2.37	2.65	1.39
p-value	**0.00*** **	**0.00*** **	**0.01** **	**0.01*** **	**0.09* **
	cash flow variables		*earning variables*		
Hypothesis	*(1b)*	*(2b)*	*(3b)*	*(4b)*	*(5b)*
	CCF	*LCF*	*NIM*	*NII*	*LLPT*
Macro variables	**24.8**	**27.0**	35.7	**23.9**	27.6
ARIMA	28.6	27.5	36.0	24.3	26.3
t-stat	1.91	1.98	0.82	2.34	-0.79
p-value	**0.03** **	**0.03** **	0.21	**0.01** **	0.78

Note: Bold indicates significance at 10%, one-tailed, Clark and West Statistic. Levels of significance (***) represents 0.01, (**) represents 0.05, and (*) represents 0.1. ARIMA order of p, q, and d will be determined by an automatic ARIMA forecasting by Hyndman & Khandakar (2008). The ARIMA order will be calculated, restricting the exogenous covariates to zero. Based on the defined order, we include the exogenous regressors for our alternative hypothesis. The benchmark ARIMA and the Macro variables with ARIMA errors will have the same ARIMA parameters, making the benchmark a restricted version of the alternative model. If β = 0, the Macro variables model with ARIMA errors and the benchmark ARIMA model will be the same.

2.4.2.3. Results for Medium banks

This segment presents similar results as Large banks. For Medium-sized banks, the macro variables model can beat the *random walk* and ARIMA benchmarks for both *cash flow* variables – *credit and liability* –with a 95% significance level, as shown in Table 2.9. Medium banks are focused on wholesale credit for medium size companies. Once again, the *earning* variables are only able to be better forecasted by the macro variables model when compared to the *random walk*, but not to the ARIMA benchmark model, which indicates that past values of NIM, NII, and LLPT are good predictors of their own future values and that exogenous macroeconomic shocks cannot be used to predict them. This finding reinforces the importance of using *cash flow* variables, as they are sensitive to macroeconomic shocks, as our out-of-sample analysis shows in Table 2.9.

Table 2.9: One-step forecast results for the Medium segment-nRMSE comparison

	cash flow variables		*earning variables*		
Hypothesis	*(1a)*	*(2a)*	*(3a)*	*(4a)*	*(5a)*
	CCF	*LCF*	*NIM*	*NII*	*LLPT*
Macro variables	**28.4**	**24.4**	25.9	**27.1**	**21.5**
Random walk	32.0	37.5	26.2	35.9	25.5
t-stat	2.43	3.00	1.16	3.34	2.08
p-value	**0.01*** **	**0.00*** **	0.13	**0.00*** **	**0.02** **
	cash flow variables		*earning variables*		
Hypothesis	*(1b)*	*(2b)*	*(3b)*	*(4b)*	*(5b)*
	CCF	*LCF*	*NIM*	*NII*	*LLPT*
Macro variables	**28.4**	**24.4**	25.9	27.1	21.5
ARIMA	32.4	28.3	26.2	24.2	21.8
t-stat	2.27	2.35	0.50	-0.06	1.17
p-value	**0.02** **	**0.01** **	0.31	0.52	0.13

Note: Bold indicates significance at 10%, one-tailed, Clark and West Statistic. Levels of significance (***) represents 0.01, (**) represents 0.05, and (*) represents 0.1. ARIMA order of p, q, and d will be determined by an automatic ARIMA forecasting by Hyndman & Khandakar (2008). The ARIMA order will be calculated, restricting the exogenous covariates to zero. Based on the defined order, we include the exogenous regressors for our alternative hypothesis. The benchmark ARIMA and the Macro variables with ARIMA errors will have the same ARIMA parameters, making the benchmark a restricted version of the alternative model. If $\beta = 0$, the Macro variables model with ARIMA errors and the benchmark ARIMA model will be the same.

2.4.2.4. Results for Small banks

For the SMALL segment, we see that, with a confidence interval of 95%, the macro variables can better predict future values of the LCF variables than the *random walk* and the ARIMA model, as shown in Table 2.10. Again, for this segment, LCF remains responsive to the prediction by the *macro variable* model.

Banks in this segment comprise small institutions that operate in niche segments and have very volatile financial performance. This portrait imposes more significant challenges in forecasting than the previous three segments of the Brazilian banking system.

Table 2.10: One-step forecast results for the Small bank segment-nRMSE comparison

	cash flow variables		*earning variables*		
Hypothesis	*(1a)*	*(2a)*	*(3a)*	*(4a)*	*(5a)*
	CCF	*LCF*	*NIM*	*NII*	*LLPT*
Macro variables	**30.6**	**28.5**	**21.0**	**22.1**	**24.1**
Random walk	34.7	34.8	21.8	25.9	27.4
t-stat	2.88	4.97	1.44	2.76	1.68
p-value	**0.00***	**0.00***	**0.08***	**0.00***	**0.05***
	cash flow variables		*earning variables*		
Hypothesis	*(1b)*	*(2b)*	*(3b)*	*(4b)*	*(5b)*
	CCF	*LCF*	*NIM*	*NII*	*LLPT*
Macro variables	30.6	**28.5**	**21.0**	22.1	24.1
ARIMA	28.6	31.4	21.7	22.0	24.4
t-stat	0.61	2.11	1.41	0.37	1.13
p-value	0.28	**0.02****	**0.09***	0.36	0.14

Note: Bold indicates significance at 10%, one-tailed, Clark and West Statistic. Levels of significance (***) represents 0.01, (**) represents 0.05, and (*) represents 0.1. ARIMA order of p, q, and d will be determined by an automatic ARIMA forecasting by Hyndman & Khandakar (2008). The ARIMA order will be calculated, restricting the exogenous covariates to zero. Based on the defined order, we include the exogenous regressors for our alternative hypothesis. The benchmark ARIMA and the Macro variables with ARIMA errors will have the same ARIMA parameters, making the benchmark a restricted version of the alternative model. If $\beta = 0$, the Macro variables model with ARIMA errors and the benchmark ARIMA model will be the same.

2.4.3. Alternative tests for inclusion of seasonality in the auto-regressive models

Foster (1977) concluded that when predicting sales and expense variables for 69 firms in the US, the AR(1) quarterly component with a seasonally adjusted model yielded good outcomes for predicting 1 step for out-of-sample forecasts. As seasonality may have an impact on bank financial data used in this study, we will include seasonality testing, both in our *macro variable* model with (S)ARIMA errors and the pure (S)ARIMA model benchmark[11], which will also be determined by automatic forecasting procedure by Hyndman & Khandakar (2008).

As shown in Table 2.11., the addition of the seasonality option didn´t change the results significantly compared to Tables 2.6 to 2.10, when seasonal terms were not included in the forecast selection. Therefore, the relative performance of the *macro variable* model to the pure (S)ARIMA model benchmark remains unchanged.

Table 2.11: One-step forecast results including seasonal terms in the ARIMA model-nRMSE comparison

		cash flow variables		*earning variables*		
	Hypothesis	*(1b)*	*(2b)*	*(3b)*	*(4b)*	*(5b)*
		CCF	*LCF*	*NIM*	*NII*	*LLPT*
All banks	Macro variables	23.00	**21.80**	29.30	11.80	21.80
	SARIMA	22.60	23.80	28.70	11.90	19.50
	t-stat	0.79	1.58	-0.42	1.17	-1.98
	p-value	0.22	**0.06***	0.66	0.13	0.97
SIB	Macro variables	23.40	**21.00**	30.40	13.50	21.30
	SARIMA	23.10	23.30	29.90	13.70	19.90
	t-stat	0.48	1.33	-0.52	0.95	-1.24
	p-value	0.32	**0.10***	0.70	0.18	0.89
LARGE	Macro variables	**24.80**	**27.00**	36.20	**23.90**	28.40
	SARIMA	28.60	27.50	36.40	24.30	27.00
	t-stat	1.91	1.98	0.78	2.31	-0.73
	p-value	**0.03****	**0.03****	0.22	**0.02****	0.76
MEDIUM	Macro variables	**28.40**	**24.40**	27.20	28.60	21.50
	SARIMA	32.40	28.30	24.00	24.90	21.80
	t-stat	2.27	2.35	-1.06	-0.56	1.17
	p-value	**0.02****	**0.01****	0.85	0.71	0.13
SMALL	Macro variables	30.60	**28.50**	19.90	21.30	29.50
	SARIMA	28.60	31.40	19.40	20.10	29.90
	t-stat	0.61	2.11	0.17	-1.17	1.05
	p-value	0.28	**0.02****	0.43	0.87	0.15

Note: Bold indicates significance at 10%, one-tailed, Clark and West Statistic. Levels of significance (***) represents 0.01, (**) represents 0.05, and (*) represents 0.1. ARIMA order of p, q, and d, and seasonal terms P, Q, and D will be determined by an automatic (S)ARIMA forecasting by Hyndman & Khandakar (2008). The (S)ARIMA order will be calculated, restricting the exogenous covariates to zero. Based on the defined order, we include the exogenous regressors for our alternative hypothesis. The benchmark (S)ARIMA and the Macro variables with (S)ARIMA errors will have the same (S)ARIMA parameters, making the benchmark a restricted version of the alternative model. If $\beta = 0$, the Macro variables model with (S)ARIMA errors and the benchmark (S)ARIMA model will be the same.

[11] If $\beta = 0$, Macro variables model with (S)ARIMA errors will be the same model as the pure (S)ARIMA model benchmark.

2.5. Concluding remarks

This paper analyses if macroeconomic variables can help to forecast a bank's future financial performance and if their predictability power varies with the choice of banking financial performance, which can either be *cash flow* or *earnings* variables. The innovative aspect of it is to see how cash flow can be an essential tool for assessing banking behavior when affected by macroeconomic shocks, increasing the forward-looking analysis of the banking system, especially with stress tests. Additionally, as there is a gap in the literature on whether macro variables are relevant to forecast bank performance, we find this to be a significant contribution. We conclude that macro variables can be valuable tools. Also, this paper raises the discussion of the use of cash flow for bank analysis, which the literature has neglected. It also shows that autoregressive models are essential tools for bank forecasting.

We could see that macroeconomic variables can be a powerful tool for predicting bank performance, but not for all measures of banking conditions. We find that the macro variables model overperforms the lower bound benchmark *random walk* models in the forecast accuracy of almost all measurements of banking conditions. However, only when predicting *cash flow* variables can the *macro variable* model consistently overperform the autoregressive model for out-of-sample forecasting. These results are partially in accordance with Guerieri & Welsh (2012), who say that the macro variables model can beat the *random walk* for many, but not all, forecasts of measures of banking condition. This conclusion is dismissed when we change the benchmark from random walk to ARIMA model. We cannot increase forecast accuracy by using the *macro variable* model when predicting the traditionally used measures of banking conditions, hence called *earning* variables. Borio *et al.* (2014) affirm that macro variables do not help predict bank financial performance. Our results diverge from their assertation, as we find that macro variables offer gain in predictivity when the used measure of banking condition is a *cash flow* variable, more specifically, the LCF variable.

For this study, it is important to note that the *cash flow* variable LCF was the most accurate forecasted measure of banking condition by the macro variables for the aggregated financial system, demonstrating the importance of cash flows for banking. According to Antunes *et al.* (2018) and De Moraes *et al.* (2019), who created this cash flow *proxy* for financial intermediation, based on previous work of De Moraes & De Mendonça (2017) and Minsk (1972, 1992), CCF and LCF are reactive to the economic cycle, which means that it is expected that CCF movements would reflect changes in the macroeconomic and financial scenario. For LARGE and MEDIUM segments, both CCF and LCF are good measures of banking conditions to be forecasted by the macro variables. For the remaining samples, the *macro variable* model outperforms both benchmark models in forecast accuracy only for the banking measure LCF. This result is important, as the supervisor and investors can determine the impact of macroeconomic variables on a bank´s funding, which determines possible liquidity constraints that might incur in the financial system due to an economic shock.

This paper indicates that *cash flow* variables for banks should be analyzed and not ignored, as these data have good information to understand bank behavior. As mentioned before, the *earnings* variables are affected by accruals, which can be discretionary. Specific periods, especially during economic crises, can become even more discretionary due to regulatory changes. An example of that can be seen when the Central Bank of Brazil released Resolutions 4.782 (Central Bank of Brazil, 2020a), 4.783 (Central Bank of Brazil, 2020b), and 4803 (Central Bank of Brazil, 2020c) in early 2020, during the pandemic. These actions were taken to maintain financial stability and to prevent a procyclical effect. In these circumstances, *cash flow* variables can become an even more critical tool, as they are not discretionary. According to Zeff (2012), the objectives of bank regulation 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 with this objective, even if it is conflicting with the Conceptual Framework (IASB, 2015). Therefore, besides showing that the macro variables can be an excellent tool for a forward-looking assessment of banks, this work showed that *cash flow* variables should also be analyzed for financial performance. We also glanced at how financial information behaves in different segments of the Brazilian banking industry. The financial intermediation literature explicitly the importance of cash flows for bank evaluation. This paper connects the financial intermediation literature to the accounting literature by providing a theoretical background for banking cash flow.

2.6. References

Aldasoro, I., Borio, C. E., & Drehmann, M. (2018). Early warning indicators of banking crises: expanding the family. *BIS Quarterly Review, March*.

Alfaro, R. A., & Drehmann, M. (2009). Macro stress tests and crises: what can we learn?. *BIS Quarterly Review December*.

Antunes, J. A. P., De Moraes, C. O., & Rodrigues, A. (2018). How financial intermediation impacts on financial stability? *Applied Economics Letters*, 1–5.

Barrell, R., Davis, E. P., Karim, D., & Liadze, I. (2010). Bank regulation, property prices and early warning systems for banking crises in OECD countries. *Journal of Banking & Finance*, *34*(9), 2255-2264.

Barth, M. E., Clinch, G., & Israeli, D. (2016). What do accruals tell us about future cash flows?. *Review of Accounting Studies*, *21*(3), 768-807.

Barth, M. E., Cram, D. P., & Nelson, K. K. (2001). Accruals and the prediction of future cash flows. *The accounting review*, *76*(1), 27-58.

Basel Committee on Banking Supervision-BCBS (2011). Global systemically important banks: assessment methodology and the additional loss absorbency requirement

Bates, J. M., & Granger, C. W. J. (1969). The combination of forecasts. *Operations Research Quarterly*, 20(4), 451.

Beck, T., (2008). Bank Competition and Financial Stability: Friends or Foes? *Policy Research Working Paper nº. 4656*, World Bank**.**

Beatty, A., & Liao, S. (2009). Regulatory capital ratios, loan loss provisioning and procyclicality. *Columbus, United States: Ohio State University. Mimeographed document*.

Beatty, A., & Liao, S. (2011). Do delays in expected loss recognition affect banks' willingness to lend?. *Journal of accounting and economics*, *52*(1), 1-20.

Beatty, A., & Liao, S. (2014). Financial accounting in the banking industry: A review of the empirical literature. *Journal of Accounting and Economics*, *58*(2-3), 339-383.

Bergmeir, C., Hyndman, R. J., & Koo, B. (2018). A note on the validity of cross-validation for evaluating autoregressive time series prediction. *Computational Statistics & Data Analysis*, *120*, 70-83.

Bhattacharya, N., Desai, H., & Venkataraman, K. (2013). Does earnings quality affect information asymmetry? Evidence from trading costs*. *Contemporary Accounting Research*, *30*(2), 482–516. https://doi.org/10.1111/j.1911-3846.2012.01161.x

Boot, A. W., & Schmeits, A. (2000). Market discipline and incentive problems in conglomerate firms with applications to banking. *Journal of financial intermediation*, *9*(3), 240-273.

Borio, C., Drehmann, M., & Tsatsaronis, K. (2014). Stress-testing macro stress testing: Does it live up to expectations? *Journal of Financial Stability*, *12*(1), 3–15. https://doi.org/10.1016/j.jfs.2013.06.001

Borio, C., Furfine, C., & Lowe, P. (2001). Procyclicality of the financial system and financial stability: issues and policy options. *BIS papers*, *1*(March), 1-57.

Bouvatier, V., & Lepetit, L. (2012). Provisioning rules and bank lending: A theoretical model. *Journal of Financial Stability*, *8*(1), 25-31.

Brown, C. O., & Dinç, I. S. (2011). Too many to fail? Evidence of regulatory forbearance when the banking sector is weak. *The Review of Financial Studies*, 24(4), 1378-1405.

Bushman, R. M., & Williams, C. D. (2012). Accounting discretion, loan loss Provisioning, and discipline of banks' risk-taking. *Journal of accounting and economics*, *54*(1), 1-18.

Central Bank of Brazil (1999) *Resolution 2.682* from the Central Bank of Brazil, Provisioning rules for loan loss Provision for credit assets.

Central Bank of Brazil (2017) *Resolution 4.553* from the Central Bank of Brazil, Segmentation of Financial Institutions Authorized to operate by the Central Bank of Brazil for Macroprudential Purposes.

Central Bank of Brazil (2018), *REF- Relatório de Estabilidade Financeira (Financial Stability Report)– Conceitos e Metodologias Teste de Estresse* (10/2018)

Central Bank of Brazil (2020a) *Resolution 4.782* from the Central Bank of Brazil, Temporary criteria for managing credit risk due to the impact of COVID-19 in the economy.

Central Bank of Brazil (2020b) *Resolution 4.783* from the Central Bank of Brazil, Change of RWA criteria for a defined period.

Central Bank of Brazil (2020c) *Resolution 4.803* from the Central Bank of Brazil, Temporary criteria for Provisioning of loan portfolio negotiations due to the impact of COVID-19 in the economy

Chen, S. S. (2009). Predicting the bear stock market: Macroeconomic variables as leading indicators. *Journal of Banking & Finance*, *33*(2), 211-223.

Cihák, M., (2007). Introduction to Applied Stress Testing, *IMF Working Paper* 07/59.

Clark, T. and K. West (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics* 138, 291–311.

Clark, T. E., & West, K. D. (2006). Using out-of-sample mean squared prediction errors to test the martingale difference hypothesis. *Journal of econometrics*, *135*(1-2), 155-186.

Covas, F. B., Rump, B., & Zakrajšek, E. (2014). Stress-testing US bank holding companies: A dynamic panel quantile regression approach. *International Journal of Forecasting*, 30(3), 691-713.

Damodaran, A. (2013). Valuing financial services firms. *The Journal of Financial Perspectives*, *1(2), 1–*

154.

