Does an increase in the banks' credit portfolios push them towards being more environmentally friendly?

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ABSTRACT

The role of banks in the transition to a greener economy has been a flourishing subject within the banking literature, as the ESG agenda is more broadly discussed. One of the ways banks play their part in this movement is through the development of green credit. But what are the factors that lead financial institutions to maintain more environmentally friendly portfolios? To answer this question, we craft a new environmental risk index for banks' loan portfolios. Through a dynamic panel data analysis, we estimate the determinants of green credit for a set of 45 Brazilian banks. The findings suggest the credit portfolios become greener as more loans are issued, and as banks raise their capital. Furthermore, results also indicate a persistence effect of green credit. Possible implications are harder access to credit for pollutant enterprises, and, in turn, easier access for innovative green businesses.

Keywords: Green credit, Climate finance, Banking, Sustainability, ESG.

RESUMO

O papel dos bancos na transição para uma economia mais verde tem sido um assunto florescente na literatura bancária, à medida que a agenda ESG é discutida de forma mais ampla. Uma das formas de os bancos participarem desse movimento é por meio do desenvolvimento do crédito verde. Mas quais são os fatores que levam as instituições financeiras a manterem carteiras mais ecológicas? Para responder a essa pergunta, criamos um novo índice de risco ambiental para as carteiras de crédito dos bancos. Por meio de uma análise de dados em painel dinâmico, estimamos os determinantes do crédito verde para um conjunto de 45 bancos brasileiros. Os resultados sugerem que as carteiras de crédito se tornam mais verdes à medida que mais empréstimos são emitidos e à medida que os bancos aumentam seu capital. Além disso, os resultados também indicam um efeito de persistência do crédito verde. As possíveis implicações são acesso mais difícil ao crédito para empresas poluentes e, por sua vez, acesso mais fácil para empresas verdes inovadoras.

Palavras-chave: Crédito verde, Finanças climáticas, Bancos, Sustentabilidade, ESG.

Indicação da área: Área 8 - Microeconomia, Métodos Quantitativos e Finanças

Classificação JEL: D53, G21, O54

1. Introduction

Nowadays, promoting social and environmental responsibility is an integral part of financial market activities (Leins, 2020). Banks, as financial intermediaries, play a relevant role in financing the transition toward a sustainable economy (Contreras et al., 2019; Mejia-Escobar et al., 2020). As establishing a solid environmental risk control framework is highly technical and thus costly for banks (Scholtens & Dam, 2007) and for the economy, a gradual transition with green credit development would address this issue more smoothly. In this sense, Miroshnichenko and Brand (2021) explained that one of the ways banks have been engaging in socially responsible investing is through the composition of their credit portfolios.

Conceptually, green credit means that banks invest resources in enterprises based on the information available, provide preferential loans and support, and transmit concepts of environmental protection and sustainable economic development to borrowers (Jeucken, 2001). Recent works indicate that banks are reducing their portfolios' carbon impact by reallocating credit from 'brown' to 'green' firms (Kacperczyk & Peydró, 2021; Lian et al., 2022).[1] Furthermore, Fan et al. (2021) pointed out that brown companies found it more difficult to access loans as green credit policies are reinforced by banks. One reason for this movement is that banks willingly adopt the Equator Principles.[2] Scholtens and Dam (2007) show that adopting Equator Principles significantly changes the banks' environmental and social policies.

A concern rises regarding how a transition to a greener economy and the development of green products affects the banking sector. Most studies in the extant green credit literature focus on the impact it has on banks, especially regarding their financial performance. Some authors pose that issuing more green credit comes at the cost of a lower short-term profitability for banks (Luo et al., 2021; Zhou et al., 2021), though there could be long-term benefits in lower risks (Lian et al., 2022; Umar et al., 2021), lower rates of non-performing loans (Cui et al., 2018; Al-Qudah et al., 2022) and improved bank core competencies (Luo et al., 2021). Other studies, in contrast, have found profitability of banks increase with the issuance of green credit (Lian et al., 2022) and with corporate social responsibility (Cornett et al., 2016).

Emerging economies maintain the most relevant natural resources on the earth. However, studies about the influence of corporate social responsibility practices in emerging markets are still scarce (see Miralles-Quirós et al., 2018). In particular, Brazil, one of the world's largest economies with a well-developed financial system, has a critical role in the planet's environment. Moreover, since 2014 Brazilian banks need to develop social and environmental policies, as per Resolution nº 4327/2014 of the Central Bank of Brazil. Therefore, Brazil is an interesting case study for assessing green credit. In this sense, this study contributes to the literature by providing empirical evidence of the determinants of green credit for Brazilian banks. Furthermore, understanding these determinants can be helpful to policymakers, as developing economies tend to face considerable challenges when attempting to raise capital for green investments (Batrancea et al., 2020).

This study makes two main contributions to the literature on green credit. First, it constructs a novel index – the Sectorial Environmental Risk Index (SERI) – used to capture the banks' behavior regarding green credit portfolios. Using a methodology anchored by the International Finance Corporation (IFC), this approach uses Brazil's available bank loan data by industry sector to classify the green credit portfolios. Second, the study analyzes, through an empirical analysis with dynamic panel data, the determinants of green credit in Brazil, clarifying which variables can affect the banks' decision to build a greener portfolio. In particular, this work

[1] The terms 'brown' and 'green' have been used to refer to firms that have a relatively high and low greenhouse gas emission level in their value chains, respectively (see Kacperczyk & Peydró, 2021). In this present study, we expand these terms' interpretations to encompass not only greenhouse gas emissions, but other forms of environmental impact and risk as well.

[2] Equator Principles are an international, voluntary set of codes of conduct that condition how banks should consider environmental and social issues in project finance (see Wright & Rwabizambuga, 2006; Macve & Chen, 2010).

wants to answer the following research question: Does an increase in the banks' credit portfolios in Brazilian banks push them towards being more environmentally friendly (more green credit)? Additionally, banks are institutions regulated by the government, and their behavior can be affected by such regulation (see de Moraes et al., 2016). Thus, this study also investigates the effects of the banks' capital adequacy ratio (CAR) in their credit portfolios' environmental risk.

The study's results suggest the banks' credit portfolios become more environmentally friendly as they grow, and as the banks' regulatory capital is raised. Hence, the regulation employed by the Central Bank of Brazil since 2014, which demands banks maintain an environmental and social policy, may be generating appropriate incentives for banks to develop and maintain more environmentally friendly portfolios by favoring lending to cleaner sectors of the economy.

Other than this first introductory section, this study is divided as follows. Section 2 presents the new index and explains its construction. Section 3 presents the methodology and data used for constructing the index and the econometric models. Section 4 depicts, interprets, and discusses the models' results. Section 5 closes with concluding remarks as well as possible implications from the results found.

