Winners x Loosers: Impact on Credit Behavior after an Uncertain Outcome in the Brazilian 2018 and 2022 Elections

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Highly contested elections, in which the outcome is not predictable, can amplify responses from the voters from either the winning or the losing side. We expect a change in financial behavior as a result after the election, where the voters of the elected candidate increase their purchases, especially of durable goods, in relation to the other voters. This increased consumption of durable and nondurable goods was captured in the corresponding credit operations. We used data from 2.3 million people provided by a Brazilian financial institution with presence throughout the country, referring to the period of highly contested Brazilian elections of 2018 and 2022. We show that voters residing in cities with a higher proportion of votes for the winning candidate increased their expenses after the elections, increasing their credit portfolio in real estate, vehicles, and general consumption. This behavior was consistent whether the winner was a left-wing or a right-wing politician. This behavior has an impact on the financial activity city-wide and, by extension, throughout the country.

Keywords: Administration, Finances, Behavior, Decision Making, Financial Institutions

INTRODUCTION

Presidential elections are known to have big effects on the economy in the event of a President change. Changes in policies and leadership can generate stimulus on different government investments of money, taxation, and financial regulations, implying movements in the economy not just to the big investors but also in investments and money search and credit financing in the households all over the country (Julio & Yook, 2012). That way, in elections that have uncertainty about the outcomes, the individual political preferences could be a deciding factor on financial decisions.

We show that political preferences impact credit market decisions. After the presidential elections results, the positivity of the voters of the elected candidate makes them search for more credit, related to increase in purchases of durable and non-durable goods. To the voters of the losing party, because their negativity towards the expectations of the future of the economy, makes them reduce the purchases and credit. We can separate the effects of political preference into other individual characteristics such as gender, age, marital status, number of children, educational level, income, and occupation, bringing to discussion this new factor that could separate the choices of individuals.

We used open data from results of the presidential election, grouped by city as a proxy for the probability of a voter residing in this city to have a political preference for a candidate. Both Brazilian Presidential elections of 2018 and 2022 were marked by the unpredictability of results. Due to the closeness of the number of estimated votes, the uncertainty about the future president and government policy until the date of the results provides us a natural experimental framework to separate the effects of the economic growth and the politics uncertainty beliefs. In 2014, the left candidate Dilma Rousseff was re-elected with 51,6% of the votes. In 2018, the right candidate Jair Bolsonaro had 55,1% of the votes making a change of political government and in 2022, the left candidate Luis Inácio Lula da Silva, elected for the third time as president, with 50,9% of the votes.

The credit data used was provided by a Brazilian financial institution with operations throughout the country, and that operates on every line of credit for individuals (Credit Cards, Overdrafts, Personal Loans, Mortgages and Vehicles Financing). It consisted of an anonymized database of more than 2,3 million registers of credit usage per month, over the electoral period of 2018 and 2022. Among the information available, default and credit product segments enable to follow the changes on the search for purchases and therefore the increase in credit among all the income segments of individuals. Furthermore, with registration information that was provided of gender, age, marital status, number of children, educational level, income, and occupation, we can explore the impacts of each characteristic and separate political preferences after the elections.

On our main model, we included a dummy variable to every month after the election results. Adding the characteristics of the group of people analyzed, we were able to understand the impacts of variables on an individual level. To improve our investigation and have more precision about the political preference impact, we used open data from the official government records of employee balance of the cities, Cadastro Geral de Empregados e Desempregados (CAGED, General Register of Employees and Unemployed), acting as a proxy to the economic output of cities. CAGED in Brazil is the only information in a city level with a monthly granularity.

Using a dif-in-dif model with fixed effects, we obtained the main finding: that the political preferences are statistically relevant to the credit decision, with individuals who voted for the losing party displaying a relative reduction in their credit wallet. These results cannot be explained by other individual characteristics, or the characteristics related to the performance of the credit portfolio, such as decrease in default rates or the maturity of the contracts. We understand that this behavior is relevant to explain the search for purchases of durable and nondurable goods after elections by individuals and by extension, by firms, because in this study we can analyze every individual separately.

In the second section, we discuss the impact of credit variation in 2018 and 2022. Our analysis finds that both in 2018 and in 2022, it has an impact on credit consistent with the hypotheses of behavior in relation to political preference and the elected candidate. Finally, in the fourth section, we also analyze the robustness and the heterogeneity of the data, and we observe that age, income, graduation, investments and gender are relevant variables to the regression.

This paper has three contributions. First, we add more empirical support that people with different political preferences have different interpretations of the economy, impacting credit decisions (Meeuwis, Parker, Schoar, & Simester, 2022; Kandel & Pearson, 1995). Second, we provide more evidence to behavioral finance, that individuals characteristics such as gender, age and marital status could be related to the variance to the risk aversion (Rad, Yazdanfar, & Öhman, 2014; Schubert, Brown, Gysler, & Brachinger, 1999). Third, we increase the analysis of the Brazilian credit data, extending the national political science. We are one of the first studies to examine the impacts in credit by political preferences after presidential elections.

THEORETICAL FOUNDATION

BEHAVIORAL BIAS

The concept of the full rationality of human beings dominated economic theory for a long time. Even though the errors and cognitive limitations of individuals were not unknown, the econometric models represented economic agents in a strictly rational way with the argument that the intelligence of most of the market would lead these individuals to make more rational decisions and that when interacting with the market, this movement would narrow relations to the point that everyone would be led to the best decision.

In contrast to this theory of complete rationality, Kahneman and Tversky (1979) were the first to compile and present studies with theory that refuted this rationalization of choices, showing through Prospect Theory that individuals do not make their decisions based on the probabilities of each event occurring, but rather on the sensation of gains and losses of each event, even though these probabilities already weighted with individual factors, such as those presented by Bernoulli (1954).

Both due to the limited cognitive capacity to receive information and make decisions, and the tendency of the brain to optimize time and resources, it makes simplifications of choices, inferences of the world that are general heuristics that decrease the probability variables. This happens because most of the time these rules, which are created from the understanding and repetition of the environment in which it is inserted, are fast and work very well given that systematic errors are low and with little relevance. However, while they can be quite useful in the everyday context, general rules can also lead to systematic bias in choices.

These biases come from the adoption of heuristics, which are based on partial information and occur mainly when there is no complete knowledge of a given topic, either due to the unavailability of all necessary information or lack of knowledge in the area. Heuristics are simple techniques that help individuals make quick and less costly decisions. The strength of this heuristic depends on the individual prior knowledge of the variables of the problem and on the similarity with situations experienced prior to the context of the problem (Which does not mean that experts on some topics are incapable of cognitive biases in it).

CREDIT DECISIONS AND CONSUMPTION

The relationship between credit and consumption is intrinsically linked. Credit seen as money in the future has existed since the early days of commerce, but credit by itself, seen in a mass manner, comes, as a business driver in the consumer society, after the industrial revolution. For Slater (2002), credit served to bring less privileged groups to consumption during the industrial revolution period and over the years brought great consumerism after the 1980s. The use of direct consumer credit for consumer goods such as clothing, furniture and food were frequent practices in department stores.

However, it clear that the use of credit is not something exclusive to low-income consumers or the need for immediate consumption. According to Berquó (2013) credit can also be understood as a moral symbol and status of “who can have” access to credit, because “credit is money”. With the expansion of the use of credit, credit began to be seen beyond loans and money in the future, but also as a form of payment, with the use of a credit card as the most prominent example.

In this way credit provides the ability to acquire goods ('experiences' can also be understood as a good, given its use as a symbol of social status and a demonstration of belonging to a group) that are intertwined with the expected utility of an individual based on the personal value V(q) mentioned above.

