Financial constraints and development policies: evidence from Brazilian development bank loans

Matheus da Costa Gomes

https://doi.org/10.1590/1808-057x20262448.en

Submitted on: 2026-05-15
Posted on: 2026-05-15 (version 1)
(YYYY-MM-DD)

DOI: 10.1590/1808-057x20262448.en

e-location: e2448

Financial constraints and development policies: evidence from Brazilian development bank loans

Matheus da Costa Gomes[1]

https://orcid.org/0000-0002-4611-6047

Email: matheusgomes@alumni.usp.br

[1] Universidade de São Paulo, Faculdade de Economia, Administração, Contabilidade e Atuária, Departamento de Contabilidade e Atuária, São Paulo, SP, Brazil

Received on 08/22/2025 – Desk acceptance on 09/10/2025 – 2nd version approved on 01/26/2026

Academic Editor-in-Chief: Andson Braga de Aguiar

Associate Editor: Andrea Maria Accioly Fonseca Minardi

Study presented at the 25º USP International Conference on Accounting, São Paulo, SP, Brazil, July 2025.

ABSTRACT

This study maps patterns of credit allocation by the Brazilian National Bank for Economic and Social Development (Banco Nacional de Desenvolvimento Econômico e Social [BNDES]) from 2002 to 2019, examining associations among firm characteristics, regional disparities, and funding access. Previous research has mainly focused on listed firms or aggregate measures, overlooking the broader business landscape. To address this, the paper assembles a granular dataset of 2,515 firms (1,537 beneficiaries and 978 non-beneficiaries), including both listed and private companies. This broader coverage allows the analysis to capture firms often absent from prior studies. Development banks are critical in environments with scarce long-term finance. Given BNDES's systemic weight, which historically accounts for over 15% of private credit and is tightly correlated with investment, understanding its allocation is central to debates on market-failure correction and inclusive growth. The results reveal BNDES's trade-offs: funds reach disadvantaged regions and strategic sectors, yet systematically flow to firms able to provide collateral. This challenges assumptions that public development banks primarily serve the most constrained firms and highlights tensions between social objectives and financial sustainability. The study employs binary logistic models on a cross-sectional firm-level sample (2,515 Brazilian firms, 2002-2019), with explanatory variables including age, size, tangibility, liquidity, profitability, leverage, and dummies for region, sector, listing, and group affiliation. A multinomial logistic model explores loan frequency, while propensity score matching ensures robustness. BNDES lending shows clear regional and sectoral targeting: firms in the Northeast and utilities are more likely to obtain credit. Beneficiaries tend to be older, more liquid, and more asset-tangible. The effects of firm size are nuanced: smaller firms are more likely to access funds than larger ones, suggesting a risk-aware tilt within the bank's developmental mandate. This creates an "allocation paradox," as support flows to priority regions and sectors but favors lower-risk corporate profiles.

Keywords: targeted credit, development bank, subsidized credit, economic development; social development.

1. INTRODUCTION

Development banks play a crucial role in financing infrastructure projects and fostering sustainable development worldwide. Their importance is particularly evident during periods of economic distress: for example, during the 2007-2008 global financial crisis, development banks acted as countercyclical agents to help stabilize economies (Cipoletta Tomassian & Abdo, 2022; Kring & Gallagher, 2019). The Brazilian National Bank for Economic and Social Development (Banco Nacional de Desenvolvimento Econômico e Social [BNDES]) stands out as one of the largest and most influential institutions of its kind.

Globally, peers such as Germany's KfW prioritize energy transition, while multilateral banks (e.g., Asian Development Bank) focus on transnational infrastructure, while Brazil's intranational inequalities distinctively shape BNDES's mandate. This challenge is paralleled in scale and complexity only by large developing economies' institutions, such as China Development Bank (in strategic scope) and India's development finance ecosystem (e.g., Exim Bank, in addressing regional divides)

(Griffith-Jones et al., 2018). BNDES shares with these counterparts a broad mandate supporting industrial and social goals. However, unlike them, its mission is fundamental in mitigating financial constraints within a country marked by acute regional and sectoral fragmentation.

Established in 1952 (as BNDE, later adding "Social" to its name in 1982 to highlight its social development mission), BNDES is Brazil's leading source of long-term project finance, often providing credit at subsidized interest rates. This approach mirrors global development banking trends whereby national institutions leverage subsidized credit for structural transformation (Cipoletta Tomassian & Abdo, 2022), but with a unique emphasis on reducing spatial disparities. Until 2015, BNDES loans accounted for over 15% of all credit to the private sector (Lazzarini et al., 2015). Moreover, the volume of BNDES disbursements is highly correlated (around 80%) with Brazil's gross investment rate, underscoring the bank's central role in capital formation and economic growth (Barboza & Vasconcelos, 2019).

Access to BNDES financing is not automatic; it depends on firm-specific factors and the bank's own selection criteria. BNDES evaluates credit applications based on project characteristics and the borrower's profile, including an analysis of risk, the nature of the project, and compliance with policy priorities and regulations (Cavalcanti & Vaz, 2017; Gomes & Valle, 2023; Sousa & Ottaviano, 2018). There are concerns that political influences can affect BNDES lending decisions, potentially leading to unequal or suboptimal allocation of resources (Lazzarini et al., 2015). These dynamics highlight the need for a detailed mapping of BNDES's allocation patterns across Brazil's heterogeneous economic landscape.

Theoretically, development banks aim to mitigate market failures, such as credit constraints arising from information asymmetries (Almeida & Braga, 2020; Campos, 1969). However, subsidized loans can have two opposing effects: on the one hand, they can support financially constrained firms and promote investment; on the other, they can exacerbate inequalities by channeling resources to firms with sufficient access to private credit. This duality is particularly relevant in Brazil, a country marked by deep regional and sectoral disparities (Kayo et al., 2023). Indeed, this tension between mitigating financial constraints and advancing development policy goals lies at the heart of BNDES's operational dilemma.

In the Brazilian context, where pronounced regional inequalities aggravate these failures, BNDES is crucial to enable investments in regions such as the North and Northeast, where firms face historical challenges in accessing credit and participating in infrastructure projects (Frischtak et al., 2017). By facilitating credit access, the bank promotes investments and productivity, enabling projects that would not occur without its intervention (Cavalcanti & Vaz, 2017; Sousa & Ottaviano, 2018). Evidence suggests that BNDES has effectively boosted investment, exports, employment, and gross domestic product (GDP), especially by supporting micro, small, and medium-sized enterprises (Barboza et al., 2023).

However, studies also indicate that BNDES-guided credit does not always reduce financial constraints of Brazilian companies (Bonomo et al., 2015; Cull et al., 2015; Lazzarini et al., 2015). For instance, large firms or those listed on the country's stock exchange, which have a greater capacity to access private financing, often benefit from BNDES resources in any event, revealing allocation patterns where low-risk firms receive disproportionate shares. This situation reflects a market logic where BNDES prioritizes loans to firms that are more able to meet their obligations, to the detriment of those facing significant financial restrictions (Kayo et al., 2023).

Moreover, development banks face challenges in ensuring the efficient distribution of subsidies. These challenges include defining clear allocation criteria, formulating specific goals, adequately monitoring beneficiaries, and applying sanctions when necessary (Antunes et al., 2015; Levy-Yeyati et al., 2004).

Against this backdrop, this article examines systematic patterns in BNDES credit allocation from 2002 to 2019, based on a comprehensive dataset spanning listed and unlisted firms – the latter representing over 75% of Brazilian enterprises. By covering an 18-year period that includes the bank's lending peak (2008-2014) and subsequent contraction (2015-2019), I deploy binary and multinomial logistic models to identify firm-level (sector, age, size, tangibility, liquidity, profitability, leverage) and regional predictors of funding access probabilities. This approach reveals how BNDES's stated dual mandate – financial constraint mitigation and development policy – translates into observable allocation patterns across Brazil's diverse economic geography, offering unprecedented granularity beyond listed firms.

2. THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

Development banks are central to reducing financial constraints, particularly in emerging economies. These constraints, rooted in information asymmetries and weak legal frameworks, limit firms' access to credit, resulting in underinvestment and slower growth (Banerjee & Duflo, 2014). By offering targeted, low-cost financing, development banks help mitigate these barriers and promote long-term investments. However, this mission entails a dual challenge: ensuring financial sustainability while advancing inclusive development objectives. This tension is evident in BNDES's allocation patterns (Gomes & Valle, 2023; Griffith-Jones et al., 2018; Levy-Yeyati et al., 2004).

In Brazil, limited institutional quality and elevated monitoring costs heighten perceived credit risk, making lenders favor firms with substantial collateral and low leverage (Antunes et al., 2015; La Porta et al., 2002). As a result, financially constrained firms, often small, young, or asset-light, struggle to secure adequate funding for expansion. Subsidized credit has proven valuable in addressing these gaps, especially for small and medium-sized enterprises (SMEs) (Quaye & Hartarska, 2016; Simpasa et al., 2015; Sousa & Ottaviano, 2018). These programs enhance investment capacity and foster productive inclusion (Banerjee & Duflo, 2014; Cavalcanti & Vaz, 2017; Gomes & Valle, 2023).

Furthermore, empirical evidence also highlights inefficiencies. Studies show that large, well-established, and low-risk firms often capture the bulk of subsidized loans, despite having access to market financing, raising concerns about adverse selection and political influence (Bonomo et al., 2015; Cull et al., 2015; Lazzarini et al., 2015).

Studies analyzing financial constraints have faced significant methodological challenges, particularly in identifying constrained firms. Commonly used criteria, such as firm size, payout ratios, and credit ratings, have been criticized for their arbitrariness and inability to fully capture the reality of financial restrictions faced by companies (Hadlock & Pierce, 2010; Whited & Wu, 2006). Additionally, the sensitivity of investments to internal cash flow, often used as an indirect measure of credit constraint, is subject to controversy. Kaplan and Zingales (1997) argued that cash flow may reflect productivity and future expectations, while Alti (2003) observed that cash flow shocks can influence investment decisions independently of financial constraints.

