On the time-varying behavior of household credit in Brazil

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Abstract

We add to the debate on access to finance by proposing an empirical exercise to address how credit, monetary, and macroeconomic variables can explain the time-specific behavior of the real variation in earmarked and non-earmarked credit issued to households in Brazil. 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. First, we estimate a standard Vector Autoregression (VAR) model. To capture the dynamic nature of household credit, we employ a Bayesian Time-Varying Coefficient VAR model (BTVC-VAR). About the messages of this paper, first we provide a methodological contribution because the joint behavior of both types of credit is crucial to understand their dynamics in the sense of a general equilibrium approach. Second, when we compare the standard VAR and BTCV-VAR, we can see how important it is to allow flexibility of parameters since the dynamics seem to have changed over time, from April 2011 to December 2023. We highlight the significant role played by non-earmarked spread, the average term of both types of credit, economic activity (IBC-BR), and the R$/US$ exchange rate. This exercise contributes to the discussion on financial stability and monetary policy and can be replicated for other emerging markets.

Keywords: Credit, monetary, and macroeconomic determinants; Time-specific parameters; Earmarked and non-earmarked household credit; Access to finance; Emerging markets.
JEL classification: C11, G21, G51.

1. Introduction

In the literature on finance and development, researchers have debated the structure, role, and evolution of financial systems over time across different countries. We add to this discussion by addressing the access to finance by Brazilian families. We propose an empirical exercise to measure how a set of variables can help to understand the pattern of household credit in this emerging country from April 2011 to December 2023.

Our experiment has three innovations to this research agenda. First, 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 developing markets [e.g., Matos (2017), Bustamante et al. (2019), Reginato et al. (2020), and Asiamah et al. (2021)]. Second, most related papers have explored credit drivers through panel estimation or standard time series approaches, while the time-varying role of determinants seems to be less explored. It would be possible to deal with that using subsample, but the available period is not so long in Brazil. Therefore, we propose to address this issue by allowing parameters to vary over time. We employ a Bayesian Time-Varying Coefficient (BTVC) VAR to analyze how economic conditions influence the dynamics of earmarked and non-earmarked credit in Brazil. Comparing these results with those from a standard VAR allows us to infer how restrictive is this assumption of constant parameters over time. Third, we provide 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.

Understanding household credit behavior in emerging markets is crucial to grasping some mechanisms in monetary policy transmission channels, asset pricing, banking, trade, financial stability, and growth. As for the former theme, some central banks control inflation by changing benchmark interest rates, and this pass-through to reduce the demand depends on the credit issued to households. Regarding asset pricing, Matos (2019) incorporates household debt and delinquency decisions into a model of lifecycle consumption-saving-investment, which helps in accounting for the cross-section behavior of domestic assets. For a discussion on trade, one can see Fanelli and Medhora (2002). Allen and Gale (2000) and Demirgüç-Kunt and Levine (2001) are relevant studies on macroeconomic and financial stability issues.

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Moreover, 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 key to understanding 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.

Concerning the role of credit as a growth driver, the literature linking the financial sector to the real economy distinguishes the effects of the credit issued to firms or households [e.g., Levine (2004)]. For instance, Beck et al. (2012) construct a new dataset from 45 developed and developing countries, and they find that enterprise credit is positively associated with economic growth and faster reductions in income inequality, whereas household credit is not. However, this finding does not hold onto the regional and state levels. 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.

Now, let us show the relevant and idiosyncratic role of household credit in Brazil.

Brazil is a bank-based economy. According to the Federal Reserve Economic Data (FRED), all financial institutions' assets to GDP rose from 121% to 185% from 2011 to 2020, while stock market capitalization to GDP ranged between 47% and 68%. From a credit market perspective, some characteristics make the Brazilian credit market stand out in comparison to other Latin American economies. [1]

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. In addition to being divergent, private credit presents an unusual pattern in its composition. 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 credit portfolio stock, households 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. In addition to being more representative, this credit issued to families significantly impacts cross-state growth in Brazil. Matos and Santos (2020) estimate an extended version of Barro-style growth panel regression from 2003 to 2017, and they find that Brazilian cross-state growth depends more on household credit evolution than firms' credit. These findings are corroborated by Matos et al. (2024).