2. Sectorial Environmental Risk Index (SERI)

To carry out this study, assessing the environmental risk of each bank's credit portfolio is paramount. A bank's loan portfolio can be seen as a composition of multiple assets, each belonging to a different sector of the economy. Depending on the sector, an asset carries a higher or lower environmental risk, or impact. To meet this demand, we constructed the Sectorial Environmental Risk Index (SERI), with the intent of capturing the environmental risk of credit portfolios for Brazilian banks, as an indication of their green credit appetite.[3]

The Central Bank of Brazil publicly provides data on Brazilian banks' loan portfolio segmented by economic activity. This segmentation is performed following the methodology of the Brazilian Institute of Geography and Statistics (IBGE), which defines the National Classification of Economic Activities (CNAE). The CNAE consists of 9 sectors: Agriculture; Transformation Industries; Construction; Public Utility Industrial Services; Extractive Industries; Trade, Repair of Vehicles; Public Administration; Transport and Storage; and Others.

With the idea of evaluating each sector's environmental impact, the IFC (International Finance Corporation – part of the World Bank Group), under the FIRST for Sustainability initiative, provides a methodology for assessing environmental and social risk by industry sector.[4] They performed 30 different sectorial appraisals, each giving their respective sector a risk rating: Low, Medium, or High.

To obtain a bank's SERI we calculated the average risk rating of each CNAE sector, weighted by the bank's exposure to them in their loan portfolio. For the purposes of SERI's construction, we attributed numerical scores to each of these ratings as follows: Low = 3; Medium = 2; and High = 1. As FIRST for Sustainability rates 30 industry sectors on their environmental risk, each had to be properly matched with one of the 9 CNAE sectors, adjusting the difference in granularity.[5] The CNAE sectors then had their ratings calculated via the

[3] To the best of the authors' knowledge, China is the only country that has clear governmental policies that characterize green credit, as well as broader access to information on which loans are considered green or not. This allows recent Chinese studies (see Lian et al., 2022; Yin et al., 2021) to use a more straightforward variable to study green credit, which is simply the ratio of green credit to the total size of the banks' loan portfolios.

[4] https://firstforsustainability.org/risk-management/risk-by-industry-sector/

[5] For further details on the sectors' matching procedure, see Table A.1 in the Appendix.

simple average of the FIRST for Sustainability sectors' ratings that composed them, and the resulting scores for every CNAE sector are displayed in Table 1.

Table 1 – CNAE sectors and their respective environmental risk scores.

CNAE Sector	Score
Agriculture, Livestock, Forestry, Fisheries and Aquaculture	2.000
Transformation Industries	1.545
Construction	1.500
Public Utility Industrial Services	1.333
Extractive Industries	1.000
Trade, Repair of Motor Vehicles and Motorcycles	2.000
Public Administration, Defense and Social Security	3.000
Transport, Storage and Mail	2.000
Others	2.000

Finally, each for each bank *i* in period *t*, their associated $SERI_{i,t}$ will be calculated via the following weighted average:

$$SERI_{i,t} = \frac{\sum_{s=1}^{S}(CNAE\ score_s *\ Sector\ exposure_{s,i,t})}{Total\ exposure_{i,t}} \tag{1}$$

where $CNAE\ score_s$ is the score for sector s as displayed in Table 1, $Sector\ exposure_{s,i,t}$ represents the exposure of bank *i* to sector *s* in semester *t* in its loan portfolio, and $Total\ exposure_{i,t}$ is the same bank's total credit portfolio amount. The summation's higher index, S, is however many FIRST for Sustainability sector were matched under sector s.

Due to the existence of an "Others" CNAE sector, we crafted two versions of the index, as a way of mitigating possible biases or omissions stemming from the matching process. $SERI_1$ considers only the first 8 sectors, excluding "Others", while $SERI_2$ takes all 9 sectors into account.

The boxplot graphs below (Figures 1 and 2) show the trajectory of both indexes from June 2014 to December 2020. A noteworthy observation, from both exhibits, is how the mean values, albeit slightly improving over time, remain under 2, which is the center of the index's interval. This can be an indication that environmentally harmful business activities still have a lot of space in the banks' portfolios.

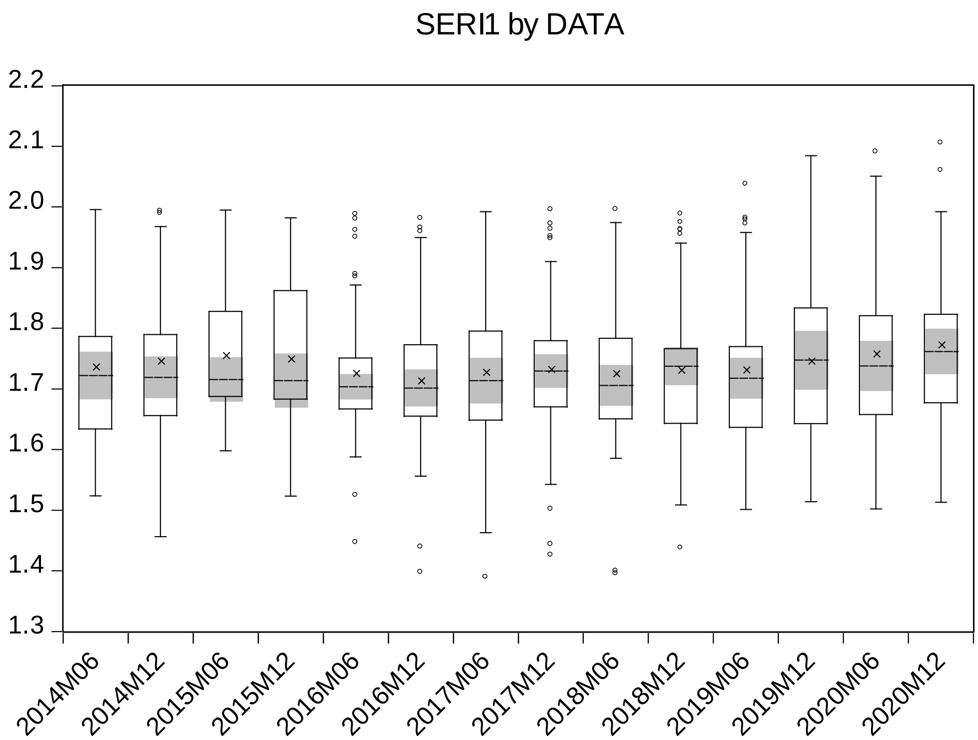

Figure 1 – Boxplot graph for $SERI_1$.