De Moraes, C. O., & de Mendonça, H. F. (2017). The bridge between macro and micro banking regulation: A framework from the model of financial flows. *Journal of Economic Studies*, 44(2), 214-225.

De Moraes, C. O., Antunes, J. A. P , Rodrigues, A., (2019). Financial intermediation analysis from financial flows. *Journal of Economic Studies, 46*(3), 727-747.

Dechow, P. M. (1994). Accounting earnings and cash flows as measures of firm performance: The role of accounting accruals. *Journal of accounting and economics, 18*(1), 3-42.

Diebold, F. X. (2015). Comparing predictive accuracy, twenty years later: A personal perspective on the use and abuse of Diebold–Mariano tests. *Journal of Business & Economic Statistics*, *33*(1), 1-1.

Dynan, K and D Maki (2001): "Does stock market wealth matter for consumption?", *Finance and Economics Discussion Series*, no 2001-23, Federal Reserve Board, May.

Estrella, A., & Mishkin, F. S. (1997). The predictive power of the term structure of interest rates in Europe and the United States: Implications for the European Central Bank. *European economic review, 41*(7), 1375-1401.

FED System Board of Governors (2015). Dodd-Frank Act Stress Test 2015: supervisory stress test methodology and results. *Accessed October, 16,* 2017.

FED System Board of Governors *(2020)*: 2020 Supervisory Scenarios for Annual Stress Tests Required under the Dodd-Frank Act Stress Testing Rules and the Capital Plan Rule. Source: Board of Governors of the Federal Reserve System: Accessed on July 8, 2020 from https://www.federalreserve.gov/newsevents/pressreleases/files/bcreg20200206a1.pdf

Flannery, M., & Nikolova, S. (2004). Market discipline of US financial firms: Recent evidence and research issues. *Market discipline across countries and industries*, 87-100.

Flores, E., & Braunbeck, G. O. (2017). What is better: to be roughly right or exactly wrong? The role of quantitative methods in financial accounting. *International Journal of Multivariate Data Analysis*, *1*(2), 162. https://doi.org/10.1504/ijmda.2017.10008563

Foglia, A., 2009. Stress testing credit risk: a survey of authorities approach. Int. J. *Central Bank.*, 9–45

Fosu, S., Ntim, C. G., Coffie, W., & Murinde, V. (2017). Bank opacity and risk-taking: Evidence from analysts' forecasts. *Journal of Financial Stability*, *33*, 81-95.

Foster, G. (1977). Quarterly accounting data: Time-series properties and predictive-ability results. *Accounting Review*, 1-21.

Francis, R. N., & Eason, P. (2012). Accruals and the naïve out-of-sample prediction of operating cash flow. *Advances in Accounting*, *28*(2), 226-234.

Francis, R. N., & Olsen, L. M. (2015). The Out-Of-Sample Prediction of Annual Operating Cash Flow: a Comparison of Regression and Naïve Forecast Models. *Advances in Financial Planning and Forecasting*, (6), 65-93.

Goodhart, C. A. (2008). The regulatory response to the financial crisis. *Journal of Financial Stability*, *4*(4), 351-358.

Guerrieri, L., & Welch, M. (2012). Can macro variables used in stress testing forecast the performance of banks? *Finance and Economics Discussion Series-FEDs*, 49.

Hubrich, K., & West, K. D. (2010). Forecast evaluation of small nested model sets. *Journal of Applied Econometrics*, *25*(4), 574-594.

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: principles and practice*. OTexts.

Hyndman, R. J., & Khandakar, Y. (2008). Automatic time series forecasting: the forecast package for R. *Journal of statistical software*, *27*(1), 1-22.

IASB, F. (2015) *Conceptual Framework*

Kalirai, H., Scheicher, M., (2002) Macroeconomic stress testing: preliminary evidence for Austria, *Financial Stability Report 3*, Österrechische Nationalbank.

Kim, M., & Kross, W. (2005). The ability of earnings to predict future operating cash flows has been increasing—not decreasing. *Journal of Accounting Research*, *43*(5), 753-780.

Krishnan, G. V., & Largay III, J. A. (2000). The predictive ability of direct method cash flow information. *Journal of Business Finance & Accounting*, *27*(1-2), 215-245.

Laeven, L., & Majnoni, G. (2003). Loan loss provisioning and economic slowdowns: too much, too late? *Journal of financial intermediation*, *12*(2), 178-197.

Lev, B., Li, S., & Sougiannis, T. (2010). The usefulness of accounting estimates for predicting cash

Lorek, K. S., & Willinger, G. L. (2010). Time series versus cross-sectionally derived predictions of future cash flows. *Advances in Accounting*, *26*(1), 29-36.

Minsky, H. P. (1975). Suggestions for a cash flow-oriented bank examination.

Minsky, H. P. (1992). The financial instability hypothesis, *The Jerome Levy Economics Institute of Bard College*, 74.

Mishkin, F. S., & Barton, A. (1999). Global financial instability: framework, events, issues. *Journal of Economic Perspectives*, 13(4), 3–20.

Ohlson, J. A. (2014). Accruals: an overview. *China Journal of Accounting Research*, *7*(2), 65-80.

Petrella, G., & Resti, A. (2013). Supervisors as information producers: do stress tests reduce bank opaqueness?. *Journal of Banking & Finance*, *37*(12), 5406-5420.

Quagliariello, M. (2008). Does macroeconomy affect bank stability? A review of the empirical evidence. *Journal of Banking Regulation*, *9*(2), 102-115.

Ravazzolo, F., & Rothman, P. (2013). Oil and US GDP: A real-time out-of-sample examination. *Journal of Money, Credit and Banking*, *45*(2-3), 449-463.

Schuermann, T. (2014). Stress testing banks. *International Journal of Forecasting*, *30*(3), 717-728.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings?. *Accounting Review*, 289-315.

Smets, F. (2014). Financial stability and monetary policy: How closely interlinked?. *International Journal of Central Banking*, *10*(2), 263-300.

Svetunkov, I., & Petropoulos, F. (2018). Old dog, new tricks: a modeling view of simple moving averages. *International Journal of Production Research*, *56*(18), 6034-6047.

Tashman, L. J. (2000). Out-of-sample tests of forecasting accuracy: an analysis and review. *International journal of forecasting*, *16*(4), 437-450.

Tirole, J. (2011). Illiquidity and all its friends. *Journal of Economic Literature*, 49(2), 287–325.

Tsatsaronis, K. (2005). Investigating the relationship between the financial and real economy. *Bank of International Settlement-BIS papers* (Issue 22).

Watts, R. L., & Leftwich, R. W. (1977). The time series of annual accounting earnings. *Journal of Accounting Research*, 253-271.

Zeff, S. A. (2012). The evolution of the IASC into the IASB, and the challenges it faces. *Accounting Review*, 87(3), 807–837. https://doi.org/10.2308/accr-10246

3. NON-INTEREST INCOME – WHAT IS AT STAKE?

Abstract

Non-interest income plays a major role in the bank industry. However, as the rise of *Fintechs* and financial innovation decreases entry barriers to new players, banks are on the brink of losing non-interest income. In this paper, using data from the Brazilian banking system, we investigate what is at stake by showing the relevance of non-interest income for banking profitability and if there is a compensatory effect to financial intermediation earnings in relation to bank profitability, which smooths earnings in economic downside, helping, thus, financial stability.

Our findings suggest that non-interest income positively impacts bank profitability, decreases bank riskiness, and presents a compensatory effect to financial intermediation earnings in relation to bank profitability. Lastly, we find that non-interest income is more relevant to profitability than financial intermediation earnings for large banks. For the small banks, financial intermediation earnings are more relevant, which shows that larger banks shall be, at first, the most affected by the potential loss of non-interest income.

Keywords: Banks, non-interest income, profitability

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

3.1.Introduction

Non-interest income (NII) plays a major role in banking. The business model of universal banks spread around the world during the late 90s and gave rise to a source of income diversification for banks that helped them increase profitability. This new business model, associated with financial deepening and technological advances, made it possible for banks to increase the share of NII over time (DeYoung & Rice, 2004; Geyfman & Yeager, 2009).

However, the rise of *Fintechs* and the further development of technology decreased the barrier of entry for many markets in the financial services industry. From the consumer's standpoint, as Bos, Kolari & Van Lamoen (2013) point out, it is good news that an increase in innovation enhances product offering and competition. However, this shift in competitive forces can cause frictions in the intermediation process and elevate the systemic risk of the financial system, as NII is a source of diversification (Feng & Serletis, 2010; Elsas Hackethal, A., & Holzhäuser, 2010; Abedifar *et al*. 2018) and can be used as a buffer against a downturn in the credit cycle (Shim, 2013). Therefore, the loss of this source of income may represent a significant source of instability, as it helps soften business cycle impacts on banks' profitability, which raises a major research problem.

In this regard, this paper delves into the relationship between NII and financial intermediation to investigate whether the role performed by NII contributes to (1) positive impact on overall profitability, (2) reduction of bank riskiness; (3) compensate changes in financial intermediation earnings; thus, smoothing bank's profitability; and (4) compete with financial intermediation earnings, reducing its relevance in banks' profitability for large banks; thus curbing financial intermediation appetite.

This study uses the Brazilian market to unveil these dynamics, as it is a large developing economy with a complex and developed financial system, which is in the middle of the process of financial innovation that may alter the business structure of the banking system (Inter-American Development Bank, 2018). In addition, it is a market in which financial intermediation is done mainly through the banking system (Central Bank of Brazil, 2021), so the dynamics of NII and financial intermediation earnings in relation to profitability can be well analyzed with a diverse bank segmentation that offers opportunities for a longitudinal study. According to the Central Bank of Brazil[12] , Brazil's credit to GDP ratio grew from 25% in March 2003 to 50% in December 2019; and its total assets increased from 60% to 93% in the

[12] http://www.bcb.gov.br

same period. Considering that Brazil had the 9th largest GDP in the world in 2019, it is an important emerging market to be studied, according to the World Bank.

With increasing competition and potential reduction in NII, understanding this relationship is of utmost relevance for policymakers and academics. First, the role played by NII is not consensus since previous literature shows that NII is an additional source of risk (Stiroh, 2004; Stiroh, 2006; Murphy, 2009; Williams, 2016; Chen *et al.*, 2017) and has no impact in bank profitability (Stiroh & Rumble, 2006; Lee *et al.*, 2014); however, it offers a greater income stabilization benefit over the business cycle (Albertazzi & Gambacorta; 2009; Shim, 2013). On the other hand, Köhler (2014) and Abedifar *et al*. (2018) document that NII has no impact on risk and actually reduces it (Köhler, 2014). Second, non-interest revenue may have a compensatory role for a bank's profitability in relation to changes in financial intermediation earnings, acting, thus, as a "friend" of financial intermediation. Lastly, this compensatory effect can lead to the unintended consequence of increasing banks' proclivity to reduce financial intermediation, as NII may become more attractive for bank profitability, acting, thus, as an "enemy" of financial intermediation.

With a sample of quarterly data, from 2003 to 2019, from 95 Brazilian banks, using an S-GMM dynamic panel approach, this paper shows that NII adds to the overall bank profitability and reduces bank riskiness. In addition, we demonstrate a compensating effect of NII and financial intermediation earnings on each other, meaning that as one increases, the other decreases in relation to their effect on overall bank profitability. Finally, we show the negative side of this compensation effect when comparing large and small Brazilian banks. NII is more relevant to profitability than financial intermediation earnings for larger banks. For this group, financial intermediation earnings have a lower impact on profitability when compared to the remaining banks in the financial system, with the opposite effect occurring with NII, indicating a propensity for larger banks to focus on non-interest products rather than financial intermediation. For small banks, financial intermediation earnings are more relevant, and NII offers a lower impact on profitability when compared to other banks in the financial system. This difference in results shows that larger banks shall be, at first, the most affected by the potential loss of NII due to an upcoming increase in competition with the *fintechs*.

The remainder of this paper is structured as follows: first, section 3.2 provides a literature review of the construction of our hypothesis. Section 3.3 presents data, model, and methodology to support our hypotheses and research questions. Section 3.4 shows results, with an alternative analysis to provide robustness, and finally, section 3.5 synthesizes our findings.

3.2. Literature review and hypothesis development

3.2.1. Competitive changes in the banking industry and the importance of non-interest income

The business model of universal banks spread worldwide during the late 90s. In many jurisdictions, the rise of financial conglomerates indicated that banks were merging to survive the new competitive environment. In Brazil, the same process of banking concentration occurred, and Brazilian banks successfully explored financial intermediation while making a substantial return from non-interest income (NII). As Apergis (2015) shows in a study that used data from 50 countries from 2010 to 2012, including Brazil, empirical evidence shows that the banking sector suffers from monopolistic competition in emerging markets.

A new business model evolved after the reversal of the Glass Steagal Act (1999) (Gramm-Leach-Bliley Act, 1999), which allowed commercial and investment banks to stay under the same umbrella. Banks became universal, offering financial intermediation and a wide range of financial services, increasing the scalability of operations, thus, increasing banking concentration. With this new model, NII became increasingly relevant for banks' earnings, and they started a consolidation process to gain economies of scale and scope in their operations. Deregulation in the banking industry made it possible for banks to compete in non-traditional niches, such as NII generated from fees and commissions from securities brokerage, annuity sales, investment banking, advisory, and derivatives trading activities (Chen *et al.*, 2017).

Bos *et al.* (2013) argue that the deregulation of prices, products, and geographic restrictions on banking activities increased the market forces that fostered financial innovation. This financial innovation, such as the creation of ATMs, offered a possibility of decentralization that increased competition in the banking system and enhanced the financial intermediation process. Some innovations, such as custodian services, cash management services, and payment infrastructure, allowed financial institutions to diversify their income beyond financial intermediation.

Financial innovation increases the array of products banks can offer to their customers. Innovations such as credit scoring increased bank lending (Frame *et al.*, 2001; Berger, Demirgüç-Kunt, Levine & Haubrich, 2004), internet usage increased small banks' profitability (DeYoung, Lang, & Nolle, 2007), and credit derivatives and risk management lowered interest spreads to customers (Saretto & Tookes, 2013). As Aghion, Harris, Howitt, & Vickers (2001) pointed out, the literature on competition argues that competition fosters innovation.

NII of current players in the banking industry is at risk due to competition and financial innovation. In November 2020, a new free payment system, PIX[13], was launched in Brazil. This payment system represents a direct assault on banks' NII since it is easy to use and available to smaller financial system participants, reducing the costs of wired transfer among individuals and companies. The lower barrier of entry in the payment system allows small banks to diversify their customer base, offering a full range of financial services, and have access to a broader deposit base, which enables them, in the future, to enhance further cross-selling of financial products.

Hence, assuming that an increase in competition from *fintechs* and financial innovation can reduce NII, affecting bank profitability, our first hypothesis aims to assess the importance of NII in overall bank profitability. As some authors say that NII has no impact on bank profitability (Stiroh & Rumble, 2006; Lee *et al*., 2014) but offers a greater income stabilization benefit over the business cycle (Albertazzi & Gambacorta, 2009; Shim, 2013), it is important to assess the overall importance of NII for Brazilian banks, and this will be noted and pointed in our first hypothesis.

Hypothesis 1: NII has an overall positive effect on bank profitability

NII can be gained in the shape of trading activities or transaction fees, and other financial services. Therefore, the riskiness that it brings to the system is not linear, depending on the region's specificity and how the financial markets evolved there. There are several contradictory studies regarding the relationship between non-interest revenue and systemic risk. Williams (2016) finds a positive risk relationship for Australian banks. Similarly, Murphy (2009) and Chen & Zhang (2017) find that trading and non–trading activities induce more bank risk, especially for small banks, which significantly increases their risk exposure when engaging in commission and fee activities. Conversely, Lepetit, Nys, Rous, & Tarazi (2008) document that a larger share in trading income is associated with lower risk exposure and lower default risk for small, listed banks, while Nguyen (2012) finds that there are diseconomies of scope in the joint production of intermediation-based and non-traditional banking activities and Kohler (2015) shows that the greater the share of NII in the bank's statements, the lower the risk. In a recent study, Brunnermeier, Dong, & Palia (2020) show that banks with higher NII contribute to systemic risk, and those with greater liquidity and interest income reduce systemic risk.

[13] Taken by the Central Bank of Brazil web site (http://https://www.bcb.gov.br/en/pressdetail/2334/nota): “To be launched in November 2020, PIX is the Brazilian instant payment scheme that will perform transfers and payments, in a few seconds, between people, companies and the government, at any time of the day — including on the weekend and on holidays — in a safe and practical way. The streamlined procedure — carried out by natural or legal persons — may start with a QR Code reading by an app or just by the costumer informing the email, cell phone number or tax identification number.”

The difference in results may be due to the unobservable fixed effects of each market. For example, the variation in non-interest revenues in other markets may not be similar to Brazil's. In addition, the composition of non-interest revenue may be different. In the USA, for example, corporate customer non-interest revenues are robust, with advisory, mergers and acquisitions, investment banking, and brokerage services. In Brazil, a large part of NII comes from retail customers through tariffs charged for services.

It should be noted that the resource management and capital market segment, which is predominant in developed financial market countries such as the USA, are not representative in Brazil. Much of the non-interest revenue of the national financial system is concentrated in fees related to payment arrangements and account maintenance. Park, Park & Chae (2019) analyzes this effect on retail banks in the USA in a structure more similar to Brazilian banks. In his work, it was found that NII was a stabilizing factor for these banks during the 2008 financial crisis.

As Lee *et al*. (2014) mention, the risk is reduced with the increase of NII. However, they find that profitability is not affected by it. Hence, considering the conflicting evidence regarding the effect of NII and risk, the second hypothesis of this study is:

Hypothesis 2: NII decreases bank riskiness

Although conflicting in the literature, due to the characteristics of the Brazilian bank industry, we expect NII positively impacts banks' profitability and negatively influence bank riskiness, as NII in Brazil is mainly made of tariffs and services charges, which provides a great contribution margin to the overall earnings and shall be a steady source of income.

3.2.2. Importance of non-interest income for earning diversification and persistence, and financial stability

An increase in competition can lead to excessive risk-taking by banks. According to Beck (2008), competition may erode the profitability of some banks' business lines, and profits serve as buffers against weaknesses and provide incentives for banks not to take excessive risk. Due to limited liability, shareholders only participate in the positive tail of risk. Therefore, when there is pressure on profit, bank management will become more prone to risk, resulting in greater fragility for the financial system. When this pressure for profits diminishes, banks may take lesser risks, favoring financial stability. In addition, with increased competition, each banking entity will gain less from the competitive advantage of having information about its customers.