However, what is considered for consumption and how the personal values impact? (Kotler & Armstrong, 2012) understand that individuals suffer external and internal factors in the decision process:

a) **Cultural Factors**: culture and subculture are associated with messages passed since birth, such as achievement and success, comfort, and efficiency. In addition to this, social stratification composes the need to belong to a subculture associated with a social class.
b) **Social Factors**: Reference groups or affinity groups, distributed by primary (family, neighbors, and friends), secondary (coworkers, religion groups or association groups). People are significantly influenced by their reference groups, either by the desire to belong, or by the need to disassociate from another group.
c) **Personal Factors**: age, profession, marital status, number of children and personality, disposable income (level, stability, and periodicity), savings and assets, debts, debt capacity and attitude towards spending and savings.
d) **Psychological Factors**: Motivation, learning, memory, and perception. A variety of needs, like physiological, safety, socialization, self-esteem, or realization can bring bias, such as selective distortion, transforming information into personal meanings in a way that fits our prejudgments.

POLITICAL PARTY AFFILIATION

Political Party Affiliation, like other affinity groups, are a form of political identification that considers all individual and social factors of an individual. To vote is to make a choice that represents what is important to an individual and how pillars such as education, religion, economy, culture, and biodiversity, must be administered by the public administrative power. In addition, as previously mentioned, belonging to a group leads to disassociation with other groups of politicians.

According to this disassociation, it is important to elucidate the terms left and right party. Those terms arise from the period of the French Revolution in which the representatives of the National Assembly who positioned themselves on the right were considered more conservative and prioritized freedom, and the representatives who positioned themselves on the left were considered more radical and prioritized equality. Nowadays, due to political diversity, the concept of left and right can designate distinct positions depending on the situation. The same individual can consider himself on the left in economics and on the right in social values, therefore, contextualization is important.

Brazilian political system consists of a multi-partisan system, with dozens of parties, but with a large concentration of legislative representatives in a few. we range of parties from the most left to the right following Maciel, Alarcon, & Gimenes (2017).

POLITICAL PARTY AFFILIATION AND BEHAVIOR

In the book *Partisan Hearts and Minds*, Green, Palmquist, and Schickler (2002) state that even today, identification with political parties determines how people interact with politics and vote. Furthermore, like religious identities, this political identity tends to persist or change only slowly over time. The stereotype, whether bad or good, determines how people interact and repel the “opposite side” in addition to generating their social bubbles, making not only their votes different.

In that way, political affiliation can explain different choices and behaviors. In health Kiviniemi, Orom, Hay, and Waters (2022), and Cakanlar, Trudel, and White (2021) predicted prevention behaviors of Covid-19 through a survey asking members of representatives. Their studies conclude that Republicans have less risk perception of Covid and fewer prevention behaviors. In global warming beliefs, Ballew et al. (2020) support the difference in behavior showing that misperceptions of public opinion about global warming changes along interactions with other individuals of the same party affiliation and their individual climate beliefs. In juridical decisions, Nagel (1961) was able to predict the difference in how judges on bipartisan appellate courts will divide when they do not agree.

Many studies have been conducted to show the difference in behavior by political party affiliations. Hong and Kostovetsky (2012) found that democrat mutual fund managers hold less of their portfolios in companies called ‘socially irresponsible’ such as tobacco, guns, or defense firms. Mian, Sufi, and Khoshkhou (2023) found that in 2008 and 2016 individuals supporting the party of the winning presidential candidate witnessed a substantial rise in optimism about the economy immediately after the election but there was no relative increase in credit cards or automobile purchases.

These differences due to party affiliation can be explained by the necessity to belong to a group, or by personal characteristics that are common to a group, generating behavioral biases. Such as:

a) **Confirmation Bias:** This bias is given by the tendency of individuals to try to interpret and even remember information in a selective way that confirms their pre-established beliefs. In this way, individuals ignore information that refutes their beliefs and favor those that endorse them.
b) **Loss Aversion Bias:** Loss aversion, as mentioned earlier, is the tendency of people to prefer to avoid losses than to have gains equivalent to this loss. This preference may be reflected in credit, where some individuals in one group may be more averse than another group.
c) **Optimism Bias:** This bias is related to individuals tendency to overestimate the probability of a positive event happening. With the election event, members of a winning political affiliation group may exhibit more optimism about the economy affecting their spending and investment.
d) **Availability Bias:** This bias is related to the tendency of individuals to judge their choices based on the closest events that are most salient in their memory. With elections, diverse groups may make different choices related to feelings of frustration or optimism related to the election results.

EXPERIMENTAL FRAMEWORK: BRAZILIAN PRESIDENTIAL ELECTIONS

The chosen experimental framework to analyze the performance discrimination of the population is the Brazilian Elections. First, for the high adherence and saliency (in Brazil, voting is mandatory), the elections detach from other international elections for having the electoral results on the same day due the electronic ballot machines. With instant results after the end time to vote, it is very precise to determine the date before and after the experiment.

Second, every Brazilian president election after 2014 was marked by a huge uncertainty about the results, similar to the USA in 2016 (Meeuwis, Parker, Schoar, & Simester, 2022). This uncertainty can in part be explained by a growing political polarization, that led to the impeachment of President Dilma Rousseff in 2016. After that, the huge ideological differences inside the movements showed up, separating the population in two ideological stances. Enhanced in 2014 (Brugnago & Chaia, 2014) by social media campaigns and social media bubbles made by algorithmic suggestions based on similarity in publications, the growth of a polarized political movement acquired elements of mutual hatred.

Brazilian elections occur in a two-round system. In the first round, all the parties that have candidates go public to compete for votes and need the absolute majority of the population to elect their candidate, that is, if a candidate gets more than 50% of all votes, there isn't a second round, and the candidate wins the election. If no candidate suffices this condition, the two most voted candidates the previous round compete on a second round of elections. This way, the parties make alliances with the new candidate that has the most affinity and expand the allotted space in the mandated media campaigns of the remaining two candidates, getting more public attention at the debates and improving their power in the congress. It is possible for the government to publish the ballot results in Brazil on the same day of the elections thanks to the use of electronic voting machines, making a movement after this exogeneous effect be clear to analysis.

PRIOR ESTIMATES REPORTS

In Brazil, the prior estimates of the outcome of the elections are conducted by private research institutes. Table 1 shows the historical electoral dispute since 2002 to 2022, showing the last estimative before the elections reported by the two main agencies of public opinion (Datafolha and Ibope) and statistics, and the official results after the elections by the Tribunal Superior Eleitoral (TSE, Superior Electoral Court) that are reported to the public. We add the difference of the estimates of the two candidates and the standard deviation of the estimates of Datafolha and Ibope (since 2014 as Ipec) from the Official Results.

Table 1 – Brazilian Report Prior Estimates X Official Election Results

The table examines the historical electoral estimate by the two main agencies of public opinion (Datafolha and Ibope). We compare with the official results provided by TSE. We segment each year in panels. In each panel, we have the difference between the left and right parties' candidate in p.p., in this table we see the decrease of the difference (right/Left) over the years.

Panel A: 2002 Brazilian Elections

	(Left-Party) Lula, L.I.	(Right-Party) Serra, J.	Difference

Datafolha	64%	36%	28%
Ibope (current Ipec)	62%	38%	24%
Official Results (TSE)	61%	39%	22%

Panel B: 2006 Brazilian Elections

	(Left-Party) Lula, L.I.	(Right-Party) Alckmin, G.	Difference
Datafolha	61%	39%	22%
Ibope (current Ipec)	61%	39%	22%
Official Results (TSE)	61%	39%	22%

Panel C: 2010 Brazilian Elections

2010	(Left-Party) Rousseff, D.	(Right-Party) Serra, J.	Difference
Datafolha	55%	45%	10%
Ibope (current Ipec)	58%	44%	14%
Official Results (TSE)	56%	44%	12%

Panel D: 2014 Brazilian Elections

	(Left-Party) Rousseff, D.	(Right-Party) Neves, A.	Difference (Right/Left
Datafolha	52%	48%	4%
Ibope (current Ipec)	53%	47%	6%
Official Results (TSE)	51%	49%	2%

Panel E: 2018 Brazilian Elections

	(Left-Party) Haddad, F.	(Right-Party) Bolsonaro, J.	Difference
Datafolha	55%	45%	10%
Ibope (current Ipec)	54%	46%	8%
Official Results (TSE)	45%	55%	10%

Panel F: 2022 Brazilian Elections

	(Left-Party)	(Right-Party)	Difference

	Lula, L.I.	Bolsonaro, J.	
Datafolha	52%	48%	4%
Ibope (current Ipec)	54%	46%	8%
Official Results (TSE)	51%	49 %	2%

We can infer from the data:

- Because of the proximity of the estimate of the broadcasting agencies, there was no certainty prior to the date of the election of 2018 and 2022 results, generating what we know as an environment of uncertainty that affects the economy.
- In Brazil, since 1998, there was no Election with the president results in the first round. This could be explained by over the years, because the number of candidates for the first round has grown.
- In 2018, occurred a change of the results from the prior estimates, improving the uncertainty.