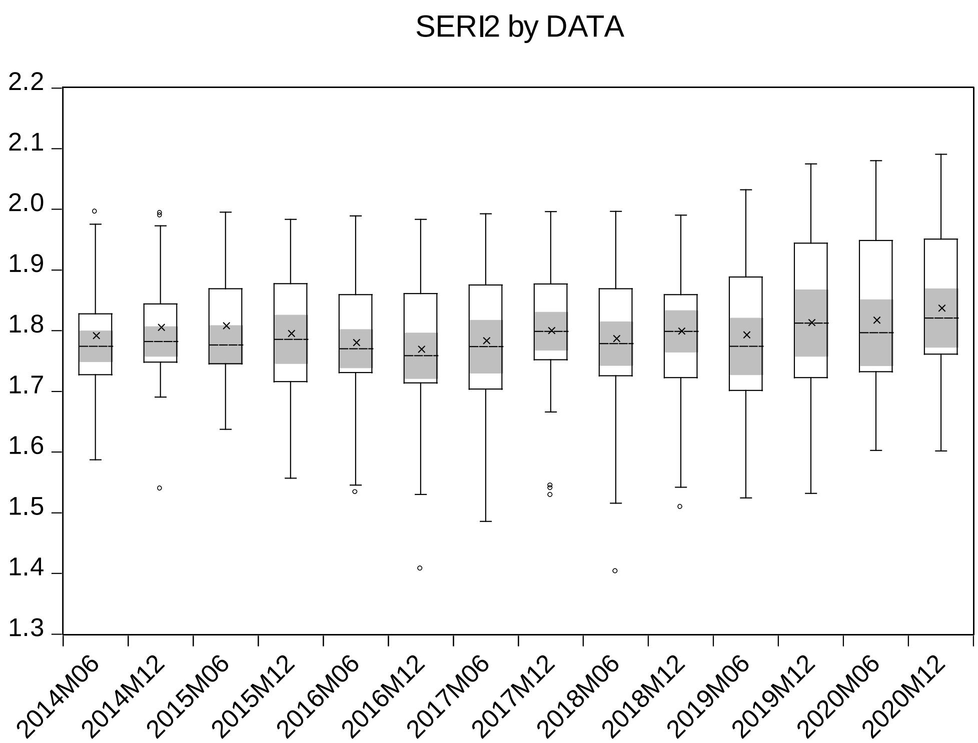

Figure 2 – Boxplot graph for $SERI_2$.

3. Data and Methodology

In order to study the determinants of green credit in Brazil, we employed dynamic panel data analysis. The original dataset used for the analyses was constructed using semi-annual data from a sample of 45 Brazilian banks, from June 2014 to December 2020, amounting to 14 semesters. The data was extracted from the Central Bank of Brazil (CBB). As not every bank provides information for National Classification of Economic Activities (CNAE), and those that do, do not necessarily do so for the entirety of this study's timeframe, the data panel formed is unbalanced. The time period was chosen due to data availability in the CNAE database of the central bank, coinciding with the CBB's Resolution nº 4327/2014 that implemented a social and environmental responsibility policy for Brazilian financial institutions. To carry out the study, the Sectorial Environmental Risk Index (SERI) is used as the dependent variable, allowing for the models to shed light on the factors that may affect a credit portfolio's environmental risk or impact.

As *SERI* is essentially an evaluation of a bank's credit portfolio, directly influenced by the institution's behavior and decisions, we use well-accepted variables in the banking loan literature to study its behavior and to control for omitted variable biases. The variables used are credit growth (CRED); regulatory capital (CAR); size of banks (SIZE); non-performing loans (NPL); profitability (ROE) and the economic growth (GDP GAP).

Following de Moraes and de Mendonça (2019), we make use of the banks' credit growth (CRED). The development of green technological and business innovations can provide new profitable opportunities for banks, as such project require proper financing (see Emtairah et al., 2005; Allen and Yago (2011); Lian et al., 2022). Thus, our main hypothesis aims to investigate if banks expand their portfolios in an environmentally friendly way, effectively becoming a catalyst for greener businesses to flourish and operate in the economy.

The capital adequacy ratio (CAR) indicates how solvent the financial institution is. Furthermore, as shown by de Moraes et al. (2016), banks tend to adjust their capital as a response to changes in regulation, thus *CAR* is also capable of capturing the policymakers' influence on banks. As a supplementary analysis, this study investigates whether more solvent banks have a higher appetite for green credit. Naili and Lahrichi (2022) have also used *CAR* to study bank loans and its relationship with default risk.

Regarding the control variables used, bank size (SIZE) is the calculated by the logarithm of the bank's total assets, following Laeven and Levine (2009) and Graham et al. (2008). A positive relation between *SIZE* and *SERI* is expected, with incumbent banks leading by example in the transition to a greener economy. The fraction of non-performing loans (NPL) is a commonly used proxy for credit risk (see Nguyen et al., 2021). It is calculated by the ratio between loans with more than 90 days overdue and the total credit portfolio. Return on equity (ROE) is a straightforward measure of profitability, in line with Bayeh et al. (2021). Other works such as Ashraf et al. (2021) have also used measures of profitability, for example return on assets, as a control variable in studying bank loans.

As pointed out by Lian et al. (2022), the level of green development in a society can affect the benefits of green credit. Finger et al. (2018) also finds regional differences may affect the consequences of employing Equator Principles for banks. Therefore, it is necessary to consider elements of the local macroeconomic scenario when studying the topic, as it may affect the banks' decisions and results. For this purpose, this study uses the difference between the GDP series and its long-term trend, obtained via the Hodrick-Prescott filter (GDP GAP) to control for the effects of the economic scenario. All of the variables and their units of measure are depicted in Table A.2, and their descriptive statistics are available in Table A.3, in the Appendix.

Furthermore, following Tiberto et al. (2020), we chose to employ a dynamic panel model, to study green credit in a parsimonious model, via the inclusion of the lagged dependent variable as an explanatory variable. This inertia effect is relevant, as the composition of a credit portfolio can be largely explained by its past self, given the long-term nature of money lending in banking. Hence, we reach the following baseline model:

$$SERI_{n,i,t} = \beta_0\, SERI_{n,i,t-1} + \beta_1\, CRED_{i,t-1} + \beta_2\, CAR_{i,t-1} + \beta_3\, X_{i,t-1} + \beta_4\, Z_{t-1} + \in_{i,t} \tag{2}$$

where $SERI_{n,i,t}$ is the proposed index for financial institution i in semester t. n = 1 and n = 2 represent $SERI_1$ and $SERI_2$, respectively. $\in_{i,t}$ is the error term. $CRED_{i,t-1}$ represents the credit portfolio growth and is our main variable of interest. $CAR_{i,t-1}$ is the capital adequacy ratio. $X_{i,t-1}$ represents the control variables, possible determinants of green credit, which are variables often used in the banking literature. Those are: total bank assets in logarithm (SIZE), non-performing loans (NPL) and return on equity (ROE). Lastly, Z_{t-1} represents macroeconomic variables, which in this study is the difference between the GDP series and its long-term trend, obtained via the Hodrick-Prescott filter (GDP GAP).

As we are working with dynamic models, that is, there is the use of the lagged dependent variable as a regressor, we might be subject to Nickell's bias (see Nickell, 1981), producing biased coefficients in fixed effects models. This is even more of a concern in studies with dynamic panel data featuring more cross-sections and less time periods ("large N, small T"), which is our case, as we have a sample of 45 banks and 14 semesters. Therefore, we elected to employ the Generalized Method of Moments (GMM) instead.

Because the dependent variable is a score based on the composition of the banks' loan portfolios, we cannot rule out the possibility of endogeneity in our models, as such composition may affect the other regressors. As a form of mitigating the possible endogeneity problem, the regressors were all lagged by one period (see Lian et al., 2022). The use of one period lags can also be interpreted as a way of assessing how variations in the explanatory variables may affect green credit after allowing for time to pass, as opposed to analyzing them in the same period, before changes have time to take their effects.

Finally, not all possible explanatory variables are known and thus considered in the models, characterizing the possibility of omitted explanatory variables. In this sense, we make use of Difference Generalized Method of Moments (D-GMM) and System Generalized Method of Moments (S-GMM), which are frameworks that can deal with these aforementioned issues.