There are more interesting and worrying findings on household credit in Brazil. Matos et al. (2015) estimate a panel from 2004 to 2013 to study the cross-state delinquent behavior of households in Brazil. They find that poverty and unemployment are the unique significant drivers of default choice. Matos and Correia (2017) propose a panel model to estimate the relationships between real per capita Brazilian household credit and a well-defined set of social, economic, and financial variables over the same period. The results suggest that demand for credit plays a more relevant role than supply.

Here are other concerning aspects of this type of credit. The average annual interest on non-earmarked household operations peaked at almost 73% at the end of 2016. In that same period, the average spread was over 60% per year, and the lowest levels of credit granting were recorded, signaling some rationality of the demand side. In this type of short-term credit, default rates have been varying between 4% and 7%, higher than earmarked values. It is worrying to observe the pace of indebtedness over time. 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? From another perspective, should society and policymakers be concerned about Brazilian families' excessive and growing debt?

According to some recent studies, the answer is positive. Garber et al. (2020) show that a sharper increase in the debt-to-income ratio at the individual level during the credit expansion period in Brazil predicts lower consumption during the subsequent crisis. Furthermore, this effect is more substantial when borrowing is concentrated on credit categories typically associated with higher interest rates. Garber et al. (2021) trace the

[1] See IMF (2013) to assess the description and evolution of consumer credit in Brazil from 2002 to 2012. For a broad overview of credit in Latin America, see Stallings and Studart (2006) and Hansen and Sulla (2013).

impact of credit stimulus on borrowers' consumption and find that the credit stimulus resulted in higher consumption volatility and lower average consumption over the cycle. Montani et al. (2023) explore the relationship between the cycles of Brazilian households' indebtedness and financial fragility based on debt service, labor underutilization, quality of loans, and delinquency rates, and their findings reinforce the concern we should have about the substantial increase in credit for families and its consequences.

We need to contextualize our contribution in the related literature on the determinants of household credit. Rubaszek and Serwa (2014) are a recent theoretical contribution. They use a lifecycle model with individual income uncertainty to investigate the determinants of credit to households. They estimate this model using international macroeconomic panel data. Their simulations based on aggregate data from OECD and EU countries indicate that the credit-to-GDP ratio depends on the lending-deposit interest rate spread and on individual income characteristics. Considering our interest in short-term analysis, we use the economic variables used in this theoretical approach, which are available in a monthly frequency in Brazil.

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 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 U.S. 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 they find that consumer loans are driven in the long run by the net labor income, net wealth of households, interest rate spread on loans, and inflation. Iacoviello (2008) calibrates 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. Once more, we incorporate the lessons learned from these empirical studies into the definition of the economic model to be estimated. Observing this literature, our study is (to our best knowledge) the first one to reconcile the insights from related contributions with the available data in Brazil to test an economic model by using the Bayesian TVC-VAR to estimate time-specific parameters. We also provide a robust analysis considering the different timing of the explanatory variables.

This paper proceeds as follows. Section 2 briefly describes 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

Our first purpose is to compare the estimates of individual equations without the counterpart credit (based on an Autoregressive model) with the results of a standard VAR with both types of credit together. In other words, when we report the estimates of the individual equation, we are trying to model the variation of the earmarked (or the non-earmarked) variation without considering cross-effects. When we use a standard VAR, we can measure these cross-effects. The idea is to show whether there are significant cross-effects. For example, we can find whether higher interest rates on earmarked credit operations encourage families to choose non-earmarked credit. Anticipating the results reported in Table 2, we evidence that joint estimation offers higher adjusted explanatory power, and we also find statistically significant cross-effects.

