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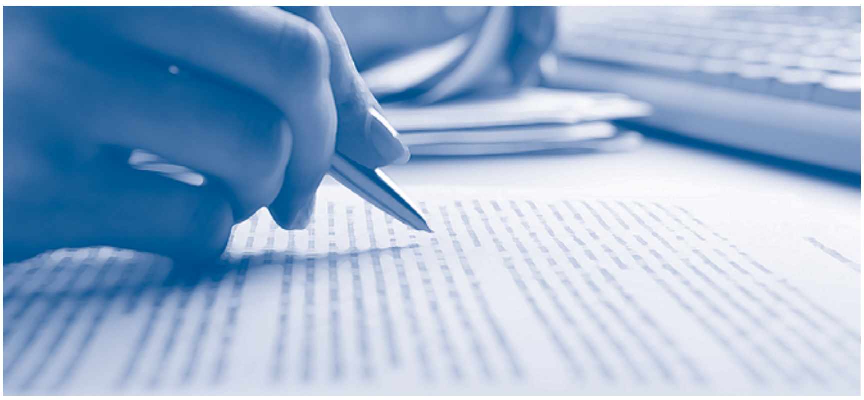

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Jaqueline Terra Moura Marins*

Myrian Beatriz Eiras das Neves**

Abstract

The Working Papers should not be reported as representing the views of the Banco Central do Brasil. The views expressed in the papers are those of the author(s) and do not necessarily reflect those of the Banco Central.

The aim of this paper is to examine empirically whether the default of borrower companies in the Brazilian market rises in downturns. To this end, a probit model for the probability of default is developed based on credit microdata taken from the Credit Information System of the Central Bank of Brazil (SCR) and on macroeconomic variables. Our results provide evidence of a strong negative relationship between business cycle and credit default, going in accord to the literature dealing with corporate data. These effects are stronger than those found in our previous article for the case of default of

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individuals. This is an expected result, since the retail credit is more sprayed than the corporate credit. The macroeconomic variables that have the greatest effect on corporate defaults were GDP growth and inflation.

Keywords: Procyclicality, Business Cycle, Corporate Credit Risk, Basel II.

JEL Classification: G21, G28, E32.

1. Introduction

Credit default is a matter that concerns regulators and financial institutions, because it is directly related to the measurement of credit risk in the financial system. The three versions of the Basel capital accord, designed respectively in 1988, 2004 and 2011, is an evidence of recurrent concern of the central banks and the banking industry with credit risk management.

In its latest version, the Basel agreement displayed more specifically the relationship between credit risk and macroeconomic conditions. Basel III, as it became known, essentially established the need for creation of capital buffers. These buffers would be established beyond the minimum requirement demanded from the banking sector during periods of high economic growth, in order to face the procyclical effects of Basel II. For having made capital requirements sensitive to the level of credit risk of the loans, the Basel II accord has eventually amplified business cycle fluctuations. In periods of recession, when the probability of default, which is a credit risk component introduced in the calculation of capital requirements, rises, these requirements also increase. This would eventually lead to an increase in capital costs and a reduction in credit supply. Such effects can amplify the recessive phase of the cycle. The opposite effect can occur during periods of economic expansion.[1]

Therefore, a necessary condition for the occurrence of procyclical effects is the existence of a negative relationship between defaults of loans and the phase of the business cycle. The authors have already observed this negative relationship in retail credit and the results showed that the relationship is significant but not as strong as those found in other countries (Correa et al., 2011). As a natural extension of that previous work, we intend here to further contribute to this literature by examining this relationship in corporate credit.

Following the same line of the previous work, we are only interested in studying the validity of the first part of the procyclicality argument previously explained, namely if the probability of default of corporate loans, in fact, rises in recession and decreases in expansion . Therefore, we do not study here the second part of the procyclicality

[1] For a detailed discussion of procyclicality and capital buffers, the following documents compile the Basel III Capital Accord: "Basel III: A global regulatory framework for more resilient banks and banking systems"; "International framework for liquidity risk measurement, standards and monitoring "; and " Guidance for national authorities operating the countercyclical capital buffer ", BIS, December 2010 and June 2011.

argument, i.e., if the increase in the probability of default, while resulting in a higher capital requirement, will be reflected in a reduction of credit supply. That would require a separation of the effects of supply and demand for credit, which is not possible given the information we have.

In this context, the aim of this paper is to examine empirically whether the default of borrower companies in the Brazilian market rises in downturns. To this end, a probit model for the probability of default is developed based on credit microdata taken from the Credit Information System of the Central Bank of Brazil (SCR) and on macroeconomic variables. In the literature of credit risk, it is common to call this type of modeling as idiosyncratic and systemic risk factor model, respectively.

Unlike previous work, we did not select any specific type of credit modality neither financial institution, working with the whole range of available transactions. This resulted in a large and unprecedented microdata base for the Brazilian market of corporate loans, which included information about more than 100,000 borrowing companies and nearly 800 lending financial institutions between 2005 and 2010.

Our results provide evidence of a strong negative relationship between business cycle and credit default, going according to the literature dealing with corporate data. These effects are stronger than those found in the previous article for the case of default of individuals. This is an expected result, since the retail credit is more sprayed than the corporate credit. The macroeconomic variables that have the greatest effect on corporate defaults were GDP growth and inflation.

The rest of the article is organized as follows. In Section 2, we review the literature on the relationship between corporate default and macroeconomic variables. In section 3, we seek evidence of this relationship, based on the observed correlations between the time series of these variables. In section 4, we describe the set of credit microdata and present some descriptive statistics of the sample. In section 5, the econometric model used to investigate the relationship is presented along with the inclusion of those microdata and, in section 6, we discuss the main results. In Section 7, some conclusions are presented.

2. Literature review

The literature on the relationship between credit default and macroeconomic conditions is still scarce. However, with the recent economic events, especially the 2008 financial crisis, studies about macro-finance interaction became more frequent.

Some recent articles associate firm-specific financial indexes with variables related to business cycle, when it comes to specification of default risk models. The financial variables are related to liquidity, profitability, efficiency, solvency, leverage and firm size.

