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Credit behavior and financial stability in an emerging economy

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ABSTRACT

One relevant issue for the management of financial stability is the monitoring of the credit market. In this sense, Basel III proposed the credit gap as the most appropriate measure to anticipate financial stability issues. However, the adoption of the credit gap has been criticized, especially for emerging markets. Through panel data analysis, this study investigates the effect of the credit gap and the credit growth rate on financial stability in Brazil, which represents a relevant emerging economy. For this purpose, we use a set of financial stability measures traditionally found in the literature: the z-score, regulatory capital and credit risk. The results suggest that the credit gap and credit growth rates are adequate metrics to indicate the sustainability of credit growth in Brazil. However, credit growth rates are more attractive, since they indicate a threshold for credit growth in the Brazilian economy concerning financial stability.

1. Introduction

The great financial crisis of 2008 has shown that excessive credit growth often leads to the accumulation of risks to financial stability, which can materialize in systemic banking crises (Jordà et al., 2010; Schularick and Taylor, 2012). However, although the relationship between excessive credit growth and financial instability is well established in the literature, as highlighted by Alessi and Detken (2018), identifying the phase of the financial cycle, as well as which instrument is more suitable to avoid risks to financial stability, is still a challenge for policymakers.

In the wake of the recent financial crisis, the Basel Committee on Banking Supervision (BCBS, 2010a) proposed the countercyclical capital buffer as a new macroprudential instrument, with the objective of protecting the banking sector from the effects of the financial cycle, that is, periods of unsustainable credit growth. As a way of assisting policymakers' decision processes, the BCBS identified the variable credit-to-GDP gap (credit gap) as the best measure to signal an increase of bank risk and, consequently, to anticipate episodes of financial crises. However, the adoption of this variable still raises discussions, especially in emerging economies.

The credit gap is defined as the difference between the indicator credit-to-GDP and its long-term trend (BCBS, 2010b). Conceptually, the credit gap reflects the ideas of the seminal work of Kaminsky and Reinhart (1999), who argue that financial crises tend

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to be preceded by rapid credit expansions. In a seminal article, Borio and Lowe (2002) suggested the credit gap as the best early warning indicator (EWI) for banking crises. This finding was subsequently confirmed by other empirical studies in the EWI literature involving different regions and periods, which aimed to verify the performance of different indicators as antecedents for banking crises (Borio and Drehmann, 2009; Drehmann et al., 2011; Hahm et al., 2013, Deryugina and Ponomarenko, 2016).

The overall adoption of the credit gap has been criticized for its low accuracy in anticipating a financial crisis, especially in emerging countries (Repullo and Saurina, 2011; Geršl and Seidler, 2012; Gonzalez et al., 2017). One problem of the credit gap measure is the way it is calculated – through the HP filter. This method suffers from the so-called endpoint problem, due to its high sensitivity to the addition of new data (Hamilton, 2018). That is, the value obtained at the endpoint (the most recent observation) can change considerably as future data become available, making estimates in real time uncertain and requiring substantial retroactive revisions. In order to allow an adequate assessment of the credit gap, the Basel Committee indicates at least 20 years of credit series (Drehmann and Tsatsaronis, 2014). Credit time series are a challenge for emerging economies, since in most of these countries credit statistics are not available for more extended periods.

In response to the criticism of using the credit gap, Drehmann and Tsatsaronis (2014) empirically analyzed the application of the credit gap in emerging economies. The authors recognize that the results reported for emerging economies are less robust when compared to those found for advanced economies. Gonzalez et al. (2017) re-evaluated the BCBS' proposed framework for emerging economies in comparison with other credit measures. They concluded that the signals emitted by the credit-to-GDP growth rate were less noisy than those of the credit gap, especially considering a robustness exercise for short series. In short, the study proposes the credit-to-GDP growth rate as a more consistent measure to anticipate financial crises.

This study presents a comprehensive approach to analyzing the effect of credit growth on financial stability in an important emerging economy, Brazil. It is essential to highlight that, as explained by De Moraes and De Mendonça (2017), financial instability does not mean a crisis. Therefore, three of the main financial stability measures adopted in the literature are used: z-score, banks' regulatory capital level and banks' loan provisions (Laeven and Levine, 2009; Skala and Weill, 2018; Foos et al., 2010). In order to investigate the BCBS' framework on the Brazilian credit market, we analyze the effect of the credit gap on financial stability. In addition, we evaluate the effect of the credit-to-GDP growth rate and the effect of the credit growth rate of each bank on financial stability, as well as investigating if there is an optimal level of credit growth for Brazil. Therefore, the main contribution of this work is the suggestion, from the Brazilian case, that the analysis of different dimensions of credit growth, ranging from aggregate measures to the growth of individual bank credit, can be applied in managing the financial stability of other emerging economies.

Through dynamic panel data analysis of 108 banks from March 2001 to December 2015, the results suggest that the credit gap and the credit growth rates are appropriate measures to indicate the sustainability of credit growth in Brazil. However, credit growth rates are more useful since they indicate a threshold for credit growth in the Brazilian economy regarding financial stability.

In addition to this introduction, the second section presents the data and methodology; the third section describes the empirical results, and, finally, the fourth section concludes with the findings of the study.