In Brazil's case, deep regional disparities exacerbate credit inequalities. The North, Northeast, and Midwest regions lack infrastructure and financial services, limiting firms' potential growth (Ehrl et al., 2022; Resende, 2013). Development banks like BNDES are thus key to mobilizing capital in these underserved areas (Frischtak et al., 2017). BNDES's indirect credit lines, such as the Constitutional Financing Funds for the North (FNO), Northeast (FNE), and Central-West (FCO), focus on stimulating investment in these underdeveloped macro-regions, which cover roughly 75% of Brazil's territory and house nearly half its population, yet account for only 30% of national GDP (Instituto Brasileiro de Geografia e Estatística [IBGE], 2023; Resende, 2013). This leads to the formulation of the first hypothesis:

> H_1 – Regional location: firms located in Brazil's North, Northeast or Midwest regions are more likely to receive BNDES credit than otherwise similar firms in more developed regions.

Moreover, sectors such as energy, sanitation, and infrastructure, essential for inclusive development, face structural barriers due to high upfront costs and long payback periods. These sectors often depend on concessional credit. According to Gomes and Valle (2023), conventional evaluation frameworks that emphasize short-term financial returns may underestimate the true value of such investments. They advocate for an economic development perspective that emphasizes long-term social and economic outcomes. Empirical reports show that infrastructure loans made up 30-45% of BNDES disbursements during the 2010s (Frischtak et al., 2017). BNDES has historically offered preferential financial conditions for sanitation, electric power, and renewable energy firms due to their strategic roles (Barboza et al., 2023; Gomes & Valle, 2023). Based on this sectoral rationale, the second hypothesis is proposed:

> H_2 – Sectoral priority: firms operating in the energy or public utility sectors are more likely to receive BNDES financing than firms in other sectors.

Credit constraints are typically more severe for small, young, and asset-light firms, particularly in developing countries. These characteristics hinder their ability to access conventional financing channels. Development banks seek to correct these market imperfections by targeting such firms. Approximately 43% of BNDES disbursements in 2017 went to micro, small, and medium-sized firms (BNDES, 2018). Additionally, Sousa and Ottaviano (2018) demonstrated that BNDES loans effectively alleviate financing gaps for credit-constrained firms, enhancing their investment capacity. Nonetheless, studies caution against elite capture, where politically connected or low-risk firms secure disproportionate credit (Bonomo et al., 2015; Lazzarini et al., 2015), revealing tensions between risk management and developmental goals. This consideration motivates the third hypothesis:

> H_3 – Financial constraints: financially constrained firms, characterized by small size, young age, low profitability, low tangibility, and/or low leverage, are more likely to receive BNDES funding than larger, more established firms.

Most studies focus on publicly traded firms, which represent a minority in Brazil. Unlisted and SME firms dominate the economy and face stronger credit constraints. This study allows a more precise examination of selection mechanisms by tracking firms' first access to BNDES credit. Such a granular approach reveals heterogeneity overlooked in aggregate studies and offers policy insights for refining development bank targeting. Drawing on the theoretical insights discussed earlier, the three hypotheses reflect

BNDES's dual mandate in addressing market imperfections and fostering inclusive development.

3. METHODOLOGICAL PROCEDURES

3.1 Sample and Data Collection

This study relies on the Standard & Poor's Capital IQ database as the source of financial statement information for companies from 2002 to 2019. The selection of companies involved applying the following filters: (i) country: Brazil only; (ii) sectors: all sectors except finance and insurance, due to the unique regulatory and accounting peculiarities of these sectors; and (iii) total assets and equity: greater than zero in at least six consecutive reporting periods (years). This final criterion ensures data consistency and excludes companies with sparse information, which would hinder variable construction and analysis. After applying these initial filters, I obtained a preliminary sample of 4,521 companies.

Subsequently, I manually processed the data to identify companies lacking essential variables for analysis, particularly those with interruptions in financial data. This step resulted in a final sample of 2,574 firms.

I classified the companies into two groups: beneficiaries of BNDES credit lines (treatment group) and non-beneficiaries (control group). The identification of beneficiary companies was based on publicly available data from the BNDES website, which lists companies that have received loans and financing since 2002. The analysis includes all BNDES financing modalities except for transactions involving the "BNDES Card," intended for small amounts (up to R$ 2 million) and predominantly accessed by SMEs and sole proprietorships operating under distinct mechanisms.

Following the identification and classification, I defined two final samples for the analyses, as detailed in Table 1. Final sample 1 contained qualitative characterization data of companies, including variables such as publicly traded company (Pub. Traded), group membership (Subsidiary), age, economic sector, and regional location (South, Southeast, Midwest, North, and Northeast). This sample enabled an initial analysis of the structural factors influencing access to BNDES credit. Final sample 2, on the other hand, expanded the analysis by incorporating economic and financial indicators such as tangibility, profitability, leverage, and liquidity in addition to the qualitative data from the previous sample. This sample allowed assessing the impact of economic and financial determinants on access to targeted credit.

Table 1
Final samples

Adopted procedures	**Number of firms**
(=) Filter 1: Brazilian companies	59,664
(=) Filter 2: All sectors except finance and insurance[i]	15,226
(=) Filter 3: Total assets and equity greater than zero in the last reported year t	7,987
(=) Filter 4: Total assets and equity greater than zero in reporting year t-1	7,701
(=) Filter 5: Total assets and equity greater than zero in reporting year t-2	6,711
(=) Filter 6: Total assets and equity greater than zero in reporting year t-3	6,040
(=) Filter 7: Total assets and equity greater than zero in reporting year t-4	5,294
(=) Filter 8: Total assets and equity greater than zero in reporting year t-5	4,521
Total sample collected from S&P Capital IQ	4,521
(-) Companies without data for all variables used (manual treatment)	1,947
Final sample collected from S&P Capital IQ	2,574
(-) Companies with inconsistent information in both databases (S&P and BNDES)[ii]	59
Final sample 1 (mostly qualitative variables)	2,515
Beneficiary companies (treatment group)	1,537
Non-beneficiary companies (control group)	978
Final sample 2 (all available variables)	1,455
Beneficiary companies (treatment group)	477
Non-beneficiary companies (control group)	978

S&P = Standard & Poor.
[i] *= The number of observations excluded because they pertain to the financial and insurance sector (59,664-15,226 = 44,438) is high due to the classification of investment funds in this sector ("Financial"). They represented the vast majority of excluded observations.* [ii] *= Some companies that presented information on loans and financing in their balance sheets were not included in the Brazilian National Bank for Economic and Social Development (Banco Nacional de Desenvolvimento Econômico e Social [BNDES]) database. Most of these cases were large conglomerates or holding companies, in which the information regarding the Bank appears on the group's consolidated balance sheet, where the beneficiary company is a subsidiary. I excluded these companies from the sample, reducing it to 59 companies.*
Source: *Elaborated by the authors.*

It is necessary to acknowledge that the control group (non-beneficiary firms) likely included two distinct subgroups: (i) firms that applied for BNDES funding and were rejected; and (ii) firms that never applied for BNDES funding. This heterogeneity arises because the data do not allow observing loan applications that were not approved or identifying firms that did not apply. This limitation, common in studies using observational data without application records (e.g., Lazzarini et al. [2015]), may introduce bias in estimates because the control group is not restricted to firms actively seeking BNDES funding. To partially address this concern, I conduct a robustness check using propensity score matching (PSM) to create a more comparable control group. However, the results should be interpreted cautiously, since the control group may still include firms with no demand for BNDES loans.

This study uses variables that encompass quantitative and qualitative characteristics of firms, as detailed in Table 2. The dependent variable is a binary indicator, taking the value 1 for firms that accessed BNDES resources from 2002 to 2019 and 0 otherwise.

Table 2

Variables used in the analysis of the determinants of the Brazilian National Bank for Economic and Social Development (Banco Nacional de Desenvolvimento Econômico e Social [BNDES]) credit concession to companies

Variables	Definition
Dependent variable	
BNDES	Binary variable with value 1 for firms that raised funds from BNDES in the period 2002-2019 and 0 otherwise
Explanatory variables	
Qualitative variables	
Publicly traded company	Dummy variable with value 1 for publicly traded firms and 0 otherwise
Subsidiary	Dummy variable with 1 denoting firms with the status of operating subsidiary, acquired, liquidating, out of business, and reorganizing, and 0 if operating
Sector	There are 10: (1) Communication Services, (2) Consumer Discretionary, (3) Consumer Staples, (4) Energy, (5) Health Care, (6) Industrial, (7) Information Technology, (8) Materials, (9) Real Estate, and (10) Utilities
Region	There are five: (i) South, (ii) Southeast, (iii) Midwest, (iv) Northeast, and (v) North
Quantitative variables	
Age	Firm age based on the year since founding up to 2020
Profitability	Earnings before interest and taxes/lagged total assets
Size	Natural logarithm of total assets
Tangibility	Fixed assets/total assets
Broad tangibility	Long-term assets (fixed assets, intangible assets, and long-term investments)/total assets
Leverage	Financial liabilities/total assets
Immediate liquidity	Short-term cash/total assets
Current liquidity	Current assets/current liabilities

Source: *Elaborated by the authors.*

The explanatory variables focus on access to financial markets and organizational support, such as publicly traded firms and members of groups. A publicly traded company, indicating whether a firm traded shares on the Brazilian stock exchange (B3 S.A. – Brasil, Bolsa, Balcão) during the analysis period, reflects its ability to access alternative financing, with publicly listed firms typically facing fewer financial constraints. Group membership, identifying whether a firm is part of a conglomerate or a subsidiary of a parent company, may enable internal financial support, reducing reliance on subsidized credit. Additionally, the economic sector and regional location (South, Southeast, Midwest, North, and Northeast) capture structural disparities in credit access. Firms in less developed regions (North, Midwest, and Northeast) often rely more heavily on subsidized credit lines due to limited financial services and economic infrastructure.