Bharath and Shumway (2008) observed that the widely used structure of the Merton’s model (1974) to forecast default probabilities, solely based on information from the companies’ market value, is not enough. Works such as Duffie, Saita and Wang (2007), Pesaran, Schuermann, Treutler and Weiner (2006), Bonfim (2009), Lando and Nielsen (2010) and Tang and Yan (2010) present empirical evidence that firm-specific factors alone are not able to fully explain variations in corporate defaults and credit ratings.

Bonfim (2009) examined the determinants of corporate loans defaults in the Portuguese banking sector, through probit models and survival analysis. Using microdata, the author found that the companies’ defaults are strongly affected by their specific characteristics, such as its capital structure, company size, profitability and liquidity, plus its recent sales performance and its investment policy. However, the introduction of macroeconomic variables substantially improved the quality of the models, especially the GDP growth rate, the lending growth rate, the average interest rate of the loans and the stock market return rate.

According to Jacobson, Lindé and Roszbach (2011), the two most important macroeconomic factors that affect corporate defaults are the nominal interest rate and the output gap. As financial firm-specific variables, the authors used the EBITDA and total assets ratio, the interest coverage index, the leverage index, the total liabilities and revenues ratio, the net assets and total liabilities ratio and finally the turning stock.

Repullo, Saurina and Trucharte (2009) investigated the possible procyclical effects of Basel II in the Spanish financial system between 1987 and 2008. The authors set out to develop a logit model for the probability of default based on credit microdata related to the loan transactions’ characteristics, the borrowing firm's characteristics and some macroeconomic variables. The estimated probabilities of default for each company were used to calculate the corresponding capital requirements of Basel II that would have been required if the agreement were on at that time. From this rebuilt capital requirement series, the procyclicality was verified by the presence of strong negative correlation with the GDP growth rate. This methodology used to investigate the procyclical effects, however, is subject to the Lucas' critique, as the authors warned.

3. Aggregate evidence of the relationship between corporate credit default and business cycle

Before studying the evidence of the relationship between default and macroeconomic fluctuations in the level of credit microdata, we should try to understand some aspects of this relationship at an aggregate level. To this end, we examined the correlation between a series of corporate credit default with some macroeconomic variables. These correlations will help us to better understand the cyclical movement between the defaults and the set of macro variables considered here and therefore to identify how these variables can be used in the probit regression model, together with microdata.

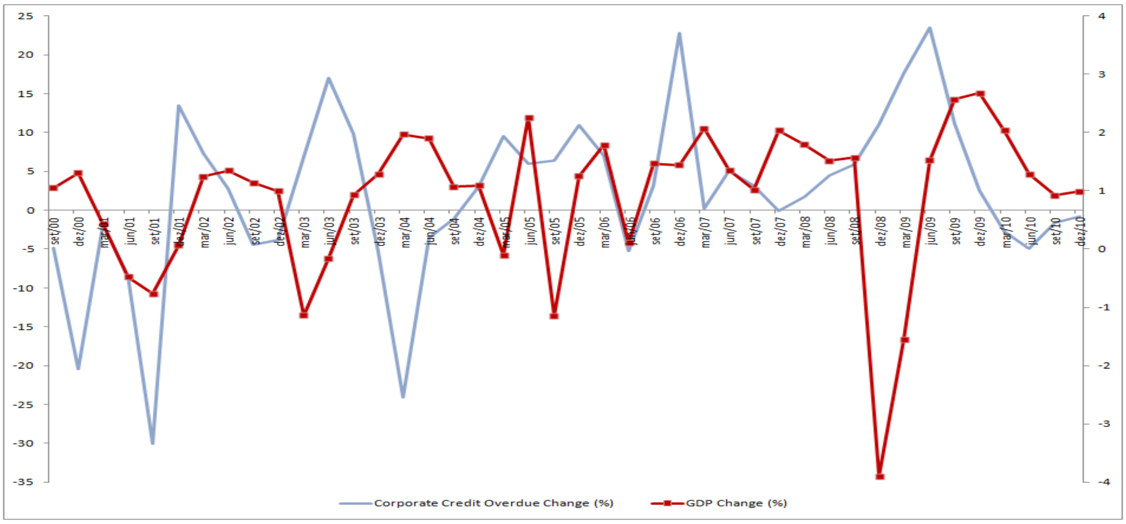
The corporate default series used here refers to the balance of principal and / or interest installments of loans more than 90 days overdue[2] .The macroeconomic series gather information regarding the level of domestic production and the granting of credit.

Graphs 1 and 2 below show the co-movements of each macroeconomic series with the corporate credit overdue series between 2000 and 2010. The variables representing the business cycle were the GDP and the credit granted to firms through unlinked resources.[3]

[2] Basel II defines default as balances of loans in arrears over 90 days.

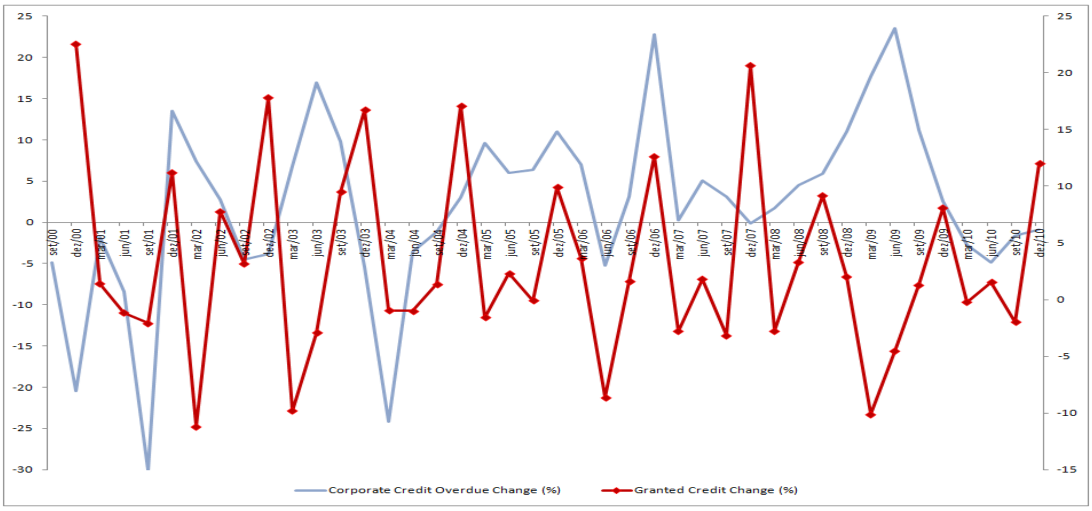
[3] The correlation between the output gap and the rate of economic activity, measured by the IBC-Br, were also assessed, but were not presented here because these series are highly correlated with the GDP itself.