Our assumption is that we can use the affinity with the political ideologies to infer the relationship with purchases and by extension, the use of credit given a specific political scenario of uncertainty. This scenario of the announcement of the presidential election result is a milestone that separates these individuals in their relationship with credit.

DATA

OPEN DATA

To start our analysis, we take the number of votes for each candidate based on the open data of the TSE. The TSE is the highest instance of the Brazilian Electoral Justice, and it is responsible for publicizing the elections and candidacies. Thus, it is possible to classify the cities with the greatest difference between the right and left candidates in the 2018 and 2022 elections. As we use the proportion in the cities of left/right as a proxy of probability of being left/right voter, it is important to exclude from the dataset cities where the probability is close 50/%50%, to remove the data with low party certainty. The data granularity is at the city level and take the number of voters per candidate in the 1st and 2nd rounds. We take the difference between the candidates in the 2nd round because, as the difference in the 1st round of both is high, we can already observe this polarity and from the 2nd round onwards we have the conclusion of the elections and the result of the next Brazilian president.

For the evaluation, we listed the 5,570 cities in 2018 and 2022 and the number of voters voting for each candidate, to define the difference between Left/Right, we used the 3,456 cities in 2018 and 2,792 cities in 2022, of which the difference between %Left and %Right is greater than 30p.p. We chose the >30p.p. due the proportion of the population, there are more than 60% of Brazilians voters in this cluster and we do not lose a lot of discrimination of the left/right.

As a result, in 2018 and 2022 for the second round, we observed the following distribution of the population, highlighting the population as commented above, in gray the cities with a High Difference between the candidates.

Table 2 – Distribution of voters 2018 and 2022

The table examines the Brazilian distribution of the voters, labeling as Left or Right voter, by the official result of each city. For example, a city in which the Right-party candidate had 93% of the votes, all the voters of this city were classified in the line "90-99 p.p". The separation of Left and Right shows the distribution of the voters using this classification method. Marked in gray in the table, the studied sample of the voters. The >30p.p. group was selected because has a minimum cut to remove cities with inaccurate allocation of votes.

	2018		2022	
	Left	Right	Left	Right
Draw	0.2%	0.2%	1.4%	1.4%
> 10p.p.	4.6%	4.7%	12.7%	12.7%
10-19 p.p.	5.2%	5.6%	9.2%	9.9%
20-29 p.p.	7.6%	10.2%	8.1%	10.4%
30-39 p.p.	9.4%	13.8%	5.7%	6.7%
40-49 p.p.	5.0%	7.7%	4.8%	4.1%
50-59 p.p.	5.6%	8.2%	4.1%	2.7%
60-69 p.p.	4.1%	3.9%	3.2%	0.9%
70-79 p.p.	2.7%	0.8%	1.5%	0.2%
80-89 p.p.	0.6%	0.1%	0.2%	0.0%
90-99 p.p.	0.0%	0.0%	0.0%	0.0%
% Total	44.9%	55.1%	50.9%	49.1%
# Total	46,987,176	57,666,176	60,193,094	58,061,090

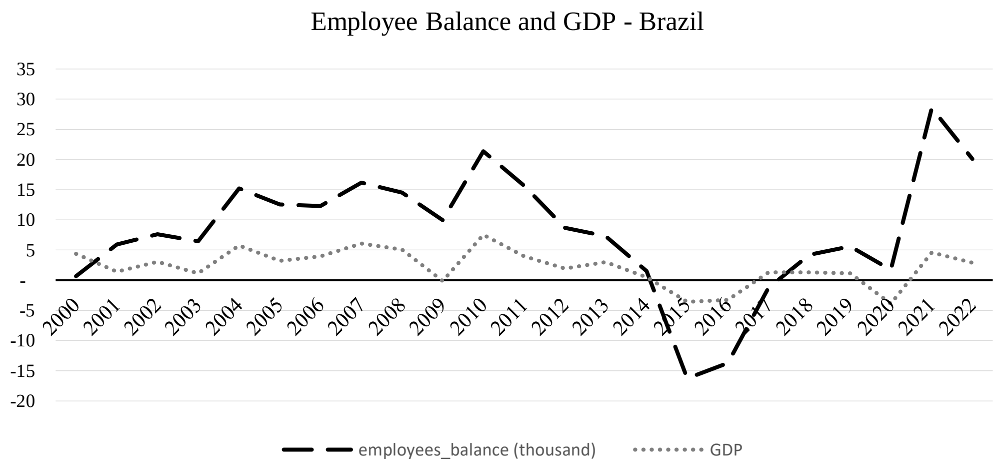
In addition, we looked for some information that could support the analysis and serve as a proxy for the income and profitability of the cities. In this way, we could remove the endogenous effect of the possibility that only the cities which candidate has won is the winner president candidate and this candidate after the Presidential Inauguration sent more financial support from the federal government, making the citizens more able to obtain credit by increasing the income and the number of employees in the region.

The data of Cadastro Geral de Empregados e Desempregados (CAGED, General Register of Employees and Unemployed) was used to solve this problem (on the tables of the article – EMPLOYEES BALANCE). With a monthly granularity and grouped by city, it can be considered an auxiliary variable to remove the previously commented effect. CAGED is an official government record and is the permanent report of admissions and dismissals of employees with the employee contract (in Portuguese, the Consolidação das Leis do Trabalho, CLT) making possible the maintenance of the Social Security Administration. In Brazil, about 36,3

Million of people has the employee contract and the CAGED data is widely used in research to analyze the labor market. It is the only source of information in the field with high geographic granularity and monthly timeliness, and it is fundamental for estimating the quarterly GDP and formulating diagnoses on the projection of employment in the country. In our study we used information on the “month over month” of the balance of jobs in the city (hiring – firing).

Figure 1 – Graphic with Employee balance and GDP – Brazil

Shows the relation between the Brazilian employees’ balance (in thousands of BRL) and the GDP. The correlation between the GDP and Employees Balance is 79.1%. The Employee Balance is used as a proxy to income and profitability of the cities in this study.



PERSONAL DATA

Our main database is the sample provided by one of the largest banking institutions in Brazil that works throughout the national territory. We had access to an anonymized and randomized database of more then 2.3 million customers (based in Brazilian Privacy Act, the Lei Geral de Proteção de Dados Pessoais, LGPD – in English, General Data Protection Law). The database contains the credit activities to every individual in all the Brazilian territory per month. The database contains the individuals with residence is in cities classified as High Difference between Left and Right.

Brazilian banks have visibility of all credit operations of their customers even accounts from outside their institution. This information is reported to all the banks and financial institutions subscribed at the system Sistema de Informações de Créditos (SCR) (in our translation, Credit Information System) granted by the Brazilian Central Bank. Thus, the credit information provided has information per person and refers to all activity in credit cards, vehicle leasing, mortgage, personal loans e overdraft. and has a separation by product type, default, and maturity.

In addition to credit related information, we also included information on age, gender, marital status, number of children, education, income, profession, and investment balance. These data were brought as control variables of our model, reducing the effect of interference of other variables. In addition, each characteristic has effects already analyzed in the academy as relevant in risk behavior.