As proposed by Arellano and Bond (1991), we first employ the Difference Generalized Method of Moments (D-GMM), removing the bias caused by cross-section specific effects. This framework makes use of instrumental variables, which prompt changes in the explanatory variables without affecting the dependent variable, allowing for causal effects to be uncovered in an unbiased manner. The past levels of the lagged dependent variable are also used as instruments, producing a more consistent estimator.

However, Arellano and Bover (1995) and Blundell and Bond (1998) point out that the use of lags can produce weak instruments, and that D-GMM has a bias for both large and small samples, as well as low accuracy. To alleviate these problems, they suggest including additional moment conditions, combining regressions in both differences and in levels into one system, characterizing the System Generalized Method of Moments (S-GMM). To deliver the most reliable results, we have employed S-GMM as well.

To verify the validity of the instruments, Sargan's J-test of over-identifying restrictions is performed in all models, as suggested by Arellano (2003). Notably, as we are working with a small number of time periods and larger number of cross-sections, if the instruments are too many, they can overfit the regressors and generate biased estimations. To address this issue, we follow the literature's suggestion of maintaining a ratio of number of instruments to number of cross-sections below 1 (see de Moraes et al., 2021). Finally, following Roodman (2009), serial correlation tests of first order (AR(1)) and second order (AR(2)) are also performed.

4. Analysis of Results

Tables 2 and 3 present the regressions for $SERI_1$ and $SERI_2$ respectively, using both the D-GMM and S-GMM frameworks. The estimated coefficients present statistical significance for all models when regarding the inertia and main hypothesis terms, and for most control variables as well.

Sargan's J-test was performed for all models, consistently failing to reject the null hypothesis that the instruments as a group are exogenous. AR(1) and AR(2) serial correlation tests were also performed for all models. In the AR(1) tests, we reject the null hypothesis for all cases. In the AR(2) tests, we fail to reject the null hypothesis of no serial correlation at the 10% significance levels for all models.

All of the models display a positive sign for credit growth (CRED), with statistical significance, in line with the hypothesis that a growing credit portfolio is associated to it becoming more environmentally friendly. This can also be interpreted as an increase in the banks' appetite for issuing green credit as they close more loan deals. Such finding indicates banks are favoring greener businesses, as well as taking advantage of the new opportunities coming from green innovation. This may also be an indication that enterprises with high environmental impact will find it harder to access loans as time progresses.

Another result is the positive inertia effect of the Sectorial Environmental Risk Index (SERI), also observed by the positive and statistically significant coefficient in the lagged dependent variable for all estimations. As *SERI* is a proxy for the issuance of green credit, this finding indicates that, given an increase in *SERI*, part of this increase will be permanently retained for the next period, shedding light into what is an opportunity for a continuous improvement of the banks' friendliness towards the environment via green credit development.

The regulatory capital (CAR) is shown to be positively related to *SERI*, indicating that when a bank is more solvent, it tends to issue more green credit. An explanation for this phenomenon is that green credit deals tend to have a higher short-term cost associated with less lending to well-established brown industries, and a more long-term benefit prospect with the development of new, greener enterprises and the mitigation of environmental risks (see Lian et al., 2022). Thus, in the short term, issuing more green credit characterizes a transition risk, which more solvent banks might be better equipped to afford taking. This finding also suggests the absence of a trade-off between the actions of policymakers, requesting higher capital from banks, and green credit development.

Regarding the control variables, the banks' size (SIZE) is also positively related to *SERI* in all estimations with statistical significance. These results suggest that bigger banks, being more exposed to the scrutiny of media, public opinion, and other stakeholders, tend to be concerned with maintaining a good reputation (see Cornett et al., 2016; Wright and Rwabizambuga, 2006). Signaling concern for the environment via issuing more green loans is a way of improving reputation (Zhou et al., 2021), explaining the positive relationship.

Non-performing loans (NPL) presents negative estimates, with statistical significance in all models. These results suggest that banks, when facing a higher default rate, fall back on lending to more conservative, well-established, and commoditized sectors, that tend to have a higher environmental risk. Performing scrutiny and crafting loan contracts with 'browner' sectors is simpler for banks, as such industries are already well-known and have their risks better mapped when compared to more innovative green ventures. Thus, resorting to brown industries may be an attempt at lowering default risks.

The banks' profitability (ROE), on the other hand, is positively related to *SERI* and retains significance in most estimations, indicating that the more profitable financial institutions are actively seeking to have greener portfolios. This result is interesting, as it goes against the notion that sustainability is an additional cost and margins must be sacrificed for its sake, implying banks can seek both profit and environmental friendliness at the same time.

As for the economic scenario's influence, *GDP GAP* is negatively related to *SERI* in all models, with statistical significance in all but one of them. These findings point that, in Brazil, a 'booming' economy still pushes banks towards a 'browner' agenda, indicating an underdeveloped green economy, where traditional and more pollutant industries and economic practices still have a lot of space. This issue might be aggravated by the way the GDP is calculated, which may encourage harmful behavior towards nature – for instance, a forest by itself might not contribute to a higher GDP but tearing it down to build a factory certainly will. Rethinking how we evaluate a country's richness to include its natural reserves and environmental assets may be a form of generating incentive to greener initiatives.

Table 2 – Estimation results – $SERI_1$.

$SERI_1$	**D-GMM**					**S-GMM**				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
$SERI_1$(-1)	**0.674*** **	**0.406** **	**0.462*** **	**0.491*** **	**0.369** **	**0.569*** **	**0.158*** **	**0.240*** **	**0.293*** **	**0.234*** **
	(0.204)	(0.181)	(0.154)	(0.159)	(0.148)	(0.215)	(0.049)	(0.025)	(0.031)	(0.040)
CRED(-1)	**0.187*** **	**0.052* **	**0.048** **	**0.044* **	**0.070*** **	**0.230** **	**0.153*** **	**0.046*** **	**0.056*** **	**0.037** **
	(0.056)	(0.030)	(0.021)	(0.024)	(0.021)	(0.091)	(0.054)	(0.011)	(0.014)	(0.017)
CAR(-1)	**0.794** **	**0.535** **	**0.225**	**0.181**	**0.208**	**0.616**	**0.161** **	**0.209*** **	**0.217*** **	**0.193*** **
	(0.318)	(0.251)	(0.192)	(0.263)	(0.265)	(0.439)	(0.078)	(0.038)	(0.028)	(0.041)
SIZE(-1)		**0.084*** **	**0.052** **	**0.053** **	**0.022**		**0.028** **	**0.030*** **	**0.034*** **	**-0.008**
		(0.026)	(0.024)	(0.025)	(0.037)		(0.014)	(0.009)	(0.008)	(0.010)
NPL(-1)			**-0.549*** **	**-0.548*** **	**-0.664*** **			**-0.699*** **	**-0.561*** **	**-0.640*** **
			(0.133)	(0.175)	(0.155)			(0.125)	(0.089)	(0.166)
ROE(-1)				**0.002**	**0.010**				**0.026*** **	**0.029*** **
				(0.016)	(0.015)				(0.006)	(0.011)
GDP GAP(-1)					**-0.066**					**-0.104*** **
					(0.044)					(0.021)
Obs.	412	375	375	375	375	449	412	412	412	412
Inst/Cross-sec	0.293	0.366	0.439	0.439	0.488	0.293	0.585	0.829	0.854	0.829
J-stat	6.721	12.775	11.922	11.330	12.922	7.153	24.604	31.619	31.175	26.260
p-value	0.666	0.308	0.534	0.501	0.454	0.621	0.217	0.337	0.357	0.504
AR(1)	-3.180	-3.277	-3.357	-3.449	-3.469	-0.596	-0.562	-0.541	-0.570	-0.532
p-value	0.002	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000
AR(2)	0.986	1.238	1.613	1.626	1.403	0.065	0.056	0.077	0.093	0.057
p-value	0.324	0.216	0.107	0.104	0.161	0.251	0.349	0.200	0.118	0.335

Notes: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. Standard errors are in parentheses. D-GMM uses two-step of Blundell and Bond (1998) without time period effects. S-GMM uses two-step of Arellano and Bover (1995) without time period effects. The J-test shows the models are properly identified. The AR(1) and AR(2) tests check for serial correlation of first and second order. The sample is an unbalanced panel of 45 banks from 2014s1 to 2020s2. Instrumental variables available upon request.

