Perspectives: on the time-varying behavior of household credit in Brazil

Abstract

The household credit market in Brazil is relevant and atypical compared to other emerging economies. We propose an innovative empirical exercise to address how a set of relevant credit, monetary, and macroeconomic variables can help to understand the time-varying behavior of the real monthly variation credit issued to households in Brazil, disaggregated in earmarked and non-earmarked. We test an economic model by reconciling Brazil's limited availability of monthly data with the insights from the theoretical model suggested by Rubaszek and Serwa (2014) and the empirical literature applied to emerging markets. We estimate time-specific parameters using the Bayesian Time-Varying Coefficient Vector Autoregression (BTVCVAR). We also provide a robust analysis considering the different timing of the explanatory variables. Summarizing our most relevant findings, the monthly variation of earmarked credit has an inertial feature, while non-earmarked credit shows a "reversion to the mean" behavior. The non-earmarked spread negatively impacts both types of credit throughout the period, with greater intensity in earmarked credit. We find that improving economic activity stimulates both types of credit granting, with a greater intensity of this effect over time in earmarked credit. In the opposite direction, the lagged variation in the R$/US$ exchange rate can also affect both credit variations throughout the period. These explanations and the robustness of the results allow us to infer that the empirical exercise is based on a well-specified, intuitive, and testable model. **Keywords:** Earmarked and non-earmarked credit; Time-specific parameters; Credit, monetary, and macroeconomic determinants. **JEL classification:** C11, G21, G51.

1. Introduction

In the extensive and growing literature on finance and development, researchers have long debated the evolution and the economic role of financial systems over time in different countries. Among many topics often addressed in this discussion, an issue less studied than others concerns access to finance. We add to this specific topic by proposing an innovative empirical exercise to address how a set of relevant credit, monetary, and macroeconomic variables can help to understand the time-varying behavior of the real monthly variation in granting concession operations to households in Brazil, disaggregated in earmarked and non-earmarked.

First, we justify our purpose to study private credit, arguing that such credit is essential to grasp some mechanisms in monetary policy, asset pricing, banking, trade, stability, and growth. [1] In relation to the first issue, Central Banks used to control inflation by changing benchmark interest rates, and this pass-through depends on the credit issued to households and firms. Regarding asset pricing, Matos (2019) incorporated household debt and delinquency decisions into a model of lifecycle consumption-saving-investment. Theoretically, such additional investor decisions can be relevant in completing markets. In practice, this approach is also helpful to account for the cross-section behavior of domestic assets. Moreover, the private credit by deposit money banks and other financial institutions measures the banking activity in one of its most relevant functions: channeling savings to investors. This channel is a strategic piece in understanding economic growth. According to Levine (2004), financial systems that are more effective at pooling the savings of individuals can affect economic development by increasing savings, exploiting economies of scale, overcoming investment indivisibilities, improving resource allocation, and boosting technological innovation.

Second, let us show the relevant role played by household credit in Brazil. The theoretical literature linking the financial sector to the real economy distinguishes the effects of the credit issued to firms or households [e.g., Levine (2004)]. Summarizing the empirical literature on growth, Beck et al. (2012) constructed a new dataset from 45 developed and developing countries to address the individual effects of enterprise and household credit. They find that the first one is positively associated with economic growth and faster reductions in income inequality, whereas household credit is not. Nevertheless, this finding does not necessarily remain when we study regions or states. Guiso et al. (2004) find that local financial development in Italy enhances the probability that an individual starts a business and promotes the growth of firms. Regarding the cross-state dimension, Matos and Santos (2020) estimate an extended version of Barro-style growth panel regression from 2003 to 2017. They find that Brazilian cross-state growth depends more on household credit evolution than on firms' credit. These findings are corroborated by Matos et al. (2024).

The third topic is: why should we study this issue in Brazil?From a credit market perspective, some characteristics make the Brazilian credit market stand out in comparison to other Latin American economies. [2]

[1] See Fanelli and Medhora (2002) for the discussion on trade, as well as Allend and Gale (2000) and Demirgüç-Kunt and Levine (2001) for the debate on macroeconomic and financial stability.

[2] For a broad overview of credit in Latin America, see Stallings and Studart (2006) and Hansen and Sulla (2013).

Brazil is a bank-based economy. All financial institutions′ assets to GDP rose from 121% to 185% over the period 2011-2020, while stock market capitalization to GDP ranged between 47% and 68%. According to Matos et al. (2013), there is no global convergence of the cross-state private credit in Brazil, with the formation of the two regional clubs. Additionally, the historical series of monthly concessions available at the Central Bank of Brazil shows that after the fiscal crisis of 2016, household granting became higher than that of enterprises, and this pattern remains until now. The average monthly grant in 2023 for families was R$ 291 billion, while firms received R$ 228 billion. Based on the credit portfolio stock, household surpassed enterprise credit at the end of 2016. At the end of 2023, both stocks were R$ 3.5 trillion and R$ 2.3 trillion, respectively.

Here are other concerning aspects. The average annual interest on non-earmarked household operations peaked at almost 73% at the end of 2016. In that same period, the spread was over 60% per year, and the lowest levels of credit granting were recorded, signaling the demand rationality. In this type of short-term credit, default rates have varied between 4% and 7%, higher than earmarked values. It is worrying the pace over time of indebtedness. Household debt was 16% in 2005. In 2016, under unfavorable non-earmarked credit conditions, the debt-to-income ratio was 38%, while in 2023 - under better interest rate conditions - it is close to 50%. Is there any reason for this debt to have increased by more than three times in less than two decades?

There are more interesting and worrying findings on household credit in Brazil. Matos et al. (2015) estimate a panel from 2004 to 2013 aiming to infer the explanatory power of main variables on the behavior of households in all Brazilian states regarding their decisions about paying or not their loans. They find that poverty and unemployment are the unique significant drivers of default choice. Matos and Correia (2017) go a step further and propose a panel model to estimate the relationships between real per capita Brazilian household credit and a set of relevant social, economic, and financial variables over the same period. The results suggest that demand for credit plays a more relevant role than supply.

We need to contextualize this study in the related literature. Despite the relevance of assessing credit dynamics, we claim that literature presenting a theoretical approach and even empirical evidence on the determinants of household credit is scarce. One of the few recent theoretical contributions is Rubaszek and Serwa (2014). This paper applies a life-cycle model with individual income uncertainty to investigate the determinants of credit to households. They show that the value of household credit to GDP ratio depends on the lending-deposit interest rate spread, individual income uncertainty, individual productivity persistence, and the generosity of the pension system.

From an empirical perspective, Shammari and El-Sakka (2018) investigate the determinants of credit growth in the private sector across 24 OECD countries, and they argue that macroeconomic stability seems vital for the flow of credit. Still on cross-country exercises, Matos (2017) assesses what has been driving the recent and heterogeneous expansion of credit to GDP in Latin America based on supply and demand variables. The most relevant findings suggest that credit reflects a financial deepening characterized by a higher bank concentration and a policy that can stimulate saving even by practicing lower deposit interest rates. Reginato et al. (2020) examine the determinants of South American bank credit, and they find that domestic deposits and liabilities to non-residents contribute positively to the growth of private credit, with domestic funding showing a more representative impact than foreign funding. Economic growth also leads to a greater demand for credit and an increase in credit, while higher domestic and US interest rates reduce credit growth.

There are also contributions applied to specific countries. Chrystal and Mizen (2005) build a vector error correction model for the U.K. and find that, in the long run, consumer loans are driven by the net labor income, the net wealth of households, the interest rate spread on loans, and inflation. Iacoviello (2008) fits his theoretical model to U.S. data and finds that income inequality increases household debt. Regarding emerging markets, Bustamante et al. (2019) analyze the drivers of lending channels in Peru, while Asiamah et al. (2021) study this issue in Ghana. In this context, our study is to our best knowledge the first to reconcile the insights from related contributions with the availability of monthly data in Brazil to propose and test an economic model. We use the Bayesian Time-Varying Coefficient Vector Autoregression to estimate time-specific parameters. We also provide a robust analysis considering the different timing of the explanatory variables.