Bellante and Green (2004) studied the population aged 70 or over. Their study supports a modest decrease in risk aversion in elderly. About gender studies, Agarwal, He, Sing, and Zhang (2016) showed women's odds of bankruptcy are 28% of the men's and this is mainly driven by risk-taking behavior. Charness & Gneezy (2012) pooled 15 experiments to assess financial risk aversion and found that women seem to be much more risk averse than men. About the effect of the family, Yao and Hanna (2005) focused in the marital status, showing that married men/women are more risk averse than single men/women, and also Browne, Jäger, Richter, and Steinorth (2021) found evidences that after a divorce, people become less risk averse, while the birth of a first child is associated to an decrease in willingness to take risk.

Hopland, Matsen, and Strøm (2016) studied with norwegian data that decision makers with high income accept more financial risks in a bet gameshow. Barros (2005) presented solid empirical evidence that suggests that individuals who manage their own business (entrepreneurs) are move overconfident, presenting less risk aversion. Clark, Lusardi, and Mitchell (2017) studied that investors who are more knowledgeable in finances had 18% more invested and presented 38% less idiosyncratic risk portfolios.

Below, we have a table with a description of the credit informations in all the analyzed 2022 period (Aug. 2022 – Jan. 2023). The data is separate by the personal characteristics in the Panel B and by product type. (In Appendix 1 – 2018)

Table 3 – Descriptive Credit Analysis – 2022

Panel A shows the main descriptive analysis of each credit product and the total in 2022 (in BRL). At the column "Total Credit", we have the total amount of credit per individual. At the column "count", we have the number of credit registers that have this line of credit.

Panel B observes the distribution of the credit registers of each product and the total in 2022, summarized by the personal characteristics of the individual.

Panel A: Summary Credit Statistics – 2022

	Credit Card	Overdraft	Personal Loan	Vehicles Financing	Mortgage	Total Credit
Count	1.898.120	628.211	637.081	280.687	258.552	2.145.531
Mean (BRL)	14.277	1.637	11.764	35.563	98.192	33.088
St.Dev (BRL)	31.312	5.749	75.341	50.825	159.821	96.672
Min (BRL)	0,01	0,01	0,01	115,0	0,33	0,01
Max (BRL)	8.217.699	687.705	13.824.304	3.454.532	6.468.812	14.733.365

Panel B: Credit Distribution by Personal Characteristics – 2022						
	Credit Card	Overdraft	Personal Loan	Vehicles Financing	Mortgage	Total Credit
By Region						
North	3.9%	4.2%	5.5%	5.4%	3.0%	4.0%
Northeast	33.2%	28.8%	31.1%	24.0%	24.5%	32.4%
Midwest	3.5%	4.0%	3.9%	4.6%	4.5%	3.5%
Southeast	33.4%	35.8%	34.3%	34.7%	35.9%	33.8%
South	26.0%	27.2%	25.2%	31.4%	32.1%	26.2%
By Age						
Under 30	6.1%	7.1%	9.3%	4.5%	2.7%	6.7%
30-40	12.0%	12.9%	15.5%	13.9%	19.0%	12.3%
40-50	31.7%	33.2%	35.6%	38.3%	43.8%	31.9%
50-60	24.6%	22.8%	21.9%	26.1%	22.7%	24.1%
Over 60	25.6%	24.0%	17.6%	17.2%	11.7%	25.0%
By Gender						
Men	50.8%	55.5%	54.7%	61.8%	59.9%	52.1%
Women	49.2%	44.5%	45.3%	38.2%	40.1%	47.9%
By Marital St.						
Married	41.8%	40.1%	36.7%	39.9%	38.9%	40.9%
Non-Married	58.2%	59.9%	63.3%	60.1%	61.1%	59.1%
By Children						
With Children	2.2%	2.2%	2.1%	2.0%	2.0%	2.1%
No Children	97.8%	97.8%	97.9%	98.0%	98.0%	97.9%
By Education						
Undergrad	48.4%	49.9%	43.9%	49.7%	58.2%	46.6%
No Grad	51.6%	50.1%	56.1%	50.3%	41.8%	53.4%
By Income						
Under 1.5k	16.3%	13.9%	16.9%	5.9%	6.1%	18.3%
1.5 – 5k	58.8%	57.5%	64.2%	60.4%	57.6%	59.0%
5k – 50k	24.6%	28.2%	18.8%	33.3%	35.8%	22.5%
Above 50k	0.3%	0.3%	0.2%	0.4%	0.5%	0.3%
By Profession						
Entrepreneur	99.0%	99.0%	99.0%	99.0%	99.0%	99.0%
No Entrepen	1.0%	1.0%	1.0%	1.0%	1.0%	1.0%
By Investment						
With Invest.	99.0%	99.0%	99.0%	99.0%	99.0%	99.0%
No Invest.	1.0%	1.0%	1.0%	1.0%	1.0%	1.0%

In the Panel A, we can observe from the descriptive analysis:

- Most Brazilians with credit have Revolving Credit, in other words, credit lines with limits that remains available even as you pay the balance (88% with Credit Cards). This could be explained by the process of open an account. In Brazil, it is common in the process of opening and Account, to have your score analyzed and have the offer of a pre-approved of a credit card and the limit in overdraft (the individual can deny the products), another national culture is the credit card in retail stores, responsible for 50% of the database.

In the Panel B, we can observe from the credit distribution:

- In guaranteed products (Vehicles Financing and Mortgages), there is a distribution with higher income and higher age. This could be explained by the life cycle of the individuals at the bank. Vehicles financing and especially Mortgages are products associated to household sharing. Another expected distribution is the increase in the Men's proportion in vehicles financing (Vehicles 62% are Men/ in Total Credit 52%), the search in the Brazilian market for vehicles are bigger in this population.

LEFT-PARTY VOTER/ RIGHT-PARTY VOTER

One of the main points of this study is to understand how to correctly define the population between Left-party and Right-party voters, and this could completely affect the distribution and results of the study. Initially, we evaluated as a proxy to Left-party person, a dummy equal 1 when the in city where the voter lives, the Left-Party candidate was won.

But we see that we lost a good part of the explanatory variable of importance. We know that the Left-Party in 2022 received 51% votes of the Brazilians, but when we use the proxy with a dummy Left-party person as explained before, we get only 30% of the population as a Left-party voter. For this reason, in our study, we use the ratio of quantity of left voters and the total population of the city as a proxy to define the probability of some individual being a Left-party voter. Making the new distribution be closer to the actual results, Official Results = 51% and the New Distribution=45%. Below, we have the table with the new Sample Distribution using the ratio as proxy to Left-party voter and using information of the registration account, we can analyze if there are differences of personal characteristics between Left/Right voters:

Table 4 – Descriptive Analysis of the Personal Characteristics – 2022

This table contains the descriptive analysis of the 2022 database. The population distribution by each personal characteristic. In the columns the "%of Left", separates in groups the population of the cities with the ranges specified of %left voters. In %Left is the probability of that specific voter being a left party voter given the residential city. In Gender, the dummy is equal 1 when is male. In Married, Graduated, With Children and Investment, both are dummy variables, equals 1 when it occurs and 0 elsewhere. In Income, we observe the mensal income for each individual.

		% of Left			
	All	0.0-0.2	0.2 – 0.4	0.6 – 0.8	0.8-1.0
count	2,328,741	10,522	1,496,521	718,157	103,541
%Left					
mean	45.10%	18.27%	30.27%	70.86%	83.48%
std	20.68%	1.13%	3.70%	3.62%	2.48%
min	11.00%	11.00%	20.00%	65.00%	80.00%
max	93.90%	19.80%	35.00%	79.90%	93.90%
Gender					
count	1,214,048	6,005	795,503	360,722	51,818
%sample	52.13%	57.07%	53.16%	50.23%	50.05%
Married					
count	955,943	4,733	636,939	273,690	40,581
%sample	41.05%	44.98%	42.56%	38.11%	39.19%
Graduated					
count	1,060,005	4,355	655,998	349,928	49,724
%sample	45.52%	41.39%	43.83%	48.73%	48.02%
With Children					
count	47,548	54	22,822	22,740	1,932
%sample	2.04%	0.51%	1.53%	3.17%	1.87%
Age					
mean	51.35	52.32	51.04	52.01	51.20
std	13.72	11.41	14.34	12.50	12.64
min	8.55	19.26	8.55	18.10	18.34
max	113.81	90.72	109.37	113.64	113.81
With Investment					
count	24,452	116	15,414	7,684	1,238
%sample	1.05%	1.10%	1.03%	1.07%	1.20%
Income					
mean	4,217.85	4,386.68	4,366.42	4,019.66	3,428.06
std	5,909.05	7,141.75	6,238.90	5,378.61	3,959.48
min	-	-	-	-	-
max	517,686.00	100,000.00	517,686.00	310,581.00	100,000.00

From the descriptive analysis we can observe that we don't have any huge differences to sample distribution, and according to Instituto Brasileiro de Geografia e Estatística (IBGE, Brazilian Institute of Geography and Statistics) the proportion of Age, Children, Income, Investment and Credit represents the same distribution of the country. but we can emphasize two differences:

1. The Brazilian population According to data from the Census carried out in 2022 by the IBGE, is 48,9% male and 51,1% female, but in our database, we have the opposite, 52 % male and 48% female. This could be by the previously commented hypothesis about Women and the difficult to access to credit.