Table 3 – Estimation results – $SERI_2$.

$SERI_2$	**D-GMM**					**S-GMM**				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
$SERI_2$(-1)	**0.358****	**0.358*****	**0.339*****	**0.322*****	**0.374*****	**0.417****	**0.605*****	**0.557*****	**0.571*****	**0.554*****
	(0.192)	(0.032)	(0.054)	(0.030)	(0.069)	(0.183)	(0.013)	(0.015)	(0.017)	(0.036)
CRED(-1)	**0.128***	**0.031*****	**0.017*****	**0.012*****	**0.013***	**0.137***	**0.058*****	**0.048*****	**0.048*****	**0.042*****
	(0.074)	(0.005)	(0.005)	(0.005)	(0.007)	(0.072)	(0.005)	(0.005)	(0.006)	(0.009)
CAR(-1)	**0.696****	**0.398*****	**0.379*****	**0.396*****	**0.317*****	**0.703****	**0.162*****	**0.188*****	**0.168*****	**0.064***
	(0.306)	(0.030)	(0.043)	(0.050)	(0.065)	(0.329)	(0.023)	(0.026)	(0.028)	(0.035)
SIZE(-1)		**0.071*****	**0.044*****	**0.059*****	**0.020**		**0.048*****	**0.044*****	**0.040*****	**0.016***
		(0.007)	(0.008)	(0.007)	(0.013)		(0.006)	(0.009)	(0.006)	(0.009)
NPL(-1)			**-0.804*****	**-0.713*****	**-0.852*****			**-0.435*****	**-0.403*****	**-0.209***
			(0.075)	(0.071)	(0.082)			(0.126)	(0.119)	(0.107)
ROE(-1)				**0.018*****	**0.028*****				**0.032*****	**0.043*****
				(0.005)	(0.007)				(0.011)	(0.009)
GDP GAP(-1)					**-0.076****					**-0.101*****
					(0.035)					(0.020)
Obs.	449	449	449	412	412	449	449	449	449	412
Inst/Cross-sec	0.293	0.854	0.854	0.829	0.829	0.293	0.854	0.854	0.854	0.829
J-stat	10.250	38.584	36.698	32.005	33.024	9.714	36.609	36.327	35.622	32.187
p-value	0.331	0.164	0.186	0.274	0.196	0.374	0.225	0.198	0.185	0.225
AR(1)	-2.761	-3.343	-2.645	-3.445	-2.094	-0.510	-0.610	-0.585	-0.589	-0.589
p-value	0.006	0.001	0.008	0.001	0.036	0.000	0.000	0.000	0.000	0.000
AR(2)	0.176	1.130	0.243	0.837	0.234	0.010	0.084	0.086	0.094	0.069
p-value	0.861	0.258	0.808	0.402	0.815	0.862	0.142	0.141	0.103	0.234

Notes: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. Standard errors are in parentheses. D-GMM uses two-step of Blundell and Bond (1998) without time period effects. S-GMM uses two-step of Arellano and Bover (1995) without time period effects. The J-test shows the models are properly identified. The AR(1) and AR(2) tests check for serial correlation of first and second order. The sample is an unbalanced panel of 45 banks from 2014s1 to 2020s2. Instrumental variables available upon request.

4.2 Analysis with interactive terms

To deepen the analysis, we have also employed models with the addition of interactive terms, as shown in Tables 4 and 5. The use of solely linear additive models can potentially fail to capture certain interactions between variables (see Kanagaretnam et al., 2010). Thus, including terms that explore the interaction between CRED and the other microeconomic variables allows us to investigate their effects simultaneously to growing the credit portfolio, as opposed to the *coeteris paribus* analyses present in the baseline model. The use of interactive terms can also capture additional marginal effects of the other banking variables while under a credit portfolio growth (see Chemmanur et al., 2009).

The interactive terms' coefficients all present statistical significance, except Model 2 in Table 4. The term CRED*CAR displays a positive relationship with SERI, indicating that growing the credit portfolio while raising the bank's regulatory capital improves the portfolio's environmental scoring. This result strengthens the absence of a trade-off between financial stability and green credit – an important finding for policymakers.

Likewise, CRED*SIZE and CRED*ROE also present positive specifications, signaling there is no damping effect of a bank's total size or profitability on their green credit appetite. On the other hand, CRED*NPL shows a negative sign, which reinforces the idea that issuing more loans while at higher default rates tend to push banks into lending to brown sectors. All other specifications regarding previous results remain with no significant change.

Table 4 – Estimation results with interactive terms – $SERI_1$.

$SERI_1$

	S-GMM							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
$SERI_1$(-1)	**0.259*** **	**0.246*** **	**0.231*** **	**0.247*** **	**0.276*** **	**0.239*** **	**0.266*** **	**0.235*** **
	(0.032)	(0.033)	(0.036)	(0.038)	(0.035)	(0.044)	(0.030)	(0.033)
CRED(-1)	**0.034*** **	**0.030** **	**0.028** **	**0.023* **	**0.063*** **	**0.044** **	**0.044*** **	**0.033** **
	(0.013)	(0.014)	(0.013)	(0.013)	(0.014)	(0.019)	(0.010)	(0.013)
CRED*CAR(-1)	**0.406*** **	**0.085**						
	(0.122)	(0.129)						
CRED*SIZE(-1)			**0.005*** **	**0.002* **				
			(0.001)	(0.001)				
CRED*NPL(-1)					**-0.717*** **	**-1.276*** **		
					(0.255)	(0.240)		
CRED*ROE(-1)							**0.260** **	**0.188*** **
							(0.110)	(0.072)
CAR(-1)	**0.154*** **	**0.161*** **	**0.166*** **	**0.186*** **	**0.236*** **	**0.249*** **	**0.153*** **	**0.169*** **
	(0.054)	(0.042)	(0.053)	(0.037)	(0.060)	(0.043)	(0.048)	(0.040)
SIZE(-1)	**0.032*** **	**-0.008**	**0.034*** **	**-0.010**	**0.037*** **	**-0.011**	**0.029*** **	**-0.004**
	(0.011)	(0.009)	(0.013)	(0.008)	(0.011)	(0.011)	(0.008)	(0.009)
NPL(-1)	**-0.588*** **	**-0.601*** **	**-0.497*** **	**-0.547*** **	**-0.608*** **	**-0.814*** **	**-0.579*** **	**-0.603*** **
	(0.121)	(0.097)	(0.133)	(0.107)	(0.171)	(0.176)	(0.164)	(0.135)
ROE(-1)	**0.014* **	**0.032*** **	**0.018** **	**0.040*** **	**0.019* **	**0.030** **	**0.036*** **	**0.036*** **
	(0.008)	(0.009)	(0.008)	(0.009)	(0.011)	(0.012)	(0.011)	(0.012)
GDP GAP(-1)		**-0.099*** **		**-0.094*** **		**-0.123*** **		**-0.096*** **
		(0.022)		(0.020)		(0.022)		(0.019)
Obs.	412	412	412	412	412	412	412	412
Inst/Cross-sec	0.854	0.854	0.854	0.878	0.854	0.854	0.854	0.854
J-stat	29.082	27.349	27.200	24.262	29.457	26.746	30.418	26.196
p-value	0.408	0.445	0.507	0.668	0.390	0.478	0.344	0.508
AR(1)	-0.535	-0.535	-0.527	-0.528	-0.576	-0.540	-0.559	-0.537
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.044	0.054	0.026	0.034	0.097	0.057	0.089	0.065
p-value	0.465	0.362	0.664	0.562	0.103	0.335	0.134	0.272