Graph 1 – Credit overdue and GDP



In both graphs, the negative correlation between the series is clear: 82% in the first graph and 76% in the second one. The performance of the macro variables in a context of deteriorating economic conditions is better mirrored in the default increase when some lags are considered.

Graph 2 – Credit overdue and Granted credit to firms



4. Data description

The information presented here come from the junction of two large databases – the Credit Information System of the Central Bank of Brazil (SCR) and Economática. From the first base, we obtained microdata related to loans granted to Brazilian companies by the national financial system between January 2005 and December 2010. All borrowers' credit transactions whose total liability exceeds five thousand reais (R$ 5,000) are recorded in the SCR, according to the information provided by the lenders themselves to the Central Bank of Brazil. Data are reported monthly and contain detailed information on loans, including some characteristics of the borrowers and the transactions, such as their risk ratings. The level of detail present in this database allows us to analyze the components of the borrowers' credit risk taking into account the heterogeneity that exist among them.

The chosen sample consists on fixed-income loans granted to firms. The observation unit combines all the transactions of each customer in a given financial institution, regardless of their credit modality. Loans with interest rates above 250% per year were eliminated because they could represent incorrect input on the system. After this filtering, the resulting credit modalities were: overdraft, working capital loans with maturities superior than 30 days, bill discount, check cashing and revolving credit. As the remaining observations were not manageable yet (7 million), a new selection became necessary. This time, we randomly selected and stratified by the economic sector of the borrower, a sample of 30% of these observations. This resulted in 61,232 borrowings companies taking credit in 640 financial institutions, amounting 91,530 "financial institution / company" units.

Jarrow and Turnbull (2000) noted that one year is the time horizon used in literature to measure credit risk issues. Despite the wealth of information present in the SCR, we considered time intervals of less than one year, like quarters, due to the small number of years available in our database (2005 to 2010).

A defaulting firm on a given institution was the one which has credit loans overdue for over 90 days. According to this, the same firm can be considered not in default in another financial institution.

Regarding the characteristics of the borrower, the SCR provides information on its size (micro, small, medium or large company), its type of control (public or private), the main economic sector of its activity (according to the CNAE's code of IBGE) and the geographic region of the credit granting agency. From this data, we constructed variables to represent the number of financial institutions with which the company has a credit relationship, the percentage of the company's portfolio that is collateralized, the portfolio´s average interest rate and the company's average total debt in the National Financial System.

We extracted financial information from Economática, the second database used in this article. As customers are not identified in the SCR for reasons of confidentiality, we could not cross the data on loans with the balance sheet data of the borrowing firm. Thus, we used sector variables extracted from the Economática related to liquidity, profitability, efficiency, solvency and leverage. We selected the following variables: return on equity, earnings to price ratio, earnings per share, liabilities to assets, total assets, EBITDA margin, nominal cost of debt, net debt to EBITDA ratio, liquidity ratio, financial leverage, financial cycle, index risk and Sharpe ratio[4]. Each sector variable was represented by its median value on a quarter and was equally allocated to all companies of the same sector in that quarter.[5]

4.1. Descriptive statistics

Based on the sample used here, Table 1 shows the total number of companies in each sector, the value of the loan portfolio in December 2010 and the average default rate. Construction is the highest default rate sector (5.3%), also with the largest loan portfolio (US$ 15 billion). Moreover, Electricity is the sector with the lowest level of delay (0.9%) and Telecommunications has the lowest loan portfolio (US$ 92 million).

[4] These variables are described in the Appendix.

[5] We redistributed the 24 CNAE's macro-sectors into the 19 Economática's sectors.

Table 1 – Default per economic sectors

Sector	Number of companies	Portfolio in Dec/2010 (R$ million)	Average Default Rate[6]
Agriculture and Fishing	2,055	2,202	4.1%
Food and Beverages	8,291	8,601	4.6%
Trade	10,297	5,575	3.9%
Construction	19,760	15,088	5.3%
Electronics	4,271	4,815	3.7%
Electric Energy	282	2,842	0.9%
Finance and Insurance	784	1,019	1.0%
Industrial Machines	3,025	3,074	3.1%
Mining	2,910	2,597	3.5%
Paper	746	1,178	3.6%
Oil and Gas	8,292	5,982	4.6%
Chemicals	3,797	4,309	2.5%
Steel and Metallurgy	2,783	3,851	2.8%
Software	8,468	5,258	4.6%
Telecommunications	80	92	1.2%
Textile	11,650	7,271	4.9%
Transportation and Services	5,649	6,394	3.7%
Vehicles	8,522	7,540	4.6%
Others	11,726	11,962	4.8%
Total	**113,388**	**99,650**	**4.4%**

Almost 80% of the analyzed companies are concentrated in São Paulo, Minas Gerais, Rio Grande do Sul, Rio de Janeiro, Paraná, Santa Catarina and Goiás, although São

[6] Average default rate given by the ratio between the value of the portfolio in arrears and the total portfolio.

Paulo holds 48.5% of the total loan transactions. Regarding the level of default, the Midwest has the highest credit overdue rate for over 90 days, with 5.63%, followed by the North, Southeast, Northeast and South, with 4.61%, 4.14%, 3.87% and 3.68% respectively.

Regarding the degree of loan concentration in financial institutions, about 85% of the analyzed companies have loan transactions in up to four financial institutions, which corroborates the concentration profile of the National Financial System. According to company size, default is higher among micro firms, with a rate of 5.5%, which decreases to 0.2% for large companies. This result is consistent with some findings in literature (Bunn and Redwood (2003) and Jiménez and Saurina (2004), among others).