This paper proceeds as follows: In Section 2, we briefly describe the methodology. In Section 3, we analyze the data. We discuss the economic model and the results in Section 4. Section 5 offers the concluding remarks.

2. Methodology

We aim to understand the reactions of the real monthly variation of both earmarked and non-earmarked granting operations in response to the current (lagged) monthly variations in credit (macroeconomic and monetary) variables. We estimate these reactions over the period from April 2011 to December 2023. Considering the behavior of banks and households for almost 14 years, it is not reasonable to believe that VAR parameters hold constant over time. Instead, we believe that the parameters switch along such a period. In order to measure time-varying reactions, we apply the Bayesian Time-Varying Coefficient Vector Autoregression (BTVCVAR) model for the analysis. This framework arises from Time-Varying Coefficient Vector Autoregression (TVCVAR) and the Bayesian approach.

Firstly, it is essential to remember that the Vector Autoregression (VAR) model, introduced by Sims (1980), captures the dynamic between time series. The model considers its own data and lagged info in the process. One can also include exogenous variables, which matter for our purpose.

Let y_t denoted the N-vector of endogenous variables in t. The BTVCVAR model proposed here is denoted by

$$y_t = x_t' B_t + e_t' \qquad (1)$$

where the covariate vector $x_t = (y_{t-1}', \dots, y_{t-p}', w_t', z_{t-1}')'$ consists of p lags of y_t, the vector of current exogenous credit market w_t and the vector of lagged exogenous macroeconomic and monetary variables z_{t-1}. B_t is the time-varying coefficient matrix, and $e_t \sim N(0, S)$ is the error term. The observation equation (1) is like VAR equation except by the time subscript attached to matrix B.

To address the time-varying behavior of economic agents, the TVCVAR model allows the coefficients to vary, enabling the dynamic change of the relationships between variables over time. This approach comprises another equation besides the observation: the process one. Realize that as we make coefficients vary, another problem occurs: overparameterization. Taken alone, the observation equation results in an over-parameterized model for any sample size. We can mitigate this issue by specifying a law of motion for the coefficients, the process equation. Typically, such mathematical relation follows a random walk process applied to the vectorized version of the coefficient matrix, given by $b_t = vec(B_t)$:

$$b_t = b_{t-1} + e_t \qquad (2)$$

where the $u_t \sim N(0, Q)$ and Q is process covariance matrix. The first element of this procedure, b_0, is considered as part of the prior specification.

Doan, Litterman, and Sims (1984) and Litterman (1986) established the Bayesian inference to estimate the VAR coefficients. Using this technique allows us to deal with overparameterization and small sample sizes. This model shows to have better forecast performance even with many variables. The Bayesian background comes from the Bayes′ rule.[3] In short, given a set of parameters θ and let Y represent the data used, the Bayes′ rule is given as

$$\pi(\theta|Y) = \frac{\pi(Y|\theta)p(\theta)}{\pi(Y)} \qquad (3)$$

The left side of (2) is the Posterior Distribution. The numerator on the right side is the product between the Likelihood Function and the Prior Distribution, which is the joint distribution of the data and parameters. On the denominator, the marginal data density is given by $\pi(Y) = \int \pi(Y|\theta)\pi(\theta)\, d\theta$. The specification of the prior distribution needs to represent previous information the researcher has about the parameters. The stronger the belief, the less likely the parameters are to be the ones desired by the data and vice versa.

As previously mentioned, the BTVCVAR combines the TVCVAR with a prior distribution. By setting the prior, we shrink the model to a simpler version. Specifying a prior with null process error variance turns the TVCVAR into a single VAR model. Shrinking the model towards the basic VAR, to some extent, estimates parameters that vary smoothly. The prior over the initial coefficient vector b_0 and covariance matrices S and Q is

[3] See Woźniak (2016) for more details.

$$\pi(b_0, S, Q) = \pi(b_0)\, \pi(S)\, \pi(Q) \qquad (4)$$

Combining the prior distribution with the likelihood function forms the posterior distribution. The following equation is an alternative representation of the Bayes′ rule.

$$\pi(b,\, S,\, Q \mid y|) \propto \pi(b_0\,,\, S,\, Q) \prod_{t=1}^{T} f(y_t \mid b_t,\, S) f(b_t \mid b_{t-1},\, Q) \qquad (5)$$

where ∝ denotes proportionality up to the normalizing constant, which means the marginal data density.

The terms on the right side of the proportionality symbol are the prior distribution, the observation equation, and the process equation, respectively. This derivation is possible thanks to the Gibbs sampler method, which is a Markov Chain Monte Carlo method for drawing samples from the posterior distribution. The Gibbs sampler iterates through sampling each parameter conditional on the current values of the other parameters.

3. Brazilian credit market

The real stock (December 2023 R$) of the household credit portfolio in Brazil rose from R$1.66 trillion in March 2011 to R$3.52 trillion in December 2023. This portfolio grew on average 6.1% per year above inflation. At the end of 2023, this portfolio amount represented more than 32% of GDP, which was close to R$10.9 trillion.

The evolution of the stock of the disaggregated portfolio shows different behavior in the earmarked and non-earmarked credit. Based on the real annual growth rate, the earmarked credit stock grew 9.7%, while the non-earmarked credit grew 4.0% in the same period. Despite this faster growth in almost 14 years, the earmarked credit portfolio stock never exceeded that of non-earmarked. According to Fig. 1, both series have different behavior in three periods. From 2011 to 2014, both stocks grew with low volatility, reducing the gap between them. From mid-2015 to the end of 2018, the real earmarked credit stock stabilized while the non-earmarked reduced and grew following a convex curvature. From then on, both series have grown again, with rare moments of reduction.

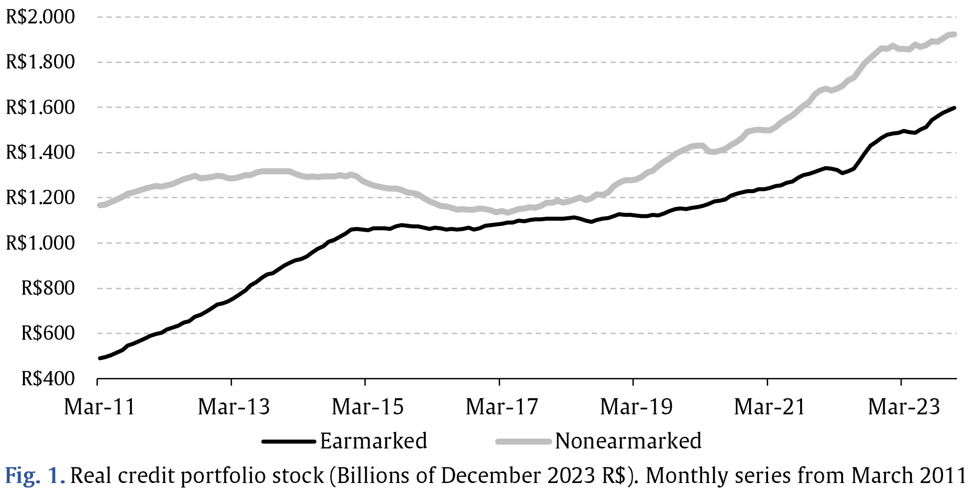

Fig. 1. Real credit portfolio stock (Billions of December 2023 R$). Monthly series from March 2011 to December 2023. Data source: Central Bank of Brazil. Series codes: 20570 (non-earmarked), 20606 (earmarked), and 433 (IPCA).

Fig. 2 shows the monthly time series of the real value of granting household earmarked and non-earmarked credit. The levels of both series are very different, as while the earmarked ranged between R$ 15 billion and R$ 62 billion, the other varied between R$ 143 and R$ 278 billion. There is also a difference in seasonality, with an apparent more evident seasonal behavior in earmarked credit. This credit granting is also more volatile, based on the coefficient of variation. The non-earmarked credit had its most significant reduction between December 2019 and March 2020 during the pandemic. The reduction was approximately R$ 81 billion monthly, equivalent to 34%.