Notes: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. Standard errors are in parentheses. S-GMM uses two-step of Arellano and Bover (1995) without time period effects. The J-test shows the models are properly identified. The AR(1) and AR(2) tests check for serial correlation of first and second order. The sample is an unbalanced panel of 45 banks from 2014s1 to 2020s2. Instrumental variables available upon request.

Table 5 – Estimation results with interactive terms – $SERI_2$.

$SERI_2$	S-GMM							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
$SERI_2$(-1)	**0.582*** **	**0.519*** **	**0.576*** **	**0.564*** **	**0.559*** **	**0.604*** **	**0.609*** **	**0.583*** **
	(0.020)	(0.033)	(0.020)	(0.036)	(0.021)	(0.042)	(0.022)	0.029)
CRED(-1)	**0.041*** **	**0.042*** **	**0.044*** **	**0.028*** **	**0.043*** **	**0.045*** **	**0.019** **	**0.021*** **
	(0.006)	(0.006)	(0.005)	(0.009)	(0.008)	(0.010)	(0.008)	(0.008)
CRED*CAR(-1)	**0.334*** **	**0.124***						
	(0.083)	(0.069)						
CRED*SIZE(-1)			**0.002** **	**0.002*** **				
			(0.001)	(0.0003)				
CRED*NPL(-1)					**-1.231*** **	**-1.709*** **		
					(0.189)	(0.356)		
CRED*ROE(-1)							**0.398*** **	**0.427*** **
							(0.064)	(0.070)
CAR(-1)	**0.098** **	**0.113** **	**0.129*** **	**0.234*** **	**0.229*** **	**0.184*** **	**0.110*** **	**0.111*** **
	(0.044)	(0.045)	(0.040)	(0.046)	(0.031)	(0.047)	(0.038)	(0.039)
SIZE(-1)	**0.041*** **	**0.008**	**0.040*** **	**0.016**	**0.042*** **	**0.019***	**0.033*** **	**0.009**
	(0.007)	(0.010)	(0.007)	(0.013)	(0.008)	(0.011)	(0.006)	(0.008)
NPL(-1)	**-0.320*** **	**-0.406*** **	**-0.348*** **	**-0.367*** **	**-0.665*** **	**-0.560*** **	**-0.253** **	**-0.311** **
	(0.119)	(0.095)	(0.124)	(0.121)	(0.105)	(0.129)	(0.124)	(0.126)
ROE(-1)	**0.024** **	**0.038*** **	**0.026** **	**0.038*** **	**0.029** **	**0.055*** **	**0.055*** **	**0.062*** **
	(0.010)	(0.014)	(0.011)	(0.010)	(0.013)	(0.011)	(0.009)	(0.011)
GDP GAP(-1)		**-0.106*** **		**-0.072*** **		**-0.113*** **		**-0.081*** **
		(0.019)		(0.026)		(0.025)		(0.019)
Obs.	449	449	449	412	449	412	412	412
Inst/Cross-sec	0.854	0.854	0.854	0.829	0.854	0.854	0.829	0.854
J-stat	33.103	32.915	34.471	27.398	34.644	30.343	30.134	30.763
p-value	0.232	0.200	0.186	0.389	0.180	0.299	0.308	0.281
AR(1)	-0.577	-0.560	-0.583	-0.565	-0.582	-0.586	-0.597	-0.579
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.058	0.045	0.070	0.042	0.093	0.071	0.090	0.070
p-value	0.314	0.432	0.226	0.472	0.104	0.224	0.125	0.230

Notes: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. Standard errors are in parentheses. S-GMM uses two-step of Arellano and Bover (1995) without time period effects. The J-test shows the models are properly identified. The AR(1) and AR(2) tests check for serial correlation of first and second order. The sample is an unbalanced panel of 45 banks from 2014s1 to 2020s2. Instrumental variables available upon request

4.3 Robustness analysis

Furthermore, to confirm the robustness of our results, we perform a final analysis, replacing the credit growth rate (CRED) by the growth of the banks' risk-weighted assets (RWA). This change is justified, as when a bank increases the total amount in their loan portfolios, they are also increasing their exposure to risk. In this sense, we make use of the RWA for credit risk, as outlined in the Basel framework.[6]

The results, presented in Table 6, are consistent with the analysis using CRED, retaining a positive sign and statistical significance in all estimations. Likewise, the coefficients of the control variables do not present any significant changes, maintaining previous results. Consequently, our estimations remain robust to the change in variable.

[6] https://www.bis.org/basel_framework/chapter/RBC/20.htm

Table 6 – Estimation results – RWA robustness check.