Table 2 – Comparing companies with and without default

Financial Indicador	Average Value for Non-Defaulting Companies	Average Value for Defaulting Companies	Mean Difference Test H0: difference = 0 Ha: difference <> 0
Leverage	1.21	1.42	0.00
Nominal cost of debt (%)	105.20	80.62	0.00
Net Debt to EBITDA ratio	0.94	1.16	0.00
Liquidity	1.22	1.14	0.00
Earnings to price ratio	4.47	4.72	0.00
EBITDA margin (%)	15.65	17.07	0.00
Risk	39.33	43.88	0.00
Sharpe	0.52	0.46	0.00

In Table 2, we split the companies in two groups: defaulting and non-defaulting firms and then we calculated the average values of the main financial indicators, in order to check for significant differences between the two groups. We noted that the hypothesis of mean equality between the groups is rejected for all indicators. Leverage, net debt to EBITDA ratio, liquidity, risk and Sharpe had the expected results. The nominal cost of debt should provide greater value for the defaulting companies group and profitability indicators, such as earnings to price ratio and EBITDA margin, should be higher for non-defaulting firms. The mean difference test shows that the sectoral variables do differentiate default, and therefore can be interesting explanatory variables for default probabilities in the absence of variables that relate directly to the company.

5. Methodology: the probit model of corporate default probability

The economic modeling underlying the empirical analysis is derived primarily from the authors' previous article (Correa et al, 2011). Adapting the theoretical model there described to the corporate case is not complicated. We can imagine that when a company decides to take a loan, it intends to use the loan to implement an investment project. The return on this project will depend on (i) the characteristics of the borrower company, in particular, the risk rating assigned to it by the lender bank, as well as of the loan transactions between this company and that lender, (ii) the macroeconomic environment in which the company is inserted, in particular, the phase of the business cycle, and, finally, (iii) other control variables associated with the economic sector of the borrowing company.

The dependence of the project's return on the phase of the cycle can be imagined by the interdependence of existing projects in the economy. In recessionary phase, projects developed by other companies may begin to present negative returns and consequently, these companies can start to become delinquent. This delinquency, coming from companies in the same industry or in different ones, may end up affecting the project's return of the original company and its ability to pay the loans.

We can then write, in a similar notation of the previous article, that:

$$\boldsymbol{y}^*_{i,j,t} = \boldsymbol{x}'_i\boldsymbol{\beta} + \boldsymbol{m}'_t\boldsymbol{\gamma} + \boldsymbol{z}'_{i,t}\boldsymbol{\theta} + \boldsymbol{c}_i + \boldsymbol{u}_{i,j,t}$$

$\boldsymbol{y}^*_{i,j,t}$ is the unobserved return of the borrowing company *i*, which took credit at the bank *j* at time *t*. $\boldsymbol{x}_i$ is a vector with observable personal characteristics of the borrower *i* and its credit transactions. $\boldsymbol{m}_t$ are macroeconomic variables at time *t*. $\boldsymbol{z}'_{i,t}$ are control variables that can change among companies and across time. $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ and $\boldsymbol{\theta}$ are parameters vectors. $\boldsymbol{c}_i$ is an unobserved individual effect of the company *i*. $\boldsymbol{u}_{i,j,t}$ is a shock affecting the project's return, which is assumed to be independent and standard normally distributed.

The borrowing company must obtain a minimum return $\boldsymbol{\alpha}$ from its investment project in order to be able to pay the loan that financed the project. Otherwise, the company will become delinquent on that loan. However, the project's payoff $\boldsymbol{y}^*_{i,j,t}$ is not observed to us, but only for the company itself. We just observe whether the company *i* has become or not delinquent on that loan granted by bank *j* in period *t*. So we can think of a binary variable $y_{i,j,t}$ which represents the latent variable $y^*_{i,j,t}$ as follows:

$$\boldsymbol{y_{i,j,t}} = \begin{cases} \mathbf{1}, \boldsymbol{if\ default}\ (\boldsymbol{y^*_{i,j,t}} \leq \boldsymbol{\alpha}) \\ \mathbf{0}, \boldsymbol{otherwise} \end{cases}$$

We can then write a probit model of default probability from this binary variable as follows:

$$\begin{aligned} \boldsymbol{Prob}\big(\boldsymbol{y_{i,j,t}} = \mathbf{1}/\boldsymbol{x'_i}, \boldsymbol{m'_t}, \boldsymbol{z'_{i,t}}, \boldsymbol{c_i}\big) &= \boldsymbol{Prob}\big(\boldsymbol{y^*_{i,j,t}} \leq \boldsymbol{\alpha}/\boldsymbol{x'_i}, \boldsymbol{m'_t}, \boldsymbol{z'_{i,t}}, \boldsymbol{c_i}\big) \\ &= \boldsymbol{Prob}\big(\boldsymbol{x'_i\beta} + \boldsymbol{m'_t\gamma} + \boldsymbol{z'_{i,t}\theta} + \boldsymbol{c_i} + \boldsymbol{u_{i,j,t}} \leq \boldsymbol{\alpha}/\boldsymbol{x'_i}, \boldsymbol{m'_t}, \boldsymbol{z'_{i,t}}, \boldsymbol{c_i}\big) \\ &= \boldsymbol{Prob}\big(\boldsymbol{u_{i,j,t}} \leq \boldsymbol{\alpha} - \boldsymbol{x'_i\beta} - \boldsymbol{m'_t\gamma} - \boldsymbol{z'_{i,t}\theta} - \boldsymbol{c_i}/\boldsymbol{x'_i}, \boldsymbol{m'_t}, \boldsymbol{z'_{i,t}}, \boldsymbol{c_i}\big) \\ &= \Phi\big(\boldsymbol{\alpha} - \boldsymbol{x'_i\beta} - \boldsymbol{m'_t\gamma} - \boldsymbol{z'_{i,t}\theta} - \boldsymbol{c_i}\big) \end{aligned}$$

It is known that, when considering the presence of unobservable individual effects on probit modeling, additional assumptions regarding the term $\boldsymbol{c_i}$ become necessary for a consistent estimation of the parameters[7]. In addition to the assumptions made in the case of linear models – strict exogeneity of the covariates conditional on $\boldsymbol{c_i}$ and conditional independence of the response variables $\boldsymbol{y_{i,j,1}}, \boldsymbol{y_{i,j,2}}, \dots, \boldsymbol{y_{i,j,T}}$ in relation to the covariates and to $\boldsymbol{c_i}$ – it is necessary to specify how $\boldsymbol{c_i}$ relates to the dependent variables in the case of nonlinear models like the probit approach. As in the previous article, here we will deal with the probit model with random individual effects, which assumes that the unobserved effects $\boldsymbol{c_i}$ are independent of the covariates and normally distributed as $N(0,\boldsymbol{\sigma^2_c})$.