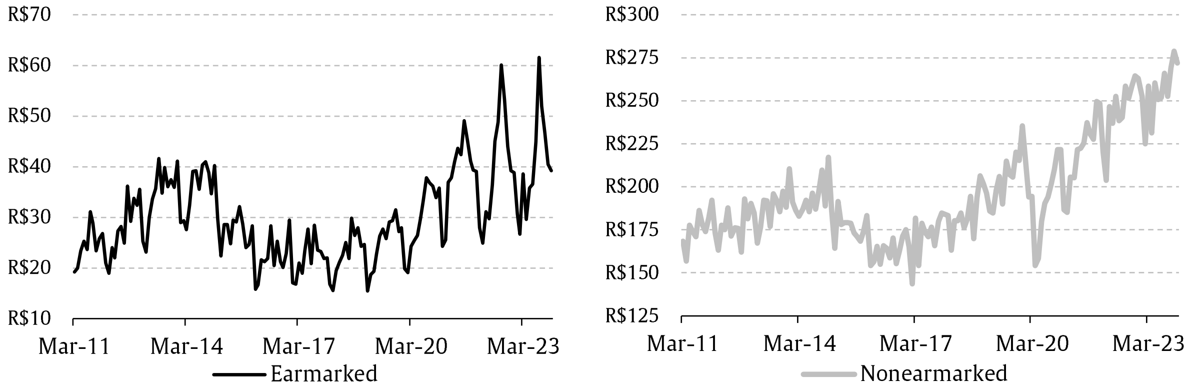

Fig. 2. Real credit granting operations (Billions of December 2023 R$). Monthly series from March 2011 to December 2023. Data source: Central Bank of Brazil. Series codes: 20662 (non-earmarked), 20698 (earmarked), and 433 (IPCA).

Fig. 3 shows the series of the most relevant household credit variables: monthly interest rate, annual spread, average term in months, and delinquency rate. From March 2011 to December 2023, the spread of earmarked credit operations ranged between 2.7% and 5.2%, while the non-earmarked spread varied between 30.0% and 61.1%. The highest spread values were observed respectively at the beginning of 2023 and between the end of 2016 and the beginning of 2017.

Earmarked credit monthly interest rates varied between 0.5% and 0.9%, while non-earmarked operations had rates between 2.7% and 4.7%. The current interest rates are slightly higher than the respective averages.

The behavior over time of non-earmarked credit granting interest rates is similar to that of the respective spread, which does not hold for earmarked credit. Regarding the average terms of operations, earmarked credit concessions take 21 years, while non-earmarked credit takes four and a half years. The earmarked term grew between 2011 and 2015, stabilizing after that, and the term of non-earmarked operations increased at a stronger pace until mid-2021.

Regarding delinquency, this risk variable ranged between 1.3% and 2.2% for almost the entire time in earmarked credit, with a peak of 2.4% during the pandemic. In non-earmarked operations, this variable oscillated between 4.0% and 7.2%. The recent levels show that default rates in earmarked credit are at low levels, while in non-earmarked credit, they are at 5.6%.

In Table 1, we report the statistics of the credit, monetary, and macroeconomic series. The series are used in difference; that is, we measure their variation because stationarity is a necessary property for estimating the VAR. The variables that showed seasonality in their monthly variations were seasonally adjusted.

4. Economic model and results

We study the time-varying behavior of the monthly variation of household credit granting by measuring period-specific coefficients based on the BTVCVAR estimates. We need to revisit the generic equation (1) to define and present the following model to be estimated

$$y_t = x_t' B_t + e_t' \qquad (6)$$

where the covariate vector $x_t = (y_{t-1}', w_t', z_{t-1}')'$ consists of one lag of y_t, the vector of current exogenous credit market variables w_t and the vector of lagged exogenous monetary, and macroeconomic variables z_{t-1}.

More specifically, y_t denotes the real monthly variation of earmarked and non-earmarked household credit grating in t. Both series have been seasonally adjusted. The vector w_t consists of the following earmarked and non-earmarked credit variables in t: i) variation of annual spread, ii) variation of monthly interest rate, iii) variation of the average term (month), and iv) variation of delinquency rate. The vector z_{t-1} consists of the macroeconomic variables in $t-1$: i) variation in the stock of formal jobs, ii) real variation in available income, iii) real variation in economic activity, iv) variation of the household debt to income, iv) variation of US$/Real foreign exchange, and vi) variation of consumer confidence index. This vector also contains the following monetary variables in $t-1$: i) variation of the term deposit, ii) demand deposit, iii) physical money held by the public, and iv) official inflation (IPCA). All other macroeconomic and monetary series needed to be seasonally adjusted except for debt to income, foreign exchange, and consumer confidence index.

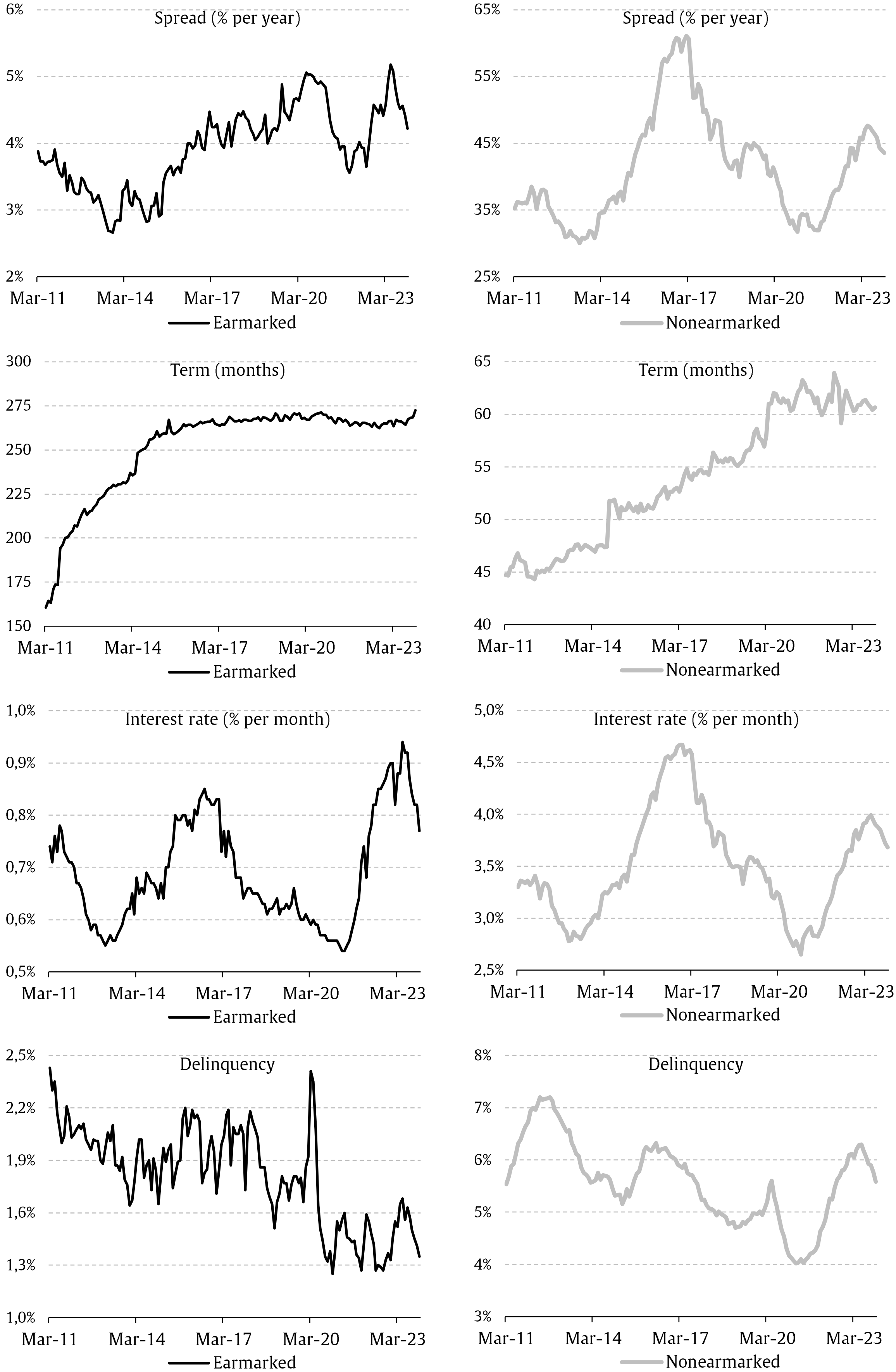

Fig. 3. Credit market variables. Monthly series from March 2011 to December 2023. Data source: Central Bank of Brazil.