The economic and financial indicators included in the analysis assess firms' ability to manage financial constraints and mitigate risks. Firm age reflects operational experience and cash flow predictability, with younger firms often facing greater financial constraints due to information asymmetries. Profitability measures a firm's internal capacity to generate capital, while size (total assets) influences its ability to provide collateral. Tangibility (fixed assets as a proportion of total assets) and broad tangibility (long-term assets as a proportion of total assets) are critical, as firms with higher tangible assets are perceived as less risky, increasing their credit eligibility. Liquidity variables, such as immediate liquidity (highly liquid resources) and current liquidity (overall short-term liquidity), indicate a firm's ability to meet obligations, with higher liquidity suggesting fewer financial constraints. Additionally, leverage, which reflects the proportion of debt relative to total assets, is an essential factor: firms facing greater financial constraints tend to have lower leverage due to their limited access to external financing. These indicators highlight the factors shaping access to subsidized credit and identify firms that rely more heavily on BNDES support to overcome barriers in private credit markets.

3.2 Binary and Multinomial Logistic Model

This study employs a binary logistic model, similar to the one proposed by Sousa and Ottaviano (2018), to analyze the determinants related to BNDES's allocation of loans and financing. The model allows for the assessment of the probability that a firm accesses BNDES resources based on its observable characteristics (both quantitative and qualitative) that directly influence its eligibility.

Binary logistic econometric model:

$$Prob\ (BNDES_i = 1 \mid X_i\ ) = f\ (\beta_0 + \beta' X_i) \qquad (1)$$

where: $Prob(BNDES_i = 1 \mid X_i\ )$ is the probability that firm i is a BNDES beneficiary considering its observable characteristics (X_i), $BNDES_i$ is a dummy variable with value of 1 if firm i accessed BNDES resources and 0 otherwise, $f\ (\cdot)$ is a logistic function that transforms the linear score into a probability, defined as $f\ (z) = \frac{1}{1+e^{-z}}$, where $z = \beta_0 + \beta' X_i$, β_0 is the intercept of the model, $\beta' X_i$ is a vector of coefficients (β') multiplied by the explanatory variables (X_i) of firm i, including observable characteristics such as publicly traded, group affiliation, sector, location, age, profitability, size, tangibility, broad tangibility, leverage, immediate liquidity, and current liquidity.

The logistic function converts the linear score (z) into a probability between 0 and 1, capturing the binary nature of the problem, where I analyze the event of obtaining BNDES financing or not. This model evaluates how specific firm characteristics, as well as sectoral and regional factors, influence the probability of accessing BNDES credit, providing a deeper understanding of the determinants of access to subsidized financing lines.

I also propose a multinomial logistic model to analyze the determinants of BNDES funding, considering subsamples of treated firms categorized by the number of times funding was granted. The multinomial logistic model follows the standard parameterization of the softmax function, generalizing binary logistic regression to multiple unordered discrete categories. In addition to the control group, composed of firms that never accessed BNDES resources, I defined five categories of treated firms: firms that accessed funding only once (CAP 1); between two and five times (CAP 2-5); between six and nine times (CAP 6-9); between 10 and 13 times (CAP 10-13); and between 14 and 18 times (CAP 14-18). This segmentation captures differences in the determinants of access based on the intensity of credit line usage.

The multinomial logistic econometric models are described as follows:

non-base categories

$$Prob\ (CAP_i = j \mid X_i) = \frac{\exp(\beta_{0j} + \beta_j{}' X_i)}{1 + \sum_{k=1}^{5} \exp(\beta_{0k} + \beta_k{}' X_i)}, \text{j} = 1, 2, 3, 4, 5 \qquad (2)$$

and base category (j = 0)

$$Prob\ (CAP_i = 0 \mid X_i) = \frac{1}{1 + \sum_{k=1}^{5} \exp(\beta_{0k} + \beta_k{}' X_i)} \qquad (3)$$

where: $Prob\ (CAP_i = j \mid X_i)$ is the probability that firm i belongs to funding category j given observable characteristics (X_i), CAP_i is the funding frequency category with six levels: CAP 0 (base category, j = 0), CAP 1 (j = 1), CAP 2-5 (j = 2), CAP 6-9 (j = 3), CAP 10-13 (j = 4), CAP 14-18 (j = 5), $\beta_j{}' X_i$ is the vector of category-specific coefficients for category j multiplied by the explanatory variables (X_i) of firm i, including observable characteristics such as publicly traded, group affiliation, sector, location, age, profitability, size, tangibility, broad tangibility, leverage, immediate liquidity, and current liquidity.

This multinomial approach complements the binary logistic model by allowing a more detailed analysis of the differences between firms that accessed credit at varying frequency levels. For instance, it enables an investigation into whether the characteristics influencing a firm that obtained credit only once differ from those determining credit access for firms that frequently relied on BNDES funding.

First, I analyzed a binary logistic econometric model using a cross-sectional sample of 2,515 firms. In this initial phase, I considered only qualitative explanatory variables and the quantitative variable “age,” since these data were uniformly available for all firms in the sample.

In the second phase, I included all explanatory variables in the models and reduced the sample to 1,455 firms (477 beneficiaries and 978 non-beneficiaries) due to the limited accounting data available in the database, particularly for treated firms. In the cross-sectional model, quantitative variables were calculated, such as the annual average for each firm. For the control group, these averages covered the period from 2002 to 2019, or with available data. For treated firms, averages were calculated using data from before the first BNDES funding, ensuring the variables reflected pre-intervention conditions.

Finally, I applied a multinomial logistic model and analyzed it using a sample of 1,448 firms and all explanatory variables. The multinomial model's objective was to explore the determinants of credit allocation, since firms access funding at different frequencies. This approach helps to understand how firm characteristics influence the likelihood of obtaining BNDES loans based on the number of times these are received.

I used the stepwise method to present the results with a 5% statistical significance level. This method identifies the best set of explanatory variables for predicting the dependent variable, avoiding issues like overfitting and ensuring greater generalizability of the model (Fávero & Belfiore, 2017).

The evaluation metrics for the binary logistic models included accuracy, sensitivity (the proportion of beneficiary firms correctly identified by the model), and specificity (the proportion of non-beneficiary firms correctly identified by the model), using a 50% cutoff. I chose a cutoff because it is often used as a standard reference point in binary classification models to maximize overall model accuracy, assuming that the costs of misclassification errors (false positives and false negatives) are equivalent (Fávero & Belfiore, 2017).

This choice is particularly suitable when the goal is to understand general patterns of credit allocation, and there is no evidence suggesting the need to prioritize one type of error over another. If significant differences existed in the costs associated with false positives (classifying a non-beneficiary firm as a beneficiary) and false negatives (classifying a beneficiary firm as a non-beneficiary), the cutoff could be adjusted to reflect these priorities.

I used a confusion matrix for the multinomial logistic models, providing detailed information about the model's performance in each category. This method enables the evaluation of accuracy in contexts of uneven class distribution, ensuring a more precise interpretation of overall accuracy. Classifications in the confusion matrix were based on the criterion of the highest predicted probability, assigning each observation to the category with the highest estimated probability. This approach ensures that classifications directly reflect the model's estimates, maximizing consistency between predictive results and estimated probabilities while offering a more robust view of the model's overall performance.

4. RESULTS AND DISCUSSION

4.1 Descriptive Statistics

Tables 3 and 4 present descriptive statistics of the full sample (n = 2,515) and refined financial-data sample (n = 1,455), respectively. These establish baseline patterns for testing the hypotheses: Table 3 compares firm characteristics between BNDES beneficiaries (treatment) and non-beneficiaries (control), while Table 4 enables granular analysis of financial determinants through a subsample with complete accounting data. Together, they reveal critical continuities and divergences in allocation patterns across regional, sectoral, and firm-level dimensions.

Table 3

Descriptive statistics of the binary model: final sample 1, treatment group, and control group

Panel A										
	Total sample			**Treatment group**			**Control group**			**Difference**
Quantitative variable	**n**	**Mean**	**SD**	**n**	**Mean**	**SD**	**n**	**Mean**	**SD**	**t-test**
Age	2,515	37.09	28.08	1,537	40.66	30.12	978	31.49	23.49	9.168***

Panel B							
Dummy variables	**n**	**%**	**n**	**%**	**n**	**%**	**z-test**
Pub. Traded	217	0.086	166	0.108	51	0.052	0.056***
Subsidiary	1,091	0.434	715	0.465	376	0.384	0.081***
Sector 1 – Communication Services	73	0.029	35	0.023	38	0.039	-0.016**
Sector 2 – Consumer Discretionary	308	0.122	173	0.113	135	0.138	-0.025
Sector 3 – Consumer Staples	303	0.120	237	0.154	66	0.067	0.087***
Sector 4 – Energy	63	0.025	42	0.027	21	0.021	0.006
Sector 5 – Health Care	124	0.049	67	0.044	57	0.058	-0.014*
Sector 6 – Industrials	634	0.252	394	0.256	240	0.245	0.011
Sector 7 – Information Technology	88	0.035	51	0.033	37	0.038	-0.005
Sector 8 – Materials	277	0.110	186	0.121	91	0.093	0.028**
Sector 9 – Real Estate	188	0.075	23	0.015	165	0.169	-0.154***
Sector 10 – Utilities	457	0.182	329	0.214	128	0.131	0.083***
Region 1 – South	611	0.243	393	0.256	218	0.223	0.033*
Region 2 – Southeast	1,682	0.669	997	0.649	685	0.700	-0.051***
Region 3 – Midwest	75	0.030	47	0.031	28	0.029	0.002
Region 4 – Northeast	135	0.054	92	0.060	43	0.044	0.016*
Region 5 – North	12	0.005	8	0.005	4	0.004	0.001