Consequently, management will tend not to be rigorous in assessing borrowers, increasing the risk to the financial system (Allen & Gale, 2004). The described situation is backed by the *competition-fragility* hypothesis, which says that concentrated banking systems have larger banks than competitive systems. As these institutions increase in size, they diversify their earning portfolio, which benefits financial stability (Beck, 2008).

Financial stability is defined as the ability of capital markets to perform their essential function, which is to channel funds to entities that have productive investments. Factors preventing the flow of these funds may generate financial instability, which can evolve towards a severe interruption of financial intermediation, inducing a financial crisis. Therefore, the system's stability is linked to the capacity of the agents of the financial system to financial intermediate (Mishkin, 1992).

The importance of NII to financial stability is that it provides a way for institutions to protect themselves from swings in the credit cycle by acting countercyclically with the flow from other types of revenues that do not result from financial intermediation. The demand for this type of income is less correlated with economic conditions than interest portfolio income; therefore, it serves as an excellent stabilizer for a bank's capital, providing compensatory income during times of scarce intermediation, as financial intermediation is procyclical with economic conditions (Borio *et al.*, 2001; Brunnermeier, Crockett, Goodhart, Persaud, & Shin, 2009). In this regard, Shim (2013) documents a negative relationship between the business cycle and the capital buffer, suggesting that the Basel III agreement that a countercyclical capital buffer in the banking sector is necessary to soften the financial system's effect exerts on the economic cycle.

Banks' behavior regarding capital buffers is likely to vary according to the stage of the business cycle and banks' own financial situation (Ayuso, Pérez, & Saurina, 2004). An important feature for reducing bank capital requirements is income diversification if the overall earnings' volatility is diminished (Shim, 2013). In this sense, NII is a great tool for bank efficiency, risk reduction, and forward-looking planning, as banks will increase or reduce investments in these types of markets according to the business cycle.

The literature points out that diversification of income is positive for the franchise value of banks because these extra revenues do not request new fixed costs or bank capital to be realized, thus increasing efficiency (Barth, Lin, Ma, Seade, & Song, 2013). This additional steady revenue is an essential capital planning strategy. According to the Pecking Order theory (Myers, 1984), companies prefer internal to external funding, so they raise capital by retaining earnings first, second by issuing debt, and lastly by issuing equity. This last option may be difficult, especially if banks' profits are deteriorated (Schuermann, 2014). So, earning NII during harsh times can be vital, as capital may be sustained with earnings retention from NII. According to Albertazzi e Gambacorta (2009), after a drop in bank profitability, if equity is low and costly to issue, banks will naturally reduce lending, which will cause a reduction in intermediation activity, potentially leading to a financial crisis. If NII can alleviate the drop in capital during harsh times, then the decline in lending will also be buffered, maintaining, thus, financial stability.

Banks benefit from cross-selling. Theories of financial intermediation stress that banks can obtain inside information by developing close relationships with clients, and thereby mitigate asymmetric information problems (Berger, 1999; Boot & Thakor, 2000), get lower collateral requirements, more available credit (Petersen & Rajan,1994; Berger & Udell, 1995), and mitigate risk (Puri, Rochell, & Steffen, 2011). There is also evidence of cross-subsidization for several NII activities and traditional lending-borrowing businesses, especially for large banks (Abedifar *et al*., 2018).

Other previous work also finds the relationship between risk and income diversification in the banking sector in different countries. Lepetit *et al.* (2008) also examine European banks and record a positive relationship between NII activities and bank risk. Nisar, Peng, Wang. & Ashraf (2018) point out that types of NII generating activities impact bank performance and stability. While fees and commission income harm the profitability and stability of South Asian commercial banks, other non-interest income has a positive impact, showing that banks can benefit from revenue diversification if they diversify into specific types of NII-generating activities. Lee *et al.* (2014) showed a different perspective when comparing the riskiness of the bank and income diversification. Their findings suggest that the effect of diversification on the riskiness of the bank depends on the type of banking specialization.

Additionally, they found that NII reduces bank profitability in Asian banks overall. A common trace in these studies is Return on Assets (ROA) as a measurement of the importance of non-interest and net-interest income in banking. ROA is vastly used in the banking literature as a profitability proxy (Molyneux &Thornton, 1992; Claessens & Laeven, 2004; Mamatzakis & Bermpei, 2016; Williams & Prather, 2010; Nguyen, 2012; Shim, 2013; De Moraes & De Mendonça, 2019).

Banks need to show resilience and sound profitability. Volatility in banks' financial statements can increase banks' risk perception and causes a higher cost of funding, narrowing the financial intermediation margin and reducing its franchise value (Couto, 2002; De Haan & Poghosyan, 2012). Not surprisingly, businesses with more persistent earnings have better equity valuations (Sloan, 1996; Richardson, Sloan, Soliman, & Tuna, 2005). Earnings persistence can be analyzed from both cash flow persistence and accruals persistence. As NII is almost free of accruals, it becomes desirable to have this kind of revenue offsetting an increase in loan loss provisions, a major cost of the financial intermediation process. It improves earning quality and levels off final earnings.

The leveling of bank profitability is an important benefit of NII when financial intermediation is reduced. Naturally, if banks lose revenue from financial intermediation, they will raise revenues from NII whenever possible. On the contrary, if they lose revenue from NII, they will try to raise revenue from financial intermediation. Banks may raise revenue from financial intermediation in two ways: by increasing the loan portfolio or by growing margins. Lopez, Rose, & Spiegel (2020) find that banks offset the interest revenue losses with the increase in NII, the rise in the volume of lending activity, and the increase in margins due to a lower cost of funding. A problem with compensating for the loss of NII with financial intermediation is that, according to the literature (Foos, Norden, & Weber, 2010; and Köhler, 2015), excessive loan growth increases bank riskiness and may jeopardize financial stability. Therefore, this may be an unwanted consequence of the change in the competitive environment, and it reinforces the question of the paper, so regulators, depositors, investors, and stockholders can be prepared by answering the following question: what is at stake?

From the importance of NII in leveling off profitability during the downcycle of financial intermediation to the importance of cross-subsidization and the negative impact that a lack of profit diversification may have on excess risk-taking by banks, we test hypothesis 3.

Hypothesis 3: There is a compensatory effect of NII and financial intermediation earnings that smooth bank profitability.

For banks, size matters, as large banks can explore economies of scale (Beck, 2008). There are divergences regarding economies of scale and scope in whether NII is beneficial for banks. Laeven & Levine (2007) and Boot (2016) also mention that diversification benefits can bring discounts to bank valuation, and economics of scope does not compensate for agency problems and inefficiencies caused by cross-subsidization. This assertion was refuted in later studies that said that economies of scale seem to play a more prominent role for small institutions, and larger ones can benefit from both economies, scale and scope, increasing, thus, banking profitability (Feng & Serletis, 2010; Elsas *et al*., 2010). Corroborating with that, Abedifar *et al*. (2018) find that large banks can cross-subsidize lending with NII. In contrast, small banks suffer from diseconomies of scope, and an increase in non-interest activities can actually decrease overall profits.

As there may be a compensatory effect between NII and financial intermediation earnings, and this relation may be affected by banks of different sizes, as economies of scope and scale come into play, we will proceed with the fourth hypothesis. An important factor to see with this preposition is whether large and small banks differ in how NII and financial intermediation earnings affect profitability to analyze which group of banks will be affected the most by the risk of losing NII to the potential market entrants in the financial services business in banking.

Hypothesis 4: NII and financial intermediation earnings have different impacts on profitability according to bank segmentation

3.3.Data and methodology

3.3.1. Sample

This paper analyses the relationship between NII and overall profitability and riskiness and investigates whether NII compensates for changes in financial intermediation earnings, smoothing bank's profitability, and competes with financial intermediation earnings, reducing its relevance in banks' profitability for large banks; thus, curbing financial intermediation appetite.

We perform a longitudinal analysis of the Brazilian banking system through a dynamic panel model to answer the research objectives. The data is from Financial Institutions/Conglomerates Balance Sheets and IF.data from the Central Bank of Brazil. Our sample comprises a quarterly panel of 95 Brazilian banks, spanning from March 2003 to December 2019, totaling 5,524 observations. The sample is representative of the Brazilian banking system, as it consists of over 90% of the system's total assets.

This sample consists of bank conglomerates and individual banks if the prior is not a conglomerate. Banks that did not have a loan portfolio for a given period were excluded from the sample. To avoid endogeneity in our data, the flow variables were scaled by one lagged period of total assets figures. Stock variables were scaled by contemporaneous figures. As there were mergers and acquisitions (M&A) during the observed period, we made the proper M&A adjustments.

3.3.2. Research design

Several studies use this dynamic model to analyze banks, such as Valverde & Fernandez (2007), De Moraes & De Mendonça (2019), Abedifar *et al*. (2018), and Albertazzi & Gambacorta (2007). According to Arellano & Bond (1991), dynamic panel models can eliminate non-observed effects on regressions, and the estimates are reliable even in the presence of omitted variables. The Generalized Method of Moments (GMM) solves this problem and provides a more consistent estimator for the author.

Blundell & Bond (1998) argue that the first difference GMM has bias and low precision, and Arellano & Bover (1995) mention that lagged levels can generate weak instruments, especially if the variables behave close to a *random walk*. To correct this problem, the latter authors propose using the System GMM (S-GMM), which provides a low bias estimator and eliminates the problems of omitted variables present in the equation. Besides these advantages, the dynamic panel allows us to build a more parsimonious model, presenting greater insightfulness and simplicity of analysis (Wawro, 2002).

In banking research, the problem of endogeneity is important, as not all explanatory variables of the models are known and measured (De Moraes & De Mendonça, 2019). Therefore, in this paper, we use the S-GMM and perform two diagnostic tests to justify it: the Hansen test for over-identifying restrictions, which validates instruments' appropriateness, and the Arellano–Bond test for the autocorrelation in residuals, which is necessary to ensure no second-order autocorrelation. In addition, we keep the number of cross-sections greater than the number of instrumental variables to avoid biased results due to overfitting (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. In addition, to account for unobserved effects, such as changes in macroeconomic conditions, we included time dummies to remove time-fixed effects.

3.3.2.1. Empirical model and explanation of variables

To answer the research questions, we examine, in equation 3.1, whether NII and financial intermediation earning affect a bank's profitability. We will use net-interest income after provision (NINC) as a variable for financial intermediation earning. For equation 3.2, we use Z-score (ZSCORE) as a *proxy* of bank riskiness and use it as a dependent and lagged dependent variable. We propose the baseline model (a) and add SIZE and LIQ (models b and c) as bank-specific controls for both equations.

$$ROA_{i,t} = \beta_0 + \beta_1 ROA_{i,t-1} + \beta_2 \boldsymbol{NII_{i,t}} + \beta_3 NINC_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 LIQ_{i,t} + \varepsilon_{i,t} \quad (3.1)$$

$$ZSCORE_{i,t} = \beta_0 + \beta_1 ZSCORE_{i,t-1} + \beta_2 \boldsymbol{NII_{i,t}} + \beta_3 NINC_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 LIQ_{i} + \mu_{i,t} \quad (3.2)$$

Here subscript i =1,2,…,94,95 is the bank; t=1,2,…,68 is the time period, and ε is the disturbance term. After understanding how NII and NINC affect bank profitability, we need to assess whether NII presents a compensatory effect on NINC. To investigate it, we interact *NII and NINC* and investigate the marginal effect of NII on NINC in equation 3.3. If the interaction term is negative, it will be an indication that both NII and NINC are relevant for bank profitability, as one of them increases (decreases), the other decreases (increases), which represents a moderating effect of NII on NINC and vice-versa.

$$ROA_{i,t} = \delta_0 + \delta_1 ROA_{i,t-1} + \delta_2 NII_{i,t} + \delta_3 NINC_{i,t} + \boldsymbol{\delta_4 NINC_{i,t} * NII_{i,t}} + \delta_5 SIZE_{i,t} + \delta_6 LIQ_{i,t} + \alpha_{i,t} \quad (3.3)$$

In addition to the moderating effects, it is important to see how NII and NINC behave for different segments of the banking system. To assess their behavior regarding NII and NINC, we will use dummy variables to distinguish two groups of banks: the larger ones, represented by the Systemically important banks (SIB), and the small banks (SMALL). The Central Bank of Brazil defines the criteria for this classification of SIB, Resolution 4.553 (Central Bank of Brazil, 2017), which segments banks according to their importance to the economy and the financial system.

$$ROA_{i,t} = \gamma_0 + \gamma_1 ROA_{i,t-1} + \gamma_2 NII_{i,t} + \gamma_3 NINC_{i,t} + \gamma_4 SIB_{i,t} + \boldsymbol{\gamma_5 SIB_{i,t}} * \boldsymbol{NII_{i,t}} + \boldsymbol{\gamma_6 SIB_{i,t}} * \boldsymbol{NINC_{i,t}} + \mathrm{v}_{i,t} \tag{3.4}$$

$$ROA_{i,t} = \gamma_0 + \gamma_1 ROA_{i,t-1} + \gamma_2 NII_{i,t} + \gamma_3 NINC_{i,t} + \gamma_4 SMALL_{i,t} + \boldsymbol{\gamma_5 SMALL_{i,t}} * \boldsymbol{NII_{i,t}} + \boldsymbol{\gamma_6 SMALL_{i,t}} * \boldsymbol{NINC_{i,t}} + \iota_{i,t} \tag{3.5}$$

The literature shows that NII can be affected by other income statement variables and bank-specific factors. The variables used in the panel study are:

ROA- Return on Assets – This is the dependent variable and the proxy for profitability. It is calculated by having the annualized ratio of $net\ earnings_t$ divided by *average total assets* of the period. This measure of profitability is well known and used in several papers, such as Williams & Prather (2010), Nguyen (2012), Shim (2013), and De Moraes & Mendonça (2019).

ZSCORE is a well-known metric in the banking literature to reflect a bank's probability of insolvency (Roy, 1952; Boyd, Graham., & Hewitt, 1993, Foos *et al.*, 2010, Bouvatier , Lepetit, Rehault, & Strobel., 2018). It is calculated by the return on assets (ROA) plus the equity to asset ratio divided by a rolling window standard deviation of ROA of the previous eight quarters. 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.

NII-Non-interest income **-** This will be our independent variable, mainly composed of fees, commissions, and service charges. It is scaled by $total\ assets_{t-1}$ and is presented in percentage terms. Previous studies from Abedifar *et al.* (2018) use this variable as an independent variable to see its partial impact on credit risk for US banks. Another work from Albertazzi & Gambacorta (2009) uses it as a dependent variable in an S-GMM estimation to assess how the business cycle impacts European banks' profitability. Nisar *et al.* (2018) and Williams (2016) also use this variable to verify whether NII affects banks' business risk, financial stability, and profitability.

NINC - Net interest income after provision — This is earnings from the financial intermediation activity. It is composed by the $net\ interest\ income_t$ minus $loan\ loss\ provision_t$. As the latter is also a major cost of financial intermediation. This variable is scaled by $total\ assets_{t-1}$ and is presented in percentage terms. It includes all the revenues from financial intermediation reduced by the costs, which are funding and provisioning costs. Many studies use only the net interest income as the source of financial intermediation profits. However, the accounting of the Brazilian banks includes this variable in the financial statement as the result of financial intermediation activity. The literature shows that it is correlated with NII and that some form of cross-subsidization can exist between them (William, 2016).

***SIZE* – Log of *total assets* $_t$.** They represent bank-specific characteristics. (Kohler, 2014; Shim, 2013, De Moraes & Mendonça 2019). The larger the bank is, the more competitive it is in non-interest products.

***LIQ* – $\boldsymbol{Liquid\ assets_t}$** . It is an important measure of risk. It acts as a buffer against bank runs or other shortfalls of asset-liability management. This variable is scaled by $total\ assets_t$ and is presented in percentage terms. Other studies use this variable as a risk factor, such as Shim (2013) and Kohler (2014).

SIB and Small - These are dummies that divide the banks into two segments. 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 March 2003. As per this classification, the segmentation is divided in our sample: SIB with eight banks and SMALL with 58 banks.

NIM - Net interest income before provision — It is composed by the $net\ interest\ income_t$ solely. It only includes the cost of funding without including the cost of provisioning. We will use this variable as an alternative robustness analysis of our findings. This variable is scaled by $total\ assets_{t-1}$ and is presented in percentage terms.

3.3.3. Preliminary analysis of the data

Table 3.1 presents summary statistics and the correlation Tables for our variables. It is interesting to note that NII and NINC have a low correlation in panel B, and NINC has a much higher correlation to ROA than NII to ROA. It is also important to observe that SIZE and ROA are uncorrelated, but SIZE and ZSCORE are positively correlated. This result can indicate that bank SIZE impacts bank riskiness more than bank profitability.

Table 3.1: Summary statistics

Panel A: Descriptive statistics

Variables	obs.	Mean	Std. Dev.	Min	Max
ROA	5,524	0.02	0.06	-0.78	0.98
ZSCORE	5,443	17.57	18.89	-6.94	277.51
NII	5,524	0.52	1.13	0.00	21.88
NINC	5,524	1.85	2.32	-21.93	28.14
NIM	5,524	2.42	2.56	-8.86	29.63
SIZE	5,524	21.76	2.30	16.15	27.89
LIQ	5,524	23.47	17.60	0.01	97.78
d.SIB	5,524	0.09	0.28	0.00	1.00
d.SMALL	5,524	0.57	0.49	0.00	1.00

Panel B: Correlation matrix*

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	ROA	1.00						
(2)	ZSCORE	0.05	1.00					
(3)	NII	0.12	-0.08	1.00				
(4)	NINC	0.48	-0.06	0.10	1.00			
(5)	NIM	0.33	-0.09	0.10	0.90	1.00		
(6)	SIZE	0.01	0.30	-0.03	-0.27	-0.27	1.00	
(7)	LIQ	0.01	-0.07	0.08	0.07	-0.00	-0.15	1.00

*Pearson correlation

3.4.Empirical results

3.4.1. xOverall bank profitability and riskiness

Table 3.2. shows the results for hypotheses 1 and 2, which testes whether NII impacts positively overall bank profitability and reduces bank riskiness, using equations 3.1 and 3.2. NII is expected to benefit bank profitability and reduce bank riskiness, which will validate both hypotheses and confirm NII's importance for the banking system.