Table 1. Summary statistics

Variables	Series code	Mean	S. D.	Min.	Max.	Skewness	Kurtosis	Stationar. test adj. t stat.
Endogenous - Real variation of credit granting operations								
Earmarked	20698	3.33%	24.77%	-39.56%	77.86%	0.51	2.59	-11.76
Nonearmarked	20662	0.93%	11.14%	-24.65%	30.95%	0.14	2.32	-23.48
Earmarked credit variables								
Spread	20837	0.00%	0.17%	-0.43%	0.56%	0.20	3.67	-11.98
Interest rate	25493	0.00%	0.03%	-0.10%	0.08%	0.02	4.95	-15.22
Average term	20878	0.73	2.67	-6.89	20.92	3.27	24.75	-13.16
Delinquency rate	21145	-0.01%	0.13%	-0.44%	0.49%	-0.07	5.19	-16.68
Nonearmarked credit variables								
Spread	20890	0.05%	1.36%	-4.48%	2.98%	-0.57	3.98	-9.54
Interest rate	25462	0.00%	0.09%	-0.24%	0.16%	-0.58	3.61	-9.38
Average term	20908	0.10	0.78	-3.50	4.38	1.07	12.24	-14.94
Delinquency rate	21112	0.00%	0.12%	-0.30%	0.31%	0.06	2.71	-8.24
Monetary variables								
Real variation of demand deposit	27790	0.12%	2.30%	-5.34%	10.67%	0.98	5.79	-9.51
Real variation of term deposit	27805	0.46%	1.93%	-4.03%	11.71%	2.48	15.78	-5.65
Real variation of physical money held by the public	27786	0.15%	1.93%	-7.16%	12.03%	1.11	15.97	-8.61
Official inflation (IPCA)	433	0.48%	0.35%	-0.57%	1.63%	0.30	4.00	-7.04
Macroeconomic variables								
Variation of the stock of formal jobs	28763	0.15%	0.42%	-2.82%	1.01%	-2.47	18.11	-4.70
Variaiton of household debt (with the NFS) to income (accumulated 12 months)	29037	0.01%	0.14%	-0.37%	0.44%	0.55	5.47	-5.16
Real variation of economic activity (IBC-BR)	24634	0.04%	1.42%	-9.65%	4.97%	-2.55	21.15	-9.58
Real variation of available gross household income	29024	0.37%	3.63%	-10.14%	10.65%	-0.00	2.52	-7.82
Variation of foreign exchange R$ - US$	3697	0.78%	3.71%	-8.70%	12.51%	0.38	3.62	-9.25
Variation of consumer confidence index	4393	-0.03%	4.23%	-13.53%	11.62%	-0.19	3.59	-11.22

Data source: Central Bank of Brazil. Monthly series from April 2011 to December 2023 (153 observations). Notes: Phillips-Perron unit root test (H0: time series has a unit root) critical values: -2.88 (5% level) and -3.47 (1% level).

Before analyzing the most relevant findings, it is necessary to emphasize some theoretical and empirically relevant aspects of the estimated model specification.

A few studies derived theoretically the determinants or drivers of demand (household) and supply (financial institutions) credit decisions. Instead, most studies addressed the impacts of credit, whether for families or companies. So, we proposed a representative model by reconciling the limited availability of credit, monetary, and macroeconomic monthly data in Brazil with the insights from the theoretical model suggested by Rubaszek and Serwa (2014) and the empirical contributions given by Matos (2017), Shammari and El-Sakka (2018), Bustamante et al. (2019), Reginato et al. (2020), and Asiamah et al. (2021). Considering the trade-off on model parsimony and period, we have chosen this specification previously mentioned, which has variables capable of explaining the supply and demand for credit.

We highlight that we also tested the model using different timing possibilities for exogenous variables. In the final version, the credit market variables are in t. The motivation lies in timing the credit decision: economic agents observe the current credit market conditions and decide to demand or offer. We assume that there is no endogeneity or reverse causality, and when we include a lag of these credit market variables, the results remain essentially unchanged. The coefficients of the credit variables in $t-1$ are nonsignificant.

Regarding the monetary and macroeconomic variables, we assume that agents only observe or perceive the economic context after releasing these variables, which occurs in the following month. Moreover, there is no need to use two lags, as most real estate credit operations (the type that takes the longest to be approved) are carried out within 40 days. Finally, when we use macroeconomic variables in t, in addition to possible problems of endogeneity or reverse causality, the coefficients are not significant at 10% over time. These explanations and the robustness of the results allow us to infer that the empirical exercise is based on a well-specified, intuitive, and testable model.

In Figures (A1 to A6) in the appendix, we report the time series of the parameters with the respective two-tailed confidence intervals (80%). In Table 2, we report only the significant results at 10%. In this chart, we show the period in which there was a significant impact, the lower and upper range of this coefficient, and the pattern or behavior (linear, curved) of the parameter value throughout this specific period in that it was significant.

The monthly variation of earmarked credit has an inertial feature (with the parameter ranging between 0.25 and 0.50). In contrast, the variation of non-earmarked credit shows a "reversion to the mean" behavior, with the coefficient varying from -0.55 to -0.65. There is rationality in decision-making for reducing new earmarked credit operation granting due to increased lagged variation in non-earmarked credit. This evidence is significant from 2016 onwards, after the height of the fiscal crisis in Brazil.

The non-earmarked spread negatively impacts both types of credit throughout the period, with greater intensity in earmarked credit. The spread is a proxy for the financial institution's gain in granting credit, which needs to be analyzed together with the risk of default, measured by delinquency or delay, for example. Better earning opportunities, i.e., higher spread, in non-earmarked operations could discourage the offer of earmarked credit. In the same context, a longer average term for non-earmarked operations seems to stimulate the supply of earmarked credit. Still, based on the current impacts of credit variables, the earmarked credit terms can negatively influence the decisions to grant both types of credit in specific years.

The rationality associated with macroeconomic variables is very interesting. Theoretically, an economic activity (IBC-BR) improvement stimulates the demand and supply of credit in the following period. We evidence this mechanism for both types of credit, with a greater intensity of this effect over time in earmarked credit (from 2.20 to 2.30). In the opposite direction, the lagged variation in the R$/US$ exchange rate can also affect both credit variations throughout the period. This negative effect is more intense in earmarked credit (from -1.05 to -1.15). The other macroeconomic variables do not show significant effects at any time. Likewise, none of the four monetary variables managed to influence credit variations, with a significance of 10%.

However, there are still some results that are not statistically significant at 10% but are intuitive, in line with economic theory. These include the negative influence of non-earmarked credit interest rates and earmarked credit default. On the other hand, we see the positive impact of the variation in the consumer confidence index, demand deposit, and physical money held by the public.