Notes: *Table 3 reports descriptive statistics for the final sample 1 (n = 2,515), including the treatment group (firms that received Brazilian National Bank for Economic and Social Development [Banco Nacional de Desenvolvimento Econômico e Social] funding) and the control group (non-recipients). The quantitative variable (firm age) is shown with mean and standard deviation (SD). Dummy variables are presented as proportions.*

The last column reports the difference in means (t-test) for continuous variables and the difference in proportions (z-test) for binary variables, calculated as treatment minus control. For definitions of all variables, see Table 2.
*Statistical significance is indicated by *** p < 0.01, ** p < 0.05, and * p < 0.10.*
Source: *Elaborated by the authors.*

Table 4
Descriptive statistics of the binary model for all explanatory variables: final sample 2, treatment group, and control group

Panel A

	Total sample			Treatment group			Control group			Difference
Quantitative variables	**n**	**Mean**	**SD**	**n**	**Mean**	**SD**	**n**	**Mean**	**SD**	**t-test**
Age	1,455	34.24	27.61	477	39.83	33.91	978	31.51	23.49	8.32***
Profitability	1,455	-0.03	4.27	477	0.17	4.53	978	-0.12	4.14	0.28
Size	1,455	11.91	2.08	477	11.95	2.26	978	11.89	1.99	0.06
Tangibility	1,455	0.33	0.29	477	0.40	0.30	978	0.29	0.28	0.11***
Broad tangibility	1,455	0.47	0.29	477	0.51	0.29	978	0.46	0.29	0.05***
Leverage	1,455	0.51	5.49	477	0.69	9.29	978	0.42	1.65	0.27
Immediate liquidity	1,455	0.10	0.12	477	0.12	0.15	978	0.09	0.10	0.03***
Current liquidity	1,455	8.59	39.88	477	4.49	19.75	978	10.59	46.52	-6.10***

Panel B

Dummy variables	**n**	**%**	**n**	**z-test**	**n**	**%**	**z-test**
Pub. Traded	182	0.125	131	0.222***	51	0.052	0.222***
Subsidiary	625	0.430	249	0.138***	376	0.384	0.138***
Sector 1 – Communication Services	57	0.039	19	0.001	38	0.039	0.001
Sector 2 – Consumer Discretionary	194	0.133	59	-0.014	135	0.138	-0.014
Sector 3 – Consumer Staples	99	0.068	33	0.002	66	0.067	0.002
Sector 4 – Energy	30	0.021	9	-0.003	21	0.021	-0.003
Sector 5 – Health Care	74	0.051	17	-0.023*	57	0.058	-0.023*
Sector 6 – Industrials	342	0.235	102	-0.032	240	0.245	-0.032
Sector 7 – Information Technology	58	0.040	21	0.006	37	0.038	0.006

Sector 8 – Materials	144	0.099	53	0.018	91	0.093	0.018
Sector 9 – Real Estate	175	0.120	10	-0.148***	165	0.169	-0.148***
Sector 10 – Utilities	282	0.194	154	0.192***	128	0.131	0.192***
Region 1 – South	340	0.234	122	0.033	218	0.223	0.033
Region 2 – Southeast	979	0.673	294	-0.084***	685	0.700	-0.084***
Region 3 – Midwest	37	0.025	9	-0.010	28	0.029	-0.010
Region 4 – Northeast	92	0.063	49	0.059***	43	0.044	0.059***
Region 5 – North	7	0.005	3	0.002	4	0.004	0.002

Notes: *Table 4 reports descriptive statistics for the final sample 2 (n = 1,455), including the treatment group (firms that received Brazilian National Bank for Economic and Social Development [Banco Nacional de Desenvolvimento Econômico e Social] funding) and the control group (non-recipients). The quantitative variables are shown with mean and standard deviation (SD). Dummy variables are presented as proportions. The last column reports the difference in means (t-test) for continuous variables and the difference in proportions (z-test) for binary variables, calculated as treatment minus control. For definitions of all variables, see Table 2.*

*Statistical significance is indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.*

Source: *Elaborated by the authors.*

The descriptive analysis reveals patterns aligned with BNDES's dual mandate, though not all hypotheses are uniformly supported. Regional distribution shows that firms in the historically underserved Northeast are consistently overrepresented among BNDES beneficiaries. In the full sample (Table 4), 6% of beneficiary firms are from the Northeast vs. 4.4% in the control group, indicating a higher likelihood of funding in this region. This partially supports H_1, consistent with the Bank's mission to reduce regional inequalities (Ehrl et al., 2022; IBGE, 2023; Resende, 2013). However, the North and Midwest regions do not exhibit the same advantage, suggesting that the Bank's regional focus is targeted rather than generalized.

Sectoral patterns provide qualified support for H_2 (sectoral priority). The utilities sector is a major recipient of BNDES credit in both samples. In the expanded sample with financial data (Table 4), utilities comprise about 32% of beneficiary firms (vs. ~19% of all firms), underscoring BNDES's emphasis on infrastructure and public utility projects. This confirms that sectors tied to long-term infrastructure – especially electricity and related utilities – have higher odds of funding, which aligns with the Bank's strategic mandate.

Other industrial sectors also show elevated participation among beneficiaries: for example, in the full sample (Table 3), consumer staples firms were 8.7% more frequent among beneficiaries than non-beneficiaries, and energy firms showed a slight overrepresentation. However, some differences diminished once financial variables were considered (Table 4). In the refined sample, the consumer staples and energy sectors lost their earlier prominence (falling to parity with or below their share in controls), suggesting that firm characteristics outside the core policy priorities might have driven initial sectoral advantages. Crucially, utilities remained a top beneficiary sector, consistent with BNDES's known focus on infrastructure investment (Barboza et al., 2023; Frischtak et al., 2017; Gomes & Valle, 2023). Conversely, the real estate sector is persistently underrepresented among funded firms (e.g., only ~2% of beneficiaries, far below its share in the economy), indicating a deliberate exclusion of non-priority sectors.

The evidence challenges H_3 at the firm level, which predicts that financially constrained firms are more likely to receive BNDES funding. On average (Table 3), funded firms are older (~40 years vs. ~31 years for non-beneficiaries), more likely to be listed companies (about 11% vs. 5%), and more frequently subsidiaries of corporate groups (46% vs. 38%). These patterns are inconsistent with the expectation that the bank primarily supports small, young, financially constrained firms (Sousa & Ottaviano, 2018). Instead, the profile suggests a preference for more established, lower-risk firms. This aligns with the concerns of Bonomo et al. (2015) and Lazzarini et al. (2015), who argue that BNDES funding tends to flow to firms that are less financially constrained, potentially due to risk-averse lending behavior and elite capture. In Table 4, tangibility (40% vs. 29%), broad tangibility (51% vs. 46%), and immediate liquidity (12% vs. 9%) are significantly higher among beneficiaries, further reinforcing this profile of financial solidity rather than constraint.

This paradox – BNDES channeling credit to ostensibly lower-risk, well-connected firms – suggests tension between the Bank's developmental mandate and its apparent risk aversion. It underlines the need for multivariate analysis to determine whether these patterns persist when controlling for interrelated factors.

4.2 Results of the Regressions

I estimated binary logistic regression models identifying which firm characteristics significantly predicted the likelihood of receiving BNDES credit. The baseline model

(Table 5) includes qualitative attributes (regional dummies, sector dummies, listing status, group affiliation) plus firm age. Consistent with the descriptive findings, the probability of BNDES funding is higher for publicly traded firms, subsidiaries, and older firms (coefficients positive and significant).

Table 5

Binary model results for qualitative variables plus the age variable

Dependent variable: BNDES	**Coeff.**	**P>z**
Pub. Traded	0.719	0.000
Subsidiary	0.295	0.002
Age	0.013	0.000
Sector 3 – Consumer Staples	1.094	0.000
Sector 4 – Energy	0.608	0.034
Sector 6 – Industrials	0.392	0.001
Sector 8 – Materials	0.478	0.002
Sector 9 – Real Estate	-1.900	0.000
Sector 10 – Utilities	0.966	0.000
Constant	-0.531	0.000
Observations	2,515	
Pseudo R^2	0.106	
Prob.	0.000	
Hosmer-Lemeshow χ^2 (8)	13.98	
Prob. > χ^2	0.082	
AUROC	0.6952	
Accuracy (50% cutoff)	67.32%	
Sensitivity (50% cutoff)	91.15%	
Specificity (50% cutoff)	29.86%	

Notes: *See Table 2 for variable definitions. I presented the results using the stepwise method, considering a 5% statistical significance level for the variables: publicly traded company (Pub. Traded), group membership (Subsidiary), age, economic sector, and regional location.*
AUROC = area under the receiver operating characteristic curve; BNDES = Brazilian National Bank for Economic and Social Development (Banco Nacional de Desenvolvimento Econômico e Social); P>z = p-values from z-tests of coefficient significance.
Source: *Elaborated by the authors.*

This result is striking because, as noted by Bonomo et al. (2015) and Lazzarini et al. (2015), publicly listed or conglomerate-affiliated companies typically face fewer credit constraints due to their access to equity and internal capital markets. My evidence thus echoes those concerns: BNDES, in practice, favored firms that were already relatively financially secure, a controversial outcome given the Bank's mission. Moreover, the positive coefficient of "Age" indicates that mature firms had greater odds of receiving subsidized loans. While older companies might seek BNDES credit for expansion or modernization, this pattern implies that younger firms, which Sousa and Ottaviano (2018) argue are more dependent on external finance, were less consistently reached by BNDES support.