Applying this model to the data we have is straight. As we observe a time series of the balances of the borrowing companies' portfolios in each financial institution, we can identify their defaults. The dependent variables, described in the previous section, were placed into the three groups previously mentioned at the beginning of this section: company-specific, economic sector-specific and macroeconomic.

In the first group there are the risk rating given to the company by the lender bank, the geographic region of the granting credit agency[8], the average interest rate on the

[7] Wooldridge, 2002.

[8] The information we have concerns to the bank's agency address code and not the borrowing company address code. Nevertheless, we can imagine that these two pieces of information are fairly coincident, mainly because we are here considering macro-geographical regions rather than states.

company's operations in each lending institution, the percentage of collateralized company's transactions at each institution, the number of financial institutions with which the company has credit relationship, the balance of company's portfolio loans in the national financial system and ultimately the economic sector where the company operates. In the second group there are the variables representing the financial indicators of the economic sectors where the companies operate, taken from Economática database. Finally and representing the third group, we have variables associated to the business cycle – the growth rate of GDP, the output gap, the growth rate of loans granted to companies, the Ibovespa stock index change and the IPCA price index change.[9]

6. Results

We estimated three specifications of this probit model to analyze the relationship between corporate defaults and the business cycle. Tables 3 and 4 present the marginal effects on the default probability for each model, evaluated on the average of the explanatory variables. In Table 3, we present two initial specifications of the model, considering only variables that are specific to the company (Model 1) and then adding some controls that relate to the financial indicators of firms (Model 2). In Table 4, we present the third specification based on four models (Models 3 to 7) that add variables measuring the business cycle to Model 2. The difference among these five models relates to the set of macroeconomic variables considered. For comparison, a linear probability model with individual unobserved effect was also estimated by random effect (Model 8).

[9] All variables are described in more detail in Appendix.

Table 3 – Marginal effects on default probability (Part I)

Variables			Model 1		Model 2	
			Coeff.	P-Value	Coeff.	P-Value
COMPANY-SPECIFIC VARIABLES	Risk rating	AA	-0.009	0.000	-0.004	0.109
		B	-0.017	0.000	-0.013	0.000
		C	0.051	0.000	0.041	0.000
		D	0.131	0.000	0.130	0.000
		E	0.635	0.000	0.723	0.000
		F	0.696	0.000	0.776	0.000
		G	0.824	0.000	0.857	0.000
		H	0.873	0.000	0.901	0.000
		HH	0.950	0.000	0.978	0.000
	Region	North	0.003	0.710	0.004	0.642
		Northest	0.024	0.000	0.024	0.000
		Midwest	0.087	0.000	0.094	0.000
		South	0.105	0.000	0.107	0.000
	Interest rate		-0.0002	0.000	0.000	0.395
	Collateral		-0.0003	0.000	0.000	0.055
	Number of FIs		-0.135	0.000	-0.107	0.000
	Total portfolio		0.040	0.000	0.024	0.000
	Economic sector	Agriculture and Fishing	-0.027	0.003	0.740	0.000
		Food and Beverages	-0.006	0.322	0.841	0.000
		Trade	0.042	0.000	0.899	0.000
		Electronics	-0.006	0.426	0.871	0.000
		Eletric energy	-0.029	0.121	0.742	0.000
		Finance and Insurance	-0.014	0.417	0.293	0.070
		Industrial Machines	-0.023	0.002	0.874	0.000
		Mining	-0.025	0.002	0.392	0.000
		Paper	-0.029	0.022	0.020	0.327
		Oil and Gas	0.005	0.408	0.687	0.000
		Chemicals	-0.011	0.141	0.835	0.000
		Steel and Metallurgy	-0.027	0.000	0.843	0.000
		Software	-0.012	0.034	0.736	0.000
		Telecommunications	-0.066	0.064	0.642	0.000
		Textile	0.021	0.000	0.926	0.000
		Transportation and Services	-0.019	0.002	0.665	0.000
		Vehicles	0.016	0.005	0.894	0.000
		Others	0.008	0.131	0.925	0.000

Table 3 – Marginal effects on default probability (Part II)

Variables		Model 1 Coeff.	Model 1 P-Value	Model 2 Coeff.	Model 2 P-Value
SECTORIAL VARIABLES	Risk	-	-	2.0544	0
	Sharpe	-	-	-3.3519	0
	Earning to Price	-	-	2.6387	0
	Net debt to Ebitda	-	-	-0.1206	0
	Nominal cost	-	-	-0.3499	0
	Liquidity	-	-	-0.158	0
	Financial cicle	-	-	0.0013	0
	Ebitda margin	-	-	-0.2177	0
	Leverage	-	-	-0.0051	0
	ROE	-	-	2.0242	0
	Earning per share	-	-	-0.1202	0
	Liabilities to assets	-	-	0.2159	0
	Total assets	-	-	0.2258	0
σ_c *		1.120	0.007	1.300	0.008
ρ *, **		0.550	0.003	0.630	0.003
% correct. predicted – Total		88.56%		84.39%	
% correct. predicted – Default		60.56%		62.64%	
% correct. predicted – Non default		98.54%		92.14%	
Log-likelihood		-241750.42		-196388.07	
# observation		833372		794433	

* σ_c is the standard deviation of the unobserved individual effect and ρ is the correlation between the composite latent error $c_i + u_{i,j,t}$ across any two time periods.
** standard-errors next to the coefficients.