2. The Brazilian population Graduated in 2019, according to the IBGE is 34.2% of the population. One hypothesis to explain this, is the origin of the database. We are using a credit database of a bank, but 39.5% (According to Instituto de Pesquisa Econômica Aplicada, Ipea) of Brazilians don't have a bank account and this is related to the most underdeveloped regions, and consequently, to areas with lower rates of people with graduation.

HISTORICAL EVOLUTIONS IN THE CREDIT PORTFOLIO

In the historical data is relevant to observe the independent variable all over the time. Below, we have the table with historical information of the credit average by person, and we are able to observe the stability without outliers in the timeline in the credit portfolio and share of credit.

This credit oscillation happens by the Brazilian inflation, in 2019 the IPCA, index closed in 4.31%. Another reason, according to the Focus-Market Readout – 2019 (by the Central Bank of Brazil, BACEN) is the monetary policy easing cycle started in October 2016. (The IPCA closed in 1.36% in the last quarter of 2022).

In this way, we can presume that the angular coefficient of the historical data close to zero. So, in our study we will explore this difference between left-party voters from right-party voters in both elections because different political parties with different ideologies have won. Other conclusion by the table below, is that we don't have any difference of the credit portfolio thought the months, so there isn't any difference of products that could give a difference in the %default or the mean all over the months.

Table 5 – Historical Credit Analysis per Month

The table shows the average credit per month (BRL) of the whole timeline studied. As observed, there is a constant increase in the credit per month. This movement is associated with the Brazilian inflation. In this way, we must observe the increase above the IPCA.

Panel A: Historical Credit – 2022

	Aug-22	Sep-22	Oct-22	Nov-22	Dec-22	Jan-23
Credit Card	11,613.21	11,657.90	11,962.95	11,619.55	10,939.45	12,028.38
Overdraft	422.74	452.05	470.86	447.05	399.00	458.11
Personal Loan	3,183.67	3,212.87	3,278.83	3,303.49	2,982.96	3,347.57
Vehicles Fin.	4,283.99	4,323.60	4,355.73	4,372.14	4,005.99	4,377.08
Mortgages	10,728.12	10,888.30	11,193.09	11,144.42	10,150.00	11,307.53
Total Credit	30,231.74	30,534.72	31,261.46	30,886.65	28,477.40	31,518.68

Panel B: Historical Credit – 2018

	Aug-18	Sep-18	Oct-18	Nov-18	Dec-18	Jan-19
Credit Card	11,926.01	12,130.91	12,022.23	11,855.17	11,863.90	12,062.68
Overdraft	561.35	581.19	547.31	526.09	576.41	582.56
Personal Loan	9,492.99	9,950.79	9,568.82	9,818.09	9,809.62	9,754.32
Vehicles Fin.	3,868.36	4,035.11	3,898.65	4,003.77	3,970.19	3,934.18
Mortgages	13,223.65	13,426.99	13,289.77	13,479.86	13,442.67	13,356.46
Total Credit	39,072.36	40,124.99	39,326.78	39,682.98	39,662.79	39,690.21

ECONOMETRIC MODEL

For our econometric model of our study, first, we organized the information of credit, registration account data and municipality performance control (balance of employees per city by CAGED) in Panel Data. We opted for the difference-in-differences method (dif-in- dif) because we can compare the performance of credit (independent variable) over time, using the probability of individuals being Left-party voters as a variable of importance.

With this method, it is possible to analyze the performance of the control and treatment groups, observing how the response variable behaves in each group. That is, for cases in which the control group and the treatment group do not differ, the result of the linear regression will be the same for both. Furthermore, with this method we reduce the interference of omitted variables in the result, as this information can be captured by the individual coefficients. Finally, the model also treats Fixed Effects of time and group so that we can analyze the interference of these variables.

We use in the regression the data by quarters, comparing (Aug-18 to Oct-18) with (Nov-18 to Jan-19). The same intervals were used in 2022, comparing (Aug-2022 to Oct-22) with (Nov-22 to Jan -23). In this way, we can see the impact of Elections in a stronger cut.

Our econometric model can be described by the following equation:

Equation 1 – Econometric Model

$$CREDIT_i = \alpha * PROB_{LEFT_i} + \gamma * POST_{ELECTION} + \beta_i * (PROB_{LEFT} * POST_{ELECTION}) \\ + \sigma * EMPLOYEE_{BALANCE_{i,t}} + \mu * lag\_CREDIT\_M12 + \rho * G_{k_i} + \epsilon$$

Where $CREDIT$ is the sum of credit operations in the month t of the individual i; $PROB\_LEFT$ is the probability that individual i voted for the Left-party candidate; $POST\_ELECTION$ is the dummy equals 1 if the date is greater than 10/28/2018 (date of the 2nd round of presidential elections in Brazil) and greater than 10/30/2022 in the 2nd regression to 2022 Elections; $EMPLOYEE\_BALANCE$ is the auxiliary variable with information of the employment balance in the month t of the city of residence of the individual i; lag_CREDIT is the sum of credit operations of the month t-12 and G_k of each individual i, are all the individuals' registration account variables: age, gender, number of children; marital status; graduation; income; entrepreneur; and investments; ϵ is the representation of the error associated with the model.

It is important to emphasize that we put a lot of information of individuals (G_k), to make the impact of the Post_Election*Prob_Left in this study more realistic and reduce the impact of external influences that can make a bias inside the study. The support variable lag_CREDIT is included to make a moving average in the regression and helps to identify the associated impact in the analyzed moment after elections, making the regression (and for consequence, the R-square) more adjusted to explain the credit portfolio.

In Table 6 and Table 7, we have the table with the main statistics of the OLS linear regression using Least Squares to find the best fit for a set of data points in the Elections of 2018 and 2022, and the information of all variables used in the regression.

In 2018, we are able to see a statistical relevant negative impact when a right-party president won with -232,83 of coefficient of difference and in 2022, we see the coefficient of 5.000,63 with statistical relevance in political affiliations with Post_election*Prob_left, with a p-value of less than 0.1%. We can perceive differences in the credit portfolio in left party and right party voters after an election of a left party president.