2. Data and methodology

The present study conducts a panel analysis of a set of 108 Brazilian financial institutions from March 2001 to December 2015. The selected institutions correspond to all active banks in the Brazilian credit market. The quarterly data we used are available on the website of the Central Bank of Brazil (CBB). It is important to highlight that the Central Bank of Brazil changed the capital requirement regulations and therefore some bank statistics after December 2015.[1] Therefore we used the available information until this reform.

The objective of this study is to evaluate the effect of credit growth on financial stability in Brazil. Consequently, the first credit measure we adopted is the credit-to-GDP gap (credit gap), calculated using the one-sided Hodrick-Prescott (HP) filter with a lambda of 400,000 as proposed by the BCBS (2010a). In addition to the credit gap, the measure credit-to-GDP growth rate (CRED1) is tested, as suggested by Gonzalez et al. (2017). CRED1 is a ratio calculated by the difference between the credit-to-GDP of the current and the previous quarter. Fig. 1 shows the behavior of these credit measures. Finally, the credit growth rate of each institution (CRED2) is considered in order to analyze the effect of the bank's individual credit growth on financial stability.

There are different channels through which the stability of a financial system can be compromised, such as corporate sector vulnerability, domestic sector weakness, external sector and financial sector vulnerability (Mendoza, 2010; Bianchi and Mendoza, 2018). We follow the Central Bank of Brazil (CBB) concerning the financial stability measures used in this study. The CBB defines financial stability as the regular functioning of the financial intermediation system between families, companies and the government over time and in any economic context. Therefore, the source of financial instability that the CBB is aware of stems from vulnerabilities in the banking system. In order to choose indicators of financial stability that reflect the structure of Brazil's financial system, we use three banking risk measures found in the modern literature on financial stability: z-score, regulatory capital (CAR), and credit risk (PROV).[2]

As pointed out by Laeven and Levine (2009), the original idea of the z-score as a measure of bank risk came from the original work of Roy (1952). Moreover, Lepetit and Strobel (2013) explain that since Boyd and Graham (1986), Hannan and Hanweck (1988), and Boyd et al. (1993a), (1993b), the z-score is seen as a relevant measure to assess bank risk as well as financial stability. In particular,

[1] https://www.bcb.gov.br/en/financialstability/Brazilian-Prudential-Financial-Regulation

[2] See De Mendonça and De Moraes (2018), and Van Dan Danga and Van Cuong Dang (2020).

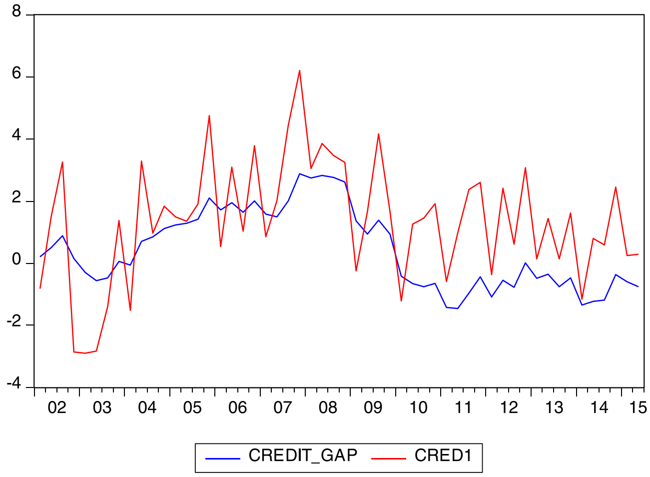

Fig. 1. Credit gap and credit-to-GDP growth rate (CRED1).

the work of Tabak et al. (2015) uses the z-score to analyze how Brazilian banks' risk-taking behavior is affected by their degree of market power. Therefore, the z-score is a measure of risk used in the empirical banking literature to reflect the probability of insolvency of financial institutions (Lepetit and Strobel, 2013). A higher z-score indicates a lower probability of insolvency, and consequently greater financial stability. It is defined as follows:

$$Zi,\, t \equiv \frac{ROAi,\, t + CAPi,\, t}{\sigma i,\, t},$$

where *ROA* represents the return on assets, *CAP* corresponds to the capital/asset ratio, and σ is defined as the standard deviation of the ROA. Following Boyd et al. (2006), the deviation is calculated using a moving average window considering three-quarters of the ROA standard deviation. The measure is calculated for each bank *i* in every quarter *t*. The result can be interpreted to reflect how far an institution is from insolvency. That is, the higher the z-score, the lower the probability of insolvency, and the higher the financial stability.

The second financial stability measure used in this study is the regulatory capital level held by financial institutions (CAR). It is represented by the capital/risk-weighted assets ratio of each institution.[3] The objective of minimum capital requirements is to restrict leverage in the financial system, and it is one of the main instruments of the prudential framework. Thus, higher capital ratios are associated with greater banking system stability. According to Skala and Weill (2018), capital adequacy ratios also reflect institutions' risk policy in adopting surplus capital reserves.

As highlighted by Nkusu (2011), the deterioration in the quality of banks' loan portfolios has been at the center of episodes of costly banking system distress and economic crises in advanced and emerging economies. Thus, following Foos et al. (2010), we use banks' loan provisions as the third proxy for financial stability. Loan provision (PROV) is measured as the loan loss provisions/gross loans ratio. As pointed out by De Moraes et al. (2016), this measure is important since it represents an expectation component that reflects the banks' risk perception. The authors argue that loan provisions have a prospective characteristic, as they represent the expected loss of banks with respect to loans. Therefore, higher loan loss provisions can be interpreted as a sign of financial instability.