	$SERI_1$					**$SERI_2$**				
	S-GMM					**S-GMM**				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
$SERI_1$(-1)	**0.211*****	**0.183*****	**0.190*****	**0.199*****	**0.119***					
	(0.024)	(0.027)	(0.022)	(0.025)	(0.063)					
$SERI_2$(-1)						**0.419*****	**0.408*****	**0.630*****	**0.202*****	**0.358*****
						(0.022)	(0.020)	(0.036)	(0.049)	(0.055)
RWA(-1)	**0.013*****	**0.008***	**0.007*****	**0.007****	**0.037****	**0.004****	**0.009*****	**0.004***	**0.025***	**0.008****
	(0.002)	(0.004)	(0.002)	(0.004)	(0.015)	(0.002)	(0.003)	(0.002)	(0.014)	(0.004)
CAR(-1)	**0.097****	**0.175*****	**0.201*****	**0.186*****	**0.238*****	**0.308*****	**0.314*****	**0.214*****	**0.146****	**0.253*****
	(0.041)	(0.033)	(0.044)	(0.072)	(0.087)	(0.025)	(0.032)	(0.043)	(0.072)	(0.051)
SIZE(-1)		**0.058*****	**0.030*****	**0.040*****	**0.007**		**0.046*****	**0.010**	**0.080*****	**-0.016**
		(0.005)	(0.005)	(0.005)	(0.017)		(0.003)	(0.008)	(0.019)	(0.013)
NPL(-1)			**-1.034*****	**-0.704*****	**-0.992*****			**-0.876*****	**-0.151**	**-0.941*****
			(0.100)	(0.098)	(0.231)			(0.078)	(0.153)	(0.188)
ROE(-1)				**0.006**	**0.041****				**0.073*****	**-0.013**
				(0.013)	(0.018)				(0.022)	(0.013)
GDP GAP(-1)					**-0.093*****					**-0.119*****
					(0.032)					(0.017)
Obs.	383	383	383	383	337	416	416	416	298	415
Inst/Cross-sec	0.872	0.872	0.872	0.897	0.667	0.875	0.875	0.875	0.622	0.897
J-stat	34.749	30.510	31.828	28.864	16.716	36.075	37.051	31.411	15.866	27.168
p-value	0.294	0.440	0.327	0.472	0.609	0.284	0.210	0.395	0.533	0.509
AR(1)	-0.570	-0.556	-0.526	-0.550	-0.529	-0.555	-0.558	-0.581	-0.528	-0.499
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.077	0.083	0.055	0.077	0.095	0.023	0.053	0.078	0.102	0.017
p-value	0.208	0.177	0.395	0.227	0.150	0.699	0.370	0.197	0.123	0.778

Notes: Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. Standard errors are in parentheses. S-GMM uses two-step of Arellano and Bover (1995) without time period effects. The J-test shows the models are properly identified. The AR(1) and AR(2) tests check for serial correlation of first and second order. The sample is an unbalanced panel of 45 banks from 2014s1 to 2020s2. Instrumental variables available upon request.

5. Concluding Remarks

This study has conducted a panel data analysis on 45 Brazilian banks, using semi-annual data ranging from the first half of 2014 to the second half of 2020. Through panel GMM estimations, using a newly-crafted indicator – the Sectorial Environmental Risk Index (SERI) – as the dependent variable, we investigated the determinants of green credit and environmentally friendly behavior for financial institutions.

The findings suggest a positive association between banks' credit rate growth and environmentally friendly behavior. This result indicates that, given the opportunity to close more loaning deals, financial institutions actively seek to lend to greener borrowers. This progression gradually pushes brown businesses to the margins and opens space for new, greener ventures. Financial intermediaries are now expected to mediate the flow of capital from lender to borrower and do so in a way that is aligned with society's interests and concerns for the well-being of planet Earth.

The banks' capital adequacy ratio also plays a role in the portfolios' behavior. Estimation outcomes suggest more solvent banks tend to issue more green credit, showing the policymakers' efforts to guarantee financial stability in the banking system can be an ally of environmentally friendly loans.

Modern financial intermediation theory states that banks have two fundamental roles in the economy: liquidity creation and risk transformation (see Berger & Bouwman, 2009). Moreover, climate risks can exert their influence in the economy in two ways: through a physical channel or a transition channel (Lee et al., 2022). In this sense, a possible implication of this study's results is that as banks increase their appetite for green credit, they transmit the climate transition risk to companies, which are increasingly encouraged to comply with green business guidelines in order to have easier access to credit. This proposition is in line with Fan et al. (2021), that observed brown firms find it more difficult to access loans as green credit policies are reinforced by banks.

APPENDIX

Table A.1 – Sector matching.

CNAE Sector	IFC Sectors
Agriculture, Livestock, Forestry, Fisheries and Aquaculture	Crops; Fishing; Forestry; Livestock.
Transformation Industries	Chemicals; Electronics; Food; Glass; Leather; Machinery; Paper; Pharmaceuticals; Precision; Textiles; Wood.
Construction	Cement; Construction.
Public Utility Industrial Services	Energy; Waste; Water.
Extractive Industries	Iron; Mining; Oil & Gas.
Trade, Repair of Motor Vehicles and Motorcycles	Garages.
Public Administration, Defense and Social Security	Low Risk Sector.
Transport, Storage and Mail	Tourism; Transport.
Others	Health; Laundry; Printing.

Table A.2 – Description of the variables.

Variable	Definition	Unit
SERI	Sectorial Environmental Risk Index	-
CRED	Variation in the size of the credit portfolio in relation to the last period	%
RWA	Difference of the natural logarithm of the bank's RWA between two consecutive periods	R$
CAR	Capital Adequacy Ratio	%
SIZE	Natural logarithm of total assets	R$
NPL	Non-performing loans in relation to total loans	%
ROE	Return on Equity	%
GDP GAP	Difference between the GDP series and its long-term trend	10^{12} R$

Table A.3 – Descriptive statistics of the variables.

	Mean	Median	Max.	Min.	Std. Dev.	Obs.
$SERI_1$	1.741	1.722	2.106	1.390	0.133	541
$SERI_2$	1.801	1.787	2.091	1.403	0.115	542
RWA	0.026	0.017	2.850	-2.182	0.336	508
CAR	0.184	0.169	0.439	-0.125	0.061	516
SIZE	23.436	23.121	28.135	19.482	2.099	560
NPL	0.036	0.029	0.409	0.000	0.041	560
ROE	0.097	0.104	2.978	-0.871	0.249	559
GDP GAP	-0.007	0.009	0.067	-0.213	0.062	560

Table A.4 – List of banks.

ABC-BRASIL	BBM	CAIXA GERAL	ING	PARANÁ BANCO
ALFA	BMG	CCB	INTER	PINE
BANCO IBM S.A.	BNC BRAZIL LTDA.	CITIBANK	ITAU	PSA FINANCE
BANCO MONEO S.A.	BOCOM	CREDIT AGRICOLE	JP MORGAN CHASE	RENDIMENTO
BANCO RANDON S.A.	BONSUCESSO	HAITONG	MERCANTIL DO BRASIL	SAFRA
BANCO TOPÁZIO S.A.	BRADESCO	HONDA	MERCEDES-BENZ	SANTANDER
BANESTES	BRB	HSBC	MIZUHO	SOCOPA
BANRISUL	BTG PACTUAL	INDUSTRIAL DO BRASIL	OMNI	VOTORANTIM
BANCO DO BRASIL	CAIXA ECONOMICA FEDERAL	INDUSVAL	PAN	XP

REFERENCES

Allen, F., & Yago, G. (2011). **Environmental Finance: Innovating to Save the Planet**. *Journal of Applied Corporate Finance*, 23(3), 99-111.

Al-Qudah, A. A., Hamdan, A., Al-Okaily, M., & Alhaddad, L. (2022). **The impact of green lending on credit risk: evidence from UAE's banks**. *Environmental Science and Pollution Research*.

Arellano, M. (2003). **Panel Data Econometrics**. *Oxford University Press*.

Arellano, M., & Bond, S. (1991). **Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations**. *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.

Ashraf, B. N., Qian, N., & Shen, Y. (2021). **The impact of trade and financial openness on bank loan pricing: Evidence from emerging economies**. *Emerging Markets Review*, 47, 100793.

Barth, M. E., & Landsman, W. R. (2010). **How did Financial Reporting Contribute to the Financial Crisis?** *European Accounting Review*, 19(3), 399-423.