The baseline regression also highlights sectoral influences in line with H_2. Several sector dummy coefficients are positive and significant, indicating higher funding probabilities relative to the excluded baseline sectors (1, 2, 5, and 7). Notably, utilities show a strong positive effect ($p < 0.01$), reinforcing that related infrastructure firms enjoy privileged access to BNDES funds. Other industrial sectors, such as consumer staples, industrials, and materials, also have positive coefficients, suggesting these sectors inherently demand more long-term capital and are more likely to obtain BNDES support. These sectors often involve significant fixed investments (e.g., heavy industry, manufacturing supply chains, or agricultural processing) and align with development priorities requiring patient capital (Gomes & Valle, 2023).

In contrast, the real estate sector shows a significant negative coefficient (-1.900 in the baseline model), confirming that such firms are much less likely to secure BNDES financing. This may reflect policy choices (e.g., reliance on other housing finance programs) or higher perceived risk in real estate, consistent with its non-priority status observed in the descriptive variables. The regression's overall fit is modest (pseudo R^2 ~0.11, area under the receiver operating characteristic curve [AUROC] ~0.70, Hosmer-Lemeshow = 13.98), indicating that while these qualitative factors matter, additional variables (particularly financial metrics) could improve explanatory power.

Accordingly, I extended the model to include firms' financial characteristics – profitability, size, asset tangibility, broad tangibility, leverage, immediate liquidity, and current liquidity – alongside the earlier variables (Table 6). This augmented model yielded a substantially better fit (pseudo $R^2 \approx 0.20$, AUROC ≈ 0.79, Hosmer-Lemeshow = 10.80), offering more profound insight into BNDES's selection criteria. Crucially, the signs of key variables confirmed a mix of developmental targeting and risk screening.

Table 6
Binary model results for all explanatory variables

Dependent variable: BNDES	**Coeff.**	**P>z**
Pub. Traded	2.260	0.000
Subsidiary	0.680	0.000
Sector 2 – Consumer Discretionary	-0.409	0.046
Sector 5 – Health Care	-0.662	0.031
Sector 9 – Real Estate	-1.691	0.000
Sector 10 – Utilities	0.903	0.000
Region 4 – Northeast	0.823	0.001
Age	0.012	0.000
Size	-0.168	0.000
Tangibility	1.022	0.000
Immediate liquidity	3.136	0.000
Constant	-0.527	0.216
Observations	1,455	
Pseudo R^2	0.204	
Prob.	0.000	
Hosmer-Lemeshow χ^2 (8)	10.80	
Prob. > χ^2	0.214	
AUROC	0.792	
Accuracy (50% cutoff)	77.04%	
Sensitivity (50% cutoff)	48.43%	
Specificity (50% cutoff)	91.00%	

Notes: *See Table 2 for variable definitions. I used the stepwise method to present the results, considering a 5% statistical significance level for the variables: publicly traded company (Pub. Traded), group membership (Subsidiary), economic sector, regional*

location, age, size, tangibility (assets and broad), liquidity (immediate and current), profitability, and leverage.
AUROC = area under the receiver operating characteristic curve; BNDES = Brazilian National Bank for Economic and Social Development (Banco Nacional de Desenvolvimento Econômico e Social); P>z = p-values from z-tests of coefficient significance.
Source: *Elaborated by the authors.*

Regarding H_1, I find that being located in the Northeast region positively and significantly affects funding likelihood (e.g., Northeast dummy coefficient ~0.8, p = 0.001). This suggests that Northeast-based firms still have higher chances when controlling for firm size, sector, and financial health, affirming that BNDES did implement a regional priority (H_1), at least for this region. However, other less-developed regions (North or Midwest) are not significant predictors in the final model – the stepwise selection may have dropped them due to insignificance. Thus, the regional policy effect is present but not broad-based, reinforcing the earlier interpretation that H_1 is only partially supported.

The sectoral priorities remain evident. The utilities sector dummy stays positive and significant, underscoring that even after accounting for firm financial health, utilities firms are markedly more likely to receive BNDES loans. This is entirely consistent with H_2. I also note that consumer discretionary firms have a negative coefficient in the extended model (-0.409, $p < 0.05$), indicating they are less likely to be funded. This might be explained by the nature of those industries (e.g., retail, services), relying more on private credit or equity and less on subsidized long-term loans.

The health care sector similarly shows a significant negative coefficient, which can be interpreted in light of the Brazilian National Health System (Sistema Único de Saúde) and direct government funding for healthcare infrastructure, areas where BNDES plays a limited role. In contrast, no other sector coefficients besides utilities stand out firmly in the final model, since some earlier sector effects (like consumer staples or energy) were muted after adding financial controls. Overall, H_2 is confirmed: the regressions demonstrate that belonging to a priority sector (notably utilities/infrastructure) increases a firm's funding probability, whereas being in non-priority sectors can hinder access.

Including financial variables provides the clearest test of H_3, and the results largely contradict that hypothesis. If BNDES were targeting financially constrained firms, one would expect positive effects for indicators of constraint (small size, low profitability, low collateral, etc.). Instead, I observe a mix of the impacts: smaller firm size does emerge as significant (with the size variable's coefficient negative at $p < 0.01$), meaning smaller firms are more likely to get BNDES loans. This finding is consistent with the bank's public stance of supporting SMEs and suggests some success in reaching companies that lack scale and might face greater credit frictions (Barboza et al., 2023). However, other financial indicators tell a different story. Age remains a positive predictor even alongside size, reinforcing that BNDES favors established firms over young ones. Tangibility has a strongly positive coefficient ($p < 0.01$), indicating that firms with more collateral assets are more likely to receive credit, the opposite of what is expected if low-tangibility (highly constrained) firms were prioritized.

The results align with findings by Lazzarini et al. (2015) that BNDES tends to select firms with solid collateral to mitigate default risk. Likewise, immediate liquidity (a high cash ratio) is associated with a significantly higher funding probability. A firm with ample liquid assets is arguably less financially constrained, yet BNDES seems to prefer such liquidity-rich firms, perhaps viewing liquidity as a sign of financial stability.

Notably, neither profitability nor leverage significantly impacted the final model (they were dropped in the stepwise selection), meaning there is no clear evidence that BNDES targets unprofitable firms or those with low debt capacity. In sum, the multivariate evidence does not support H_3 except for firm size. Instead, it suggests BNDES has been risk-averse, favoring smaller companies (fulfilling an SME focus to some extent) but also older ones, with greater collateral and liquidity.

This outcome highlights a core tradeoff: BNDES's allocation criteria seem to balance developmental goals with prudent lending. While such an approach safeguards the Bank's portfolio (by selecting lower-risk borrowers), it may come at the expense of excluding the most credit-constrained firms, a point that raises questions about how effectively the bank is mitigating market failures.

The control group's composition warrants caution in interpretation. Non-beneficiary firms likely include companies that applied for BNDES funding but were rejected and those that never sought it. This heterogeneity may confound the model's ability to distinguish actual eligibility patterns, partially explaining the observed sensitivity-specificity gap (48.43% vs. 91% in Table 6). In section 4.3, I present robustness tests to minimize this limitation.

Table 7 presents the results of the multinomial logistic regression model using sample 2 of 1,455 firms (477 beneficiaries and 978 non-beneficiaries) and all the explanatory variables. The model achieved an accuracy of 72.03%, with stronger predictive power for identifying "non-events." Table 8 displays the confusion matrix, which provides an assessment of the number of observations correctly classified in each category, as well as misclassifications. Notably, the model was particularly effective in classifying firms that did not access funding (category "No CAP"), correctly identifying 945 out of 978 non-beneficiary firms. This performance underscores the robustness of the whole model in capturing recurring patterns among firms that did not access BNDES credit.

Table 7

Multinomial model results for all explanatory variables

	CAP 1	**CAP 2-5**	**CAP 6-9**	**CAP 10-13**	**CAP 14-18**
	Coeff. **P>z**	**Coeff.** **P>z**	**Coeff.** **P>z**	**Coeff.** **P>z**	**Coeff.** **P>z**
Pub. Traded	2.14 0.00***	1.99 0.00***	2.30 0.00***	2.94 0.00***	2.33 0.00***
Subsidiary	0.85 0.00***	0.51 0.01**	0.79 0.02**	1.38 0.00**	0.20 0.76
Sector 9 – Real Estate	-0.95 0.02**	-2.43 0.00***	-17.50 0.99	-16.36 0.99	-16.99 0.99
Sector 10 – Utilities	1.33 0.00***	0.81 0.00***	-0.09 0.84	0.19 0.76	-17.49 0.99
Region 2 – Southeast	0.52 0.02**	0.06 0.80	-0.93 0.01**	0.18 0.73	-1.50 0.02**
Region 4 – Northeast	1.37 0.00***	0.66 0.07*	0.10 0.85	1.57 0.04**	-0.04 0.98
Age	0.00 0.49	0.01 0.00***	0.02 0.00***	0.04 0.00***	0.02 0.02*
Size	-0.33 0.00***	-0.07 0.17	0.23 0.01**	0.25 0.05**	0.49 0.01**
Tangibility	0.70	1.22	2.80	5.51	6.51

	0.06*	0.02**	0.02**	0.03**	0.05**
Broad tangibility	0.76	-0.69	-1.40	-4.92	-5.51
	0.09*	0.18	0.28	0.07*	0.09*
Leverage	-1.59	0.01	-0.49	-0.72	0.01
	0.00***	0.64	0.45	0.41	0.96
Immediate liquidity	2.02	3.76	3.06	2.95	1.04
	0.01**	0.00***	0.04**	0.16	0.77
Constant	0.63	-2.41	-7.34	-10.36	-11.12
	0.27	0.00**	0.00***	0.00***	0.00***
Observations	1,455				
Pseudo R^2	0.2166				
Prob.	0.000				
LR χ^2 (60)	660.27				
Prob. > LR	0.000				
Deviance χ^2 (1390)	1345.90				
Prob. > deviance	0.797				
Accuracy	72.03%				