Following the financial stability literature, we use a set of bank indicators as control variables (Demirgüç-Kunt et al., 2008; Fu et al., 2015; Fazio et al., 2015; De Mendonça and Barcelos, 2015): Size of banks (SIZE), defined as the logarithm of total assets; banking liquidity (LIQUI), represented by liquid assets/total assets ratio; and return on equity (ROE), measured by the net income/shareholders equity ratio, which represents the rate of return on shareholders' equity.

Financial stability is also affected by the state of the economy (Demirgüç-Kunt and Detragiache, 1998). The output growth and the interest rate are used by Jokivuolle et al. (2015) when examining bank loan losses in Europe from 1982 to 2012. In this way, the effects of the business cycle (GDP) and the monetary policy interest rate (IR) on financial stability are considered. The business cycle is calculated as proposed by Hamilton (2018).

The description of all variables used in this study and the descriptive statistics are presented in Table 1.

In order to consider the effect of the international financial crisis, a dummy variable (*CRISIS*) is added in the model. As pointed out by De Moraes et al. (2016), for the Brazilian economy, the dummy CRISIS assumes a value of 1 for the period between the fourth quarter of 2008 and the first quarter of 2011 and zero otherwise. Finally, in order to capture the effect of persistence, the dependent variables are lagged by one period and included as explanatory variables in the model, with the following general specifications for the credit gap:

[3] The Basel III Agreement states that total capital (capital level 1 plus capital level 2) should be at least 8.0% of the risk-weighted assets. For more details, see BCBS (2010c).

Table 1
Variable descriptions, sources and descriptive statistics.

	Description	Mean	Median	Std. dev.	Min.	Max.	Obs.
Z-SCORE	Capital/assets ratios (CAP) plus return on assets (ROA) divided by the ROA standard deviation	16.69	34.11	75.12	-1.22	2134.77	4955
CAR	Regulatory capital	24.56	18.23	20.83	0	259.32	5242
PROV	Coverage for loan t losses provided by the banks'/ total loan volume ratio	5.14	3.74	6.14	0	100	5094
CREDGAP	Calculated using the Hodrick-Prescott (HP) one-sided filter with a lambda of 400,000, as proposed byBCBS (2010a)	0.38	0.03	1.20	-1.46	2.88	6480
CRED1	Aggregate credit growth rate. Calculated by the credit-to-GDP difference of one quarter in relation to the previous quarter in terms of percentage of the first value	1.14	1.37	2.41	-9.36	6.21	6372
CRED2	Growth rate of individual bank's credit. Calculated by the difference of the credit of each bank of a quarter in relation to the previous quarter in terms of percentage of the first value	0.13	0.03	1.98	-0.98	97.49	5226
SIZE	Log of total banks' assets	21.41	21.38	2.24	15.43	27.75	5508
LIQUI	Liquid assets/total assets ratio	26.74	22.44	19.89	0.00	100	5508
ROE	Net income/shareholder's equity ratio	13.6	12.21	26.58	-99.98	239.54	5264
GDP	Difference between GDP and the potential output (Hamilton filter)	9.3	9.6	6.22	-9.66	20.99	4644
IR	Monetary policy interest rate (SELIC)	13.78	12.66	4.48	7.15	26.32	6428

$$\mathrm{EF}_{i,t} = \beta_0 + \beta_1 \mathrm{EF}_{i,t-1} + \beta_2 \text{Credit gap}_{t-1} + \beta_3 Z_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

where *EF* represents the measures of financial stability (z-score, CAR and PROV); *Credit gap* is the indicator proposed by the BCBS; Z the control variables (SIZE, LIQUI, ROE, GDP, IR and CRISIS); $i = 1,2,\ldots 108$ the financial institutions, t the time period (quarterly basis) and $\varepsilon_{i,t}$ the random error term.

Following Horváth and Vasko (2016) and Kasman and Kasman (2015), who test the nonlinear effect of transparency and competition on financial stability, the quadratic terms of the variables CRED1 and CRED2 are considered, named CRED1_Q and CRED2_Q, respectively. Credit growth on financial stability and the square of each credit growth rate are added to the model.

$$\mathrm{EF}_{i,t} = \beta_0 + \beta_1 \mathrm{EF}_{i,t-1} + \beta_2 \mathrm{CRED}_{i,t-1} + \beta_3 \mathrm{CRED\_Q}_{i,t-1} + \beta_4 Z_{i,t-1} + \alpha_{i,t} \tag{2}$$

where *CRED* represents the two measures of the credit growth rate (CRED1 and CRED2); *CRED_Q* denotes the quadratic forms of credit growth rates, Z the control variables and $\alpha_{i,t}$ the random error term.

This study makes use of dynamic panel data analysis. The use of a lagged dependent variable in the models may lead to a correlation problem with the error term, which therefore causes bias and inconsistency in OLS estimators (Baltagi, 2005). Furthermore, the possibility of endogeneity cannot be neglected. Arellano and Bond (1991) propose the estimation of first-difference GMM panel data (D-GMM) as a solution. However, Blundell and Bond (1998) show that this method implies weak instruments and has a bias as well as low accuracy. In order to deal with these issues, Arellano and Bover (1995) and Blundell and Bond (1998) proposed the system GMM panel data (S-GMM). The S-GMM combines regression equations in differences and in levels into one system and uses lagged differences and lagged levels of the variables in the model as instruments (Bond et al., 2001).