Table 6 – Linear Regression Results – 2018

*The table below shows the results of the study with dif-in-dif linear regressions with the dependent variable prob left*post-election Every other variable (gender, age, with children, graduated, married, income, with investment, entrepreneur, employee balance and lag credit) are control variables in this study. The variable gender is a dummy equal 1 when the individual is male. With children(married/graduated/entrepreneur) is a dummy equal 1 when the individual has a declared child (married/have a graduation or above/has a firm). Income is the mensal income of the individual. The Full model, with all the control variables in the linear regression. Model 2, where we add lag credit M-1. We presented the coefficients with the p-value marked with *. In ***, the p-value less than 0.1%, ** the p-value less than 1% and * the p-value less than 5%. Below to each coefficient, the T-statistic.*

	Full Model	Model 2
Prob Left*Post Election	-0.0035***	-0.0146***
	(2.25)	(3.20)
Prob Left	-0.0698***	-0.2585***
	(65.262)	(77.97)
Post Election	0.0072***	0.0125***
	(5.298)	(6.22)
Gender	0.0927***	0.1616***
	(124.717)	(146.95)
Age	-0.0413***	0.002***
	(53.734)	(47.26)
With Children	0.0021***	0.0303***
	(2.822)	(8.46)
Graduated	0.1106***	0.2127***
	(146.268)	(187.79)
Married	-0.0061***	0.0237***
	(7.907)	(20.69)
Income	0.3036***	0.4678***
	(401.43)	(362.22)
With Investment	-2.95E-18***	1.0682***
	(3.096)	(410.14)
Entrepreneur	-3.58E-17***	1.0682***
	(48.831)	(410.14)
Employee Balance	0.0248***	1.83E-05***
	(32.028)	(4.92)
Lag Credit		0.8254***
		(213.56)
R-Squared	0.141	0.143
Durbin-Watson	0.373	0.425

Table 7 – Linear Regression Results – 2022

*The table below shows the results of the study with dif-in-dif linear regressions with the dependent variable "prob left*post-election" Every other variable (gender, age, with children, graduated, married, income, with investment, entrepreneur, employee balance and lag credit) are control variables in this study. The variable gender is a dummy equal 1 when the individual is male. With children(married/graduated/entrepreneur) is a dummy equal 1 when the individual has a declared child (married/have a graduation or above/has a firm). Income is the mensal income of the individual and lag credit is the information of the usage of credit of the month M-1. The Full model, with all the control variables in the linear regression. Model 2, where changed the lag credit to lag M-1. We presented the coefficients with the p-value marked with *. In ***, the p-value less than 0.1%, ** the p-value less than 1% and * the p-value less than 5%. Below to each coefficient, the T-statistic.*

	Full Model	Model 2
Prob Left*Post Election	0.0259***	0.0104***
	(49.96)	(4.20)
Prob Left	-0.0244***	-0.1806***
	(85.91)	(102.41)
Post Election	0.0162***	-2.59E-01***
	(80.23)	(206.81)
Gender	-0.011***	0.0656***
	(51.92)	(126.52)
Age	0.0018***	0.0024***
	(8.81)	(126.01)
With Children	0.0231***	0.0357***
	(111.61)	(18.21)
Graduated	0.0007***	0.1267***
	(3.28)	(233.73)
Married	0.0996***	0.0254***
	(453.10)	(44.77)
Income	-1.20E-17***	0.6124***
	(102.56)	(903.86)
With Investment	7.67E-18***	4.31E-01***
	(85.47)	(341.16)
Entrepreneur	0.0049***	4.31E-01***
	(23.96)	(341.16)
Employee Balance	0.8381***	6.76E-06***
	(3863.34)	(21.99)
Lag Credit M12	0.0259***	0.273***
	(49.96)	(1251.38)
R-Squared	0.777	0.40
Durbin-Watson	1.903	0.423

In both regressions, with a R-square in the model of more than 0.70, we have a strong fitting with the points, representing the credit portfolio post-election that is able to analyze the coefficients of the model. By the support individuals' variables, we see different behavioral biases; the variable dummy Gender (when Male=1) is statistical relevant in both regressions, with a p-value of less than 0.1% in 2018 and 2022, and both with the coefficients signal positive, showing that Men spends more with credit than Women. Adding to academy to another credit and behavioral studies about the difference of gender and risk avoidance, such a behavioral meta-analysis with 150 articles explaining how independent of age, degree or problem framing, women are more risk averse (Byrnes, Miller, & Schafer, 1999) experimental studies based in gender differences associated the women risk aversion to their greater perception of negative outcomes and perceptions of severity of potential outcomes (Harris & Jenkins, 2006). Age, Graduation and Income are significant in both regressions, with the coefficient signal positive, emphasizing again that, with the increase of age, the increase of years of schooling and the increase of income there is an increase in the credit portfolio. Other articles compose the behavioral studies of age and risk tolerance. Bellante and Green (2004) show in their article a decrease of risk aversion to elderly people aged above 70; Bellante and Saba (1986) support life-cycle patterns, showing a risk aversion over the lifetime. Investments and entrepreneur, because the low number of points are not stable to have a good performance in the regression.

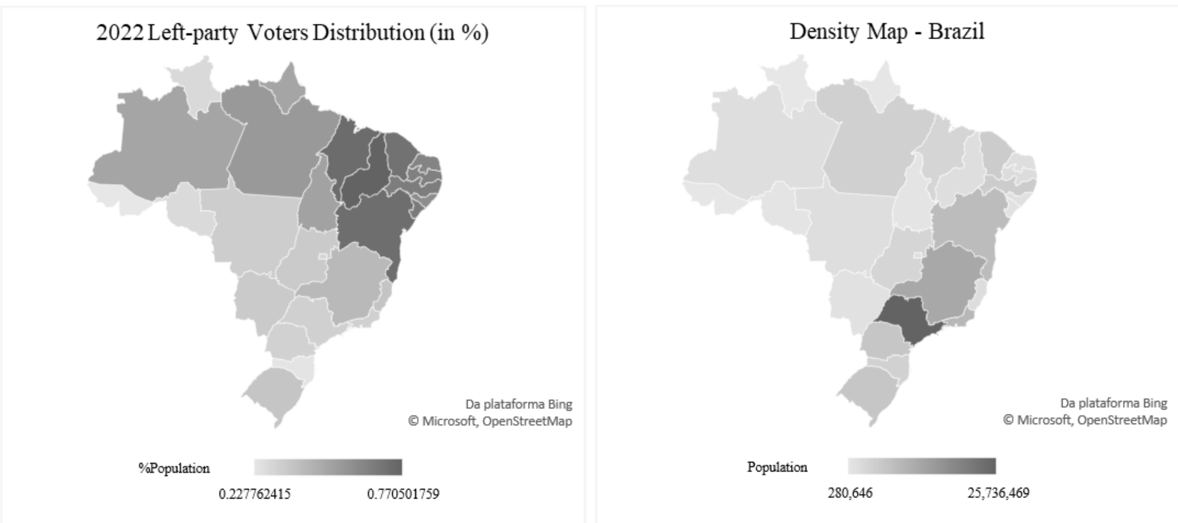
ROBUSTNESS ANALYSIS

To compose our analysis and analyze the robustness, we separate the regression per credit product and by region of country. In this way, we can control many characteristics that could interfere in our analysis, improving the hypothesis of the behavioral interference in the credit risk. Observing if there is any heterogeneity in the sample, we can see the impact of the region in the polarity of voters that could invalidate our main hypothesis.

Comparing the Density Map of Voters and Distribution of Left-Party voters we able to observe the heterogeneity of the data per region. The Southeast region of Brazil holds 50% of the Brazilian voter population. This distribution is reflected in the credit data and could take the results influenced by a typical movement of a state/region. So, it is important to analyze if the regressions can be explained even when we look for each region.

Figure 2 – Left Voters Distribution X Density Map

The map on the left shows the distribution of the left party voters per Brazilian state, obtained through open data of the cities results. To the right, we have the Brazilian populational density map.



Both in 2018 and in 2022, we see no difference by Brazilian region. Thus, showing that the econometric model adheres regardless of the region in which it is located. Only for the North region in 2018 there is an inversion of the data, however both the North region and the Midwest region do not have enough points for it to be defined as a statistically relevant regression. Thus, even though the Midwest has a similar post_election*prob_left coefficient to the other regions, its coefficient indicator cannot be defined as stable either.