Notes: *See Table 2 for variable definitions. I used the stepwise method to obtain each model, considering a statistical significance level of 5%.*
CAP 1 = firms that accessed funding only once (1 year); CAP 2-5 = firms that accessed funding between 2 and 5 years; CAP 6-9 = firms that accessed funding between 6 and 9 years; CAP 10-13 = firms that accessed funding between 10 and 13 years; CAP 14-18 = firms that accessed funding between 14 and 18 years; LR = likelihood ratio; P>z = p-values from z-tests of coefficient significance.
*The results are presented based on rejecting the null hypothesis at the following significance levels: ***significant at 1%, **significant at 5%, and *significant at 10%.*
Source: *Elaborated by the authors.*

Table 8
Confusion matrix of the multinomial model

	Model-estimated classification (highest likelihood criterion)						
	No CAP	**CAP 1**	**CAP 2-5**	**CAP 6-9**	**CAP 10-13**	**CAP 14-18**	**Real total**
No CAP	945	13	12	5	3	0	978
CAP 1	127	68	6	2	0	1	204
CAP 2-5	124	15	26	0	8	0	173
CAP 6-9	31	2	12	2	4	0	51
CAP 10-13	13	1	8	6	7	0	35
CAP 14-18	9	0	2	2	1	0	14
Estimated total	1,249	99	66	17	23	1	1,455

No CAP = firms that did not access the Brazilian National Bank for Economic and Social Development (Banco Nacional de Desenvolvimento Econômico e Social) funding during the 2002-2019 period; CAP 1 = firms that accessed funding only once (1 year); CAP 2-5 = firms that accessed funding between 2 and 5 years; CAP 6-9 = firms that accessed funding between 6 and 9 years; CAP 10-13 = firms that accessed funding between 10 and 13 years; CAP 14-18 = firms that accessed funding between 14 and 18 years.
Source: *Elaborated by the authors.*

I based the classification in Table 8 on the criterion of the highest probability assigned to each observation. For each of the six estimated categories in Table 7 (including "No CAP"), I calculated the probability of belonging and classified each observation in the category with the highest probability estimate. This approach ensured a more accurate interpretation of overall accuracy while accounting for the limitations in distinguishing categories with fewer observations.

The multinomial logistic regression refines these findings by examining the intensity of BNDES use (no funding, one-time funding, or multiple funding events). The determinants observed in the binary model generally persist. Firms publicly listed, subsidiaries, or in the utilities sector consistently show higher probabilities of accessing BNDES credit, and repeatedly confirming a sustained relationship with the bank over time (Kayo et al., 2023).

Regarding regional effects, firms from the Northeast are overrepresented among both one-time and recurring beneficiaries, strengthening the evidence for a targeted regional priority (Ehrl et al., 2022). However, firms in the Southeast are more likely to receive one-time financing but less likely to become recurrent users, which may reflect their greater access to private capital markets.

The multinomial model also highlights that smaller firms are more likely to be one-time beneficiaries, whereas larger firms tend to receive multiple loans. This suggests that BNDES primarily acts as a long-term partner for large-scale firms, while it functions more as a one-time supporter of smaller enterprises (Barboza et al., 2023). Similarly, firm age positively affects repeated funding: older firms are more likely to maintain long-term relationships with the bank.

Nevertheless, this relationship may involve endogeneity bias, since firms that borrow frequently over the years tend to appear more mature in the model, creating a direct association between time/age and higher borrowing categories. This dynamic suggests caution in interpreting the effect of age, which may reflect recurrent borrowing rather than an initial preference by the BNDES.

In line with the binary model, tangibility and immediate liquidity remain strong predictors of repeated funding, underscoring the Bank's risk-averse approach that favors firms with robust balance sheets. Conversely, firms with high levels of intangible assets (broad tangibility) or lower collateral are less likely to become recurring beneficiaries: a pattern that reflects the Bank's preference for firms offering strong tangible guarantees (Cull et al., 2015; Lazzarini et al., 2015).

In prioritizing firms with lower default risks, the data confirm that BNDES's default rate is significantly lower than the national financial system's average, reflecting the Bank's conservative risk mitigation policies (BNDES, 2018).

Regarding leverage, the study found a significant negative relationship only for firms that borrow from BNDES on a one-time basis. This result can be interpreted in two ways: first, low initial leverage may reflect evidence of financial constraints, indicating that these firms have less access to other financing sources and rely more on subsidized credit. Alternatively, it may signal lower default risk, aligned with BNDES's conservative profile in selecting firms with a greater ability to meet their financial obligations.

However, the lack of significance for firms that borrow frequently contrasts with studies such as those by Bonomo et al. (2015), suggesting that leverage increases since BNDES intervenes in firms' capital structures due to the long-term nature and lower cost of subsidized credit. These results indicate that while BNDES may influence firms' leverage over time, the initial credit allocation decision may be more closely associated with other factors, such as tangibility and liquidity. As for the variable profitability, which was not statistically significant in any model presented, this study demonstrates that it is not a critical determinant of accessing resources through Brazil's leading development bank.

4.3 Robustness and Sensitivity Checks

I performed several checks to ensure the robustness of these results. First, to address potential selection bias in the sample (the fact that non-beneficiaries include firms that may never have applied for BNDES credit), I applied PSM. Treated firms (BNDES beneficiaries) were matched with similar non-beneficiaries based on the propensity to receive BNDES funding (using the baseline model predictors). The matching process resulted in a sample of 857 firms (382 control and 475 treated), smaller than the original sample but more balanced.

After matching, I re-ran the logistic regression on this matched sample (Table 9). The core determinants remained essentially unchanged. Publicly traded firms, group affiliation, and belonging to the utilities sector stay positive and highly significant, as do older age, high tangibility, high immediate liquidity, and small size. This confirms that my earlier conclusions are not driven by sample composition or observable differences between treated and control groups.

Table 9

Determinants of BNDES access – PSM-matched sample

Dependent variable: BNDES	**Coeff.**	**P>z**
Pub. Traded	1.285	0.000
Subsidiary	0.522	0.001
Sector 10 – Utilities	0.821	0.000
Age	0.012	0.000
Size	-0.178	0.000
Tangibility	1.116	0.000
Immediate liquidity	2.973	0.000
Constant	0.531	0.264
Observations	857	
Control group (n)	382	
Treatment group (n)	475	
Pseudo R^2	0.1101	
Prob.	0.000	

Notes: *See Table 2 for variable definitions. I used the stepwise method to present the results, considering a 5% statistical significance level for the variables: publicly traded company (Pub. Traded), group membership (Subsidiary), economic sector, regional location, age, size, tangibility (assets and broad), liquidity (immediate and current), profitability, and leverage. To address potential selection bias, I performed propensity score matching (PSM) using a logit model with nearest-neighbor matching (neighbor[2]), a caliper of 0.2 standard deviations, and common support restriction. The matching was based on Table 5's specification (publicly traded, subsidiary, sector, region, and age variables), resulting in matched treatment (Brazilian National Bank for Economic and Social Development [Banco Nacional de Desenvolvimento Econômico e Social] beneficiaries, n = 475) and control (non-beneficiaries, n = 382) groups. I then re-estimated this matched sample (n = 857) using the full specification from Table 6.*

P>z = p-values from z-tests of coefficient significance.

Source: *Elaborated by the authors.*

One noteworthy difference is that the Northeast regional effect disappears in the matched sample model. This suggests that once firms are matched based on other characteristics, being in the Northeast alone no longer adds additional explanatory power, possibly because the matching already pairs firms by region or because the sample size reduction limits detection. In practical terms, the evidence of regional targeting is sensitive to model specification: it was strong in the full sample, but less so in the matched subset. Nevertheless, the fact that all other key variables retained their sign and significance after PSM underscores the robustness of my main findings.

Second, I examined whether the results hold across different time sub-periods, given that BNDES's strategy may have evolved from 2002 to 2019. I divided the data into three phases: pre-peak (2002-2007), credit boom (2008-2014), and post-2014 contraction. I then re-estimated the complete logistic model for each period, with and without PSM (Tables 10 and 11).

Table 10

Determinants of BNDES access by period (unmatched samples)

		Period	
Variable	**2002-2007**	**2008-2014**	**2015-2019**
Pub. Traded	3.052***	1.608***	1.670**
Subsidiary	0.752*	0.565***	0.682*
Sector 8 – Materials	0.926*	-	-
Sector 7 – Information Technology	1.565*	-	-
Sector 9 – Real Estate	-	-1.872***	-
Sector 10 – Utilities	1.512***	0.410*	2.008***
Region 4 – Northeast	-	0.942***	0.878*
Age	0.033***	-	-
Size	0.192*	-0.136**	-0.440***
Tangibility	5.530***	0.819**	1.102**
Broad tangibility	-4.992***	-	-
Leverage	-	-	-1.494**
Immediate liquidity	-	3.032***	2.634**
Constant	-7.467***	-0.838	1.370
Observations	1109	1215	1087
Control group (n)	978	978	978
Treatment group (n)	131	237	109
Pseudo R^2	0.4920	0.1222	0.2689
Prob.	0.000	0.000	0.000

Notes: *See Table 2 for variable definitions. Results reflect period-stratified binary logistic regressions using the full specification from Table 6 on unmatched samples. The control group remains fixed at 978 non-beneficiaries across all periods, while treatment groups comprise first-time Brazilian National Bank for Economic and Social Development (Banco Nacional de Desenvolvimento Econômico e Social) beneficiaries within each economic phase: pre-peak (2002-2007; n = 131), credit boom (2008-2014; n = 237), and contraction (2015-2019; n = 109).*
*Statistical significance: *** $p < 0.01$, ** = $p < 0.05$, and * $p < 0.10$.*
Source: *Elaborated by the authors.*