Although the S-GMM estimation approach is suitable for a small number of time periods t and a large number of cross-sections, in the case of small samples, when the instruments are many, the results may be biased (Roodman, 2009). Thus, with the intention of avoiding the use of an excessive number of instruments in the regressions, and thereby losing the power of the tests, the number of instruments/and number of cross-sections considered in each regression is less than 1. In addition, to check the validity of the instruments in the models, the over-identification test of restrictions (J-test) is performed, as suggested by Arellano (2003). In addition, first-order (AR1) and second-order (AR2) serial correlation tests are performed.

3. Empirical evidence

In this section, we present empirical evidence on the effect of credit growth on financial stability in Brazil. The section is subdivided into four subsections. The first subsection analyzes the effects of the credit measures on the banks' solvency measured by the z-score, and the second subsection presents the effects of the credit on the banks' capital level (CAR). The third subsection analyzes the effects of the credit measures on the loan provisions (PROV) and, finally, in the fourth subsection, a robustness analysis of the results is presented.

3.1. Z-score

As shown in models 1–3 in Table 2, the negative and statistically significant coefficients on the credit gap suggest that when credit grows above its long-term trend, it affects financial stability negatively. Regarding models 4–6 in Table 2, the positive sign and significance of the coefficient on the variable CRED1 and the negative sign and significance of the coefficient on its quadratic term (CRED1_Q) allow us to infer that credit growth improves financial stability. However, there is a limit from which credit growth affects financial stability negatively. Finally, models 7–9, which analyze the effects of the banks' credit growth rate on the z-score, report similar results. That is, they indicate a nonlinear effect of credit growth on financial stability, in which the growth of individual bank's credit, from a specific limit, generates negative impacts on stability. The results of the estimations allow us to argue that a credit growth above its long-term trend, as well as an accelerated credit growth, is a risk to financial stability. Thus, from this result, it is possible to suggest that the credit gap and the credit growth rate are appropriate metrics to analyze the sustainability of credit growth in Brazil. However, the credit growth rate measures are more informative since they indicate a sustainable growth limit.

Regarding the control variables related to the individual characteristics of the banks shown in Table 2, the variable that measures the banks' size reports positive and significant coefficients in some of the models. This relationship indicates that larger banks incur lower profit volatility, thus suggesting greater financial stability, which is in line with the results found by Laeven and Levine (2009), and Kasman and Kasman (2016). Concerning liquidity, the negative signs and significance of the coefficients confirm the results found by Fazio et al. (2015). As highlighted by De Mendonça and De Moraes (2018), since liquidity assets have low yields, a possible consequence of an increase in liquidity may be an increase in banks' appetite for risk. The coefficients on ROE, in turn, suggest a negative effect on the z-score, which may be associated with potential credit losses in a classic case of a trade-off between risk and return (De Mendonça and Barcelos, 2015).

Concerning the macroeconomic controls, the positive sign and significance of the GDP variable in most of the models indicate that economic growth positively affects financial stability. Regarding the monetary policy interest rate (IR), the fact that almost all coefficients are negative and significant shows that the interest rate has a negative effect on the z-score. As suggested by Demirgüç-Kunt and Detragiache (1998), these results indicate that the macroeconomic scenario, such as low growth and high interest rates, has negative impacts on financial stability. Finally, the negative sign of the coefficients on the dummy variable suggests an adverse effect of crises on financial stability.

Table 2
Effect of credit on the Z-score.

	CREDGAP			CRED1			CRED2		
Regressors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Z-SCORE (−1)	0.2378 ***	0.2112 ***	0.2496 ***	0.2450 ***	0.1661 ***	0.1551 ***	0.2531 ***	0.2569 ***	0.2534 ***
	(0.0071)	(0.0124)	(0.0015)	(0.0026)	(0.0140)	(0.012)	(0.0022)	(0.0020)	(0.0024)
CREDGAP(−1)	-8.8404 ***	-8.8533 ***	-4.1268 ***						
	(1.6977)	(2.6891)	(0.4452)						
CRED1 (−1)				1.3713 **	3.8675 **	4.0037 **			
				(0.6646)	(1.6112)	(1.6067)			
CRED1_Q (−1)				-0.2802 **	-1.0999 ***	-1.1704 ***			
				(0.1170)	(0.3846)	(0.3807)			
CRED2 (−1)							0.4955 ***	0.2586 **	0.2592 **
							0.1288	0.1175	0.1257
CRED2_Q (−1)							-0.6573 ***	-0.3694 **	-0.3892 *
							(0.2114)	(0.1743)	(0.2024)
SIZE (−1)	-4.7711	-19.9151	3.1241 **	6.6056 ***	-2.6079	-7.5482	8.9576 ***	9.8751 ***	6.8777 ***
	(6.0184)	(12.5209)	(1.3182)	(1.6000)	(13.4544)	(11.8374)	(1.8133)	(1.4619)	(1.3272)
LIQUI (−1)	-4.8370 ***	-6.8891 ***	-0.3759 ***	-0.4609	-5.6305 ***	-4.2800 ***	-0.0179	-0.1289	-0.1718
	(0.8473)	(1.6610)	(0.060)	(0.3109)	(1.6343)	(1.4652)	(0.1326)	(0.1136)	(0.1270)
ROE (−1)	0.2727	-0.5702	-0.1321 **	-0.4559 ***	-1.1504 **	-1.4450 **	-0.3433 ***	-0.3575 ***	-0.4021 ***
	(0.2583)	(0.5351)	(0.052)	(0.1319)	(0.5685)	(0.5801)	(0.1137)	(0.1034)	(0.1104)
GDP (−1)		0.6801 *	0.3126 ***		2.0642 ***	1.9453 ***		0.1655	0.1083
		(0.3703)	(0.0560)		(0.4339)	(0.4031)		(0.1135)	(0.1231)
IR (−1)		-3.3204 ***	-0.3820 ***		-5.0113 ***	-5.0176 ***		0.0201	-0.5336 **
		(0.9593)	(0.1392)		(1.2250)	(1.1341)		(0.1947)	(0.2138)
CRISIS			-9.9174 ***			-11.459 ***			-13.368 ***
			(0.8193)			(4.2951)			(1.3685)
N. Obs.	3468	3485	3430	3450	3566	3566	3406	3406	3406
Inst./Cross	0.43	0.42	0.61	0.49	0.40	0.41	0.48	0.50	0.50
J-statistic	47.51	39.85	67.62	49.24	33.83	35.56	45.62	51.30	51.79
Prob.(Jstatistic)	0.19	0.34	0.13	0.30	0.47	0.39	0.40	0.24	0.19
AR(1)	-0.44	-0.42	-0.47	-0.46	-0.42	-0.43	-0.43	-0.45	-0.45
Prob.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2)	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
Prob.	0.10	0.19	0.11	0.10	0.13	0.14	0.14	0.15	0.14