Please realize that we are modeling the reactions of the real monthly variation of both earmarked and non-earmarked granting operations in response to the current and lagged monthly variations in credit, macroeconomic, and monetary variables from April 2011 to December 2023. Considering the short-run behavior of banks and households for almost 14 years, our second purpose is to know whether these relationships remain stable over time. In practice, we propose to test whether or not this restriction of constant parameters over time is binding. This motivates our second empirical exercise.

Instead of estimating a traditional VAR introduced by Sims (1980) for sub-samples of time, we intend to determine if the parameters can change over almost 14 years. In order to measure time-varying reactions, we employ the Bayesian Time-Varying Coefficient Vector Autoregression (BTVCVAR) model, a valuable tool for analyzing the behavior of macroeconomic time series. Lubik and Matthes (2015) argue that the attractiveness of a Time-Varying-Parameter VAR (TVP-VAR) is based on the recognition that many macroeconomic time series exhibit some form of nonlinearity, mainly over long periods. For example, they mention that the unemployment rate tends to rise much faster at the start of a recession than it declines at the onset of a recovery. The analysis of household credit in Brazil (Section 3) shows that it also happens here, even if for distinct underlying structural reasons. Most of these nonlinearity examples in macroeconomic time series can be captured using the flexible TVP-VAR framework. [2]

It is well known that Vector Autoregression (VAR) considers endogenous variables to depend on their own lagged data and exogenous variables. TVP-VAR preserves this structure and, in addition, models the coefficients as stochastic processes. In the most common application, the assumption is that the parameters follow random walks, specifically the intercept, the lag coefficient, the variance, and the covariance of the error terms. Conditional on the parameters, this time-varying framework is still a linear VAR, but the overall model is highly nonlinear. While the assumption of random walk behavior may seem restrictive, it provides a flexible, functional form to capture various forms of nonlinearity.

Let y_t denotes the N-vector of endogenous variables in t. We consider the following observation equation

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

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 variables 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.

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, this process equation 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 et al. (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. 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 (3) 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. 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 estimates parameters that vary smoothly. The prior over the initial coefficient vector b_0 and covariance matrices S and Q is

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

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

[2] See Mumtaz and Surico (2009) and Fischer et al. (2023) for macroeconomic applications of TVP-VARs.

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

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.

The prior hyper-parameters are $b_0, B_{0,}S, s, Q,$ and q. We have to set prior hyper-parameters through the six scalar quantities $T_0, \tau_0, \tau_1, \tau_2, \nu_1$ and ν_2. T_0 is the prior sample size, τ_0 is a scaling factor controlling the prior variance of b_0, τ_1 and τ_2 are prior scaling factors for S and Q, respectively, and $\nu_1 = s$ and $\nu_2 = q$ are prior degrees of freedom parameters. Since our sample is not so long, we choose not using a prior sample, i.e., $T_0 = 0$. The respective mapping is given by $b_0 = 0, B_0 = \tau_0 I, S = \tau_1 I$ and $Q = \tau_2 I$. The choice for the values of the remaining scalar quantities follows the default setting of the literature. They are reported in the respective table of results.

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 represented more than 32% of GDP, close to R$10.9 trillion. Compared with enterprise credit, household credit surpassed its stock at the end of 2016. At the end of 2023, the stock of credit to firms was R$ 2.3 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 the non-earmarked. According to Fig. 1, both series have different behaviors 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 credit stock reduced and grew following a convex curvature. From then on, both series have grown again, with rare moments of reduction.