Table 11

Determinants of BNDES access by period (PSM-matched samples)

	Period		
Variable	**2002-2007**	**2008-2014**	**2015-2019**
Pub. Traded	0.775**	0.690**	2.211***
Subsidiary	-	0.541***	-
Sector 6 – Industrials	-	-	0.989**
Sector 7 – Information Technology	-	-	-
Sector 9 – Real Estate	-	-	-
Sector 10 – Utilities	0.772*	-	1.876***
Region 4 – Northeast	-	-	-
Age	-	-	-
Size	-	-0.094*	-0.404***
Tangibility	5.878***	1.125***	-
Broad tangibility	-5.667***	-	-
Leverage	-1.134**	-	3.648***
Immediate liquidity	-	3.482***	3.421**
Constant	0.383	-0.114	3.648***
Observations	219	508	233
Control group (n)	99	271	130
Treatment group (n)	120	237	103
Pseudo R²	0.1303	0.0584	0.2352
Prob.	0.000	0.000	0.000

Notes: *See Table 2 for variable definitions. Results reflect period-stratified binary logistic regressions using the full specification from Table 6 on performed propensity score matching (PSM)-matched samples. Propensity score matching was applied separately for each period using a logit neighbor(2) caliper(0.2) common support, based on Table 5 variables (publicly traded, subsidiary, sector, region, and age). Treatment and control group sizes vary across periods due to common support requirements.*
*Statistical significance: *** p < 0.01, ** p < 0.05, and * p < 0.10.*
BNDES = Brazilian National Bank for Economic and Social Development (Banco Nacional de Desenvolvimento Econômico e Social).
Source: *Elaborated by the authors.*

The determinants of credit access remain qualitatively similar in most periods, but there are some noteworthy shifts. The Northeast dummy is positive and significant during the boom (2008-2014) and contraction (2015-2019) phases, but not in the early period. This indicates that regional targeting (H_1) became more pronounced after 2008, perhaps due to stronger government directives or specific programs aimed at reducing regional inequalities in the later years.

Firm size shows an interesting reversal: in the earliest period, larger firms were more likely to receive funding (contrary to H_3), whereas in the subsequent periods, the coefficient on size becomes negative (smaller firms are more likely) and significant. This pattern implies that BNDES's focus shifted over time toward smaller enterprises, consistent with policy changes around 2008-2009, when the Bank expanded SME credit lines, and from 2015, when large-scale investments waned. Despite these dynamics, listing status, group affiliation, and the utilities sector remained positive drivers in virtually all sub-periods, confirming their central role in BNDES allocation across different political and economic cycles.

The adverse effect of the real estate sector was most pronounced during the credit boom, which is aligned with the observation that even at the peak of BNDES disbursements, specific non-priority sectors were systematically left out. These temporal consistency checks reinforce that my main conclusions are not driven by a particular era: BNDES's tendency to favor certain regions (notably the Northeast in later years), strategic sectors, and relatively safer firms holds over the 18 years, albeit with some adjustments in emphasis.

The analysis of BNDES credit allocations from 2002 to 2019 reveals a complex interplay between development objectives and prudent lending practices. H_1 (regional) is partially upheld: BNDES did channel funds to less-developed regions, most clearly to the Northeast, though not evenly to all target regions. H_2 (sectoral) is confirmed, with a clear prioritization of infrastructure-related sectors, especially utilities, and reduced emphasis on sectors outside its strategic scope. H_3 (financial constraints) is largely refuted: instead of systematically favoring small, young, high-need firms, BNDES favored firms that are smaller in scale but also older, more liquid, and asset-rich, indicating a bias towards lower-risk profiles.

These findings suggest that BNDES's allocation strategy reconciles its developmental mission with financial sustainability. The result is an allocation paradox: the bank supports projects in priority regions and sectors (advancing public policy goals) while simultaneously selecting firms that can offer collateral and credibility (mitigating credit risk). This nuanced behavior highlights the challenge development banks face in reaching the truly constrained frontier of firms. It also contributes to the debate in the literature by empirically demonstrating how a central development bank's practice may diverge from its theoretical mandate, supporting some arguments that BNDES funds firms that potentially could access private capital (Lazzarini et al., 2015) and echoing concerns about the limited impact on alleviating financial frictions (Bonomo et al., 2015; Cull et al., 2015). However, the Bank's influence appears through other channels, particularly its regional and sectoral development initiatives.

5. FINAL REMARKS

Brazil has one of the world's largest development banks, and this study aimed to map patterns in credit allocation by BNDES from 2002 to 2019. Using binary and multinomial logistic models, I explored the dynamics of credit access among firms, focusing on understanding the bank's role in mitigating financial constraints and promoting regional and sectoral development.

The analysis included a robust sample of 2,515 firms, of which 1,537 were BNDES beneficiaries, and 978 were non-beneficiaries. The results indicated that the variables public listing, being a subsidiary, operating in specific sectors (especially public utilities), and being located in the Northeast region increased the probability of obtaining BNDES funding. These findings highlight the influence of specific firm characteristics and regional and sectoral contextual factors in accessing BNDES credit.

The financial variables size, age, tangibility, and immediate liquidity also played significant roles. Smaller firms with higher immediate liquidity and tangible assets were more likely to access the Bank's resources. However, the preference for older companies with higher liquidity and tangibility suggests a conservative approach that might limit the Bank's impact in supporting financially vulnerable firms.

Additionally, the sectoral analysis revealed significant disparities: while utilities were more likely to receive funding, sectors such as real estate, health care, and discretionary consumer goods faced additional barriers. These differences could be related to sector-specific characteristics, such as perceived risks, specific financing requirements, and alignment with BNDES's strategic priorities.

Although the favoritism given to publicly traded firms and subsidiaries of conglomerates has raised criticisms of BNDES's policies, particularly in the context of financial constraints, it is essential to consider that the Bank may prioritize projects that, even involving less constrained firms, have significant social, environmental, and/or strategic impacts. This perspective highlights the complexity of balancing market failure mitigation with the efficient allocation of public resources.

Among the limitations of this study are the exclusion of BNDES participation through equity acquisition (carried out by BNDES-Par) due to the small number of observations, the challenge of constructing an entirely genuine control group, and the omission of subsidized credit provided by other public/governmental national or international institutions, such as the Financier of Studies and Projects (Financiadora de Estudos e Projetos), the FNE, the Agricultural Bank of China, or the International Bank for Reconstruction and Development, among others.

This study contributes to understanding the determinants and patterns of BNDES credit allocation, highlighting the diverse factors that shape this process. The findings offer insights for refining the bank's policies to better balance financial prudence with inclusive support for more vulnerable firms and regions. Future research could build on this by incorporating information on the financed projects, such as loan amounts, financial conditions, and project purposes (e.g., modernization, working capital, expansion, or innovation), to assess how these characteristics influence credit decisions and translate into long-term economic and social outcomes.

REFERENCES

Almeida, H. T. V., & Braga, J. P. C. H. (2020). The Brazilian Development Bank impact thesis: A methodology to address the development goals of the knowledge and sustainable new economy. F. Matos, V. Vairinhos, I. Salavisa, L. Edvinsson, & M. Massaro (Eds.), *Knowledge, people, and digital transformation. Contributions to management science*. Springer. https://doi.org/10.1007/978-3-030-40390-4_16

Alti, A. (2003). How sensitive is investment to cash flow when financing is frictionless? *The Journal of Finance*, *58*(2), 707-722. https://doi.org/10.1111/1540-6261.00542

Antunes, A., Cavalcanti, T., & Villamil, A. (2015). The effects of credit subsidies on development. *Economic Theory*, *58*(1), 1-30. https://doi.org/10.1007/s00199-014-0808-0

Banco Nacional de Desenvolvimento Econômico e Social. (2018, October 19). *Fato: A taxa de inadimplência do BNDES é inferior à do Sistema Financeiro Nacional*. https://agenciadenoticias.bndes.gov.br/detalhe/fatoboato/Fato-A-taxa-de-inadimplencia-do-BNDES-e-inferior-a-do-Sistema-Financeiro-Nacional/

Banerjee, A. V., & Duflo, E. (2014). Do firms want to borrow more? Testing credit constraints using a directed lending program. *The Review of Economic Studies*, *81*(2), 572-607. https://doi.org/10.1093/restud/rdt046

Barboza R. M., Pessoa, S., Roitman, F., & Ribeiro, E. P. (2023). What have we learned about national development banks? Evidence from Brazil. *Brazilian Journal of Political Economy*, *43*(3), 646-669. https://doi.org/10.1590/0101-31572023-3467

Barboza, R. M., & Vasconcelos, G. F. R. (2019). Measuring the aggregate effects of the Brazilian Development Bank on investment. *The North American Journal of Economics and Finance*, *47*, 223-236. https://doi.org/10.1016/j.najef.2018.12.013