Batrancea, I., Batrancea, L., Maran Rathnaswamy, M., Tulai, H., Fatacean, G., & Rus, M.-I. (2020). **Greening the Financial System in USA, Canada and Brazil: A Panel Data Analysis**. *Mathematics*, 8(12), 2217.

Bayeh, A., Bitar, M., Burlacu, B., & Walker, T. (2021). **Competition, securitization, and efficiency in US banks**. *The Quarterly Review of Economics and Finance*, 80, 553-576.

Berger, A. N., & Bouwman, C. H. S. (2009). **Bank Liquidity Creation**. *The Review of Financial Studies*, 22(9), 3779-3837.

Blundell, R., & Bond, S. (1998). **Initial Conditions and Moment Restrictions in Dynamic Panel Data Models**. *Journal of Econometrics*, 87(1), 115-143.

Chemmanur, T. J., He, S., & Nandy, D. K. (2009). **The Going-Public Decision and the Product Market**. *The Review of Financial Studies*, 23(5), 1855-1908.

Contreras, G., Bos, J. W. B., & Kleimeier, S. (2019). **Self-regulation in sustainable finance: The adoption of the Equator Principles**. *World Development*, 122, 306-324.

Cornett, M. M., Erhemjamts, O., & Tehranian, H. (2016). **Greed or good deeds: An examination of the relation between corporate social responsibility and the financial performance of U.S. commercial banks around the financial crisis**. *Journal of Banking & Finance*, 70, 137-159.

Cui, Y. J., Geobey, S., Weber, O., & Lin, H. Y. (2018). **The impact of green lending on credit risk in China**. *Sustainability*, 10(6).

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

de Moraes, C. O., Galvis-Ciro, J. C., & Gargalhone, M. (2021). **Financial access and interest rate spread: An international assessment**. *Journal of Economics and Business*, 114, 105958.

de Moraes, C. O., Montes, G. C., & Antunes, J. A. P. (2016). **How does capital regulation react to monetary policy? New evidence on the risk-taking channel**. *Economic Modelling*, 56, 177-186.

Ehlers, T., Elsenhuber, U., Jegarasasingam, A., & Jondeau, E. (2022). **Deconstructing ESG scores: how to invest with your own criteria**. Available at: https://www.bis.org/publ/work1008.htm

Emtairah, T., Hansson, L., & Hao G. (2005). **Environmental challenges and opportunities for banks in China: The case of industrial and commercial bank of China**. *Greener Management International*, 50, 85-95.

Fan, H., Peng, Y., Wang, H., & Xu, Z. (2021). **Greening through finance?** *Journal of Development Economics*, 152, 102683.

Finger, M., Gavious, I., & Manos, R. (2018). **Environmental risk management and financial performance in the banking industry: A cross-country comparison**. *Journal of International Financial Markets, Institutions and Money*, 52, 240-261.

Graham, J. R., Li, S., & Qiu, J. (2008). **Corporate misreporting and bank loan contracting**. *Journal of Financial Economics*, 89(1), 44-61.

Jeucken, M. (2001). **Sustainable Finance and Banking: The Financial Sector and the Future of the Planet**. Earthscan, London.

Kacperczyk, M. T., & Peydró, J. (2021). **Carbon Emissions and the Bank-Lending Channel**. Available at: https://dx.doi.org/10.2139/ssrn.3915486.

Kanagaretnam, K., Lobo, G. J., & Yang, D.-H. (2010). **Joint Tests of Signaling and Income Smoothing through Bank Loan Loss Provisions**. *Contemporary Accounting Research*, 21(4), 843-884.

Laeven, L., & Levine, R. (2009). **Bank governance, regulation and risk taking**. *Journal of Financial Economics*, 93(2), 259-275.

Lee, C.-C., Wang., C.-W., Thinh, B. T., & Xu, Z.-T. (2022). **Climate risk and bank liquidity creation: International evidence**. *International Review of Financial Analysis*, 82, 102198.

Leins, S. (2020). **‘Responsible investment’: ESG and the post-crisis ethical order**. *Economy and Society*, 49:1, 71-91.

Lian, Y., Gao, J., & Tao, Y. (2022). **How does green credit affect the financial performance of commercial banks? — Evidence from China**. *Journal of Cleaner Production*, 344, 131019.

Luo, S., Yu, S., & Zhou, G. (2021). **Does green credit improve the core competence of commercial banks? Based on quasi-natural experiments in China**. *Energy Economics*, 100, 105335.

Macve, R., & Chen, X. (2010). **The “equator principles”: a success for voluntary codes?** *Accounting, Auditing & Accountability Journal*, 23(7), 890-919.

Mejia-Escobar, J. C., González-Ruiz, J. D., & Duque-Grisales, E. (2020). **Sustainable Financial Products in the Latin America Banking Industry: Current Status and Insights**. *Sustainability*, 12(14), 5648.

Miralles-Quirós, M. M., Miralles-Quirós, J. L., & Valente Gonçalves, L. M. (2018). **The Value Relevance of Environmental, Social, and Governance Performance: The Brazilian Case**. *Sustainability*, 10(3), 574.

Miroshnichenko O. S., & Brand N. A. (2021). **Banks Financing the Green Economy: A Review of Current Research**. *Finance: Theory and Practice*, 25(2), 76-95.

Naili, M., & Lahrichi, Y. (2022). **Banks' credit risk, systematic determinants and specific factors: recent evidence from emerging markets**. *Heliyon*, 8(2), e08960.

Nguyen, D. T. T., Diaz-Rainey, I., Roberts, H., & Le, M. (2021). **Loans from my neighbours: East Asian commercial banks, financial integration, and bank default risk**. *International Review of Financial Analysis*, 74, 101659.

Nickell, S. (1981). **Biases in Dynamic Models with Fixed Effects**. *Econometrica*, 49(6), 1417-1426.

Roodman, D. (2009). **How to do xtabond2: An introduction to difference and system GMM in Stata**. *The Stata Journal*, 9(1), 86-136.

Scholtens, B., & Dam, L. (2007). **Banking on the Equator. Are Banks that Adopted the Equator Principles Different from Non-Adopters?** *World Development*, 35(8), 1307-1328.

Tiberto, B. P., de Moraes, C. O., & Corrêa, P. P. (2020). **Does transparency of central banks communication affect credit market? Empirical evidence for advanced and emerging markets**. *The North American Journal of Economics and Finance*, 53, 101207.

Umar, M., Ji, X., Mirza, N., & Naqvi, B. (2021). **Carbon neutrality, bank lending, and credit risk: Evidence from the Eurozone**. *Journal of Environmental Management*, 296, 113156.

Wright, C., & Rwabizambuga, A. (2006). **Institutional Pressures, Corporate Reputation, and Voluntary Codes of Conduct: An Examination of the Equator Principles**. *Business and Society Review*, 111(1), 89-117.

Yin, W., Zhu, Z., Kirkulak-Uludag, B., & Zhu, Y. (2021). **The determinants of green credit and its impact on the performance of Chinese banks**. *Journal of Cleaner Production*, 286, 124991.

Zhou, G., Sun, Y., Luo, S., & Liao, J. (2021). **Corporate social responsibility and bank financial performance in China: The moderating role of green credit**. *Energy Economics*, 97, 105190.