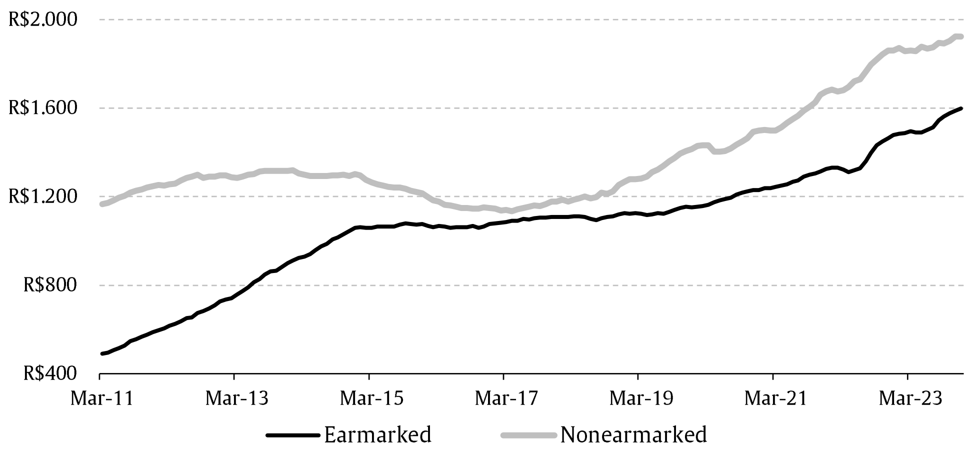

Fig. 1. Real credit portfolio stock (Billions of December 2023 R$). Monthly series from March 2011 to December 2023. Data source: Central Bank of Brazil. Series codes: 20570 (non-earmarked), 20606 (earmarked), and 433 (IPCA).

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 the earmarked ranged between R$ 15 billion and R$ 62 billion, while the other varied between R$ 143 billion and R$ 278 billion. There is also a difference in seasonality, with a 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%.

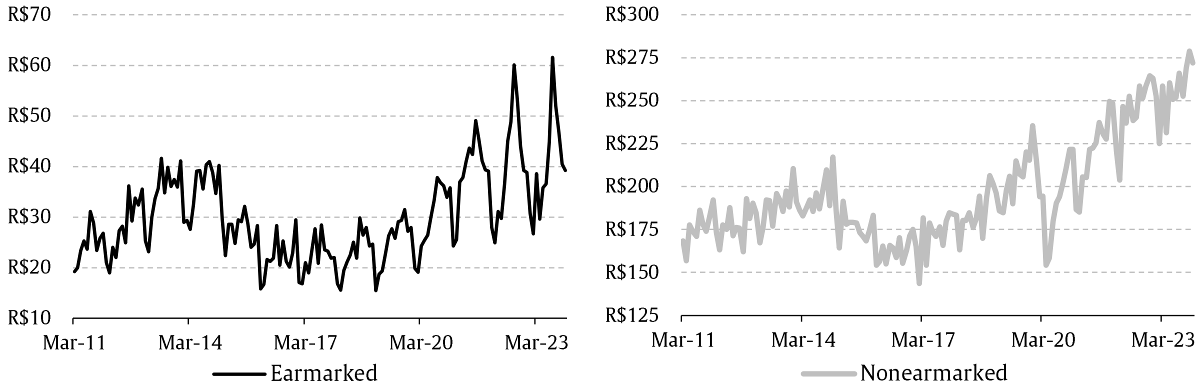

Fig. 2. Real credit granting operations (Billions of December 2023 R$). Monthly series from March 2011 to December 2023. Data source: Central Bank of Brazil. Series codes: 20662 (non-earmarked), 20698 (earmarked), and 433 (IPCA).

Fig. 3 shows the series of the most relevant household credit variables used here: 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 like 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 low, while in non-earmarked credit, they are at 5.6%. In Table 1, we report the statistics of the monthly variation in credit, monetary, and macroeconomic series. The variables that showed seasonality in their monthly variations were seasonally adjusted using STL decomposition, a method that uses a filtering algorithm based on LOESS regressions.

4. Economic model and results

4.1. Economic model

We aim to study the behavior of the monthly variation of household credit granting by measuring coefficients based on the standard VAR and the BTVCVAR estimates.

Let us emphasize some theoretical and empirical relevant aspects to set the model specification.

A few theoretical studies derived 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 propose 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). Our broad set of monetary, credit and macroeconomic determinants is aligned to this literature, and it is capable of explaining the supply and demand for credit.

Now, 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}.