Notes: Marginal significance levels: (***) denotes 0.01, (**) 0.05 and (*) 0.1. Dependent variable: z-score; main independent variables: credit gap, CRED1 and CRED2. The consistent covariance matrix of White's heteroskedasticity was applied in the regressions. Standard errors are in parentheses. S-GMM uses two steps of Arellano and Bover (1995). The tests for AR (1) and AR (2) verify the presence of first and second order serial correlation in the first difference residues.

Table 3
Effect of credit growth on capital.

	CREDGAP			CRED1			CRED2		
Regressors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
CAR (−1)	0.6622 ***	0.7715 ***	0.6973 ***	0.7385 ***	0.7147 ***	0.7032 ***	0.3905 ***	0.3333 ***	0.3816 ***
	(0.0093)	(0.0065)	(0.014)	(0.004)	(0.0064)	(0.0066)	(0.0269)	(0.0306)	(0.0430)
CREDGAP (−1)	-0.5468 ***	-0.0876 **	-0.1753 ***						
	(0.0927)	(0.042)	(0.065)						
CRED1 (−1)				-0.308 ***	-0.2009 ***	-0.2069 ***			
				(0.046)	(0.059)	(0.059)			
CRED1_Q (−1)				-0.018 **	-0.0341 ***	-0.0291 **			
				(0.0084)	(0.012)	(0.0124)			
CRED2 (−1)							0.0483 ***	0.0525 ***	0.0608 ***
							(0.0124)	(0.0203)	(0.0192)
CRED2_Q (−1)							-0.0398 **	-0.0432 *	-0.0564 **
							(0.0181)	(0.0233)	(0.02279)
SIZE (−1)	-2.5306 ***	-0.4946 **	-0.7967 **	-1.545 ***	-1.3870 ***	-1.1432 ***	-4.2517 ***	-3.5581 **	-2.0669
	(0.3053)	(0.2083)	(0.3111)	(0.1793)	(0.2564)	(0.2587)	(1.0189)	(1.5170)	(1.4353)
LIQUI (−1)	0.0830 ***	0.1113 ***	0.1862 ***	0.0080	0.0907 ***	0.1167 ***	1.0155 ***	1.2877 ***	1.2176 ***
	(0.0258)	(0.023)	(0.033)	(0.0072)	(0.0238)	(0.0264)	(0.1115)	(0.1509)	(0.1750)
ROE (−1)	-0.0121	-0.0116 *	-0.0089	-0.0139 ***	-0.0048	-0.0023	-0.0371	-0.0363	-0.0588 *
	(0.013)	(0.0068)	(0.011)	(0.0048)	(0.010)	(0.011)	(0.0235)	(0.0313)	(0.0352)
GDP (−1)		-0.0144 **	0.0088		0.0034	0.0079		0.0221	0.0037
		(0.007)	(0.013)		(0.007)	(0.0085)		(0.0504)	(0.0460)
IR (−1)		0.0237	0.0495 *		-0.0339	-0.0053		0.4327 ***	0.5359 ***
		(0.0156)	(0.0259)		(0.024)	(0.0262)		(0.1238)	(0.1300)
CRISIS			0.9749 ***			0.5209 ***			1.2800
			(0.3187)			(0.1551)			(0.8181)
N. Obs.	3346	3267	3405	3073	3205	3205	3392	3379	3390
Inst/Cross sec.	0.45	0.56	0.48	0.63	0.54	0.54	0.44	0.45	0.44
J-statistic	48.14	60.16	53.06	64.77	57.37	57.20	46.50	37.30	39.44
Prob.(J statistic)	0.23	0.15	0.11	0.25	0.16	0.14	0.22	0.54	0.36
AR(1)	-0.47	-0.48	-0.46	-0.48	-0.47	-0.47	-0.40	-0.34	-0.35
Prob.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2)	-0.00	-0.00	-0.00	-0.00	-0.00	-0.02	-0.02	0.00	0.01
Prob.	0.63	0.61	0.41	0.78	0.58	0.55	0.22	0.94	0.54