Table 2. Summary of the statistically significant results

Exogenous variables with statistically significant (10%) coefficient in some period between April 2011 and December 2023	Endogenous variables					
	Real variation of earmarked credit granting operations			Real variation of nonearmarked credit granting operations		
	period	time-varying coefficient range	pattern over time	period	time-varying coefficient range	pattern over time
Lagged real variation of earmarked credit	2011 to 2023	0.25 to 0.50				
Lagged real variation of nonearmarked credit	2016 to 2023	-0.85 to -1.40		2011 to 2023	-0.55 to -0.65	
Variation of spread of nonearmarked credit	2011 to 2023	-2.40 to -2.50		2011 to 2023	-1.30 to -1.40	
Variation of aver. term of nonearm. credit	2022 to 2022	0.08 to 0.10				
Variation of aver. term of earmarked credit	2012 to 2012	-0.05 to -0.07		2018 to 2018	-0.04 to -0.05	
	2018 to 2018	-0.06 to -0.07				
	2023 to 2023	-0.06 to -0.10				
Lagged variation of foreign exchange	2011 to 2023	-1.05 to -1.15		2011 to 2023	-0.15 to -0.25	
Lagged variation of IBC-BR	2011 to 2023	2.20 to 2.30		2011 to 2023	1.65 to 1.80	

Results based on Bayesian Time Varying Coefficient Vector Autoregression (BTVCVAR) approach applied to model (1) from April 2011 to December 2023. Notes: Hyper-parameters: $T_0 = 0, \tau_0 = 5, \tau_1 = 1, \tau_2 = 0.01, \nu_1 = 5, \nu_2 = 5$. Simulation smoother: Cholesky factor algorithm (CFA) with no stability method. Posterior sample size: 5000 (burn-in-size: 5000). Confidence interval (two-tailed): 80%.

5. Conclusion

The private credit market in Brazil is representative and atypical compared to other emerging economies. This market is relevant, as the stock in 2023 was R$ 5.8 trillion, equivalent to more than 53% of GDP. It is also atypical because, in addition to being unequal among Brazilian states, household credit is leading compared to enterprise credit. In addition to having a stock of 60% of total private credit, empirical evidence robustly shows that household credit's ability to explain cross-state growth is greater than that of credit to firms. It is essential, therefore, to understand the time-varying role of the determinants of the decision by banks to offer and families to demand, considering both earmarked and non-earmarked credit.

Regarding this discussion, our empirical findings are essential from the point of view of i) behavioral economics, ii) asset pricing, iii) monetary policy, and iv) short-term growth. In practice, our exercise can be replicated for other developing countries, as well as there is a methodological contribution since the significant "cross results" show that the choices for both types of credit need to be analyzed jointly in the sense of a general equilibrium approach. Regarding the extension of this research agenda, the intuitive but nonsignificant results can be revisited using more extended time series, a broader set of variables, or other quantitative techniques. We also point out the disaggregation of earmarked credit into rural credit, mortgage and microcredit, as well as non-earmarked into personal credit, purchase of vehicles, and credit cards, for example.

Data Availability

The corresponding author will share the article's data at a reasonable request.

Conflict of interest/Ethical statement

We have no conflicts of interest to declare. We agree with the manuscript's contents, and there is no financial interest to report. We certify that the submission is an original work and is not under review at any other publication. We declare that this submission follows the policies outlined in the Guide for Authors and the Ethical Statement.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this study, we have used Google translate service, Grammarly and Word grammar check in order to write some sentences and translate a few specific words from Portuguese language to English language.

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References

Allend, F., Gale, D. (2000). Comparing financial systems. MIT Press. https://mitpress.mit.edu/9780262511254/comparing-financial-systems/

Asiamah, T., Steel, W., Ackah, C. (2021). Determinants of credit demand and credit constraints among households in Ghana. Heliyon 7, 1–8. https://doi.org/10.1016/j.heliyon.2021.e08162

Beck, T., Buyukkarabacak, B., Rioja, F., Valev, N. (2012). Who Gets the Credit? And Does It Matter? Household vs. Firm Lending Across Countries. The B.E. Journal of Macroeconomics, 12, 1–44. https://doi.org/10.1515/1935-1690.2262

Bustamante, J., Cuba, W., Nivin, R. (2019). Determinants of credit growth and the bank lending channel in Peru: a loan level analysis. BIS Working Papers No 803. https://www.bis.org/publ/work803.htm

Chrystal, K., Mizen, P. (2005). A dynamic model of money, credit, and consumption: a joint model for the UK household sector. Journal of Money, Credit, and Banking, 75, 119–143. https://doi.org/10.1353/mcb.2005.0002

Demirgüç-Kunt, A., Levine, R (2001). Financial structure and economic growth. MIT Press. https://mitpress.mit.edu/9780262541794/financial-structure-and-economic-growth/

Doan, T., Litterman, R., Sims, C. (1984). Forecasting and Conditional Projection Using Realistic Prior Distributions. Econometric Reviews, 3, 1–100. https://doi.org/10.1080/07474938408800053

Fanelli, J., Medhora, R. (2002). Finance and competitiveness in developing countries. Routledge and CRC Press. https://www.routledge.com/Finance-and-Competitiveness-in-Developing-Countries/Fanelli-Medhora/p/book/9780415459211?srsltid=AfmBOorphMQdMHWViZwSINvgFKCj-9G7JUK5fuw8ABOLP03w5u7gdN7o

Guiso, L., Sapienza, P., Zingales, L. (2004). Does Local Financial Development Matter? The Quarterly Journal of Economics, 119, 929–969. http://hdl.handle.net/10.1162/0033553041502162

Hansen and Sulla (2013). Credit growth in Latin America: financial development or credit boom? IMF Working Paper 13/106. https://www.imf.org/external/pubs/ft/wp/2013/wp13106.pdf

Iacoviello, M. (2008). Household debt and income inequality, 1963–2003. Journal of Money, Credit, and Banking, 40, 929–965. https://doi.org/10.1111/j.1538-4616.2008.00142.x

Levine, R. (2004). Finance and growth: theory and evidence. NBER Working Paper 10766. http://www.nber.org/papers/w10766

Litterman, R. B. (1986). Forecasting with Bayesian Vector Autoregressions: Five Years of Experience. Journal of Business & Economic Statistics, 4, 25–38. http://www.jstor.org/stable/1391384

Matos, P. (2017). On the Latin American Credit Drivers. Emerging Markets Finance and Trade, 53, 306-320. http://dx.doi.org/10.1080/1540496X.2016.1210508

Matos, P. (2019). The role of household debt and delinquency decisions in consumption-based asset pricing. Annals of Finance, 15, 179–203. https://doi.org/10.1007/s10436-019-00344-1

Matos, P., Correia, J. (2017). What Drives Inequality of Brazilian Cross-State Household Credit? Revista Brasileira de Economia, 71, 347–359. https://doi.org/10.5935/0034-7140.20170016

Matos, P., Costa, L., Simonassi, A. (2024). The role of capital and current expenditures of state and municipal governments in the Brazilian cross-state growth from 2003 to 2019. Revista Brasileira de Economia, 78, 1–15. https://orcid.org/0000-0003-2099-8456

Matos, P., Sampaio, R., Moura, L. (2015). On the key drivers of Brazilian household loan delinquency. International Economics Letters, 4, 80–90. https://www.ceeol.com/search/article-detail?id=330147

Matos, P., Santos, D. (2020). A Note on the Effect of Decomposing Credit for Explaining Brazilian Cross-State GDP Growth. Revista Brasileira de Economia, 74, 155–166. https://doi.org/10.5935/0034-7140.20200009

Matos, P., Vasconcelos, J., Penna, C. (2013). Política Creditícia No Brasil: O Sertão Vai Virar Mar? EconomiA ANPEC, 14, 1 – 29. https://repositorio.ufc.br/handle/riufc/30370

Reginato, V., da Cunha, M., Vasconcelos, M. (2020) Determinants of South American bank credit: An approach to panel data. Estudios Econômicos, XXXVII, 37–70. https://www.scielo.org.ar/pdf/estec/v37n74/v37n74a02.pdf

Rubaszek, M., Serwa, D. (2014). Determinants of credit to households in a life-cycle model. Economic Systems, 38, 572–587. https://doi.org/10.1016/j.ecosys.2014.05.004

Shammari and El-Sakka (2018). Macroeconomic Determinants of Credit Growth in OECD Countries. International Journal of Business, 23, 217–234. https://ijb.cyut.edu.tw/var/file/10/1010/img/864/V233-1.pdf

Sims, C. (1980). Macroeconomics and Reality. Econometrica, 48, 1–48. https://doi.org/10.2307/1912017