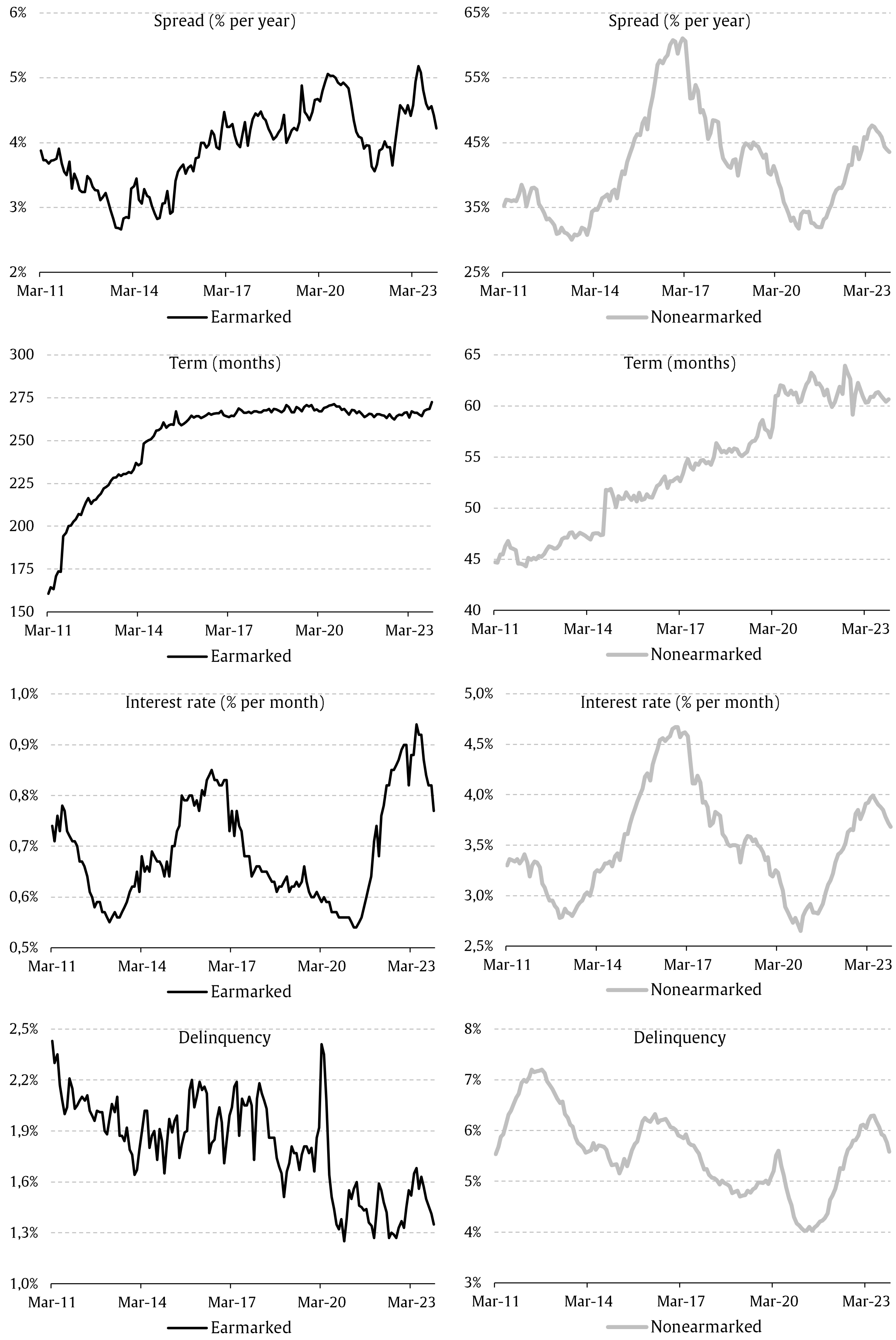

Fig. 3. Credit market variables. Monthly series from March 2011 to December 2023. Data source: Central Bank of Brazil.