Notes: Marginal significance levels: (***) denotes 0.01, (**) 0.05 and (*) 0.1. Dependent variable: CAR; main independent variables: credit gap, CRED1 and CRED2. The consistent covariance matrix of White's heteroskedasticity was applied in the regressions. Standard errors are in parentheses. S-GMM uses Arellano and Bover's (1995) two steps. The tests for AR (1) and AR (2) verify the presence of first and second order serial correlation in the first difference residues.

3.2. Capital

The estimations regarding the effect of credit on regulatory capital are presented in Table 3. Concerning models 1–3, the negative signs and statistical significance of all the coefficients on credit gap suggest that a credit growth above its long-term trend lowers banks' capital and thus generates adverse effects on financial stability. In relation to models 4–6, the negative sign and significance of the coefficients on CRED1 and its quadratic term (CRED1_Q) do not suggest the occurrence of a nonlinear effect of aggregate credit growth on capital. This result is expected because aggregate credit growth always reduces CAR. Regarding models 7–9, the positive sign and significance of the coefficients on the variable CRED2, and the negative and statistically significant coefficients of its quadratic term, CRED2_Q, suggest a nonlinear effect of the banks' individual credit growth on financial stability. Therefore, the results reveal that the credit growth rate of each bank shows different behavior than aggregate credit growth, indicating a threshold effect of credit growth on regulatory capital in the case of individual bank analyses. A possible explanation for this dichotomy between aggregate credit growth and individual credit growth is that individual credit growth allows controlling for individual heterogeneity, reducing the influence of large banks on aggregate credit.

Regarding the control variables, the negative and significant coefficients on the variable SIZE indicate that larger banks maintain a lower level of capital. The positive signal and statistical significance of liquidity (LIQUI) suggest that banks with more liquid assets increase regulatory capital, which is similar to the findings of De Moraes and De Mendonça (2019). The negative effect of ROE on CAR, as suggested by the sign and significance of the coefficient, allows us to infer that the higher the cost of capital maintenance (ROE), the lower is the regulatory capital held by banks, confirming the results of Bikker and Metzemakers (2004).

The negative and significant coefficient of GDP suggests that banks react to economic growth in a way to reinforce the business cycle, showing a procyclical attitude of the banks. Concerning the impact of monetary policy on capital, the positive and significant coefficient indicates that banks react to the monetary policy interest rate by raising capital, as documented by De Moraes et al. (2016). Finally, the positive and significant sign found for the coefficients on the CRISIS dummy suggests that banks react to a scenario of crisis by raising the level of their capital, i.e., more significant risk aversion.

3.3. Provisions

As shown in models 1–3 (see Table 4), the positive and statistically significant coefficients on the credit gap suggest that a positive credit gap induces banks to increase loan provisions. Since loan provisions represent the coverage maintained by banks to support probable loan losses, an increase in provisions suggests an expectation of worsening the bank's credit portfolio. Regarding models 4–6 in Table 4, in which the effects of aggregate credit variation are analyzed, the negative signs and significance of the coefficients on CRED1 and the positive and statistically significant coefficients on its quadratic terms, CRED1_Q, once again suggest a nonlinear effect of credit on financial stability. Models 7–9, which analyze the effects of banks' individual credit growth on provisions, report similar effects.

The identification of a nonlinear credit effect on stability permits us to infer that there is an optimal point for credit growth in Brazil. That is, credit growth is beneficial to stability up to a specific level, as it has a positive effect on credit risk. These findings are consistent with the results reported in other empirical studies. Garcia-Escribano and Han (2015) and Barajas et al. (2007) emphasize that credit provided by banks improves financial development, and consequently, economic growth. However, both point out that too rapid credit growth is often associated with an increase in financial instability and bank crises.

The variable size of the banks, also in Table 4, in general reports positive and significant coefficients, in line with Skała and Weill (2018), indicating that larger banks maintain higher levels of provisions for loan losses. The positive effect of liquidity suggests that an increase in liquidity may lead to a reduction in the quality of loans granted by banks. This can be justified by the fact that liquidity assets have low yields, which may lead to an increase in banks' risk appetite (De Mendonça and De Moraes, 2018). According to Amidu and Wolfe (2013), the negative and significant coefficient on ROE suggests that banks that provide better quality loans are more profitable, since they do not have to raise provisions to cover default losses.

Regarding the macroeconomic controls, the estimations indicate a negative and significant effect of GDP on banking provisions, suggesting procyclical behavior due to a decrease in the perception of credit risk by the banks in periods of economic growth (Bikker and Metzemakers, 2005). Concerning the interest rate, the coefficients are positive and significant in line with De Mendonça and De Moraes (2018), denoting the presence of a risk-taking channel. Finally, the positive and significant signs of all coefficients on the dummy indicate that banks respond to crises by raising provisions based on a higher perception of risk.