Table 3.2: S-GMM for overall bank profitability and riskiness

	Panel A			Panel B		
VARIABLES	(1a) ROA	(1b) ROA	(1c) ROA	(2a) ZSCORE	(2b) ZSCORE	(2c) ZSCORE
ROA (-1)	0.1602***	0.0721**	0.0678*			
	(0.051)	(0.036)	(0.035)			
ZSCORE (-1)				0.8897***	0.8891***	0.8891***
				(0.014)	(0.014)	(0.014)
NII	0.0104*	0.0115**	0.0105**	0.1392***	0.1481***	0.1461***
	(0.006)	(0.006)	(0.004)	(0.041)	(0.041)	(0.042)
NINC	0.0039**	0.0161***	0.0169***	-0.1912***	-0.1364***	-0.1387***
	(0.002)	(0.004)	(0.003)	(0.045)	(0.042)	(0.042)
SIZE		0.0158	0.0042***		0.2060***	0.1971***
		(0.024)	(0.001)		(0.071)	(0.070)
LIQ			-0.0001			-0.0063
			(0.000)			(0.007)
Constant	0.0104	-0.3740	-0.1043***	1.9262**	-2.6960	-2.3589
	(0.009)	(0.530)	(0.031)	(0.832)	(1.707)	(1.690)
Observations	5,435	5,436	5,436	5,353	5,353	5,353
Number of banks	95	95	95	95	95	95
Instr./Cross Sec.	0.82	0.79	0.81	0.79	0.80	0.81
Time effect	Yes	Yes	Yes	Yes	Yes	Yes
J-statistic	15.81	4.49	7.40	4.69	4.47	4.67
p-value	*0.05*	*0.34*	*0.19*	*0.46*	*0.49*	*0.46*
AR(1)	-3.69	-3.71	-3.66	-5.11	-5.10	-5.11
p-value	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
AR(2)	1.53	0.95	0.95	-0.13	-0.13	-0.13
p-value	*0.13*	*0.34*	*0.34*	*0.90*	*0.90*	*0.90*

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.

As expected, in Table 3.2, both NII and NINC are statistically relevant for bank profitability. As we add bank-specific controls for these two variables, the model specification improves and the values and significance of the coefficients change slightly, showing the results' robustness. The NINC coefficient is marginally higher than NII's, indicating that NII is also important to bank profitability compared to NINC. The result documented in Table 3.2 is opposite to Stiroh & Rumble (2006), who show that NII has no impact on bank profitability, and to Lee *et al.* (2014), who document an adverse effect of NII on banks' profitability. This disparity in the results may come from differences in the source of NII in the countries studied. As mentioned priorly, NII for Brazil is mainly composed of tariffs, which according to Kohler (2014) and Park *et al.* (2019), reduces bank riskiness and increase profitability. Therefore, the relative performance of NII to NINC concerning profitability and risk is favorable to NII, as it is a more steady form of income. In other countries, a considerable amount of NII comes from trading activities, which is volatile and may increase bank riskiness. It is noteworthy that SIZE positively impacts profitability, which indicates that the larger the bank is, the greater the benefits from economies of scale and scope. (Feng & Serletis, 2010; Elsas *et al*., 2010; Abedifar *et al*. 2018).

There is an interesting result regarding bank riskiness. NII has a positive impact on ZSCORE, which means that it decreases banks' distance-to-default. At the same time, NINC harms ZSCORE, with its coefficient having the opposite sign of NII. As NINC increases bank riskiness, NII reduces it, indicating the importance of NII in leveling off bank riskiness. The result for ZSCORE is a further indication of how NII and NINC are complementary.

This result reinforces the literature that says that NII reduces bank riskiness (Kohler, 2014; Park *et al.*, 2019). This relation can be explained by the nature of NII in Brazil, which is mainly composed of fees from retail banking (Inter-American Development Bank, 2018; Park *et al.*, 2019).

As our results show that NII positively affects overall bank profitability and reduces bank riskiness, *ceteris paribus*, we find that hypotheses 1 and 2 are confirmed. These results contradict Stiroh & Rumble (2006) and Lee *et al.* (2014), as they affirm that NII has no impact on bank profitability. Concerning bank riskiness, the result is in conformance with Stiroh & Rumble (2006), Lee *et al.* (2014), Kohler (2014), and Park *et al.* (2019), who also suggest that NII reduces bank riskiness depending on bank specialization. Their studies indicate that NII effects on banking are not linear and depend on NII products' characteristics.

3.4.2. Compensatory effect of NII and NINC on bank profitability

In this section, differently from hypotheses 1 and 2, where we assess NII impact on bank profitability and risk, *ceteris paribus*, we test hypothesis 3, which tries to uncover whether NII and NINC have a compensatory effect on each other in relation to bank profitability, by using the marginal effect interaction based on equation 3.3. The results can be seen in Table 3.3, panel A below. If there is a compensation effect, the interaction term will be significant and negative.

Table 3.3: S-GMM for marginal effect of NII and NINC on bank profitability and segmented analysis of the effect of NII and NINC on bank profitability

	Panel A			Panel B	
	(3a)	(3b)	(3c)	(4a)	(4b)
VARIABLES	ROA	ROA	ROA	ROA	ROA
ROA (-1)	0.0445	0.0533**	0.0634*	0.0589**	0.0611*
	(0.039)	(0.021)	(0.033)	(0.023)	(0.036)
NII	0.0114*	0.0248**	0.0199***	0.0119**	0.0408***
	(0.006)	(0.011)	(0.006)	(0.005)	(0.012)
NINC	0.0194***	0.0271***	0.0224***	0.0236***	0.0134***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
NII*NINC	-0.0014**	-0.0031***	-0.0023***		
	(0.001)	(0.001)	(0.001)		
d.SIB				-0.3368**	
				(0.156)	
NII* d.SIB				0.0629**	
				(0.030)	
NINC* d.SIB				-0.0284***	
				(0.007)	
d.SMALL					0.1514**
					(0.070)
NII* d.SMALL					-0.0316**
					(0.013)
NINC* d.SMALL					0.0109***
					(0.004)
SIZE		0.0908***	0.0598**	0.0687**	0.0509**
		(0.023)	(0.028)	(0.031)	(0.022)
LIQ			0.0010	0.0022	0.0021
			(0.003)	(0.002)	(0.002)
Constant	-0.0167***	-2.0391***	-1.3820**	-1.5819**	-1.2931**
	(0.005)	(0.516)	(0.637)	(0.700)	(0.550)
Observations	5,436	5,436	5,436	5,436	5,436
Number of banks	95	95	95	95	95
Instr./CrossSec.	0.88	0.82	0.88	0.89	0.92
Time effect	Yes	Yes	Yes	Yes	Yes
J-statistic	16.97	4.76	12.36	7.64	14.72
p-value	*0.20*	*0.58*	*0.34*	*0.66*	*0.26*
AR(1)	-3.32	-3.74	-3.57	-3.83	-3.78
p-value	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
AR(2)	0.38	-0.43	0.18	0.17	0.27
p-value	*0.70*	*0.67*	*0.86*	*0.86*	*0.79*

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.

As we see in Table 3.3, for hypotheses 3a to 3c on panel A, bank profitability is affected by the interaction of NII and NINC. Hypothesis 3a shows no statistical significance of the lagged dependent variable, which indicates that it is not a proper model. As the variable SIZE is added to the equation, the lagged dependent variable becomes significant, improving the model. This relation shows the importance of bank size to the relation of NII and NINC to bank profitability. The literature mentions that bank diversification is important for income stabilization (Albertazzi & Gambacorta; 2009, Shim, 2013. Lopez *et al*., 2020), confirmed by hypothesis 3. As per Beck (2008), Feng & Serletis (2010), Elsas *et al*. (2010), and Abedifar *et al*. (2018), bank size may play a role in this, as larger banks, which follow the universal bank model, may have higher benefits from NII than other banks in the financial system.

The interaction of NII and NINC in hypotheses 3b and 3c presents a negative relationship with ROA, suggesting a moderating or compensatory effect between these two forms of income in relation to bank profitability. It is interesting to note that this compensatory effect refers to the entire banking industry. This negative interaction term shows us that a decrease (increase) in NINC is accompanied by a higher (lower) impact of NII on ROA. This negative interaction can also be a consequence of cross-subsidization, as pointed out by Williams (2016) and Abedifar *et al*. (2018). Another explanation for it is that a decrease in profitability from NINC during the downtrend of the credit cycle leads banks to pursue more NII to compensate for the loss of revenue from financial intermediation, which is similar to what Lopez *et al*. (2020) found.

At first sight, this would be a good outcome, as it levels off the bank's business cycle, which is important to reduce bank procyclicality of profits that can jeopardize financial stability (Borio *et al.*, 2001; Brunnermeier *et al.*, 2009). In addition, as Allen & Gale (2004) mentioned, banks may reduce the scrutiny of borrowers, increasing the total risk of the system. Another important factor is that banks may focus on NII and forgo the financial intermediation activity, as the latter is riskier and more capital intensive.

An additional analysis of how NII and NINC interact can be seen in Figures 3.1 and 3.2, with the predictive margins and the average marginal effects graphs. The predictive margin graph in Figure 3.1 shows the effect of the changes of NII on profitability, taking into consideration the marginal effect of NII on ROA given a change in NINC, with the coefficients based on hypothesis 3c from Table 3.3.

Specifically, Figure 3.1 shows that as NINC increases, the impact of NII on ROA decreases, which indicates a negative marginal effect. The plotted line flattens when it reaches the threshold mark of 10 for NINC (% of total assets), and it inverts when NINC moves further up from the threshold. This predictive margin graph shows that after the threshold point of 10 for NINC is reached, an increase in NII will have a negative impact on bank profitability, defined by ROA. This relation can also be observed in the average marginal effect graph, which isolates the effect of NII on ROA given a change in NINC. It shows that NII has a negative marginal relation to ROA given a positive change in NINC and that after the mark of NINC=10, additional NII will have a negative impact on overall bank profitability.

The same compensatory effect of NII on NINC exists. As we see in Figure 3.2, when NII increases, it diminishes the impact of NINC on profitability. Until the threshold point of NII= 8, an additional unit of NINC increases ROA. After the threshold mark, an increase in NINC will have an overall negative impact on ROA.

Thus, this analysis shows that banks can maintain profitability by increasing/decreasing NINC/NII whenever needed and possible. The loss of this compensating effect may cause additional volatility in banking earnings. As the graph shows, the loss of NII may put banks overly dependent on NINC to maintain profitability. An increase in NINC is a consequence of a prior increase in the credit portfolio. According to the literature, excessive loan growth increases bank riskiness (Foos *et al.*, 2010; Köhler, 2015). Therefore, as the graph of the interactive effect suggests, banks may try to compensate for the loss of NII with an increase in NINC, which may elevate the riskiness of the financial system.

Figure 3.1: Predictive and the marginal effect of NII on ROA given a change in NINC

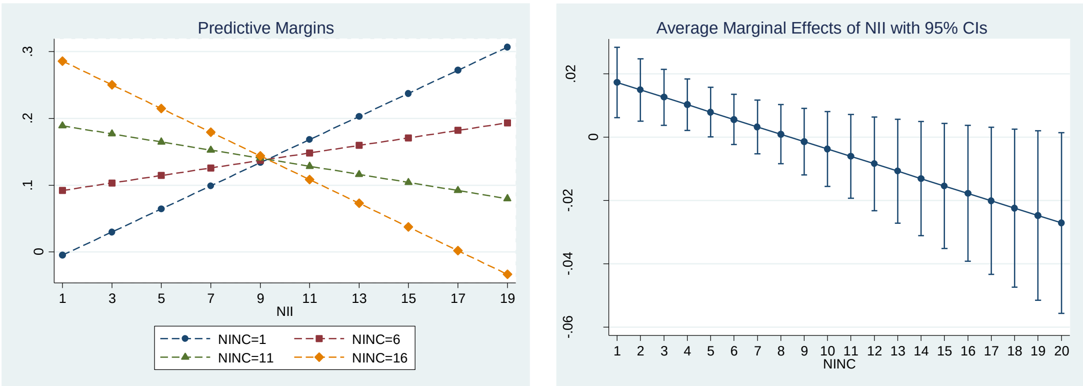
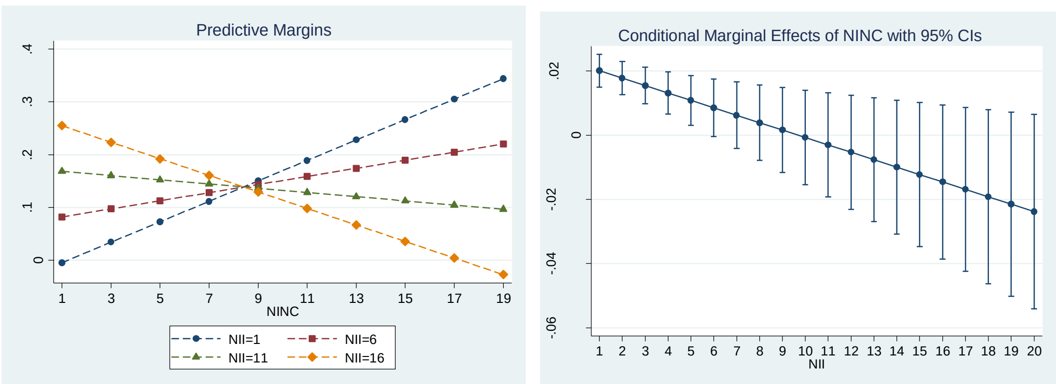


Figure 3.2:Predictive and the marginal effect of NINC on ROA given a change in NII



The results for Table 3.3 show a compensatory effect of NII and NINC. Unlike hypothesis 1, which assesses whether NII and NINC affect a bank's profitability, *ceteris paribus*, hypothesis 3 tests how these two variables interact with each other in relation to the bank's ROA. At this point, we see that both NII and NINC affect overall bank profitability, but as one increases/decreases, the other decreases/increases in relation to ROA, indicating a stabilizing effect of these two variables on the bank's return. As the banking system in Brazil has a high degree of heterogeneity, the next section will answer hypothesis 4, which assesses whether NII and NINC affect bank profitability to the same degree for different bank segments, specifically SIBs and Small banks.

3.4.3. Non-interest income for the Systemically Important and Small banks

The segmented analysis in Table 3.3, panel B, hypotheses 4a and 4b, confirms that the systemically important banks – SIBs use NII to a great extent, thus reducing NINC relevance to profitability. This result confirms hypothesis 4 that NII and NINC are different in relevance for bank profitability depending on bank segmentation. We see that by analyzing the dummy slopes [14]***NII*d.SIB*** *and* ***NINC*d.SIB***. When comparing these coefficients, we see that the dummy slope ***NII*d.SIB*** is positive, which indicates that NII is more profitable for SIBs than for the rest of the banking system. In opposite, the dummy slope ***NINC*d.SIB*** is negative, which indicates that NINC has a lower relevance for profitability when compared to the rest of the Brazilian banking system for the larger banks. Thus, for this segment, NII is a more attractive line of business than NINC, raising banks' propensity to curb financial intermediation and focus on NII products.

For the group of small banks, the coefficient of ***NINC*d.SMALL.*** is positive and statistically significant in hypothesis 4b. The opposite result is found for ***NII*d.SMALL***, whose coefficient is negative. These results indicate that NII is lower and NINC is higher in relevance for bank profitability of small banks. It also shows that small banks may have the propensity to focus on financial intermediation more than the largest banks, which supports Abedifar *et al*. (2018), which say that larger banks can take advantage of NII in a better way than small institutions. In addition, other previous studies show that small banks cannot capture economies

[14] Many authors do not include dummy intercepts when analyzing dummy slopes. We decided to include the intercepts in this paper, as their exclusion might increase the problem of omitted variable and have a bias in the dummy slope, although it has no economic value.

of scope for NII, and they might actually lose profitability from it (Feng & Serletis, 2010; Elsas *et al.*, 2010; and Abedifar *et al.* 2018).

It is notable comparing the results from Table 3.3 to the predictive margin in Figures 3.1 and 3.2. For SIBs, the predictive margin in Figure 3.2 offers clear visualization of the trade-off between NII and NINC. As NII is more relevant for bank profitability, additional units of NINC will cause a negative impact on bank profitability. For Small banks, the predictive margin in Figure 3.1 offers the same frame of the trade-off. As NINC is more relevant for bank profitability, additional units of NII will cause a negative impact on bank profitability.

Hypothesis 4 shows that NII “competes” with NINC, reducing the relevance of the latter in banks' profitability for large banks. As larger banks hold approximately 80% of the system's total assets, a possible reduction of NII will undoubtedly alter the dynamics of financial intermediation in Brazil, as SIB banks may end up lending more to make up for the loss of revenue of interest-earning products. A possible setback from a higher income from a non-interest revenue stream is the low propensity of larger banks to lend. If the propensity to lend increases due to the loss of NII, then a higher level of financial intermediation will be achieved, which is beneficial for the economy. At the same time, the loss of NII may induce banks to excessively lend to make up for the loss of profitability of non-interest revenue products. Additionality, the loss of the compensatory effect of NII on financial intermediation may increase bank riskiness and cause financial instability.

3.4.4. Additional analysis

As a *proxy* of financial intermediation earnings, this paper uses *net interest income after provision*-NINC. It reflects all the revenues and costs of financial intermediation, which are interest revenues, interest expenses, and loan loss provision. Additionally, this is how Brazilian banks report their earnings in relation to financial intermediation. As many authors in the literature use *net-interest income before provisions*-NIM (Albertazzi & Gambacorta, 2009; Nuyen, 2012; Shim, 2013, Abedifar *et al.* 2018), we will replace this variable as the new *proxy* for financial intermediation earnings for equations 3.1 through 3.4, as a robustness test for our previous results.

As it can be seen in Table 3.4, the results corroborate the previous findings presented in Tables 3.4 and 3.5, concluding that: (1) both NII is relevant for bank profitability and (2) decreases bank riskiness; (3) the marginal effects of NII and NIM on bank profitability are negative, indicating a moderating effect between these two variables.

In addition, Table 3.5 shows that (4) NII and NIM have different relevance to profitability for SIBs and small banks. NII has a higher relevance on bank profitability doe SIBs when compared to other segments. In contrast, still for larger banks, NIM is less relevant to bank profitability. For small banks, NIM has a higher relevance on bank profitability when compared to other segments of the banking system. These findings indicate that SIBs may have the propensity to focus more on NII than NIM, as NII is more profitable than NIM. The opposite occurs with small banks that may focus more on NIM, as it has a more positive impact on profitability than NII.