Table 8 – Linear Regression by Geographic Region – 2018

*This table shows the proposed econometric model of linear regression per Brazilian Region in 2018.In the table, is presented the coefficients with the p-value marked with *. In ***, the p-value less than 0.1%, ** the p-value less than 1% and * the p-value less than 5%. Below each coefficient, the T-statistic. The North and Midwest regions are regions with low number of points to evaluate.*

	Linear Regression				
	North	Northeast	Midwest	Southeast	South
Prob Left*Post Election	-0.0034***	-0.0076***	0.0015***	-0.0014***	-0.0023***
	(0.33)	(0.48)	(0.07)	(0.38)	(0.37)
Prob Left	-0.0689***	-0.0405***	-0.0318***	-0.0346***	-0.0073***
	(10.14)	(20.14)	(5.01)	(19.37)	(3.93)
Post Election	0.0101***	0.0093***	0.0064***	0.0066***	0.0067***
	(1.09)	(0.59)	(0.34)	(1.86)	(1.11)
Gender	0.064***	0.063***	0.1149***	0.1031***	0.1066***
	(13.30)	(45.78)	(25.31)	(81.04)	(80.74)
Age	-0.0022***	0.0038***	-0.0239***	-0.0579***	-0.0606***
	(0.44)	(2.69)	(5.09)	(43.75)	(44.04)
With Children	0.0159***	0.0046***	-0.0056***	0.0017***	-0.0019***
	(3.33)	(3.37)	(1.25)	(1.33)	(1.47)
Graduated	0.0777***	0.1086***	0.1179***	0.1131***	0.1103***
	(15.77)	(77.72)	(25.42)	(87.48)	(82.02)
Married	-0.0278***	0.0016***	-0.0186***	-0.0055***	-0.008***
	(5.69)	(1.142)	(3.97)	(4.15)	(5.79)
Income	0.335***	0.3481***	0.3251***	0.2985***	0.2753***
	(68.15)	(249.05)	(70.25)	(230.56)	(204.58)
With Investment	5.01E-17***	2.91E-17***	-1.54E-17***	-1.69E-18***	-3.52E-17***
	(14.28)	(5.22)	(5.07)	(-0.58)	(9.15)
Entrepreneur	-1.49E-17***	-1.35E-16***	-6.40E-17***	-1.11E-17***	1.61E-16***
	(1.89)	(1.55)	(70.39)	(15.78)	(10.83)
Employee Balance	0.0086***	0.03***	0.0005***	0.0058***	0.0078***
	(1.64)	(20.3)	(0.10)	(4.56)	(5.90)
R-Squared	0.14	0.16	0.17	0.14	0.12
Durbin-Watson	1.92	1.94	2.00	2.11	1.97
Count	38,856	370,791	35,404	400,423	344,116

Table 9 – Linear Regression by Geographic Region -2022

*This table show the proposed econometric model of linear regression per Brazilian Region in 2022. In the table, is presented the coefficients with the p-value marked with *. In ***, the p-value less than 0.1%, ** the p-value less than 1% and * the p-value less than 5%. Below to each coefficient, the t-statistic. North and Midwest are regions with small number of points to evaluate.*

	Linear Regression				
	North	Northeast	Midwest	Southwest	South
Prob Left*Post Election	0.0022***	0.0101**	-0.0106	0.0035**	0.0018**
	(0.71)	(2.01)	(1.57)	(2.582)	(0.68)
Prob Left	-0.0214***	-0.0058***	-0.005	-0.0147***	-0.0021***
	(10.81)	(10.61)	(2.75)	(27.004)	(3.64)
Post Election	-9.10E-03***	-1.59E-02***	9.90E-03***	-6.60E-03***	-5.20E-03**
	(3.13)	(3.18)	(1.49)	(-5.05)	(2.00)
Gender	0.014***	0.011***	0.025***	0.0209***	0.0225***
	(10.66)	(28.42)	(19.42)	(54.08)	(55.39)
Age	0.0022***	-0.006***	-0.0013***	-0.0156***	-0.0141***
	(1.60)	(14.98)	(0.99)	(38.447)	(32.85)
With Children	0.0005*	0.0018	0.002	0.0019***	0.0018***
	(0.42)	(4.56)	(1.54)	(4.962)	(4.57)
Graduated	0.0208***	0.0265***	0.0253***	0.0273***	0.0256***
	(15.21)	(66.53)	(19.24)	(68.85)	(61.51)
Married	-0.0013**	0.0015	1.16E-05**	0.0013**	0.0003*
	(0.98)	(3.76)	(0.01)	(3.26)	(0.71)
Income	0.1304***	0.129***	0.1243***	0.1089***	0.0969***
	(88.55)	(300.13)	(88.21)	(258.84)	(222.57)
With Investment	3.85E-17***	5.73E-17***	2.27E-17***	2.14E-17***	-1.93E-16***
	(37.15)	(11.01)	(7.14)	(33.70)	(227.33)
Entrepreneur	-5.68E-17***	6.09E-18***	-1.55E-16***	1.12E-17***	-3.39E-17***
	(55.98)	(0.90)	(29.25)	(17.44)	(16.84)
Employee Balance	-0.0137***	-0.0072***	-0.0049***	-0.0074***	-0.0079***
	(8.87)	(18.57)	(3.64)	(18.2)	(18.68)
Lag Credit M12	0.0022***	0.0101***	-0.0106***	0.0035***	0.0018***
	(0.71)	(2.01)	(1.57)	(2.58)	(0.68)
R-Squared	0.64	0.79	0.76	0.78	0.78
Durbin-Watson	2.29	2.07	2.16	2.17	2.09
Count	93,029	748,707	82,103	787,578	617,324

Another study to improve our analysis, is the analysis by product. As we showed before, we have a more frequent use in revolving credits, approximately 80% of the data are in these types of credit, and we could be seeing an impact that just occurs in specific credits. Another problem is in mortgages that even if they represent only 10% of the database, this credit is prioritized in the default payments and the amount of debit represents much more of the individual and familiar income.

Another problem analyzing all the portfolio is in vehicles financing and mortgages, both credit lines are more associated to families and there is a factor not able to be studied in here, the household risk aversion and income. In this study, we are analyzing the credit portfolio of individuals, but it is known that credit lines such mortgages and financing are used composing the incomes of the couples. In that way, observing each product we can see if this impact can be observed just in a few products.

In the Table 10 and 11 we can observe the results. In the Tables, we see a stability in the products, just in vehicles financing we do not see statistical relevance. But an important result that can be observed is that in 2022, all the credit products have a statistical relevance in the variable post_election * prob_left and the same coefficient signal of total credit in Table 7. This can explain that even if credit lines have their particularities, this is not relevant in the impact of this analyzed bias. Therefore, from the first quarter after the election results, we can observe this movement in all products.

This conclusion has an interesting particular result. In Brazil, the average time of mortgages evaluation is 40 days, according to Associação Brasileira das Entidades de Crédito Imobiliário e Poupança (Abecip, in our translation, Brazilian Association of Real Estate Credit and Savings Entities). In that way, we see a fast movement in mortgages considering that more than one month are occupied just with the credit analysis. Showing us that for the impact on mortgages to be perceived in the first quarter, probably these individuals should have already prepared their credit choices for both electoral scenarios, and after the results they execute what was planned before.

Table 10 – Linear Regression by Credit Product – 2018

*This table shows the proposed econometric model of linear regression by product in 2018. In the table, is presented the coefficients with the p-value marked with *. In ***, the p-value less than 0.1%, ** the p-value less than 1% and * the p-value less than 5%. Below to each coefficient, the t-statistic. North and Midwest are regions with low number of points to evaluate.*