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								
Variation of Spread	20837	0.00%	0.17%	-0.43%	0.56%	0.20	3.67	-11.98
Variation of Interest rate	25493	0.00%	0.03%	-0.10%	0.08%	0.02	4.95	-15.22
Variation of Average term	20878	0.73	2.67	-6.89	20.92	3.27	24.75	-13.16
Variation of Delinquency rate	21145	-0.01%	0.13%	-0.44%	0.49%	-0.07	5.19	-16.68
Nonearmarked credit variables								
Variation of Spread	20890	0.05%	1.36%	-4.48%	2.98%	-0.57	3.98	-9.54
Variation of Interest rate	25462	0.00%	0.09%	-0.24%	0.16%	-0.58	3.61	-9.38
Variation of Average term	20908	0.10	0.78	-3.50	4.38	1.07	12.24	-14.94
Variation of 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 variation 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).

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.

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 (household) or offer (banks). We assume that there is no endogeneity, 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 perceive the context after releasing these variables, which occur 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. This context and the robustness of the results allow us to infer that the empirical exercise is based on a well-specified, intuitive, and testable model.

4.2. VAR results

In the first columns of Table 2, we report the estimates of the individual models, i.e., the results based on an Autoregressive estimation of the single equation that explains the variation of the earmarked or the non-earmarked variation. In this case, there are no cross-effects. The other columns on the right side of the table are analogous with the estimates of the joint model, i.e., we use a Vector Autoregressive approach to estimate the system of equations that explain the variations of both types of credit.

Considering that the parameters of the spread, interest rates, and average term of earmarked credit are statistically significant in explaining the variation of non-earmarked credit in this reduced form VAR and that the joint model's explanatory power is superior to the individual models for both credits, we argue that the grant of both types of credit needs to be analyzed jointly in the sense of a general equilibrium approach. We use this joint specification as our benchmark to compare with the Bayesian TVP-VAR approach results.

Regarding the role of lagged endogenous variables, we find a positive (0.39) parameter of the lagged monthly variation of earmarked credit, while the lagged variation of non-earmarked credit has a negative parameter (-0.58). We also find a reduction of new earmarked credit operation granting due to increased lagged variation in non-earmarked credit. The spread and interest rate of earmarked credit affect new current concessions of both types of credit, maintaining the same signs of the parameters, but with a greater intensity of effect on earmarked credit itself. The interest rates of non-earmarked credit also plays an important and negative role in driving non-earmarked credit issued to households in Brazil. There is no statistical relevance regarding monetary variables. Debt to income discourages both types of credit, while an increase in disposable income encourages non-earmarked credit.

4.3 Bayesian TVP-VAR results

Before analyzing the time-varying results, it is necessary to understand the technique and what the results can tell us or not. Unlike the frequentist approach, the Bayesian approach incorporates prior and current information to obtain probability distributions over the parameters and make inferences. Its version with time-varying parameters offers flexibility to capture a wide range of time variation and nonlinear data features, making estimation and inference quite complicated. In this sense, let us remember that a TVP-VAR can be regarded as the reduced-form representation of an underlying dynamic model in which there is time variation.