Table 3.4: S-GMM for overall bank profitability and riskiness

	Panel A			Panel B		
VARIABLES	(1a) ROA	(1b) ROA	(1c) ROA	(2a) ZSCORE	(2b) ZSCORE	(2c) ZSCORE
ROA (-1)	0.1652***	0.0809**	0.0994***			
	(0.038)	(0.036)	(0.029)			
ZSCORE (-1)				0.8913***	0.8944***	0.8938***
				(0.013)	(0.016)	(0.016)
NII	0.0107	0.0146*	0.0185***	0.1466***	0.1427***	0.1363***
	(0.013)	(0.008)	(0.007)	(0.050)	(0.050)	(0.049)
NIM	0.0035***	0.0205***	0.0225**	-0.1409***	-0.1044***	-0.1073***
	(0.001)	(0.008)	(0.009)	(0.036)	(0.034)	(0.035)
SIZE		0.0742*	0.0801*		0.1993***	0.1898**
		(0.044)	(0.045)		(0.076)	(0.076)
LIQ			0.0039			-0.0070
			(0.004)			(0.006)
Constant	0.0004	-1.6497*	-1.8868*	2.1696***	-2.3940	-2.0111
	(0.006)	(0.975)	(1.059)	(0.811)	(1.723)	(1.726)
Observations	5,436	5,437	5,437	5,354	5,354	5,354
Number of banks	95	95	95	95	95	95
Instr./Cross Sec.	0.78	0.81	0.84	0.77	0.80	0.81
Time effect	Yes	Yes	Yes	Yes	Yes	Yes
J-statistic	2.46	6.04	6.25	2.12	3.94	4.21
p-value	*0.65*	*0.42*	*0.62*	*0.55*	*0.56*	*0.52*
AR(1)	-4.00	-3.61	-3.74	-5.08	-5.10	-5.10
p-value	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
AR(2)	1.55	0.20	-0.28	-0.11	-0.11	-0.11
p-value	*0.12*	*0.84*	*0.78*	*0.91*	*0.91*	*0.91*

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.

Table 3.5: S-GMM for marginal effect of NII and NIM on bank profitability and segmented analysis of the effect of NII and NIM on bank profitability

	Panel A			Panel B	
	(3a)	(3b)	(3c)	(4a)	(4b)
VARIABLES	ROA	ROA	ROA	ROA	ROA
ROA (-1)	0.0682*	0.0962**	0.0713*	0.0971***	0.1055**
	(0.036)	(0.044)	(0.037)	(0.035)	(0.049)
NII	0.0122	0.0211**	0.0138**	0.0134***	0.0295**
	(0.008)	(0.008)	(0.005)	(0.005)	(0.014)
NIM	0.0173***	0.0212***	0.0172***	0.0210***	0.0086**
	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)
NII*NIM	-0.0014*	-0.0021***	-0.0014**		
	(0.001)	(0.001)	(0.001)		
d.SIB				-0.3204*	
				(0.164)	
NII* d.SIB				0.0558**	
				(0.025)	
NIM* d.SIB				-0.0373**	
				(0.015)	
d.SMALL					0.0292
					(0.074)
NII* d.SMALL					-0.0187
					(0.014)
NIM* d.SMALL					0.0127***
					(0.005)
SIZE		0.0484*	0.0051***	0.0740**	0.0172
		(0.029)	(0.002)	(0.034)	(0.019)
LIQ			0.0000	0.0040*	0.0017
			(0.000)	(0.002)	(0.002)
Constant	-0.0284***	-1.0939*	-0.1358***	-1.7448**	-0.4676
	(0.006)	(0.639)	(0.049)	(0.773)	(0.469)
Observations	5,437	5,437	5,437	5,437	5,437
Number of banks	95	95	95	95	95
Instr./CrossSec.	0.88	0.85	0.91	0.91	0.92
Time effect	Yes	Yes	Yes	Yes	Yes
J-statistic	16.17	6.12	12.57	10.05	14.37
p-value	*0.24*	*0.73*	*0.48*	*0.53*	*0.28*
AR(1)	-3.32	-3.69	-3.52	-3.68	-3.54
p-value	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
AR(2)	0.40	0.40	0.40	0.02	0.67
p-value	*0.69*	*0.69*	*0.69*	*0.98*	*0.50*

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 in order 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.

3.5.Concluding remarks

This paper analyzed the effect of non-interest income (NII) in the banking system in Brazil, focusing on its overall impact on bank profitability and riskiness, and its compensatory effects on financial intermediation earnings (NINC) in relation to bank profitability.

With a sample of quarterly data, from 2003 to 2019, from 95 Brazilian banks, using an S-GMM dynamic panel approach, we show that NII increases overall bank profitability and decreases bank riskiness. These results for bank profitability contradict Stiroh & Rumble (2006); and Lee *et al.*, 2014, as they find that NII has no impact on overall bank profitability. The results for bank riskiness are in conformance with Köhler (2014) and Abedifar *et al*. (2018), which say that NII can actually reduce bank riskiness. The difference in the results of our study may be due to the differences in the NII products in each market, as in Brazil, NII is mainly composed of fees and services charges (Inter-American Development Bank, 2018; Park *et al*. 2019), providing a steady stream of income with low risk. In addition, these extra revenues do not require many new fixed costs or bank capital to be realized, which leads to an improvement in bank efficiency (Barth *et al.*, 2013).

Additionally, they have a compensating effect on each other, meaning that as one increases (decreases), the other decreases (increases) in relation to their effect on overall bank profitability. This effect can be positive during a downturn in the economic cycle (Albertazzi & Gambacorta; 2009; Shim, 2013), reducing the procyclicality in the banking industry, which according to Borio *et al.* (2001) and Brunnermeier *et al.*(2009), jeopardizes financial stability. However, the compensating effect has its negative consequence due to the higher opportunity cost to undertake financial intermediation when NII becomes relevant. As Abedifar *et al*. (2018) show, larger banks can capture the benefits of NII in a better way than small institutions. As NII is profitable and reduces risk, the natural tendency is to focus on it to the detriment of financial intermediation activities. This relation is evident when we compared the large and small banks in Brazil and how NII was more relevant to bank profitability for the large banks than for small ones. This potential trade-off may turn financial intermediation in Brazil into a less than optimal activity.

This work added to the literature by unveiling how the NII impacts overall profitability and reduces bank riskiness, compensating or moderating the reduction in NINC. Also, we revealed how NII could compete with NINC, reducing the relevance of the latter in banks' profitability. As technology changes the banking industry by lowering the barrier of entry to new entrants, banks are at risk of losing non-interest revenues.

We suggest further exploring this deviation from financial intermediation towards NII for future studies and how this affects bank spreads. Also, it is important to assess the impact of non-interest revenue on the monetary policy channel, as the propensity of the financial system to act as a financial intermediator shall become less sensitive to monetary policy, as NII provides a desired profitability for banks that make them less keen to engage in financial intermediation.

3.6. References

Aghion, P., Harris, C., Howitt, P., & Vickers, J. (2001). Competition, imitation and growth with step-by-step innovation. *The Review of Economic Studies, 68*(3), 467-492.

Abedifar, P., Molyneux, P., & Tarazi, A. (2018). Non-interest income and bank lending. *Journal of Banking & Finance, 87,* 411-426.

Albertazzi, U., & Gambacorta, L. (2009). Bank profitability and the business cycle. *Journal of Financial Stability*, *5*(4), 393-409.

Allen, F. and Gale, D. (2004) Competition and financial stability. *Journal of Money,Credit, and Banking* 36:3 Pt.2, 433-80.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, *58*(2), 277-297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, *68*(1), 29-51.

Apergis, N. (2015). Competition in the banking sector : New evidence from a panel of emerging market economies and the financial crisis. *Emerging Markets Review, 25,* 154–162. https://doi.org/10.1016/j.ememar.2015.08.001

Ayuso, J., Pérez, D., & Saurina, J. (2004). Are capital buffers procyclical?: Evidence from Spanish panel data. *Journal of financial intermediation*, *13*(2), 249-264.

Barth, J. R., Lin, C., Ma, Y., Seade, J., & Song, F. M. (2013). Do bank regulation, supervision and monitoring enhance or impede bank efficiency?. *Journal of Banking & Finance*, *37*(8), 2879-2892.

Beck, T., (2008). Bank Competition and Financial Stability: Friends or Foes? *Policy Research Working Paper nº. 4656,* World Bank**.**

Berger, A. N., & Udell, G. F. (1995). Relationship lending and lines of credit in small firm finance. *Journal of business*, 351-381.

Berger, A. N., Demirgüç-Kunt, A., Levine, R., & Haubrich, J. G. (2004). Bank concentration and competition: An evolution in the making. *Journal of Money, Credit and Banking*, 433-451.

Berger, A. N., Demsetz, R. S., & Strahan, P. E. (1999). The consolidation of the financial services industry: Causes, consequences, and implications for the future. *Journal of Banking & Finance*, *23*(2-4), 135-194.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics, 87*(1), 115-143.

Boot, A. W. (2016). Understanding the future of banking scale and scope economies, and fintech. *The Future of Large, Internationally Active Banks*, 55, 431.

Boot, A. W., & Thakor, A. V. (2000). Can relationship banking survive competition?. *The journal of Finance*, 55(2), 679-713.

Borio, C., Furfine, C., & Lowe, P. (2001). Procyclicality of the financial system and financial stability: issues and policy options. *BIS papers*, *1*(March), 1-57.

Bos, J. W., Kolari, J. W., & van Lamoen, R. C. (2013). Competition and innovation: Evidence from financial services. *Journal of Banking & Finance*, *37*(5), 1590-1601.

Bouvatier, V., Lepetit, L., Rehault, P. N., & Strobel, F. (2018). Bank insolvency risk and Z-score measures: caveats and best practice. *Available at SSRN 2892672*.

Boyd, J. H., Graham, S. L., & Hewitt, R. S. (1993). Bank holding company mergers with nonbank financial firms: Effects on the risk of failure. *Journal of banking & finance*, *17*(1), 43-63.

Brunnermeier, M., Crockett, A., Goodhart, C. A., Persaud, A., & Shin, H. S. (2009) The fundamental principles of financial regulation. Geneva London: *International Center for Monetary and Banking Studies Centre for Economic Policy Research*.

Brunnermeier, M. K., Dong, G. N., & Palia, D. (2020). Banks' non-interest income and systemic risk. *The Review of Corporate Finance Studies*, *9*(2), 229-255.

Central Bank of Brazil (2017) *Resolution 4.553* from the Central Bank of Brazil, Segmentation of Financial Institutions Authorized to operate by the Central Bank of Brazil for Macroprudential Purposes.

Central Bank of Brazil (2021), *REF- Relatório de Estabilidade Financeira (Financial Stability Report* (04//2021)

Chen, C. R., Huang, Y. S., & Zhang, T. (2017). Non-interest income, trading, and bank risk. *Journal of Financial Services Research*, *51*(1), 19-53.

Claessens, S., & Laeven, L. (2004). What drives bank competition? Some international evidence. *Journal of money, credit and banking*, 563-583.

Couto, R. L. R. (2002). *Framework for the assessment of bank earnings*. Bank for International Settlements, Financial Stability Institute.

De Mendonça, H. F., & Barcelos, V. Í. (2015). Securitization and credit risk: Empirical evidence from an emerging economy. *The North American Journal of Economics and Finance*, *32*, 12-28.

De Moraes, C. O., & de Mendonça, H. F. (2019). Bank's risk measures and monetary policy: Evidence from a large emerging economy. *The North American Journal of Economics and Finance*, *49*, 121-132.

De Haan, J., & Poghosyan, T. (2012). Size and earnings volatility of US bank holding companies. *Journal of Banking & Finance*, 36(11), 3008-3016.

DeYoung, R., g, W. W., & Nolle, D. L. (2007). How the Internet affects output and performance at community banks. *Journal of Banking & Finance*, *31*(4), 1033-1060.

DeYoung, R., & Rice, T. (2004). Non-interest income and financial performance at US commercial banks. *Financial review*, *39*(1), 101-127.

Elsas, R., Hackethal, A., & Holzhäuser, M. (2010). The anatomy of bank diversification. *Journal of Banking & Finance*, 34(6), 1274-1287.

Feng, G., & Serletis, A. (2010). Efficiency, technical change, and returns to scale in large US banks: Panel data evidence from an output distance function satisfying theoretical regularity. *Journal of Banking & Finance*, 34(1), 127-138.

Frame, W. S., Srinivasan, A., & Woosley, L. (2001). The effect of credit scoring on small-business lending. *Journal of money, credit and banking*, 813-825.

Foos, D., Norden, L., & Weber, M. (2010). Loan growth and riskiness of banks. *Journal of Banking & Finance*, *34*(12), 2929-2940.

Geyfman, V., & Yeager, T. J. (2009). On the riskiness of universal banking: Evidence from banks in the investment banking business pre-and post-GLBA. *Journal of Money, Credit and Banking*, *41*(8), 1649-1669.

Köhler, M., (2014), "Does Non-Interest Income Make Banks More Risky? Retail- versus Investment-Oriented Banks," *Review of Financial Economics* 23, 182-93.

Köhler, M. (2015). Which banks are more risky? The impact of business models on bank stability. *Journal of Financial Stability*, 16, 195-212.

Inter-American Development Bank; IDB Invest; Finnovista. (2018). *Fintech: Latin America 2018: Growth and Consolidation.* https://doi.org/http://dx.doi.org/10.18235/0001377

Laeven, L., & Levine, R. (2007). Is there a diversification discount in financial conglomerates?, *Journal of financial economics*, 85(2), 331-367

Lee, C. C., Yang, S. J., & Chang, C. H. (2014). Non-interest income, profitability, and risk in banking industry: A cross-country analysis. *The North American Journal of Economics and Finance*, *27*, 48-67.

Lepetit, L., Nys, E., Rous, P., & Tarazi, A. (2008). Bank income structure and risk: An empirical analysis of European banks. *Journal of banking & finance*, *32*(8), 1452-1467.

Lopez, J. A., Rose, A. K., & Spiegel, M. M. (2020). Why have negative nominal interest rates had such a small effect on bank performance? Cross country evidence. *European Economic Review*, *124*, 103402.

Mamatzakis, E., & Bermpei, T. (2016). What is the effect of unconventional monetary policy on bank performance?. *Journal of International Money and Finance*, *67*, 239-263.

Mishkin, F. S. (1992) Anatomy of a financial crisis. *Journal of Evolutionary Economics*, n. 2, p. 115-130.

Molyneux, P., & Thornton, J. (1992). Determinants of European bank profitability: A note. *Journal of banking & Finance*, 16(6), 1173-1178.

Murphy, K.J. (2009) Compensation structure and systematic risk. *Marshall Research Paper series Working Paper PBE-34-09*, University of Southern California

Myers, S. C. (1984). Capital structure puzzle (No. w1393). *National Bureau of Economic Research.*

Nguyen, J. (2012). The relationship between net interest margin and non-interest income using a system estimation approach. *Journal of Banking & Finance*, 36(9), 2429-2437.

Nisar, S., Peng, K., Wang, S., & Ashraf, B. N. (2018). The impact of revenue diversification on bank profitability and stability: empirical evidence from south Asian countries. *International journal of financial studies*, 6(2), 40.

Park, B., Park, J., & Chae, J. (2019). Non-interest income and bank performance during the financial crisis. *Applied Economics Letters*, *0*(0), 1–6. https://doi.org/10.1080/13504851.2019.1591592

Petersen, M. A., & Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *The Journal of Finance*, *49*(1), 3-37.

Puri, M., Rochell, J. and Steffen, S. (2011) On the importance of prior relationship in bank loans to retail customers, *ECB Working Paper No. 1395* .

Richardson, S. A., Sloan, R. G., Soliman, M. T., & Tuna, I. (2005). Accrual reliability, earnings persistence and stock prices. *Journal of Accounting and Economics*, 39(3), 437–485.

Roy, A. D. (1952). Safety first and the holding of assets. Econometrica: *Journal of the econometric society*, 431-449.

Saretto, A., & Tookes, H. E. (2013). Corporate leverage, debt maturity, and credit supply: The role of credit default swaps. *The Review of Financial Studies, 26*(5), 1190-1247.

Schuermann, T. (2014). Stress testing banks. *International Journal of Forecasting*, *30*(3), 717-728.

Shim, J. (2013). Bank capital buffer and portfolio risk: The influence of business cycle and revenue diversification. *Journal of Banking & Finance*, *37*(3), 761-772.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings?. *Accounting review*, 289-315.

Stiroh, K. J., & Rumble, A. (2006). The dark side of diversification: The case of US financial holding companies. *Journal of banking & finance*, *30*(8), 2131-2161.

Stiroh, Kevin, (2006), "A Portfolio View of Banking with Interest and Non-interest Activities," *Journal of Money, Credit and Banking* 38, 2131-2161.

Stiroh, Kevin, (2004), "Diversification in Banking: Is Non-interest Income the Answer?" *Journal of Money, Credit and Banking* 36, 853-882.

Valverde, S. C., & Fernández, F. R. (2007). The determinants of bank margins in European banking. *Journal of Banking & Finance*, *31*(7), 2043-2063.

Wawro, G. (2002). Estimating dynamic panel data models in political science. *Political Analysis,-Cambridge University Press* 25-48.

Williams, B. (2016). The impact of non-interest income on bank risk in Australia. *Journal of Banking and Finance*. https://doi.org/10.1016/j.jbankfin.2016.07.019

Williams, B., & Prather, L. (2010). Bank risk and return: the impact of bank non-interest income. *International journal of managerial finance*.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of econometrics*, 126(1), 25-51.

4. LOAN GROWTH AND FORWARD-LOOKING PROVISION: 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. Accounting regulations worldwide changed in later years to account for foreseeable credit risk; thus, it is crucial to assess whether the increase in bank riskiness generated by new loans is softened by a concomitant increase in expected loss provision. As a country with a mixed model of incurred and expected loss recognition, Brazil is uniquely suited to respond to this research question. Using a sample of bi-annual data from 2003 to 2019 from 95 Brazilian banks, which account for over 90% of the banking system's total assets, we use an S-GMM dynamic panel to answer our research question and a panel-VAR to reinforce our conclusions.

The results indicate that contemporaneous loan growth increases bank riskiness, but banks increase expected loss provisions respectively, which shows that they act prudently regarding provisioning, benefiting, thus, financial stability. In addition, it was found that when loan growth occurs during higher financial uncertainty times, banks allocate more expected loss provisions to account for an increase in credit risk. Lastly, as Brazilian banks are heterogeneous, we find that larger and small banks differ in setting additional expected loss provisions when the credit portfolio increases, with the smaller banks setting additional expected loss provisions.