Table 4 – Marginal effects on default probability
(Part I)

Variables			Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
			Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value
COMPANY-SPECIFIC VARIABLES	Rsik rating	AA	0.007	0.000	-0.002	0.174	0.003	0.082	-0.001	0.586	-0.003	0.259	-0.001	0.275
		B	-0.008	0.000	-0.002	0.051	-0.009	0.000	-0.003	0.008	-0.013	0.000	-0.008	0.000
		C	0.021	0.000	0.021	0.000	0.026	0.000	0.020	0.000	0.034	0.000	0.017	0.000
		D	0.091	0.000	0.102	0.000	0.104	0.000	0.096	0.000	0.119	0.000	0.043	0.000
		E	0.830	0.000	0.920	0.000	0.813	0.000	0.915	0.000	0.738	0.000	0.346	0.000
		F	0.881	0.000	0.948	0.000	0.861	0.000	0.946	0.000	0.793	0.000	0.389	0.000
		G	0.943	0.000	0.970	0.000	0.927	0.000	0.972	0.000	0.874	0.000	0.686	0.000
		H	0.967	0.000	0.987	0.000	0.956	0.000	0.987	0.000	0.915	0.000	0.795	0.000
		HH	0.995	0.000	0.999	0.000	0.993	0.000	0.999	0.000	0.980	0.000	0.906	0.000
	Region	North	-0.003	0.586	-0.003	0.405	-0.002	0.792	-0.003	0.366	0.001	0.885	-0.001	0.843
		Northeast	0.014	0.001	0.009	0.002	0.016	0.000	0.008	0.002	0.024	0.000	0.008	0.000
		Midwest	0.072	0.000	0.051	0.000	0.078	0.000	0.050	0.000	0.096	0.000	0.028	0.000
		South	0.078	0.000	0.056	0.000	0.085	0.000	0.055	0.000	0.111	0.000	0.036	0.000
	Interest rate		0.000	0.383	0.000	0.004	0.000	0.025	0.000	0.017	0.000	0.393	0.000	0.216
	Collateral		0.000	0.252	0.000	0.348	0.000	0.097	0.000	0.209	0.000	0.238	0.000	0.000
	Number of FIs		-0.054	0.000	-0.024	0.000	-0.067	0.000	-0.025	0.000	-0.088	0.000	-0.030	0.000
	Total Portfolio		0.017	0.000	0.010	0.000	0.023	0.000	0.011	0.000	0.020	0.000	0.007	0.000
	Economic Sector	Agriculture and Fishing	0.767	0.000	0.280	0.000	0.586	0.000	0.163	0.208	0.763	0.000	0.243	0.000
		Food and Beverages	0.826	0.000	0.022	0.009	0.566	0.000	-0.006	0.000	0.817	0.000	0.268	0.000
		Trade	0.955	0.000	0.114	0.000	0.844	0.000	0.042	0.000	0.894	0.000	0.315	0.000
		Electronics	0.952	0.000	0.697	0.000	0.895	0.000	0.499	0.000	0.886	0.000	0.340	0.000
		Eletric energy	0.651	0.000	-0.033	0.000	0.247	0.000	-0.031	0.000	0.655	0.000	0.193	0.000
		Finance and Insurance	0.187	0.200	-0.032	0.000	0.040	0.647	-0.031	0.000	0.024	0.800	0.079	0.000
		Industrial Machines	0.950	0.000	0.628	0.000	0.873	0.000	0.465	0.000	0.881	0.000	0.369	0.000
		Mining	0.370	0.000	-0.037	0.000	0.046	0.001	-0.036	0.000	0.329	0.000	0.111	0.000
		Paper	0.000	0.997	-0.034	0.000	-0.070	0.000	-0.033	0.000	0.049	0.028	0.072	0.000
		Oil and Gas	0.665	0.000	-0.042	0.000	0.259	0.000	-0.043	0.000	0.668	0.000	0.222	0.000
		Chemicals	0.863	0.000	-0.009	0.085	0.605	0.000	-0.021	0.000	0.840	0.000	0.261	0.000
		Steel and Metallurgy	0.922	0.000	0.165	0.000	0.725	0.000	0.060	0.000	0.838	0.000	0.280	0.000
		Software	0.914	0.000	-0.024	0.000	0.690	0.000	-0.029	0.000	0.726	0.000	0.341	0.000
		Telecommunications	0.433	0.000	-0.032	0.000	0.087	0.206	-0.031	0.000	0.534	0.000	0.151	0.000
		Textile	0.972	0.000	0.732	0.000	0.899	0.000	0.559	0.000	0.927	0.000	0.356	0.000
		Transportation and Services	0.629	0.000	-0.035	0.000	0.176	0.000	-0.036	0.000	0.611	0.000	0.211	0.000
		Vehicles	0.952	0.000	0.470	0.000	0.827	0.000	0.303	0.000	0.886	0.000	0.329	0.000
		Others	0.972	0.000	0.428	0.000	0.879	0.000	0.222	0.000	0.926	0.000	0.383	0.000

Table 4 – Marginal effects on default probability (Part II)

	Variables	Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
		Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value
SECTORIAL VARIABLES	Risk	0.686	0.000	0.275	0.000	1.030	0.000	0.254	0.000	1.234	0.000	0.623	0.000
	Sharpe	-4.224	0.000	1.264	0.000	-3.159	0.000	1.512	0.000	1.906	0.000	1.348	0.000
	Earning to Price	1.493	0.000	0.005	0.895	2.076	0.000	0.081	0.021	1.521	0.000	1.455	0.000
	Net debt to Ebitda	-0.007	0.005	-0.034	0.000	-0.045	0.000	-0.038	0.000	-0.060	0.000	-0.023	0.000
	Nominal cost	-0.054	0.000	0.026	0.000	0.073	0.000	0.015	0.000	-0.206	0.000	-0.068	0.000
	Liquidity	-0.112	0.000	-0.041	0.000	-0.167	0.000	-0.053	0.000	-0.117	0.000	-0.003	0.221
	Financial cicle	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.001	0.000
	Ebitda margin	-0.020	0.000	-0.025	0.000	-0.011	0.000	-0.025	0.000	-0.051	0.000	-0.047	0.000
	Leverage	-0.002	0.000	0.000	0.000	-0.003	0.000	0.000	0.000	-0.003	0.000	-0.001	0.000
	ROE	0.403	0.000	0.371	0.000	0.647	0.000	0.355	0.000	1.175	0.000	0.218	0.000
	Earning per share	-0.102	0.000	0.049	0.000	-0.096	0.000	0.058	0.000	-0.042	0.000	-0.073	0.000
	Liabilities to assets	0.148	0.000	-0.143	0.000	0.016	0.151	-0.193	0.000	0.317	0.000	-0.005	0.431
	Total assets	0.144	0.000	0.134	0.000	0.150	0.000	0.117	0.000	0.197	0.000	0.104	0.000
MACRO VARIABLES	Credit growth (-2)	2.596	0.000	-1.011	0.000	2.186	0.000	-	-	-0.749	0.000	-0.262	0.000
	Output gap	-	-	-0.043	0.000	-	-	-0.039	0.000	-	-	-	-
	Output gap (-2)	-2.628	0.000	-	-	-	-	-	-	-	-	-	-
	GDP growth (-2)	-	-	-	-	1.171	0.000	-	-	-5.948	0.000	-6.031	0.000
	Ibovespa change	0.773	0.000	0.278	0.000	1.105	0.000	0.291	0.000	-	-	-	-
	Ibovespa change (-2)	-	-	-	-	-	-	-	-	-0.353	0.000	-0.282	0.000
	Expected IPCA	-	-	-	-	-	-	-	-	-	-	-	-
	IPCA	-8.298	0.000	-1.921	0.000	-7.342	0.000	-2.616	0.000	-	-	-	-
	IPCA (-2)	-	-	-	-	-	-	-	-	4.202	0.000	3.639	0.000
σ_c *		1.700	0.011	1.980	0.011	1.560	0.010	1.970	0.011	1.400	0.009	0.086	
ρ *, **		0.740	0.002	0.790	0.002	0.700	0.003	0.790	0.002	0.660	0.003	0.100	
% correct. predicted – Total		86.14%		86.38%		85.25%		86.31%		85.36%		85.54%	
% correct. predicted – Def		73.95%		76.80%		68.38%		76.47%		68.62%		68.53%	
% correct. predicted – Non default		90.49%		89.80%		91.26%		89.81%		91.32%		91.60%	
Log-likelihood		-142810.23				-149857.33		-113585.21		-175448.56		-	
# observation		794433				794433		794433		794433		794433	