3.4. Robustness analysis

The results of the previous section indicate that credit growth above its long-term trend, such as accelerated credit growth, puts financial stability at risk. On the other hand, the findings suggest that credit growth up to a specific limit does not affect financial stability negatively. In order to verify the validity of these results, estimations are performed considering another credit risk measure, non-performing loans (NPL), following Horvath and Vaško (2016). As highlighted by Podpiera (2004), although there may be different reasons for increased non-performing loans, a high level of NPL often indicates problems in the banking sector. The Central Bank of Brazil recently changed some bank statistics such as NPL. We therefore use the database from De Mendonça and De Moraes (2018) for the robustness test.

The results of the estimations are shown in Table 5. As shown in models 1–3 in Table 5, the positive and statistically significant coefficients on the credit gap measure confirm that credit growth above its long-term trend affects financial stability negatively by

Table 4
Effect of credit growth on provisions.

	CREDGAP			CRED1			CRED 2		
Regressors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
PROV (−1)	0.7734 ***	0.7418 ***	0.6127 ***	0.7775 ***	0.7728 ***	0.7153 ***	0.7264 ***	0.7372 ***	0.6113 ***
	(0.0083)	(0.0084)	(0.0130)	(0.0037)	(0.0043)	(0.0050)	(0.0082)	(0.0064)	(0.0107)
CREDGAP(−1)	0.1037 ***	0.1680 ***	0.0863 *						
	(0.0218)	(0.0242)	(0.0478)						
CRED1 (−1)				-0.0549 ***	-0.0995 ***	-0.0690 ***			
				(0.0170)	(0.0197)	(0.0211)			
CRED1_Q (−1)				0.0165 ***	0.0257 ***	0.0258 ***			
				(0.0030)	(0.0035)	(0.0039)			
CRED2 (−1)							-0.0392 ***	-0.0334 ***	-0.0355 ***
							(0.0064)	(0.0061)	(0.0075)
CRED2_Q (−1)							0.1538 ***	0.1663 ***	0.1855 ***
							(0.0532)	(0.0437)	(0.0486)
SIZE (−1)	0.2609 ***	0.2134 ***	0.7934 ***	0.1383 ***	0.1109 ***	0.2311 ***	-0.0590	0.1201	0.0820
	(0.0606)	(0.0646)	(0.2067)	(0.0313)	(0.0315)	(0.0375)	(0.0759)	(0.0981)	(0.1713)
LIQUI (−1)	-0.0012	0.0053	0.2153 ***	-0.0020	-0.0012	0.0064 *	0.0238 ***	0.0255 ***	0.1148 ***
	(0.0109)	(0.0162)	(0.0302)	(0.0026)	(0.0024)	(0.0037)	(0.0026)	(0.0063)	(0.0183)
ROE (−1)	-0.0072 **	-0.0220 ***	-0.0203 ***	-0.0059 **	-0.0110 ***	-0.0191 ***	0.0008	0.0070	-0.0040
	(0.0029)	(0.0029)	(0.0056)	(0.0027)	(0.0025)	(0.0028)	(0.0046)	(0.0048)	(0.0056)
GDP (−1)		-0.0365 ***	-0.0197 **		-0.0126 ***	-0.0117 ***		-0.0164 ***	-0.0210 ***
		(0.0038)	(0.0077)		(0.0027)	(0.0025)		(0.0040)	(0.0068)
IR (−1)		0.0203 *	0.1585 ***		0.0249 ***	0.0614 ***		0.0318 ***	0.1117 ***
		(0.0119)	(0.0256)		(0.0054)	(0.0066)		(0.0107)	(0.0165)
CRISIS			1.0598 ***			0.9974 ***			1.1691 ***
			(0.1839)			(0.0813)			(0.1386)
N. Obs.	3474	3536	3538	3401	3401	3401	3477	3479	3573
Inst./Cross sec.	0.42	0.43	0.47	0.55	0.53	0.53	0.43	0.45	0.43
J-statistic	50.76	49.23	41.73	63.15	53.02	57.14	51.48	48.98	44.25
Prob.(J. stat.)	0.11	0.12	0.23	0.11	0.25	0.25	0.10	0.15	0.16
AR(1)	-0.36	-0.40	-0.36	-0.36	-0.36	-0.36	-0.44	-0.46	-0.46
Prob.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2)	-0.00	0.00	-0.00	-0.00	0.00	0.01	0.00	0.00	0.00
Prob.	0.94	0.62	0.70	0.90	0.75	0.45	0.90	0.53	0.80

Notes: Marginal significance levels: (***) denotes 0.01, (**) 0.05 and (*) 0,1. Dependent variable: Provision; main independent variables: credit gap, CRED1 and CRED2. The consistent covariance matrix of White's heteroskedasticity was applied in the regressions. Standard errors are in parentheses. S-GMM uses Arellano and Bover's (1995) two steps- The tests for AR (1) and AR (2) verify the presence of first and second order serial correlation in the first difference residues.

Table 5
Effect of credit growth on NPL.