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

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

4.1.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 still very incipient in the world (Lopez-Espinola, Ormazabal, & Sakasai., 2021), this work analyses whether this model of provisioning can balance the risks that institutions incur when banks grow their loan portfolios.

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 to provided 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, as Ozili & Outa (2017) pointed out, provisions are intended for expected losses, and micro/macro prudential objectives of financial stability and stability of earnings are a consequence of it. 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 bi-annual time observations with 95 banks (2,459 bi-annual-bank observations). 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. Additional findings point out that when loan growth occurs during higher financial uncertainty times, banks allocate more expected loss provisions to account for an increase in credit risk. Finally, the results show that larger and small banks differ in setting additional expected loss provisions when the credit portfolio increases, with the smaller banks setting additional expected loss provisions.

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.

4.2.Literature review and hypothesis development

The relationship between loan growth and business risk was first reviewed by Keeton (1999). According to the author, 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.

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

Concerning loan growth in developing countries, Dang (2019) finds that it caused an increase in LLP for subsequent years for the Vietnamese banking system. In addition, the author points out that solvency risk, represented by the Z-Score metric, is also affected negatively by loan growth. 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; Ozili, 2017). 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. According to Saurina (2009), it is a system in which banks report higher LLPs during good economic times and fewer LLPs during a low economic growth scenario. The most studied country where this system was adopted is Spain. Jiménez, Ongena, Peydró, & Saurina (2017) find that dynamic provisioning smooths credit supply cycles and, in bad times, supports firm performance. Fillat & Montoriol-Garriga (2010) test the dynamic provisioning system in the US financial system and 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 (Boulivier & 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 conversion will occur soon. 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.

A common factor that affects both loan growth and provisions is the effect of economic uncertainty on expected losses LLP. Danisman, Demir, & Ozili (2021) conclude that banks tend to increase their LLPs in times of higher economic policy uncertainty. In addition, they assess that US banks in uncertain times use provisions for income smoothing rather than capital management. Valencia (2015) finds that financial frictions in raising external finance can induce banks to self-insure against future shocks by holding more bank capital. Using another measure of bank self-insurance, Berger, Guedhami, & Kim (2020) assert that banks increase liquidity in response to changes in uncertainty. In the same path, Hu & Gong (2019) find that an increase in uncertainty diminishes bank lending, but the effect depends on bank characteristics. In particular, larger and riskier banks tend to have slower credit growth at a time of high uncertainty. In addition, the author found that more liquid and diversified banks suffer less from uncertainty than their peers. In the same direction, Danisman *et al.*(2021) indicate that economic uncertainty causes a significant decrease in overall bank credit.

Further analysis of loan types shows that the highest negative impact of economic uncertainty is observed on corporate loans. Francis, Hasan, & Zhu (2014) indicate that fluctuations in the political environment impose additional costs on the loan contract. So, political uncertainty is transmitted to financial uncertainty and is related to 11.90 basis points of additional spreads in a cross-country study with 52,967 loan facilities of 7,947 firms. In a similar study, Waisman, Ye, & Zhu (2015) find that uncertainty leads to an increase in the cost of debt for corporations in the USA. It is important to note that the higher cost of debt comes with a decline in investment and an increase in credit risk, which was empirically verified by Julio & Yook (2012), Durnev (2010), and Pástor & Veronesi (2013). According to Tillman (2016), in a study with emerging economies in Asia, uncertainty can be transmitted through some financial indicators to emerging economies, such as the VIX – Volatility of the S&P 500-, and the EMBI – calculated and provided by |JP Morgan and that is considered a proxy for financial country risk for emerging markets. So, as seen in the literature, uncertainty increases credit risk, affects LLP, and decreases loan growth. As loan growth in banks is heterogeneous, meaning that each bank has its characteristics and will grow credit the credit portfolio at different times, it would be interesting to find whether the increase in loan growth during uncertain times increases the allocation of expected losses on LLP, which lead to the third hypothesis of this study.

Hypothesis 3: Loan growth has a higher impact on expected loan loss provision when economic uncertainty is high.

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 4 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 4: 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 earning management in these two systems.

As expected loss accounting models are pretty 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.

4.3. Data and methodology

This paper performs a longitudinal analysis of the Brazilian banking system through a sample of 95 Brazilian banks comprising bi-annual data ranging from June 2003 to December 2019, yielding 2,459 bi-annual observations. 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. Banks with large gaps in loan data and public development banks were excluded from our analysis.

The analyses were conducted by using dynamic panel models, which are often used in relevant banking and financial literature, such as Foos *et al.* (2010), Bouvatier & Nicolas (2017), and De Moraes & De Mendonça (2019). Specifically, according to Arellano & Bond (1991), dynamic panel models can eliminate non-observed effects on regressions, provide a low bias estimator, and the estimates are robust even in the presence of omitted variables. Moreover, since lagged levels can generate weak instruments, the first difference GMM may be low in precision estimates (Blundell & Bond, 1998; Arellano & Bover, 1995). To correct this problem, we follow Blundell & Bond (1998). They propose 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).

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.

4.3.1. Empirical model

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 4.1 and 4.2 are used to test hypotheses 1 and 2, respectively.

$$RISK_{i,t}= \beta_0 + \beta_1 RISK_{i,t-1} + \beta_2 LGRW_{i,t} + \beta_3 \Delta NPL_{i,t-2} + \beta_4 \Delta NPL_{i,t-1} + \beta_5 \Delta NPL_{i,t+} \beta_6 \Delta NPL_{i,t+1} + \sum_{k=7}^{10} \beta_k BANK_{i,t} + \varepsilon_{i,t} \tag{4.1}$$

Where subscript *i* is the cross-section number of banks; *t* is the time (bi-annual) period, and ε is the disturbance. For equation 4.1, 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.

$$LLP_{i,t} = \beta_0 + \beta_1 LLP_{i,t-1} + \beta_2 LGRW_{i,t} + \beta_3 \Delta NPL_{i,t-2} + \beta_4 \Delta NPL_{i,t-1} + \beta_5 \Delta NPL_{i,t+} \beta_6 \Delta NPL_{i,t+1} + \sum_{k=7}^{10} \beta_k BANK_{i,t} + \varepsilon_{i,t} \tag{4.2}$$

For equations 4.2, 4.6, and 4.7, 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*)[15]*, 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[16]. 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}$1 = minimum regulatory allowance of *i* at *t* [1]*

$$LLA_{{expected}_{it}} = LLA\ {total}_{it} - LLA_{{incurred}_{it}}\ 15^{*}, \tag{4.3}$$

$$EXL_{it} = (\ LLA_{{expected}_{it}} - LLA_{{expected}_{it-1}}) - M\&A\ adjustments^{16}, \tag{4.4}$$

$$INL = LLPT_{it} - EXL_{it} \tag{4.5}$$

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.

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[15] *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).

[16] 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.

LGRW[17] *– 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 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.

$$EXL_{i,t} = \beta_0 + \beta_1\, EXL_{i,t-1} + \beta_2 LGRW_{i,t} + \beta_3 UNCERTAINTY_{i,t} + \beta_4 LGRW * UNCERTAINTY_{i,t} + \beta_5 \Delta NPL_{i,t-2} + \beta_6 \Delta NPL_{i,t-1} + \beta_7 \Delta NPL_{i,t+} \beta_8 \Delta NPL_{i,t+1} + \sum_{k=9}^{12} \beta_k BANK_{i,t} + \varepsilon_{i,t} \tag{4.6}$$

In addition, equation 4.6 tests Hypothesis 3, including the UNCERTAINTY variables, which include financial variables that are *proxies* for financial uncertainty and can alter the credit risk that affects the forward-looking provisioning. It represents macroeconomic uncertainty measures that will be used to test hypothesis 4. It will be composed of three variables that have a good representation of the uncertainty of the Brazilian and international financial markets. These variables are FOREX, which is the forex % change of Brazilian currency to the US Dollar[18], EMBI, which represents the country risk of Brazil by averaging

[17] 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.
[18] Provided by the Central Bank of Brazil, www.bcb.gov.br

the risk premia of Brazilian bonds traded in global markets[19], or UNCERT, an economic uncertainty index calculated by IBRE/FGV, a leading economic research center in Brazil. The variables EMBI and UNCERT are first differenced to assure stationarity.

$$EXL_{i,t} = \beta_0 + \beta_1 EXL_{i,t-1} + \beta_2 LGRW_{i,t} + \beta_3 d.SEGMENT_{i,t} + \beta_4 LGRW * d.SEGMENT_{i,t} + \beta_5 \Delta NPL_{i,t-2} + \beta_6 \Delta NPL_{i,t-1} + \beta_7 \Delta NPL_{i,t+} \beta_8 \Delta NPL_{i,t+1} + \sum_{k=9}^{12} \beta_k BANK_{i,t} + \varepsilon_{i,t} \tag{4.7}$$

For hypothesis 4, equation 4.7 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*

[19] Calculated by JP Morgan Chase and available from IPEA, www.ipeadata.gov.br

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.

Tables 4.1 and 4.2 show the descriptive statistics and the correlation matrix of our variables. As expected, LLPT is much more correlated to INL than to EXL, indicating that the former variable may be dominant in influencing LLPT. Also, contemporaneous NPL change is positively correlated to LLPT, which is also a clue to the timeliness of the INL. As for LGRW, we see a higher correlation between LGRW and EXL than for LGRW and INL, which is an indication that LGRW has a strong influence on EXL.

Table 4.1: Descriptive statistics

Variables	obs.	Mean	Std. Dev.	Min	Max
LLPT	2,459	0.02	0.04	-0.43	0.46
INL	2,459	0.02	0.04	-0.40	0.45
EXL	2,459	0.00	0.02	-0.30	0.20
CAR	2,351	0.21	0.11	-0.36	1.07
ZSCORE	2,446	29.91	38.70	-2.20	426.59
ROASTD	2,446	3.22	4.55	-6.95	50.49
LEVSTD	2,446	26.69	35.24	0.21	426.33
LGRW	2,459	0.07	0.20	-1.00	1.04
ΔNPL_{t-2}	2,459	0.00	0.04	-0.66	0.59
ΔNPL_{t-1}	2,459	0.00	0.04	-0.50	0.47
ΔNPL_{t}	2,459	0.00	0.04	-0.70	0.47
ΔNPL_{t+1}	2,459	0.00	0.04	-0.70	0.47
EBTP	2,459	0.02	0.03	-0.29	0.32
SIZE	2,459	21.90	2.23	16.58	27.83
LIQ	2,459	0.23	0.17	0.00	0.98
LEV	2,459	0.19	0.15	0.02	0.99
Δ EMBI	2,459	-0.13	0.97	-2.68	2.19
Δ% FOREX	2,459	0.01	0.13	-0.20	0.38
Δ UNCERT	2,459	0.83	10.33	-17.90	29.90
C_GAP	2,459	5.14	5.28	-5.30	11.92
O_GAP	2,459	13.41	0.28	13.00	13.86
d.SIB	2,459	0.08	0.28	0.00	1.00
d.SMALL	2,459	0.58	0.49	0.00	1.00

Table 4.2: Pearson correlation matrix

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1)	LLPT	1.00																				
(2)	INL	0.90	1.00																			
(3)	EXL	0.34	-0.11	1.00																		
(4)	CAR	0.03	0.06	-0.08	1.00																	
(5)	ZSCORE	-0.07	-0.07	-0.01	-0.02	1.00																
(6)	ROASTD	-0.09	-0.09	0.00	-0.09	0.79	1.00															
(7)	LEVSTD	-0.07	-0.07	-0.01	-0.01	1.00	0.74	1.00														
(8)	LGRW	0.07	-0.01	0.18	-0.09	-0.04	0.03	-0.05	1.00													
(9)	ΔNPL_{t-2}	0.09	0.08	0.01	-0.05	-0.02	-0.03	-0.02	-0.06	1.00												
(10)	ΔNPL_{t-1}	0.06	0.09	-0.06	-0.08	-0.02	-0.03	-0.02	-0.00	-0.27	1.00											
(11)	ΔNPL_{t}	0.36	0.41	-0.08	0.09	-0.02	-0.04	-0.02	-0.11	-0.04	-0.23	1.00										
(12)	ΔNPL_{t+1}	-0.07	-0.15	0.17	-0.06	0.00	0.02	-0.00	0.05	-0.06	-0.07	-0.32	1.00									
(13)	EBTP	0.41	0.39	0.11	0.12	-0.02	0.14	-0.04	0.17	0.02	-0.03	0.07	0.04	1.00								
(14)	SIZE	-0.01	-0.03	0.05	-0.47	0.24	0.34	0.22	-0.00	0.01	0.00	-0.01	0.02	-0.04	1.00							
(15)	LIQ	0.00	0.00	-0.00	0.25	-0.04	-0.03	-0.04	-0.07	-0.01	-0.04	-0.01	-0.07	-0.07	-0.02	1.00						
(16)	LEV	0.04	0.08	-0.09	0.82	-0.05	-0.16	-0.03	-0.12	-0.06	-0.04	0.05	-0.06	0.09	-0.58	0.13	1.00					
(17)	Δ EMBI	0.03	0.04	-0.01	-0.03	0.00	-0.01	0.01	-0.00	0.02	-0.03	0.03	0.04	-0.05	0.05	-0.02	-0.01	1.00				
(18)	Δ% FOREX	0.02	0.02	-0.00	-0.03	0.04	-0.01	0.04	-0.06	-0.01	-0.00	0.02	0.07	-0.09	0.08	-0.02	-0.01	0.79	1.00			
(19)	Δ UNCERT	0.01	0.02	-0.03	0.02	-0.01	-0.02	-0.01	-0.07	0.02	-0.04	0.06	0.03	-0.04	0.01	-0.02	0.01	0.64	0.56	1.00		
(20)	C_GAP	0.05	0.02	0.05	-0.08	-0.13	-0.04	-0.13	0.19	0.03	0.04	0.04	0.05	0.02	-0.06	-0.05	-0.08	0.16	0.02	-0.02	1.00	
(21)	O_GAP	0.04	0.04	-0.00	-0.13	0.03	-0.01	0.04	-0.02	0.02	0.01	0.04	0.07	-0.12	0.11	-0.05	-0.07	0.34	0.42	0.07	0.46	1.00

4.4.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 4.3, we expect that LGRW increases solvency risk, as previous literature (Foos *et al.* 2010, Köhler, 2015; Dang, 2019) 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 4.3: 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)	0.7114***	0.6832***						
	(0.068)	(0.073)						
ZSCORE (-1)			0.6512***	0.6699***				
			(0.067)	(0.059)				
ROASTD (-1)					0.5664***	0.5721***		
					(0.037)	(0.039)		
LEVSTD (-1)							0.7345***	0.7083***
							(0.064)	(0.071)
LGRW	-0.0434***	-0.0426***	-4.9468**	-5.5214**	0.3395	0.6474	-4.2702**	-3.4766
	(0.014)	(0.014)	(2.433)	(2.795)	(0.358)	(0.417)	(2.097)	(2.540)
ΔNPL (-2)	0.0674	0.0153	-14.1574	-16.0724	0.5182	-0.2715	-13.5158*	-8.1014
	(0.131)	(0.113)	(9.494)	(9.840)	(1.000)	(1.128)	(7.196)	(9.197)
ΔNPL (-1)	0.2461	0.1604	-23.8247*	-27.9105	0.5146	-0.4916	-23.1280**	-14.7753
	(0.220)	(0.185)	(14.094)	(17.403)	(1.806)	(1.806)	(10.416)	(15.087)
ΔNPL	0.4499	0.3790	-41.3762**	-58.1984**	-4.7703**	-5.6432***	-30.5259***	-38.5497*
	(0.343)	(0.290)	(17.849)	(23.318)	(2.140)	(2.071)	(10.839)	(22.079)
ΔNPL (+1)	0.8585	0.6958	-62.3940*	-92.8540**	1.5474	0.9998	-46.5174**	-53.9586
	(0.552)	(0.494)	(34.257)	(46.744)	(1.905)	(1.718)	(20.396)	(42.520)
LIQ	0.1740***	0.1630***	-2.9369	-2.9110	0.8697	0.8937	1.8268	0.8018
	(0.062)	(0.051)	(7.183)	(6.671)	(1.218)	(1.267)	(5.832)	(6.719)
EBTP	0.3807**	0.3929***	33.4463	38.6633**	8.8221	8.1008	3.3190	17.2831
	(0.171)	(0.146)	(20.760)	(16.066)	(13.620)	(16.722)	(13.395)	(15.775)
SIZE	-0.0062**	-0.0066***	1.0894***	1.1578***	0.2940***	0.2902***	0.8688***	0.8976***
	(0.003)	(0.002)	(0.342)	(0.316)	(0.049)	(0.057)	(0.264)	(0.273)
C_GAP		-0.0009**		-0.1365*		-0.0103		-0.1559**
		(0.000)		(0.080)		(0.018)		(0.068)
O_GAP		0.0050		3.3893**		-0.1743		3.5394**
		(0.006)		(1.500)		(0.496)		(1.651)
Constant	0.1552**	0.1061	-13.9316*	-60.9313***	-5.0592***	-3.0550	-13.9903**	-59.3792**
	(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 4.3, 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; and Dang, 2019), 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 4.4. We segregated the INL and EXL from the LLPT and put them as dependent variables.

Table 4.4: Impact of LGRW on provisions

VARIABLES	(2a) INL	(2b) INL	(2c) EXL	(2d) EXL	(2e) LLPT	(2f) LLPT
INL (-1)	0.2538***	0.1369**				
	(0.081)	(0.058)				
EXL (-1)			-0.2025***	-0.2077***		
			(0.039)	(0.040)		
LLPT (-1)					0.1525*	0.1620**
					(0.085)	(0.071)
LGRW	0.0060	0.0044	0.0165***	0.0168***	0.0139***	0.0114**
	(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)	0.1163**	0.1228**	0.0196	0.0368	0.0016	0.1149*
	(0.050)	(0.051)	(0.041)	(0.037)	(0.098)	(0.064)
ΔNPL	0.4053***	0.3819***	0.0849**	0.0961***	0.2602***	0.3693***
	(0.054)	(0.074)	(0.037)	(0.033)	(0.094)	(0.050)
ΔNPL (+1)	-0.0500	-0.1386	0.1047**	0.1189**	-0.3257	-0.1317
	(0.146)	(0.235)	(0.053)	(0.053)	(0.225)	(0.125)
LIQ	-0.0202	-0.0153	0.0075	0.0029	0.0084	-0.0086
	(0.016)	(0.018)	(0.034)	(0.017)	(0.113)	(0.010)
EBTP	0.1089	0.0421	0.0207	0.0194	0.2029	0.2305**
	(0.106)	(0.186)	(0.026)	(0.025)	(0.148)	(0.101)
SIZE	0.0016	0.0009	-0.0009	-0.0006	-0.0002	-0.0009
	(0.001)	(0.005)	(0.004)	(0.002)	(0.005)	(0.001)
LEV	0.0568	0.0716	-0.0112	-0.0115	-0.0497	-0.0446*
	(0.045)	(0.139)	(0.024)	(0.019)	(0.128)	(0.023)
C_GAP		-0.0001		-0.0001		-0.0001
		(0.000)		(0.000)		(0.000)
O_GAP		0.0007		0.0005		0.0035
		(0.005)		(0.002)		(0.003)
Constant	-0.0314	-0.0217	0.0187	0.0073	0.0169	-0.0080
	(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 bank	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 4.4 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 4.4. 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.