* σ_c is the standard deviation of the unobserved individual effect and ρ is the correlation between the composite latent error $c_i + u_{i,j,t}$ across any two time periods.
** standard-errors next to the coefficients.

In Model 1, the default probabilities among risk ratings seem to have been well differentiated: as the rating gets worse, the company's default probability rises. In the extreme case, when the company receives the lowest risk rating from the creditor institution (HH), its default probability is almost 100% higher than the default probability of companies with the lowest risk level (AA).[10]

The geographic region of the borrowing company also well identifies different default probabilities. Considering the richest region, Southeast, as the baseline one, the other regions are associated with higher default probabilities. The only exception is region North, which despite having shown a sign as expected, was not significant.

[10] Here we considered rating A as the baseline level.

The average interest rate for the loan transactions was significant in explaining delinquency. However, its marginal contribution to explain the default is virtually nil.

The percentage of company's collateralized transactions, although significant, also appears with a very low negative coefficient, indicating that the more collateralized the company loans are, the lower their default probability will be.[11]

The number of financial institutions with which the company has credit relationship also proved significant in explaining delinquency. His sign, however, indicates that the more creditors the company has, the lower their default probability. Repullo, Saurina and Trucharte (2009) do not expect a negative sign in this case, imagining that the more relationship a company has, the more restricted it might be in terms of liquidity and, therefore, the greater its default probability. The negative relationship found only seems reasonable if we think that a larger network of creditors available to a company might mean that this company is well regarded by banks precisely because it has a history of low defaults.

The total balance of the company’s loan portfolio also proved significant in explaining delinquency. As this variable was created as a proxy for the size of the company, its positive sign indicates that larger firms are more likely to default. Bonfim (2007) found a similar result in her empirical database as well as in her regression models.

The results for the dummy variables identifying the economic sector of the borrowing firm suggest that there are significant differences in the default probability for most sectors. Of the 19 economic sectors considered, only eight were not significant to differentiate the default probabilities of the respective sectors. Most of these non-significant sectors presented much change in the sign of their respective coefficient across the different models considered.

To measure the performance of the model, we calculated the percentage of correctly predicted observations in three groups: total observations, observations in default and observations not in default. We use a cutoff of 50% to define when the predicted probability correctly predicts the company defaults. The correctly predicted percentages from Model 1 are high (88%, 60% and 98% respectively) and, therefore, this model seems to have already done a good job in terms of goodness of fit.

[11] In fact, credit risk literature is controversial with respect to this signal. Some authors show that banks demand more collateral from those companies perceived as riskier. (Berger and Udell, 1990 and Jimenez, Salas and Saurina, 2006).

Even the company-specific variables having presented an important role to predict default probability, their performance deserves to be revised considering controls that relate to financial indicators of the companies. As our data do not allow us to identify the company name, we had to deal with financial indicators representing the economic sectors of each company. Therefore, in Model 2, we add to Model 1 indicators of liquidity, profitability, efficiency, solvency and leverage.

Generally, the signals and the significance of the firm-specific variables remained robust. This time, however, only two economic sectors were not significant to explain the companies' default, namely: Finance/Insurance and Paper. All others sectors had default probabilities higher than the basal one (Construction). The financial variables introduced were all significant, but not all of them had signal as expected. However, the model performance in terms of percentage of observations correctly predicted remained high: 84% for total observations, 62% for observations in default and 92% for observations not in default. So this model also had a high goodness of fit. Therefore, we decided to keep all financial variables in the following specification.

In the third specification, we add macroeconomic variables, to evaluate the effect of the business cycle on corporate defaults (Models 3 to 7). These models differ with respect to the lags of the variables considered. The variables are the GDP growth rate, the output gap (used instead of GDP growth), the growth rate of loans granted to firms, the Ibovespa stock index change and the IPCA price index change. In fact, we noted that the effect of the cycle variables on default is not contemporary, since Model 7, which considers all variables lagged two quarters, showed the best results in terms of expected signals and significance of the macroeconomic variables.

In general, the signals and the significance of the existing variables remained robust after the inclusion of macroeconomic variables. This time, however, only the financial sector remained not significant to explain the companies' defaults. All others presented higher default probabilities than the Construction sector probabilities. The quality of the model, in terms of percentage of correctly predicted observations, was not affected by the inclusion of macroeconomic variables: 85% for total observations, 68% for observations in default and 91% for observations in non default. Furthermore, in Model 7, all macroeconomic variables considered were significant, with expected signals and strong marginal effects. Our estimates suggest that an additional percentage point in the GDP growth rate reduces the default probability of a company in 6% two quarters ahead. In the case of an inflation decrease, measured by the IPCA index, reduces the default probability in 4% two quarters ahead. Regarding the granted credit, the effect on reducing the corporate default probability is much lower: 0.74%. Finally, a positive performance in the stock market, which generally reflects an improvement in the companies' financial condition, reduces their default probabilities in only 0.35% two quarters ahead.