	Linear Regression				
	Credit Card	Overdraft	Personal Loan	Vehicle Financing	Mortgage
Prob Left*Post Election	-0.0035**	-0.0752**	-0.001*	-0.144**	-0.3175**
	(2.28)	(29.54)	(0.31)	(46.44)	(117.43)
Prob Left	-0.0184***	0.1351***	-0.0339***	0.1907*	0.2165**
	(17.38)	(94.60)	(15.12)	(112.62)	(146.65)
Post Election	0.0047**	4.69E-17***	0.01***	1.95E-17***	-1.5E-17**
	(3.47)	(89.43)	(3.51)	(26.84)	(24.80)
Gender	0.0577***	0.0453***	0.0486***	0.0225***	0.0383**
	(78.66)	(32.36)	(30.93)	(13.53)	(26.90)
Age	0.124***	0.3346***	0.062***	0.3357***	0.6078**
	(163.83)	(234.35)	(38.68)	(177.26)	(355.407
With Children	-0.0022*	0.0084	-0.0051**	-0.01***	-0.0193**
	(3.04)	(2.90)	(3.27)	(2.95)	(6.61)
Graduated	0.0901***	3.83E-05***	0.0648***	-0.0071***	0.0015**
	(120.91)	(0.02)	(40.29)	(4.34)	(1.08)
Married	0.0247***	0.0319	0.004**	0.0632***	0.0782**
	(32.71)	(22.37)	(2.50)	(37.38)	(53.87)
Income	0.4392***	0.0216***	0.3294***	0.0358***	-0.1177**
	(588.28)	(14.87)	(205.97)	(20.80)	(80.59)
With Investment	1.40E-17***	-1.38E-17***	7.86E-18***	-1.17E-17***	1.51E-16**
	(69.68)	(41.81)	(24.52)	(17.67)	(256.89)
Entrepreneur	7.97E-18***	2.14E-02***	-8.93E-17***	-3.90E-03***	5.20E-02**
	(46.60)	(14.65)	(88.63)	(2.28)	(35.15)
Employee Balance	0.0426***	-0.0332***	0.0146***	0.0007**	-0.0112**
	(55.57)	(16.48)	(9.04)	(0.29)	(5.43)
R-Squared	0.244	0.148	0.131	0.153	0.427
Durbin-Watson	0.424	0.759	0.421	0.471	0.545

Table 11 – Linear Regression by Credit Product – 2022

*This table shows the proposed econometric model of linear regression by product in 2022. In the table, is presented the coefficients with the p-value marked with *. In ***, the p-value less than 0.1%, ** the p-value less than 1% and * the p-value less than 5%. Below to each coefficient, the t-statistic. North and Midwest are regions with small number of points to evaluate.*

	Linear Regression				
	Credit Card	Overdraft	Personal Loan	Vehicle Financing	Mortgage
Prob Left*Post Election	0.0041***	0.0097***	0.0073***	0.0168***	0.0209***
	(7.33)	(12.78)	(8.00)	(32.01)	(43.53)
Prob Left	-0.0007***	-0.0108***	-0.0091***	-0.0138***	-0.0156***
	(2.13)	(26.067)	(17.98)	(48.00)	(59.34)
Post Election	0.0111***	0.0103***	0.0081***	0.0086***	0.0061***
	(50.74)	(34.714)	(22.69)	(42.11)	(32.68)
Gender	0.0154***	-0.0024***	0.0126***	-0.0027***	-0.0142***
	(67.29)	(7.764)	(33.59)	(12.50)	(72.18)
Age	0.0014***	3.53E-05***	-0.0006***	0.0004***	0.0004***
	(6.61)	(0.12)	(1.77)	(1.74)	(2.26)
With Children	0.0224**	0.0074	0.0126***	0.002**	0.0076***
	(100.35)	(24.462)	(34.11)	(9.39)	(39.54)
Graduated	0.0089***	0.0005***	0.0023***	-0.0035***	-0.0002***
	(39.06)	(1.537)	(6.20)	(16.17)	(0.88)
Married	0.1488***	0.0395**	0.1037***	0.0301***	0.043***
	(594.10)	(129.602)	(265.06)	(142.23)	(219.36)
Income	4.14E-17***	1.13E-16***	-7.96E-18***	9.22E-17***	-2.89E-18***
	(219.09)	(575.465)	(58.68)	(524.58)	(18.39)
With Investment	-6.99E-17***	6.44E-17***	-8.17E-17***	-2.12E-18***	1.58E-17***
	(926.79)	(264.564)	(947.39)	(46.02)	(405.97)
Entrepreneur	0.0045***	0.0044***	0.0034***	0.0015***	0.0023***
	(20.14)	(14.504)	(9.47)	(7.17)	(12.26)
Employee Balance	0.795***	0.7134***	0.8254***	0.8723***	0.8868***
	(3196.86)	(2421.92)	(2163.82)	(4260.46)	(4660.73)
Lag Credit M12	0.0041***	0.0097***	0.0073***	0.0168***	0.0209***
	(7.33)	(12.78)	(8.00)	(32.01)	(43.53)
R-Squared	0.775	0.51	0.77	0.769	0.79
Durbin-Watson	1.877	1.94	2.19	1.97	1.99

At last, we need to evaluate the robustness of the econometric model in 2018 and 2022. Particularly in 2022 (in Table 7) when we removed the control variables, there was a change in the coefficient. So, to assess the impact, we made an Econometric Model, changing the Linear Regression (OLS) to the Generalized Method of Moments (GMM), using the mean of the moments. The GMM is used when we are not so sure about the endogeneity of the variables and can analyze the robustness of the proposed Model (Equation 2).

Table 12 – Linear Regression Results – 2022

*The table below shows the results of the study with dif-in-dif linear regressions with the dependent variable prob left*post-election. All the other variables (gender, age, with children, graduated, married, income, with investment, entrepreneur, employee balance and lag credit) are control variables in this study. The variable gender is dummy equal 1 when is a Man. With children(married/graduated/entrepreneur) is a dummy equal 1 when the individual has a declared child (married/have a graduation or above/has a firm). Income is the mensal income of the individual and lag credit is the information of the usage of credit of the month M-1. The Full Model (OLS), present the model with all the control variables in the linear regression. Model GMM, we have the same variables but by Generalized Method of Moments to make the comparison of Methods. . In the table, is presented the coefficients with the p-value marked with *. In ***, the p-value less than 0.1%, ** the p-value less than 1% and * the p-value less than 5%. Below to each coefficient, the t-statistic.*

	OLS	GMM
Prob Left*Post Election	0.0259***	0.0104***
	(49.966)	(4.20)
Prob Left	-0.0244***	-0.1806***
	(85.916)	(102.41)
Post Election	0.0162***	-2.59E-01***
	(80.236)	(206.81)
Gender	-0.011***	0.0656***
	(51.921)	(126.52)
Age	0.0018***	0.0024***
	(8.819)	(126.01)
With Children	0.0231***	0.0357***
	(111.614)	(18.21)
Graduated	0.0007***	0.1267***
	(3.28)	(233.73)
Married	0.0996***	0.0254***
	(453.108)	(44.77)
Income	-1.20E-17***	0.6124***
	(102.568)	(903.86)
With Investment	7.67E-18***	4.31E-01***
	(85.476)	(341.16)
Entrepreneur	0.0049***	4.31E-01***
	(23.964)	(341.16)
Employee Balance	0.8381***	6.76E-06***
	(3863.342)	(21.99)
Lag Credit M12	0.0259***	0.273***
	(49.966)	(1251.38)
R-Squared	0.777	0.39

As observed, both the proposed OLS econometric model and the GMM model present a positive coefficient for the Prob_Left*Post_Election in 2022, indicating the stability of the model, removing the hypothesis that there may be endogeneity that affects the variable of interest.

CONCLUSION

We show empirical validations of different people choices in economy caused by their different political affiliations. In an external event such the elections, the beliefs of left-party and right-party voters affect their purchases and by extension, the credit search in financial institutions. People who vote left (right) use less credit when right (left) party candidate wins a closed election.

Observing the data of 2018 and 2022, we observed both 2018 and 2022, we were able to see a different credit portfolio between both groups. The winner group had an increase after the elections of R$ 1,139.67 (approximately 2.36% of their credit portfolio). We made many statistical tests to remove the hypothesis of external factors, including the employees balance as a proxy of GDP, to remove the external factor of the local economy; including registration information to remove other behavioral bias and including information of investments and default to remove the financial knowledge impact.

Polls measured a correlation between income and voting right-party candidates. Wealthy people are responsible for a huge part of total consumption in most economies; thus, their behavior has a strong impact on the country aggregate consumption level. Similarly, firm owners and managers tend to be wealthier and extend their spending and credit behavior to the firms they manage. The presence of this belief disagreement effect on firms remains as a suggestion for further research. If confirmed that companies have the same behavior – to increase (decrease) their spending when a right-party (left) candidate wins – the consequence can also be relevant on the aggregate level. study can not only be applied to individuals but also can be applied, by extension, to the public of firms and it is the best way to understand this search for purchases and therefore credit in companies.

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