With hypothesis 3, in Table 4.5, we see that the amount of expected provisions set aside by banks when loans are granted during times of increased economic uncertainty is higher. As uncertainty increases credit risk, it is important to assess whether loan growth during uncertain times affects expected provision differently than in normal times.

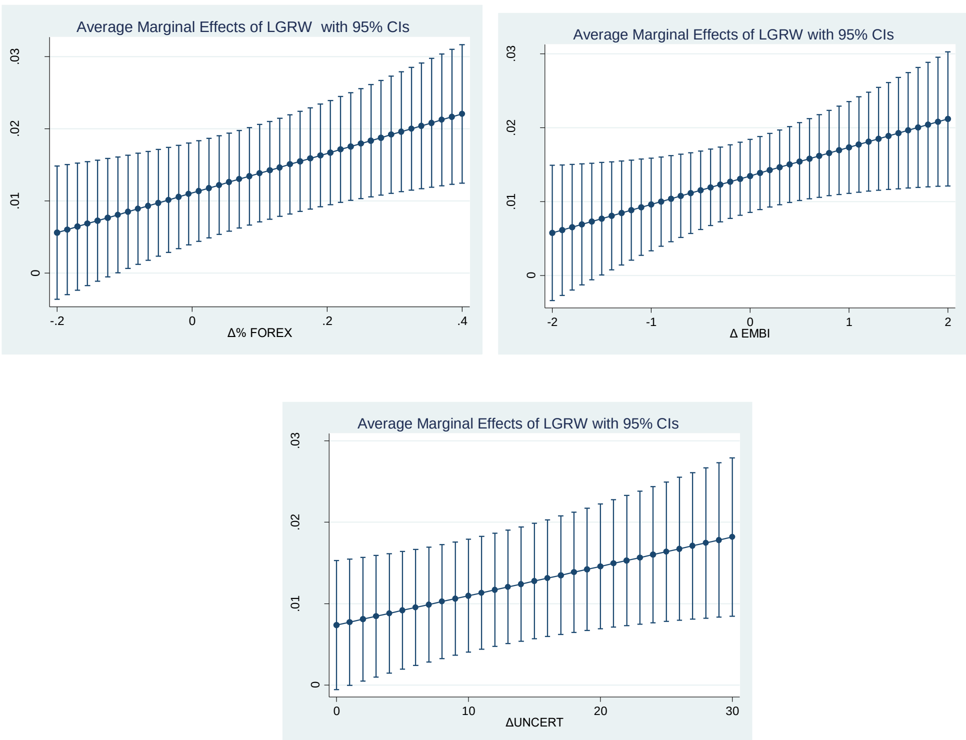
Table 4.5: Impact of loan growth on EXL, given uncertainty

	(3a)	(3b)	(3c)	(3d)	(3e)	(3f)
VARIABLES	EXL	EXL	EXL	EXL	EXL	EXL
EXL (-1)	-0.1437***	-0.1954***	-0.1744***	-0.1689***	-0.1619***	-0.1677***
	(0.054)	(0.044)	(0.049)	(0.047)	(0.060)	(0.055)
LGRW	0.0143***	0.0111***	0.0120***	0.0137***	0.0126**	0.0074*
	(0.004)	(0.004)	(0.004)	(0.003)	(0.006)	(0.004)
Δ%FOREX	0.0003	-0.0002				
	(0.003)	(0.002)				
LGRW * Δ%FOREX		0.0274**				
		(0.011)				
ΔEMBI			-0.0001	-0.0003		
			(0.000)	(0.000)		
LGRW * ΔEMBI				0.0039**		
				(0.002)		
ΔUNCERT					-0.0000	-0.0000
					(0.000)	(0.000)
LGRW * ΔUNCERT						0.0004** (0.000)
ΔNPL (-2)	0.0086	0.0003	-0.0024	0.0087	-0.0003	-0.0132
	(0.016)	(0.016)	(0.014)	(0.029)	(0.019)	(0.022)
ΔNPL (-1)	0.0143	0.0112	0.0079	0.0198	0.0206	-0.0017
	(0.037)	(0.031)	(0.028)	(0.038)	(0.047)	(0.039)
ΔNPL	0.0552	0.0504*	0.0454*	0.0461	0.0273	0.0263
	(0.043)	(0.029)	(0.026)	(0.033)	(0.060)	(0.039)
ΔNPL (+1)	0.0753***	0.0884	0.1069*	0.0958	0.0522	0.0198
	(0.025)	(0.055)	(0.058)	(0.108)	(0.106)	(0.065)
LIQ	0.0110	0.0107	0.0133**	0.0150	0.0107	-0.0031
	(0.008)	(0.008)	(0.006)	(0.010)	(0.012)	(0.008)
EBTP	0.0053	0.0671	0.0773	0.0470**	0.0508**	0.0733
	(0.104)	(0.058)	(0.091)	(0.022)	(0.025)	(0.050)
LEV	-0.0056	0.0037	0.0019	0.0029	-0.0324*	-0.0221*
	(0.019)	(0.026)	(0.013)	(0.027)	(0.019)	(0.013)
SIZE	0.0002	0.0008	0.0006	0.0007	-0.0008	-0.0018
	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)
C_GAP	0.0000	0.0000	-0.0000	0.0000	-0.0001	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
O_GAP	-0.0008	-0.0003	0.0002	-0.0009	0.0006	0.0026
	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Constant	0.0057	-0.0176	-0.0209	-0.0091	0.0122	0.0089
	(0.029)	(0.026)	(0.029)	(0.025)	(0.029)	(0.025)
Observations	2,457	2,457	2,457	2,457	2,457	2,457
Number of banks	95	95	95	95	95	95
Instr./CrossSec.	0.28	0.35	0.33	0.28	0.19	0.32
Time effect	No	No	No	No	No	No
Macro variables	Yes	Yes	Yes	Yes	Yes	Yes
J-statistic	16.02	19.16	17.39	8.87	4.09	12.77
p-value	*0.25*	*0.38*	*0.43*	*0.71*	*0.39*	*0.62*
AR(1)	-2.80	-2.43	-2.72	-2.66	-2.68	-2.61
p-value	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*	*0.01*
AR(2)	-0.04	-0.46	0.04	-0.09	-0.37	-0.62
p-value	*0.97*	*0.65*	*0.97*	*0.93*	*0.71*	*0.54*

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 autocorrelation. Time effects are included to account for unobserved macroeconomic effects that might affect the relation of our variables. Macro variables controls and uncertainty variables cannot be in the same equation due to the multicollinearity of S-GMM.

For hypothesis 3, we ran equations 4.6 in Table 4.5, which uses three different measures of uncertainty for the Brazilian economy: EMBI, FOREX, and UNCERT. The regressions show that these measurements of uncertainty do not change the level of EXL *ceteris paribus*. When we interact the *proxies* for uncertainty with LGRW, the interaction coefficients are positive and significant. This result shows that changes in economic uncertainty affect EXL through LGRW, which means that the growth of loans during uncertain times will lead to more EXL than at other times. This finding is related to Dasnisman *et al.* (2021), which say that financial and political uncertainty affects LLPT. The difference between the author's finding and ours is that the LLPT they are measuring is mainly INL, but the convergence in the results is that uncertainty affects credit risk. In figure 4.1 we can observe the plot of these results, with the average marginal effects for the three variables: FOREX, EMBI, and UNCERT. It reinforces that uncertainty will lead to higher EXL given growth in the loan portfolio.

Figure 4.1: Marginal effects of LGRW on EXL given a change in Δ% FOREX, ΔEMBI, or ΔUNCERT



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 4.6: Bank segmentation and the impact of LGRW on EXL

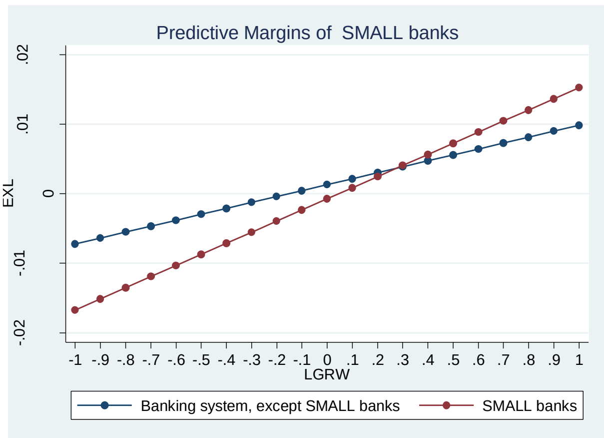
VARIABLES	(4a) EXL	(4b) EXL	(4c) EXL	(4d) EXL
EXL (-1)	-0.1789*** (0.052)	-0.1925*** (0.053)	-0.1872*** (0.053)	-0.1570*** (0.057)
LGRW	0.0156*** (0.004)	0.0145*** (0.004)	0.0085*** (0.003)	0.0074*** (0.002)
d.SIB	-0.0006 (0.002)	0.0003 (0.001)		
LGRW*d.SIB	-0.0034 (0.005)	-0.0050 (0.004)		
d.SMALL			-0.0020 (0.008)	0.0009 (0.002)
LGRW*d.SMALL			0.0074* (0.004)	0.0082** (0.004)
ΔNPL (-2)	-0.0449 (0.063)	0.0037 (0.021)	-0.0069 (0.026)	-0.0689 (0.053)
ΔNPL (-1)	0.0046 (0.032)	0.0187 (0.026)	0.0051 (0.035)	-0.0016 (0.027)
ΔNPL	0.0753** (0.038)	0.1002** (0.046)	0.0879** (0.035)	0.0454* (0.028)
ΔNPL (+1)	0.1107 (0.068)	0.1573** (0.069)	0.1467 (0.094)	0.0951 (0.119)
LIQ	0.0118 (0.007)	0.0128* (0.007)	0.0092 (0.009)	0.0167 (0.010)
EBTP	0.0252 (0.023)	0.0253 (0.039)	0.0281 (0.021)	0.0527** (0.023)
SIZE	0.0004 (0.000)	0.0002 (0.000)	-0.0005 (0.003)	0.0005 (0.002)
LEV	-0.0038 (0.011)	-0.0087 (0.010)	-0.0098 (0.023)	-0.0045 (0.037)
C_GAP		-0.0000 (0.000)		0.0000 (0.000)
O_GAP		-0.0011 (0.001)		-0.0006 (0.002)
Constant	-0.0117 (0.013)	0.0084 (0.021)	0.0107 (0.071)	-0.0082 (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 4.6, 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 4.2. we show the predictive margins graph showing the difference in plots of SMALL and non-SMALL banks, based on hypothesis 4c from Table 4.6. When LGRW is positive and passes the threshold point of .2, we see that SMALL banks allocate more EXL than non-SMALL banks.

Figure 4.2: Predictive margins of SMALL banks and non-SMALL banks



4.4.1. 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 (Love & Zicchino, 2006). 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).

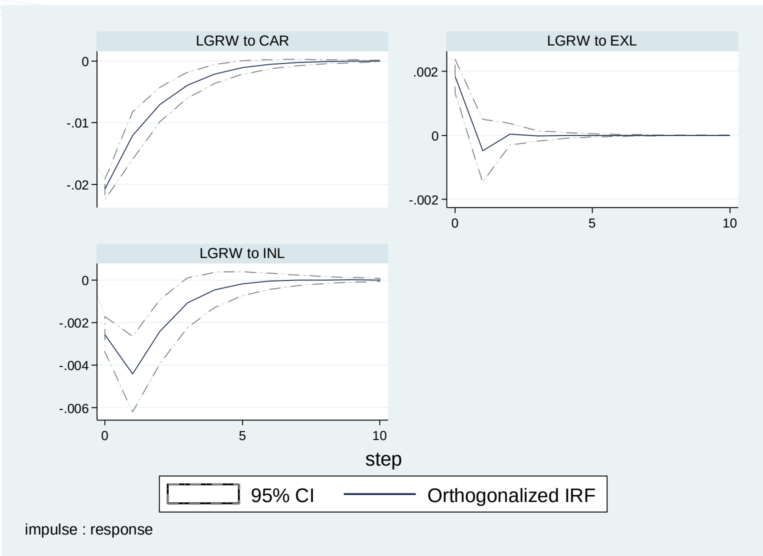
For the pVAR model, we include the variables EXL, INL, LGRW, and CAR as endogenous, and the variables $\Delta NPL_{i,t-2}$, $\Delta NPL_{i,t-1}$, $\Delta NPL_{i,t}$, $\Delta NPL_{i,t+1}$, EBTP, LIQ, LEV, and SIZE as exogenous. All variables were tested for stationary using the Fisher – Augmented Dickey-Fuller test's panel unit root test, shown in Table 4.7 in the appendix. Also, following Andrews & Lu (2001), the optimal lag for the model selection was based on the first-order pVAR, as shown in Table 4.8 in the appendix. Additional robustness of the pVAR is the stability graph, which shows that pVAR satisfies the stability conditions. According to Abrigo & Love (2016), Hamilton (1994), and Lutkepohl (2005), a VAR model is stable if all the companion matrices are strictly less one and the eigenvalues lie with the unit circle.

As we see in Figure 4.3, we get similar results of pVAR to the results of equations 4.1 and 4.2 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, which is what Figure 4.1 shows. 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 4.3: Impulse-response of LGRW on EXL, INL, and CAR



4.5.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 bi-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.

Furthermore, we show that (iii) as economic uncertainty impacts credit risk, it triggers higher expected loss provision when banks have a loan growth. Banks allocate more provisions during uncertain times for new loans than in regular times, which corroborates with Danisman *et al.* (2021), that say that banks provision more when uncertainty is high. This extra provision allocation is an interesting result, as more provisions decrease banks' margins and is a disincentive for future loans. We show that expected provisions are not affected by uncertainty itself or *ceteris paribus* but rather by the interaction of uncertainty variables with loan growth.

Lastly, it was important to know whether (iv) 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.

4.6.References

Abedifar, P., Molyneux, P., & Tarazi, A. (2018). Non-interest income and bank lending. *Journal of Banking & Finance*, *87*, 411-426.

Abrigo, M. R., & Love, I. (2016). Estimation of panel vector autoregression in Stata. *The Stata Journal*, *16*(3), 778-804.

Ahmed, A. S., Takeda, C., & Thomas, S. (1999). Bank loan loss provisions: a reexamination of capital management, earnings management and signaling effects. *Journal of accounting and economics*, *28*(1), 1-25.'

Amador, J. S., Gómez-González, J. E., & Pabón, A. M. (2013). Loan growth and bank risk: new evidence. *Financial Markets and Portfolio Management*, *27*(4), 365-379.

Andrews, D. W., & Lu, B. (2001). Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *Journal of econometrics*, *101*(1), 123-164.

Araújo, A. M. H. B. D., Lustosa, P. R. B., & Dantas, J. A. (2018). A Ciclicidade da Provisão para Créditos de Liquidação Duvidosa nos Bancos Comerciais do Brasil. *BBR. Brazilian Business Review*, *15*(3), 246-261.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, *58*(2), 277-297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, *68*(1), 29-51.

Ayuso, J., Pérez, D., & Saurina, J. (2004). Are capital buffers procyclical? Evidence from Spanish panel data. *Journal of financial intermediation*, *13*(2), 249-264.

Basel Committee on Banking Supervision -BCBS. (2011). Guidance for national authorities operating the countercyclical capital buffer. Basel, Switzerland.

Beatty, A., & Liao, S. (2009). Regulatory capital ratios, loan loss provisioning and procyclicality. *Columbus, United States: Ohio State University. Mimeographed document*.

Beatty, A., & Liao, S. (2014). Financial accounting in the banking industry: A review of the empirical literature. *Journal of Accounting and Economics*, *58*(2-3), 339-383.

Berger, A. N., & Udell, G. F. (2004). The institutional memory hypothesis and the procyclicality of bank lending behavior. *Journal of financial intermediation*, *13*(4), 458-495.

Berger, A. N., Guedhami, O., Kim, H. H., & Li, X. (2020). Economic policy uncertainty and bank liquidity hoarding. *Journal of Financial Intermediation*, 100893.

Bikker, J. A., & Hu, H. (2002). *Cyclical patterns in profits, provisioning and lending of banks*. De Nederlandsche Bank.

Bikker, J. A., & Metzemakers, P. A. (2005). Bank provisioning behaviour and procyclicality. *Journal of international financial markets, institutions, and money*, *15*(2), 141-157.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, *87*(1), 115-143.

Borio, C., Furfine, C., & Lowe, P. (2001). Procyclicality of the financial system and financial stability: issues and policy options. *BIS papers*, *1*(3), 1-57.

Bouvatier, V., & Lepetit, L. (2008). Banks' procyclical behavior: Does provisioning matter?. *Journal of international financial markets, institutions and money*, *18*(5), 513-526.

Bouvatier, V., & Lepetit, L. (2012). Provisioning rules and bank lending: A theoretical model. *Journal of Financial Stability*, *8*(1), 25-31.

Boyd, J. H., Graham, S. L., & Hewitt, R. S. (1993). Bank holding company mergers with nonbank financial firms: Effects on the risk of failure. *Journal of banking & finance*, *17*(1), 43-63.

Central Bank of Brazil (1999) *Resolution 2.682* from the Central Bank of Brazil, Provisioning rules for loan loss provision for credit assets.

Central Bank of Brazil (2000) *Resolution 2.697* from the Central Bank of Brazil, Loan classification criteria and disclosure on the explanatory note of financial statements.