Model 8, which is the linear probability model used as a benchmark, provided the same evidence of the best probit model (Model 7), namely: significant economic variables and negative signals as expected. However, its marginal effects are somewhat smoother.

Tables 3 and 4 also show the standard deviation of the unobserved individual effect (σ_c) and the correlation between the composite latent error $\boldsymbol{c_i} + \boldsymbol{u_{i,j,t}}$ across any two time periods (ρ). This correlation also measures the ratio of the variance of $\boldsymbol{c_i}$ to the variance of the composite error and that is why it is a useful measure of the relative importance of the individual unobserved effect. Our estimates suggest that the individual effect accounts for approximately 70% of the variance of the composite error and that this effect is significantly different from zero in all models.

Finally, it is worth mentioning that other models were tested, considering, for example, other business cycle variables such as the Selic interest rate, the expected inflation rather than the actual inflation rate and the IBC-Br economic activity index, as well as other time lags to evaluate the robustness of the results. We do not present these results here because these models underperformed the presented ones, and several of its variables were not significant and/or with expected signs.

An interesting extension to the present work is to consider some interactions in the above specifications. Since the companies' financial variables are also subject to fluctuations over the business cycle, we can represent these co-movements adding interactions between these variables and GDP growth to the model. Besides, we could try to estimate separate models for different group of firms, according to their size, age and economic sector for example. This would allow us to see if default probabilities are driven by different factors in each of these groups.

7. Conclusion

This article focused on the relationship between credit default and macroeconomic conditions in the corporate world, proposing to examine the validity of the first part of the Basel II procyclicality argument for the Brazilian credit market. The idea of this argument is that economic downturns would increase the credit default probability and therefore would require a recomposition of capital requirements. In a second moment, this consequent rearrangement of capital would lead to a credit crunch that would further intensify the preexisting recession. The inability to separate credit supply from credit demand with the available information prevents us from analyzing this second part of the argument.

A probit model for the default probability was developed from a large and unique database of micro credit taken from the Credit Information System of the Central Bank of Brazil (SCR), from Economática's financial indicators and from macroeconomic variables. Our sample included information on more than 60,000 borrowing companies and nearly 700 creditor financial institutions between 2005 and 2010.

In general, the variables built from micro credit transactions data were significant for predicting default probabilities of companies. The risk ratings of the companies, the geographic region of the granting credit agency and the economic sectors in which the companies operate well differentiate their default probabilities. The model's goodness of fit, in terms of percentage of correctly predicted observations, remained high even after the introduction of controls representative of sectoral financial indicators and of macroeconomic variables.

When macro variables were introduced, the obtained results allowed us to conclude that they have an important contribution to explain the delinquency of companies in the Brazilian credit market. As expected, this contribution was stronger than in the already studied case in a previous article by the authors on default from individuals[12]. The macroeconomic variables with the greatest effect on corporate defaults were GDP growth and inflation. Our estimates suggest that an additional percentage point in the GDP growth rate reduces the companies' default probability in 6% two quarters ahead. Regarding an inflation decrease, measured by the IPCA price index change, it reduces the default probability in 4% two quarters ahead.

[12] Correa et al, 2011.

An interesting point for future research would be to explicitly include interactions between macroeconomic variables and financial sector indicators in the above modeling. We could also try to estimate separate models for different group of firms, according to their size, age and economic sector for example. This would allow us to see if default probabilities are driven by different factors in each of these groups. Furthermore, a natural extension of the article would be to extend the sample period used in order to include at least one complete economic cycle.

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Appendix

Variables description

Leverage: quarterly sectoral variable that represents the median of debt capital and equity ratio.

ROE: quarterly sectoral variable that represents the median of the return on equity.

Earnings per share ratio: quarterly sectoral variable that represents the median of total earnings per company stock.

Liabilities to total assets ratio: quarterly sectoral variable representing the median of liabilities and assets ratio.

Total asset: quarterly sectoral variable that represents the median of total assets.

Total portfolio: quarterly sectoral variable representing the sum of the client portfolio balances in all financial institutions with which he has credit transactions. Measured in logarithm terms.

Financial cycle: quarterly sectoral variable that represents the median of the following expression: average collection period + average term of stock – average payment period.

Net debt to Ebitda ratio: quarterly sectoral variable that represents the median of net debt and Ebitda ratio.

Nominal cost of debt: quarterly sectoral variable that represents the median of interest paid and average debt ratio.

Earning to price ratio: quarterly sectoral variable that represents the median of earnings and price ratio.

Liquidity: quarterly sectoral variable that represents the median current assets and current liabilities ratio.

Ebitda margin: quarterly sectoral variable that represents the median of Ebitda and net operating revenue ratio.

Risk: quarterly sectoral variable that represents the median of the standard deviation of daily stock returns.

Sharpe: quarterly sectoral variable that represents the median of the difference between the stock return and the risk-free return and stock returns standard deviation ratio.

Default: quarterly variable of binary type being 1 if the client defaults in a given institution or 0 otherwise. The default criteria used was the existence of positive balance in overdue credits for more than 90 days and/or positive balance of written offs loans.

Collateral: quarterly variable that represents the percentage of collateralized portfolio of a company in a given institution.

Number of FIs: quarterly variable representing the number of financial institutions in which a given client maintains active credit transactions.

Region: geographic region of the credit granting agency – north, northeast, midwest, south and southeast.

Risk rating: quarterly variable representing the risk ratings mode of all the transactions of a client in the same financial institution. If there is no mode, the worst rating is considered. These ratings are based on CMN Resolution 2.682/99.

Economic sector: classification of economic sectors in which the borrowing companies operate, consisting of 19 categories.

Interest rate: quarterly variable representing the average annual interest rates of loans transactions of each company in a given institution.

Type of control: identifies if the company controller is private or public.
Ibovespa change: quarterly variable that represents the percentual change of IBOVESPA stock index.

Expectation of IPCA: quarterly variable that corresponds to the market expectation of IPCA price index change provided by FOCUS.

IPCA: quarterly variable that corresponds to the actual IPCA price index change.

Credit growth: quarterly variable that corresponds to the growth rate of loans, financing, advances and leases granted to corporations.

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