Stallings, B., Studart, R. (2006). Finance for development: Latina America in comparative perspective. Brooking Institution Press. https://ideas.repec.org/b/ecr/col014/1913.html

Woźniak, T. (2016). Bayesian vector autoregressions. Australian Economic Review, 49(3), 365-380. https://doi.org/10.1111/1467-8462.12179

Appendix

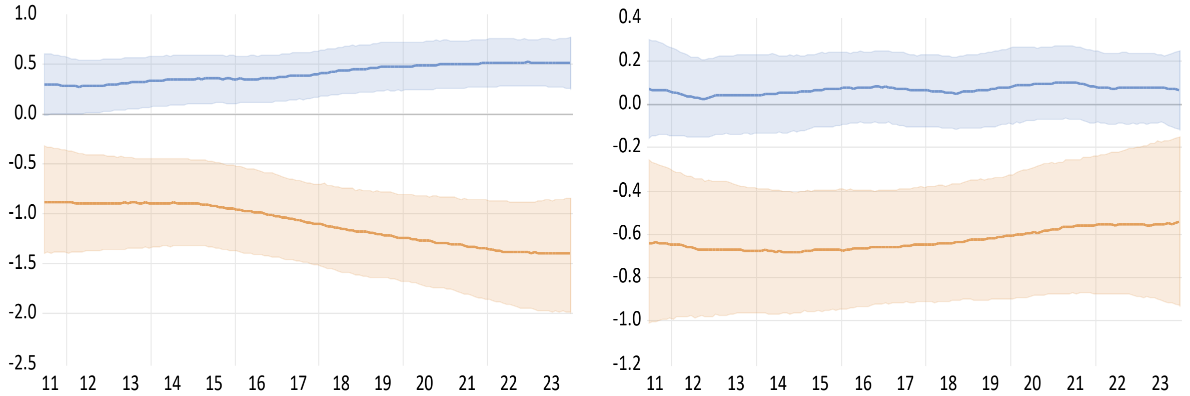

Fig. A.1. BTVCVAR equation coefficients of the lagged ($t-1$) real variation of earmarked (blue) and non-earmarked (red). Endogenous: Real variation in t of earmarked (left) and non-earmarked (right) credit grant. Posterior medians, 80% CIs. Monthly series from April 2011 to December 2023. Data source: Central Bank of Brazil.

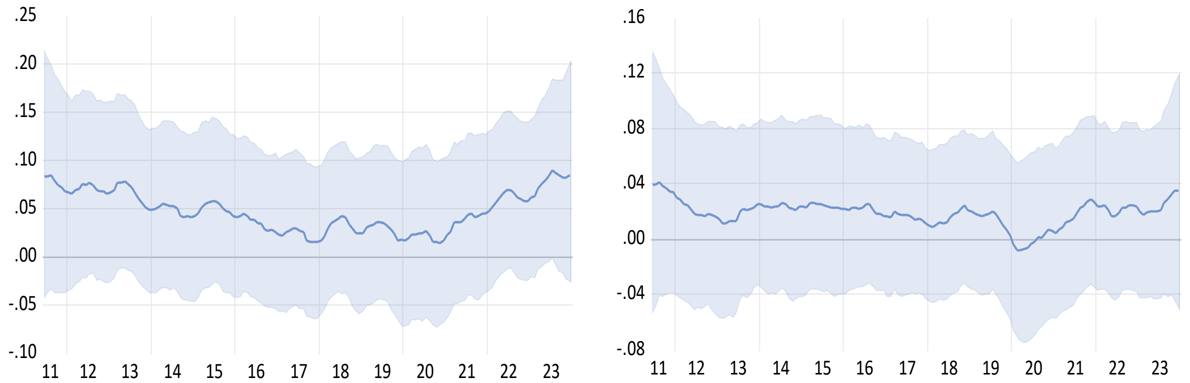

Fig. A.2. BTVCVAR equation constant. Endogenous: Real variation in t of earmarked (left) and non-earmarked (right) credit grant. Posterior medians, 80% CIs. Monthly series from April 2011 to December 2023. Data source: Central Bank of Brazil.

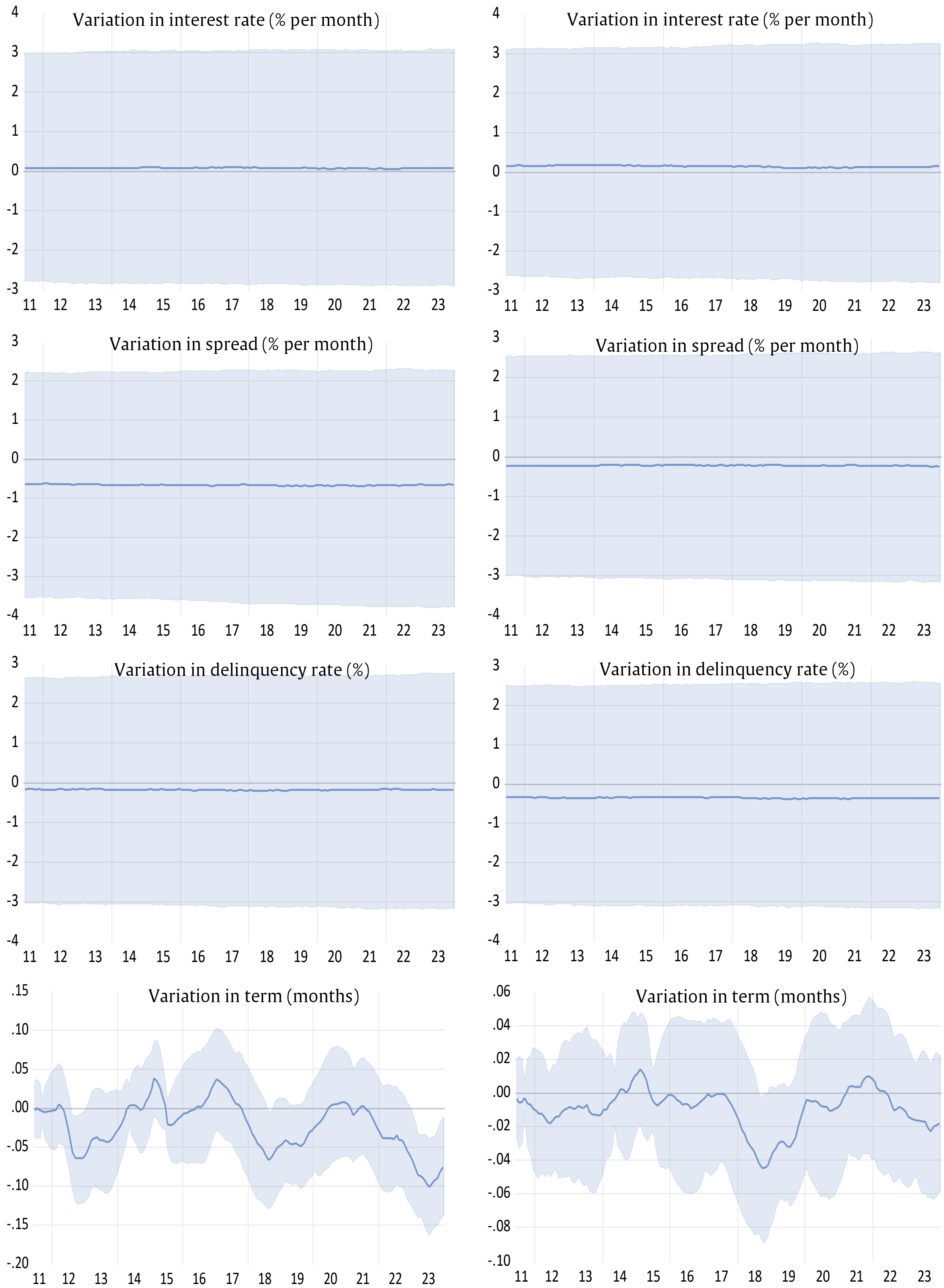

Fig. A.3. BTVCVAR equation coefficients of the earmarked credit variables in t. Endogenous: Real variation in t of earmarked (left) and non-earmarked (right) credit grant. Posterior medians, 80% CIs. Monthly series from April 2011 to December 2023. Data source: Central Bank of Brazil.