Bonomo, M., Brito, R. D., & Martins, B. (2015). The after crisis government-driven credit expansion in Brazil: A firm level analysis. *Journal of International Money and Finance*, *55*, 111-134. https://doi.org/10.1016/j.jimonfin.2015.02.017
Campos, R. O. (1969). A retrospect over Brazilian development plans. In H. S. Ellis (Ed.), *The economy of Brazil*. University of California Press. https://doi.org/10.1525/9780520325906-017
Cavalcanti, T., & Vaz, P. H. (2017). Access to long-term credit and productivity of small and medium firms: A causal evidence. *Economics Letters*, *150*, 21-25. https://doi.org/10.1016/j.econlet.2016.10.043
Cipoletta Tomassian, G., & Abdo, T. (2022). *Development bank financing in the context of the COVID-19 crisis in Latin America and the Caribbean*. Economic Commission for Latin America and the Caribbean. https://hdl.handle.net/11362/47882
Cull, R., Li, W., Sun, B., & Xu, L. C. (2015). Government connections and financial constraints: Evidence from a large representative sample of Chinese firms. *Journal of Corporate Finance*, *32*, 271-294. https://doi.org/10.1016/j.jcorpfin.2014.10.012
Ehrl, P., Pereira, G. A., & Zanchi, V. V. (2022). Lending and regional growth in Brazil: The development bank BNDES versus private and public banks. *Estudos Econômicos*, *52*(3), 503-532. https://doi.org/10.1590/1980-53575232pgv
Fávero, L. P. L., & Belfiore, P. (2017). *Manual de análise de dados: estatística e modelagem multivariada com Excel®, SPSS® e Stata®*. Elsevier.
Frischtak, C., Pazarbasioglu, C., Byskov, S., Perez, A. H., & Carneiro, I. A. (2017). *Towards a more effective BNDES*. World Bank. https://openknowledge.worldbank.org/handle/10986/28398
Gomes, M. C., & Valle, M.R. (2023). Do companies that benefit from development banks' funding invest more? New evidence from Brazil. *Economic Modelling*, *127*, 106476. https://doi.org/10.1016/j.econmod.2023.106476
Griffith-Jones, S., Ocampo, J. A., Rezende, F., Schclarek, A., & Brei, M. (2018). The future of national development banks. In S. Griffith-Jones & J. A. Ocampo (Eds.), *The future of national development banks, initiative for policy dialogue.* Oxford University Press. https://doi.org/10.1093/oso/9780198827948.003.0001
Hadlock, C. J., & Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies*, *23*(5), 1909-1940. https://doi.org/10.1093/rfs/hhq009
Instituto Brasileiro de Geografia e Estatística (2023, June 28). *Between 2010 and 2022, Brazilian population grows 6.5%, reaches 203.1 million*. https://agenciadenoticias.ibge.gov.br/en/agencia-news/2184-news-agency/news/37245-between-2010-and-2022-brazilian-population-grows-6-5-reaches-203-1-million#:~:text=Highlights,million%20persons%20in%20the%20period.
Kaplan, S. N., & Zingales, L. (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints? *The Quarterly Journal of Economics*, *112*(1), 169-215. https://doi.org/10.1162/003355397555163
Kayo, E. K., Silva, W. E., & Martelanc, R. (2023). The two faces of subsidized loans. *Finance Research Letters*, *56*, 104149. https://doi.org/10.1016/j.frl.2023.104149
Kring, W. N., & Gallagher, K. P. (2019). Strengthening the foundations? Alternative institutions for finance and development. *Development and Change*, *50*(1), 3-23. https://doi.org/10.1111/dech.12464

La Porta, R., Lopez-De-Silanes, F., & Shleifer, A. (2002). Government ownership of banks. *The Journal of Finance*, *57*(1), 265-301. https://doi.org/10.1111/1540-6261.00422

Lazzarini, S. G., Musacchio, A., Bandeira-de-Mello, R., & Marcon, R. (2015). What do state-owned development banks do? Evidence from BNDES, 2002-09. *World Development*, 66, 237-253. https://doi.org/10.1016/j.worlddev.2014.08.016

Levy-Yeyati, E. L., Micco, A., & Panizza, U. (2004). *Should the government be in the banking business? The role of state-owned and development banks* [Working Paper]. Social Science Research Network. https://doi.org/10.2139/ssrn.1818717

Quaye, F. M., & Hartarska V. (2016). investment impact of microfinance credit in Ghana. *International Journal of Economics and Finance*, *8*(3), 137-150. https://doi.org/10.5539/ijef.v8n3p137

Resende, G. M. (2013). Regional development policy in Brazil: A review of evaluation literature. *Revista de Desenvolvimento Regional*, *18*(3), 202-225. https://www.redalyc.org/articulo.oa?id=552056834011

Simpasa, A., Shimeles, A., & Salami, A. O. (2015). Employment effects of multilateral development bank support: The case of the African Development Bank. *African Development Review*, *27*(S1), 31-43. https://doi.org/10.1111/1467-8268.12137

Sousa, F. L., & Ottaviano, G. I. P. (2018). Relaxing credit constraints in emerging economies: The impact of public loans on the productivity of Brazilian manufacturers. *International Economics*, *154*, 23-47. https://doi.org/10.1016/j.inteco.2017.11.002

Whited, T. M., & Wu, G. (2006). Financial constraints risk. *The Review of Financial Studies*, *19*(2), 531-559. https://doi.org/10.1093/rfs/hhj012

AUTHOR CONTRIBUTIONS

Matheus da Costa Gomes

Conceptualization: equal;
Data curation: equal;
Formal analysis: equal;
Funding acquisition: equal;
Investigation: equal;
Methodology: equal;
Writing – original draft: equal;
Writing – review and editing: equal.

CONFLICT OF INTEREST

The author declares that there is no conflict of interest.

DATA AVAILABILITY STATEMENT

The entire dataset supporting the results of this study can be made available upon request to its author.

GENERATIVE AI DISCLOSURE

The author declares that no generative artificial intelligence was used in any stage of the production of this manuscript (including research, writing, data analysis, formula generation, or the creation of graphic elements).

FUNDING

The author is grateful to the following institutions for funding this research project: Universidade Paulista (UNIP), Vice-Rectory for Graduate Studies and Research, under the Individual Research Program for Faculty Members (Programa Individual de Pesquisas para Docentes), Finance Code: 7-04-1194/2023.

Appendix A
Table 1
Descriptive statistics of the multinomial model for all explanatory variables: control group and treatment groups

Panel A

	No CAP (978)			CAP 1 (204)			CAP 2-5 (173)			CAP 6-9 (51)			CAP 10-13 (35)			CAP 14-18 (14)		
Quantitative variables	**n**	**Mean**	**SD**	**n**	**Mean**	**SD**	**n**	**Mean**	**SD**	**n**	**Mean**	**SD**	**n**	**Mean**	**SD**	**n**	**Mean**	**SD**
Age	978	31.51	23.49	204	25.13	24.08	173	40.62	33.68	51	56.94	33.07	35	86.14	29.18	14	66.21	23.10
Profitability	978	-0.12	4.14	204	-0.09	6.06	173	0.29	2.61	51	0.12	0.13	35	1.09	5.76	14	0.13	0.06
Size	978	11.89	1.99	204	11.12	1.98	173	12.07	2.35	51	13.24	1.95	35	13.62	1.65	14	13.56	1.53
Tangibility	978	0.29	0.28	204	0.43	0.35	173	0.36	0.27	51	0.42	0.23	35	0.40	0.19	14	0.41	0.19
Broad tangibility	978	0.46	0.29	204	0.57	0.33	173	0.46	0.27	51	0.49	0.23	35	0.44	0.19	14	0.44	0.21
Leverage	978	0.42	1.65	204	0.25	0.23	173	1.44	15.43	51	0.28	0.21	35	0.27	0.19	14	0.38	0.21
Immediate liquidity	978	0.09	0.10	204	0.12	0.14	173	0.14	0.16	51	0.10	0.15	35	0.10	0.10	14	0.09	0.11
Current liquidity	978	10.59	46.52	204	6.36	26.96	173	3.02	6.93	51	4.85	23.84	35	1.48	1.04	14	1.46	0.84

Panel B

Dummy variables	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
Pub. Traded	51	0.052	27	0.132	49	0.283	24	0.471	23	0.657	8	0.571
Subsidiary	376	0.384	122	0.598	80	0.462	24	0.471	19	0.543	4	0.286
Sector 1 – Communication Services	38	0.039	7	0.034	10	0.058	1	0.020	1	0.029	0	0.000
Sector 2 – Consumer Discretionary	135	0.138	18	0.088	27	0.156	5	0.098	8	0.229	1	0.071
Sector 3 – Consumer Staples	66	0.067	7	0.034	13	0.075	7	0.137	5	0.143	1	0.071
Sector 4 – Energy	21	0.021	3	0.015	4	0.023	2	0.039	0	0.000	0	0.000
Sector 5 – Health Care	57	0.058	9	0.044	4	0.023	3	0.059	1	0.029	0	0.000
Sector 6 – Industrials	240	0.245	38	0.186	45	0.260	9	0.176	5	0.143	5	0.357
Sector 7 – Information Technology	37	0.038	11	0.054	7	0.040	3	0.059	0	0.000	0	0.000
Sector 8 – Materials	91	0.093	12	0.059	16	0.092	11	0.216	7	0.200	7	0.500
Sector 9 – Real Estate	165	0.169	8	0.039	2	0.012	0	0.000	0	0.000	0	0.000
Sector 10 – Utilities	128	0.131	91	0.446	45	0.260	10	0.196	8	0.229	0	0.000
Region 1 – South	218	0.223	47	0.230	40	0.231	20	0.392	8	0.229	7	0.500
Region 2 – Southeast	685	0.700	126	0.618	114	0.659	25	0.490	23	0.657	6	0.429
Region 3 – Midwest	28	0.029	4	0.020	3	0.017	2	0.039	0	0.000	0	0.000
Region 4 – Northeast	43	0.044	26	0.127	14	0.081	4	0.078	4	0.114	1	0.071
Region 5 – North	4	0.004	1	0.005	2	0.012	0	0.000	0	0.000	0	0.000

Note: *See Table 2 for variable definitions.*

No CAP = firms that did not access the Brazilian National Bank for Economic and Social Development (Banco Nacional de Desenvolvimento Econômico e Social) funding during the 2002-2019 period; CAP 1 = firms that accessed funding only once (1 year); CAP 2-5 = firms that accessed funding between 2 and 5 years; CAP 6-9 = firms that accessed funding between 6 and 9 years; CAP 10-13 = firms that accessed funding between 10 and 13 years; CAP 14-18 = firms that accessed funding between 14 and 18 years; SD = standard deviation.