Central Bank of Brazil (2017) *Resolution 4.553* from the Central Bank of Brazil, Segmentation of Financial Institutions Authorized to operate by the Central Bank of Brazil for Macroprudential Purposes.

Cohen, B. H., & Edwards, G. (2017). The new era of expected credit loss provisioning. *BIS Quarterly Review, March*.

Dang, V. (2019). The effects of loan growth on bank performance: Evidence from Vietnam. *Management Science Letters*, *9*(6), 899-910.

Danisman, G. O., Demir, E., & Ozili, P. (2021). Loan loss provisioning of US banks: Economic policy uncertainty and discretionary behavior. *International Review of Economics & Finance*, *71*, 923-935.

Dantas, J. A., de Medeiros, O. R., & Lustosa, P. R. B. (2013). The role of economic variables and credit portfolio attributes for estimating discretionary loan loss provisions in Brazilian banks. *Brazilian Business Review*, *10*(4), 65-90.

De Mendonça, H. F., & Barcelos, V. Í. (2015). Securitization and credit risk: Empirical evidence from an emerging economy. *The North American Journal of Economics and Finance*, *32*, 12-28.

De Moraes, C. O., & de Mendonça, H. F. (2019). Bank's risk measures and monetary policy: Evidence from a large emerging economy. *The North American Journal of Economics and Finance*, *49*, 121-132.

Drehmann, M., & Yetman, J. (2018). Why you should use the Hodrick-Prescott filter–at least to generate credit gaps.

Durnev, A. (2010). The real effects of political uncertainty: Elections and investment sensitivity to stock prices. *Available at SSRN 1549714*.

Edwards, G. A. (2014). The upcoming new era of expected loss provisioning. *SEACEN Financial Stability Journal*, *2*, 13-24.

Fahlenbrach, R., Prilmeier, R., & Stulz, R. M. (2012). This time is the same: Using bank performance in 1998 to explain bank performance during the recent financial crisis. *The Journal of Finance, 67*(6), 2139-2185.

Fillat, J. L., & Montoriol-Garriga, J. (2010). Addressing the procyclicality of capital requirements with a dynamic loan loss provision system. *Federal Reserve Bank of Boston, Boston MA.*

Fonseca, A. R., & Gonzalez, F. (2008). Cross-country determinants of bank income smoothing by managing loan-loss provisions. *Journal of Banking & Finance, 32*(2), 217-228.

Foos, D., Norden, L., & Weber, M. (2010). Loan growth and riskiness of banks. *Journal of Banking & Finance*, *34*(12), 2929-2940.

Francis, B. B., Hasan, I., & Zhu, Y. (2014). Political uncertainty and bank loan contracting. *Journal of Empirical Finance*, *29*, 281-286.

Galati, G., & Moessner, R. (2013). Macroprudential policy–a literature review. *Journal of Economic Surveys*, *27*(5), 846-878.

Galdi, F., De Moura, A., & França, R. (2021). Loan loss provision models in Brazilian banks. *Meditari Accountancy Research*.

Gaston, E., & Song, M. I. (2014). Supervisory roles in loan loss provisioning in countries implementing IFRS. *International Monetary Fund.*

Grossmann, A., Love, I., & Orlov, A. G. (2014). The dynamics of exchange rate volatility: A panel VAR approach. *Journal of International Financial Markets, Institutions and Money*, *33*, 1-27.

Hamilton, J. D. (1994). Time Series Analysis, Princeton University Press.

Hamilton, J. D. (2018). Why you should never use the Hodrick-Prescott filter. *Review of Economics and Statistics*, *100*(5), 831-843.

Hu, S., & Gong, D. (2019). Economic policy uncertainty, prudential regulation, and bank lending. *Finance Research Letters*, *29*, 373-378.

Huizinga, H., & Laeven, L. (2019). The procyclicality of banking: Evidence from the euro area. *IMF Economic Review*, 67(3), 496-527.

IASB, F. (2015) *Conceptual Framework*

Jesus, S., & Gabriel, J. (2006). Credit cycles, credit risk, and prudential regulation.

Jiménez, G., Ongena, S., Peydró, J. L., & Saurina, J. (2017). Macroprudential policy, countercyclical bank capital buffers, and credit supply: Evidence from the Spanish dynamic provisioning experiments. *Journal of Political Economy*, 125(6), 2126-2177.

Julio, B., & Yook, Y. (2011). Policy uncertainty and cross-border flows of capital. *SSRN Working Papers*.

Julio, B., & Yook, Y. (2012). Political uncertainty and corporate investment cycles. *The Journal of Finance*, *67*(1), 45-83.

Keeton, W. R. (1999). Does faster loan growth lead to higher loan losses?. *Economic review-Federal reserve bank of Kansas City*, *84*, 57-76.

Köhler, M. (2015). Which banks are more risky? The impact of loan growth and business model on bank risk-taking.

Laeven, L., & Majnoni, G. (2003). Loan loss provisioning and economic slowdowns: too much, too late?. *Journal of financial intermediation*, *12*(2), 178-197.

Laidroo, L., & Männasoo, K. (2014). Perils of excessive credit growth: evidence from 11 new EU member states. *Baltic Journal of Economics*, *14*(1-2), 17-34.

López-Espinosa, G., Ormazabal, G., & Sakasai, Y. (2021). Switching from Incurred to Expected Loan Loss Provisioning: Early Evidence. *Journal of Accounting Research*.

Love, I., & Zicchino, L. (2006). Financial development and dynamic investment behavior: Evidence from panel VAR. *The Quarterly Review of Economics and Finance*, *46*(2), 190-210.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer Science & Business Media.

Messai, A. S., & Jouini, F. (2013). Micro and macro determinants of nonperforming loans. *International journal of economics and financial issues*, *3*(4), 852.

Minsky, H. P. (1992). The financial instability hypothesis. *The Jerome Levy Economics Institute Working Paper*, (74).

Nichols, D. C., Wahlen, J. M., & Wieland, M. M. (2009). Publicly traded versus privately held: implications for conditional conservatism in bank accounting. *Review of accounting studies*, *14*(1), 88-122.

Nicoletti, A. (2018). The effects of bank regulators and external auditors on loan loss provisions. *Journal of Accounting and Economics*, *66*(1), 244-265.

Ozili, P. K. (2017). Discretionary provisioning practices among Western European banks. *Journal of Financial Economic Policy*.

Ozili, P. K., & Outa, E. (2017). Bank loan loss provisions research: A review. *Borsa Istanbul Review*, *17*(3), 144-163.

Pástor, Ľ., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of financial Economics*, *110*(3), 520-545.

Peterson, O. K., & Arun, T. G. (2018). Income smoothing among European systemic and non-systemic banks. *The British Accounting Review*, *50*(5), 539-558.

Roy, A. D. (1952). Safety first and the holding of assets. *Econometrica: Journal of the econometric society*, 431-449.

Saurina, J. (2009). Loan loss provisions in Spain. A working macroprudential tool. *Revista de Estabilidad Financiera*, *17*, 11-26.

Schechtman, R. & Takeda, T. , (2018). Capital (and Earnings) Incentives for Loan Loss Provisions in Brazil: evidence from a crisis-buffering regulatory intervention, *Working Papers Series 477, Central Bank of Brazil, Research Department*.

Shim, J. (2013). Bank capital buffer and portfolio risk: The influence of business cycle and revenue diversification. *Journal of Banking & Finance*, *37*(3), 761-772.

Skała, D. (2015). Saving on a rainy day? Income smoothing and procyclicality of loan-loss provisions in central European banks. *International Finance*, *18*(1), 25-46.

Stolz, S., & Wedow, M. (2011). Banks' regulatory capital buffer and the business cycle: Evidence for Germany. *Journal of Financial Stability*, *7*(2), 98-110.

Tillmann, P. (2016). Unconventional monetary policy and the spillovers to emerging markets. *Journal of International Money and Finance*, *66*, 136-156.

Tölö, E., & Virén, M. (2021). How much do nonperforming loans hinder loan growth in Europe? *European Economic Review*, 103773.

Valencia, F. (2016). Bank capital and uncertainty. *Journal of Banking & Finance*, *69*, S1-S9.

Waisman, M., Ye, P., & Zhu, Y. (2015). The effect of political uncertainty on the cost of corporate debt. *Journal of Financial Stability*, *16*, 106-117.

Wezel, T., Chan-Lau, M. J. A., & Columba, M. F. (2012). *Dynamic Loan Loss Provisioning: Simulationson Effectiveness and Guide to Implementation*. International Monetary Fund

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. Journal of econometrics, 126(1), 25-51.

Zeff, S. A. (2012). The Evolution of the IASC into the IASB, and the Challenges it Faces. *The accounting review*, *87*(3), 807-837.

Appendix

Table 4.7: Unit root panel ADF stationary test

Variables		p-value
EXL	3156.65***	0.00
INL	1541.55***	0.00
LLPT	1605.27***	0.00
CAR	668.41***	0.00
LGRW	1559.08***	0.00
LEV	704.09***	0.00
LIQ	838.32***	0.00
ΔNPL_{t-2}	2695.21***	0.00
ΔNPL_{t-1}	2831.71***	0.00
ΔNPL_{t}	2879.28***	0.00
ΔNPL_{t+1}	2879.28***	0.00
SIZE	575.23***	0.00

Table 4.8: Lag-length criteria based on Andrews & Lu (2001) for pVAR

Lag	CD	MBIC	MAIC	MQIC
1	0.96	-588.11	-47.26	-245.51
2	0.97	-509.76	-59.05	-224.27
3	0.97	-404.78	-44.21	-176.38
4	0.83	-320.49	-50.07	-149.20

Table 4.9: pVAR coefficients and standard errors.

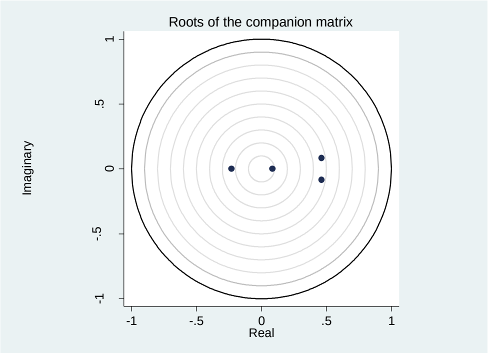
VARIABLES	(1) LGRW	(2) INL	(3) EXL	(4) CAR
LGRW (-1)	0.1244***	-0.0142***	-0.0006	-0.0078
	(0.048)	(0.003)	(0.002)	(0.007)
INL (-1)	-1.1129**	0.4646***	0.0102	0.3057***
	(0.529)	(0.084)	(0.029)	(0.094)
EXL(-1)	-1.8291***	0.3105***	-0.1726***	0.1489
	(0.695)	(0.074)	(0.055)	(0.124)
CAR (-1)	0.9476***	0.0029	-0.0005	0.4571***
	(0.198)	(0.013)	(0.010)	(0.042)
ΔNPL (-2)	-0.7581**	0.0287	-0.0090	0.0044
	(0.377)	(0.028)	(0.016)	(0.052)
ΔNPL (-1)	-0.3070	-0.0169	0.0032	-0.1389**
	(0.366)	(0.040)	(0.025)	(0.063)
ΔNPL	-0.8866***	0.3957***	0.0005	0.1787***
	(0.314)	(0.043)	(0.025)	(0.060)
ΔNPL (+1)	-0.3899	-0.0307	0.0829***	0.0864**
	(0.255)	(0.031)	(0.019)	(0.042)
EBTP	3.2839***	-0.1128	0.0720***	-0.0518
	(0.597)	(0.081)	(0.027)	(0.106)
LIQ	0.1552	0.0087	-0.0106	0.0055
	(0.235)	(0.014)	(0.008)	(0.037)
LEV	-4.3214***	0.0230	-0.0424	0.8079***
	(0.659)	(0.050)	(0.027)	(0.123)
SIZE	-0.0473***	-0.0024**	-0.0016**	-0.0037
	(0.014)	(0.001)	(0.001)	(0.003)
Observations	2,236	2,236	2,236	2,236

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.10: pVAR Stability matrix

Eigenvalue		
Real	Imaginary	Modulus
0.49	-0.09	0.50
0.49	0.09	0.50
-0.18	0.00	0.18
0.08	0.00	0.08

Figure 4.4: Unit circle stability test



5. CONCLUDING REMARKS

The three essays of this thesis fill the literature gap by addressing important research questions on factors of banking riskiness and performance that are important to financial stability. First, we show macroeconomic variables that can be used to forecast future bank performance, what is at stake with the potential loss of non-interest income (NII) due to the new entrants in the financial system, and the low entry barriers from an increase in financial innovation. Lastly, we show that the new accounting regulation, such as IFRS 9, may be beneficial to soften the credit cycle by showing that banks act prudentially by increasing expected loss provision when loan growth occurs. Previous to this work, the literature was inconclusive on whether macroeconomic variables can be used to forecast future bank performance (Alfaro & Drehmann, 2009; Guerrieri & Welch, 2012; Borio *et al.,* 2014). Additionally, it is uncertain whether NII was an important factor in increasing bank profitability and decreasing bank riskiness (Stiroh, 2004; Stiroh, 2006; Murphy, 2009; Lee *et al.*, 2014; Williams, 2016; Chen *et al.*, 2017). Finally, the literature did not provide great evidence on whether banks could act countercyclically by using expected loss provision to counterbalance the inherent increase in credit risks that accompanied growth in the loan portfolio.

The first essay shows that macroeconomic variables can be a powerful tool for predicting bank performance but not for all measures of banking conditions. We show that only when predicting *cash flow* variables, can the *macro variable* model overperform the autoregressive model, the upper bound benchmark model, with the out-of-sample forecasting. Borio *et al.* (2014) affirm that macro variables do not help predict bank financial performance. Our results diverge from their conclusion, as we find that macro variables offer gain in predictivity when predicting *cash flow* variables, more precisely, the cash flow from liability (LCF).

The second essay shows that NII increases overall bank profitability and decreases bank riskiness. In Brazil, NII mainly comprises fees and services charges (Inter-American Development Bank, 2018; Park *et al.*, 2019), supplying a stable income stream with low risk. Additionally, these extra revenues do not require many new fixed costs or bank capital to be invested, which improves bank efficiency (Barth *et al.*, 2013). We also show that NII has a compensating effect on financial intermediation earnings, which is positive during a downturn in the economic cycle (Albertazzi & Gambacorta, 2009, Shim, 2013). Finally, when comparing large and small banks in Brazil, we see how NII is more relevant for the large banks, which may increase the propensity to invest in non-interest business at the expense of financial intermediation. It also shows that this group of banks has more to lose from the rise of *fintech*.

The third essay shows an increase in bank riskiness with loan growth. However, as loan growth increases credit risk, expected loss provisions also increase. This result shows that the new accounting rules that bring the concept of expected loss provisioning can effectively offset an increase in credit risk from loan growth, as the Brazilian market shows. In addition, as economic uncertainty impacts credit risk, banks increase the amount of expected loss provision when banks increase the loan portfolio during times of financial uncertainty. Finally, we see that size matters, as small banks allocate more expected loss provision when their loan portfolio grows, indicating that the Brazilian banking system is heterogeneous, and that adverse selection may play an important role in this difference in extra provisioning.

The need for financial stability and the search for a correct assessment of bank performance and riskiness connect these three essays. The first essay brings innovation by using the novel *cash flow* variables, which are *proxies* of financial intermediation for forecasting bank performance. It tries to fill the gap of whether macro variables are relevant to forecast performance and it also shows that autoregressive models are essential tools for forecasting. Furthermore, this work connects financial intermediation to the banking accounting literature. The second essay unveiled how NII increases overall profitability and reduces bank riskiness, compensating or moderating the reduction in financial intermediation earnings. Also, we revealed how NII could “compete” with financial intermediation earnings, reducing the relevance of the latter in banks' profitability. As technology changes the banking industry by lowering the barrier of entry to new entrants, banks are at risk of losing non-interest revenues. Finally, the third essay gave extra evidence that the accounting standards' intention of loan loss provisioning to provision when risks appear, not when they are materialized, is achieved when banks can use expected loss provisioning.

5.1.References

Albertazzi, U., & Gambacorta, L. (2009). Bank profitability and the business cycle. *Journal of Financial Stability*, *5*(4), 393-409.

Alfaro, R. A., & Drehmann, M. (2009). Macro stress tests and crises: what can we learn? *BIS Quarterly Review December*.

Barth, J. R., Lin, C., Ma, Y., Seade, J., & Song, F. M. (2013). Do bank regulation, supervision and monitoring enhance or impede bank efficiency?. *Journal of Banking & Finance*, *37*(8), 2879-2892.

Borio, C., Drehmann, M., & Tsatsaronis, K. (2014). Stress-testing macro stress testing: Does it live up to expectations? *Journal of Financial Stability*, *12*(1), 3–15. https://doi.org/10.1016/j.jfs.2013.06.001

Chen, C. R., Huang, Y. S., & Zhang, T. (2017). Non-interest income, trading, and bank risk. *Journal of Financial Services Research*, *51*(1), 19-53.

Guerrieri, L., & Welch, M. (2012). Can macro variables used in stress testing forecast the performance of banks? *Finance and Economics Discussion Series-FEDs*, 49.

Inter-American Development Bank; IDB Invest; Finnovista. (2018). *Fintech: Latin America 2018: Growth and Consolidation*. https://doi.org/http://dx.doi.org/10.18235/0001377

Lee, C. C., Yang, S. J., & Chang, C. H. (2014). Non-interest income, profitability, and risk in banking industry: A cross-country analysis. *The North American Journal of Economics and Finance*, *27*,

Murphy KJ (2009) Compensation structure and systematic risk. *Marshall Research Paper series Working Paper PBE-34-09*, University of Southern California

Park, B., Park, J., & Chae, J. (2019). Non-interest income and bank performance during the financial crisis. *Applied Economics Letters*, *0*(0), 1–6. https://doi.org/10.1080/13504851.2019.1591592

Shim, J. (2013). Bank capital buffer and portfolio risk: The influence of business cycle and revenue diversification. *Journal of Banking & Finance*, *37*(3), 761-772.

Stiroh, Kevin, (2004), "Diversification in Banking: Is Non-interest Income the Answer?" *Journal of Money, Credit and Banking* 36, 853-882.

Stiroh, Kevin, (2006), "A Portfolio View of Banking with Interest and Non-interest Activities," *Journal of Money, Credit and Banking* 38, 2131-2161.

Williams, B. (2016). The impact of non-interest income on bank risk in Australia. *Journal of Banking and Finance*. https://doi.org/10.1016/j.jbankfin.2016.07.019