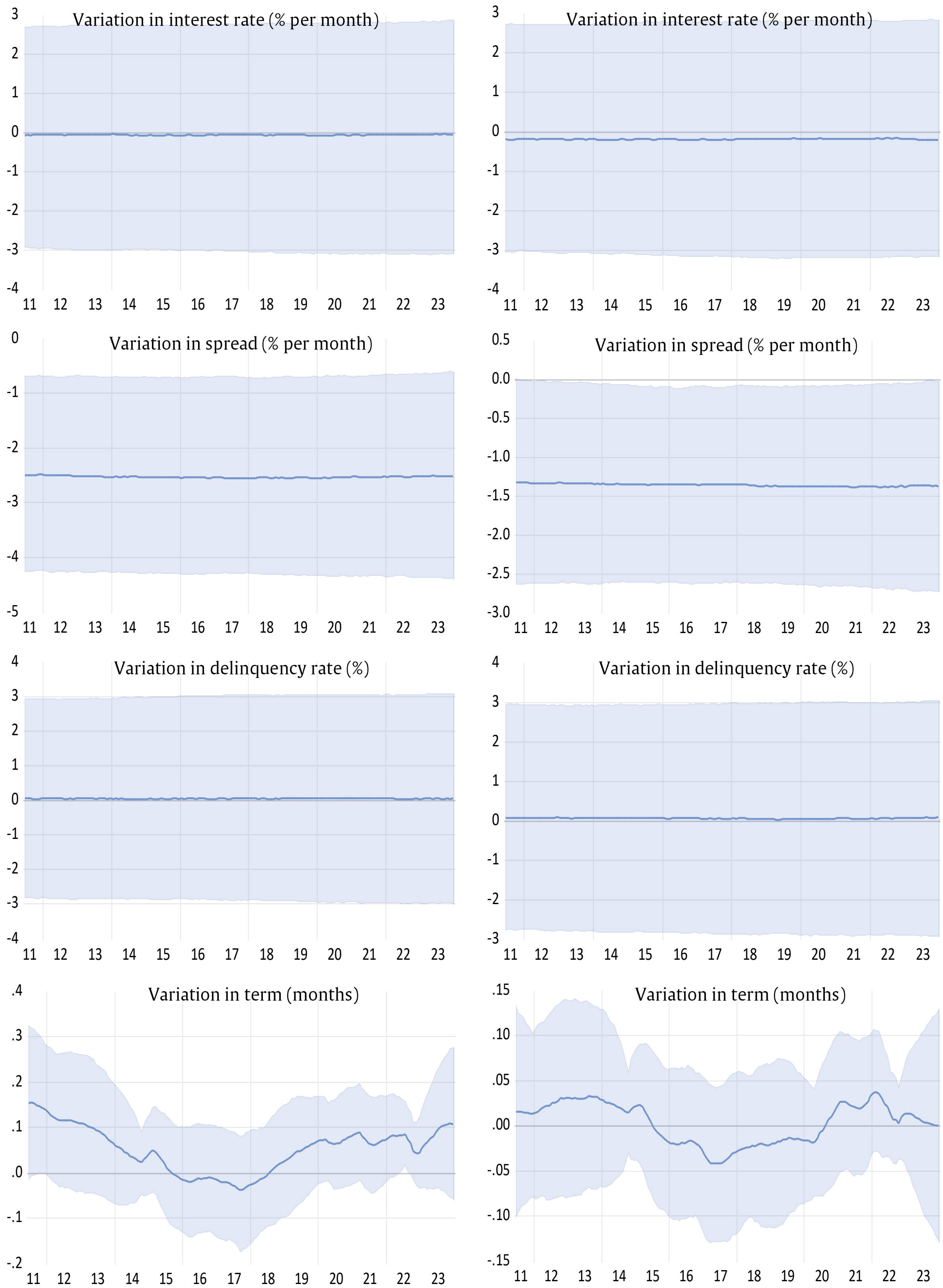

Fig. A.4. BTVCVAR equation coefficients of the non-earmarked credit variables in t. Endogenous: Real variation in t of earmarked (left) and non-earmarked (right) credit grant. Posterior medians, 80% CIs. Monthly series from April 2011 to December 2023. Data source: Central Bank of Brazil.

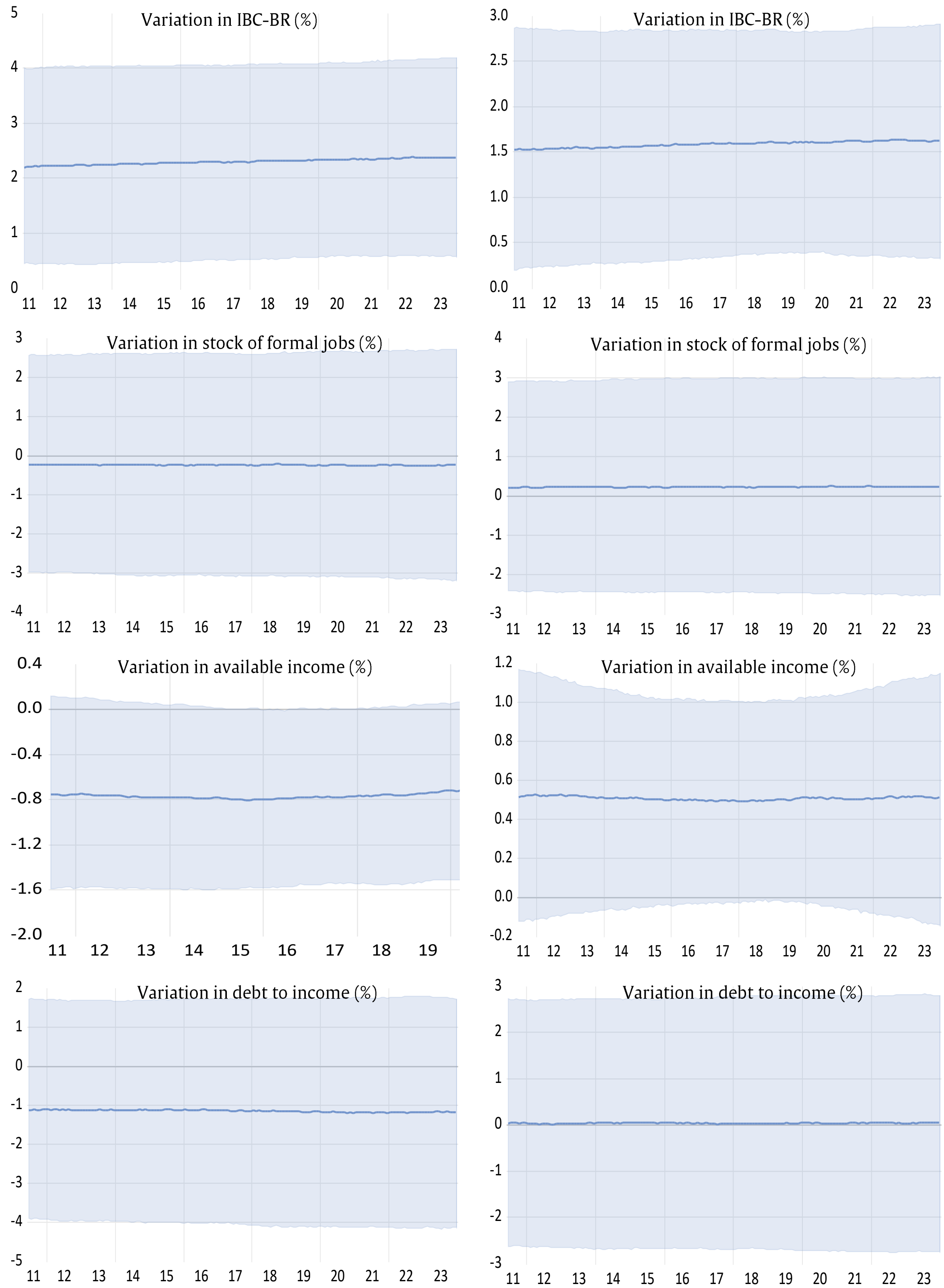

Fig. A.5. BTVCVAR equation coefficients of the macroeconomic variables in $t-1$. Endogenous: Real variation in t of earmarked (left) and non-earmarked (right) credit grant. Posterior medians, 80% CIs. Monthly series from April 2011 to December 2023. Data source: Central Bank of Brazil.