	CREDIT GAP			CRED1			CRED2		
Regressors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
NPL (−1)	0.7126 ***	0.7037 ***	0.7064 ***	0.7157 ***	0.6988 ***	0.7101 ***	0.7229 ***	0.7219 ***	0.7194 ***
	(0.0006)	(0.0018)	(0.0009)	(0.0007)	(0.0011)	(0.0011)	(0.0025)	(0.0026)	(0.0025)
CREDGAP(−1)	0.1300 ***	0.1261 ***	0.0210 ***						
	(0.0075)	(0.0116)	(0.0080)						
CRED1 (−1)			-0.0869 ***	-0.0486 ***	-0.0465 ***				
				(0.0081)	(0.0113)	(0.0122)			
CRED1_Q (−1)			0.0832 ***	0.0423 ***	0.0701 ***				
				(0.0020)	(0.0032)	(0.0036)			
CRED2 (−1)						-0.0137 ***	-0.0102 ***	-0.0109 ***	
							(0.0017)	(0.0017)	(0.0017)
CRED2_Q (−1)						0.0049 ***	0.0027 ***	0.0035 ***	
							(0.0007)	(0.0007)	(0.0006)
SIZE (−1)	0.3508 ***	0.4542 ***	0.2806 ***	0.4101 ***	0.3846 ***	0.3415 ***	0.1948 ***	0.3712 ***	0.3420 ***
	(0.0168)	(0.0360)	(0.0240)	(0.0183)	(0.0328)	(0.0246)	(0.2777)	(0.0345)	(0.0315)
LIQUI (−1)	-0.0121 ***	-0.0115 ***	-0.0103 ***	-0.0135 ***	-0.0101 ***	-0.0114 ***	-0.0035 *	-0.0012	-0.0027
	(0.0003)	(0.0017)	(0.0218)	(0.0004)	(0.0015)	(0.0006)	(0.0019)	(0.0018)	(0.0017)
ROE (−1)	-0.0212 ***	-0.0296 ***	-0.0179 ***	-0.0241 ***	-0.0252 ***	-0.0236 ***	-0.0198 ***	-0.0202 ***	-0.0208 ***
	(0.0008)	(0.0089)	(0.0008)	(0.0009)	(0.0019)	(0.0014)	(0.0023)	(0.0026)	(0.0026)
GDP (−1)		-0.0340 ***	-0.0152 ***		-0.0519 ***	-0.0529 ***		-0.0370 ***	-0.0171 ***
		(0.0037)	(0.0024)		(0.0044)	(0.0024)		(0.0047)	(0.0044)
IR (−1)		0.0358 ***	0.0082 ***		0.0033 ***	-0.0001		0.0210 ***	0.0234 ***
		(0.0040)	(0.0030)		(0.0046)	(0.0040)		(0.0045)	(0.0046)
CRISIS			1.1571 ***			1.0971 ***			1.1027 ***
			(0.0326)			(0.0373)			(0.0582)
N. Obs.	4352	4561	4363	4352	4504	4352	4501	4501	4501
Inst./Cross sec.	0.86	0.70	0.82	0.86	0.72	0.82	0.67	0.67	0.67
J-statistic	99.78	86.26	96.94	102.60	88.27	99.43	80.24	81.34	81.68
Prob. (J statist.)	0.22	0.15	0.14	0.15	0.10	0.17	0.23	0.16	0.14
AR(1)	-0.62	-0.57	-0.62	-0.61	-0.59	-0.61	-0.59	-0.58	-0.59
Prob.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2)	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Prob.	0.11	0.20	0.11	0.20	0.14	0.17	0.11	0.20	0.13

Notes: Marginal significance levels: (***) denotes 0.01, (**) 0.05 and (*) 0.1. Dependent variable: NPL; main independent variables: credit gap, CRED1 and CRED2. The consistent covariance matrix of White's heteroskedasticity was applied in the regressions. Standard errors are in parentheses. S-GMM uses Arellano and Bover (1995)'s two steps. The tests for AR (1) and AR (2) verify the presence of first and second order serial correlation in the first difference residues.

raising credit risk defaults. The results of the estimations from models 4–6 in the same table again suggest a nonlinear effect of credit on financial stability, given the negative signs and significance of coefficients CRED1 and the positive signs and statistical significance of its quadratic terms CRED1_Q coefficients. Likewise, models 7–9, which analyze the effects of the growth of individual banks' credit on NPL, confirm the results found in the previous section. Moreover, in general, the effects of the control variables remain the same in the robustness test.

Based on the results, the present study suggests that an increase in credit improves financial stability. Nevertheless, too much growth, measured as a nonlinear effect, may harm financial stability. In particular, the non-linearity of aggregate and individual banks' credit growth rates allows a specific threshold mark, beyond which credit growth could potentially destabilize the financial system. It is important to highlight that the measurement of a specific limit depends on the period analyzed, the sample and the specification. As an exercise, we follow Arcand et al. (2015) to find a threshold point, calculating the marginal effects represented in Table 5 as d (Cred) = 0. The result varies with the model, e.g., model 4 is 0522, while model 5 is 0574, which indicates that within the 75th to 90th percentile interval, these thresholds represent limits in which financial stability is out of threat.

4. Conclusion

Based on data from the Brazilian banking system, this study investigated the relationship between credit growth and financial stability in Brazil. The findings permit us to infer that a positive credit gap worsens financial stability in Brazil, which is in line with the literature pointing to the credit gap as a good measure of risk to anticipate financial instability in emerging economies (Hahm et al., 2013).

Through credit growth rate measures, the results also suggest a nonlinear effect of credit on financial stability. Therefore, it is possible to show the existence of an optimum point of credit growth for financial stability in the Brazilian economy. The evidence thus suggests that monitoring the pace of credit growth is relevant, since a too rapid pace of growth may jeopardize financial stability.

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