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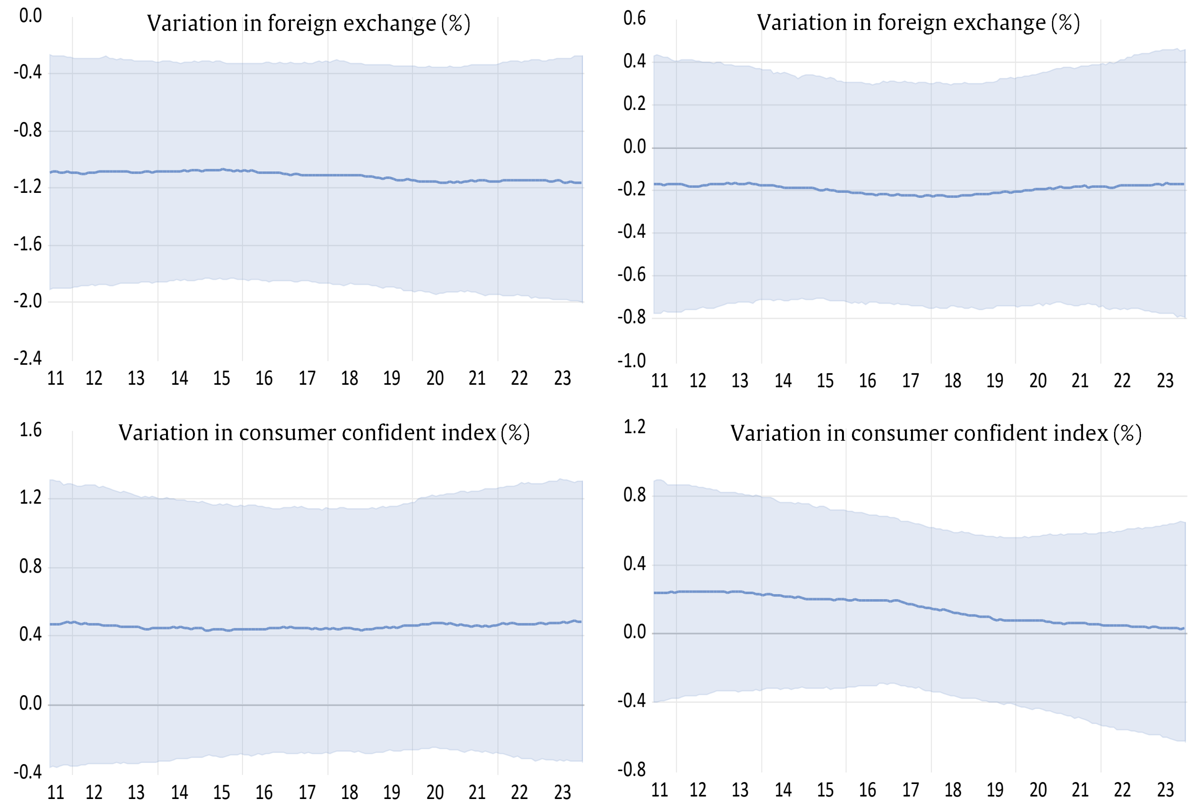

Fig. A.5. BTVCVAR equation coefficients of the macroeconomic variables in $t-1$. Endogenous: Real variation in t of earmarked (left) and non-earmarked (right) credit grant. Posterior medians, 80% CIs. Monthly series from April 2011 to December 2023. Data source: Central Bank of Brazil.

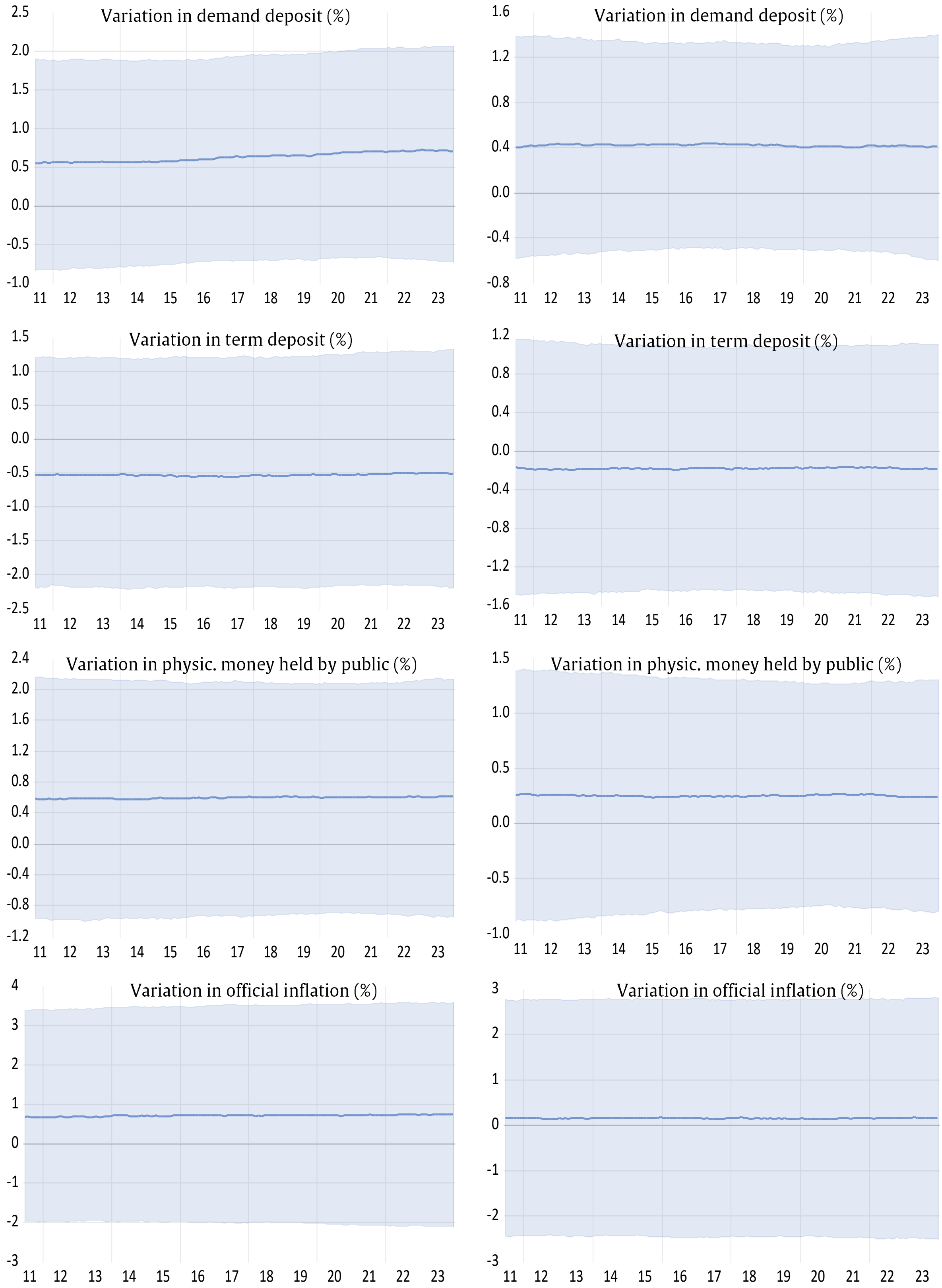

Fig. A.6. BTVCVAR equation coefficients of the monetary variables in $t-1$. Endogenous: Real variation in t of earmarked (left) and non-earmarked (right) credit grant. Posterior medians, 80% CIs. Monthly series from April 2011 to December 2023. Data source: Central Bank of Brazil.