Table 2. Standard VAR estimates

Exogenous Variables	Individual estimates				Joint estimates			
	Variation in earmaked credit		Variation in nonearmaked credit		Variation in earmaked credit		Variation in nonearmaked credit	
Lagged Real variation in credit granting operations	Parameter	T-statist.	Parameter	T-statist.	Parameter	T-statist.	Parameter	T-statist.
Earmarked	0.080	0.999			**0.393 ****	3.563	0.058	1.370
Nonearmarked			**-0.539 ****	-8.302	**-1.001 ****	-4.246	**-0.579 ****	-6.394
Current Earmarked credit variables								
Spread	**-37.273 ****	-3.148			**-30.191 ****	-2.586	**-10.156 ***	-2.263
Interest rate	**290.333 ****	3.817			**219.114 ****	2.907	**114.156 ****	3.940
Average term	**-0.013 ***	-1.760			-0.011	-1.615	**-0.005 ***	-1.781
Delinquency rate	-8.812	-0.526			-12.576	-0.715	-5.600	-0.829
Current Nonearmarked credit variables								
Spread			0.374	0.219	-0.998	-0.230	2.513	1.509
Interest rate			-42.459	-1.382	-35.135	-0.455	**-73.651 ****	-2.483
Average term			0.004	0.460	0.021	0.862	-0.003	-0.363
Delinquency rate			4.751	0.683	25.705	1.372	1.444	0.201
Lagged Monetary variables								
Real variation in demand deposit	1.077	1.129			0.881	0.967	0.439	1.254
Real variation in term deposit	-0.052	-0.043			-1.000	-0.866	-0.652	-1.469
Real variation in physical money held by the public	1.083	0.791			0.529	0.411	0.181	0.366
Official inflation (IPCA)	2.644	0.409			5.179	0.836	2.884	1.211
Lagged Macroeconomic variables								
Variation in the stock of formal jobs	7.288	1118,00	2.073	0.827	5.320	0.875	2.527	1.082
Variation of household debt to income	**-24.072 ****	-2.979	-4.550	-1.476	**-22.693 ****	-3.028	**-5.376 ***	-1.866
Real variation in economic activity (IBC-BR)	0.707	0.425	**1.467 ***	2.231	2.414	1.488	1.157 *	1.856
Real variation in available gross household income	-0.654	-1.145	**0.593 ****	**2.755**	-0.846	-1.585	**0.560 ****	2.731
Variation of foreign exchange R$ - US$	-0.626	-1.166	-0.144	-0.693	-0.776	-1.530	-0.099	-0.509
Variation of consumer confidence index	-0.499	-0.960	0.142	0.762	0.010	0.019	0.071	0.373
Adjusted R2	0.185		0.400		0.305		0.487	

Results based on the standard Vector Autoregression approach applied to model (6) from April 2011 to December 2023. * Significance at 5%, ** Significance at 1%.

This time variation in the underlying data-generating process (DGP) carries over to its reduced form, which is approximated by a TVP-VAR. We have also emphasized that the entire posterior distribution is the complete summary of the inference about any parameter in the model. In essence, the posterior distribution is the inference. However, for our application, we need to summarize this information somehow, i.e., the best estimate of the unknown parameter.[3] In the Bayesian framework, a point estimate of a parameter is a summary statistic of the posterior distribution. Decision theory methodology leads to optimal choices of point estimates by defining the quality of an estimator through a loss function. We follow this literature by using the median as the optimal point estimator.

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 3, 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.

Regarding the role of lagged endogenous variables, we corroborate previous findings. The parameter of lagged monthly variation of earmarked credit ranges between 0.25 and 0.50. In contrast, the coefficient of the lagged variation of non-earmarked credit is varying from -0.55 to -0.65. There is rationality in decision-making for reducing new earmarked credit granting due to increased lagged variation in non-earmarked credit. This evidence is more intense from 2016 onwards, after the height of the fiscal crisis in Brazil.

This finding strongly corroborates the results of estimating the system with a standard VAR with constant parameters. Moreover, the parameter values in Table 2 are within the respective ranges in Table 3. This evidence seems to be rational, considering that it is a long-term decision mainly associated with acquiring real estate or rural credit. It is timely to understand the behavior of non-earmarked credit variation, a type of short-term credit which is sometimes motivated by ephemeral reasons of consumerism and financial disorganization of families. This specific issue of the insolvent behavior of earmarked and non-earmarked household credit in Brazil is addressed by Matos and de Jesus Filho (2019).

For both types of credit, the non-earmarked spread parameter is negative throughout the period, with a higher value 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. This finding on the negative role of spread corroborates one of the main findings reported by Rubaszek and Serwa (2014), based on panel estimation using data from 1995 to 2009 for 36 countries, including those OECD and EU economies.

Once more, for both types of credit, we find a negative value for the earmarked credit term parameter in specific years. Observing the behavior of earmarked credit, we see a positive value for the average term for the non-earmarked operations parameter. The rationality associated with macroeconomic variables is very interesting. Theoretically, an improvement in economic activity (IBC-BR) stimulates the demand and supply of credit in the following period. In the reduced-form estimate, we evidence this mechanism for both types of credit, given the positive value of the IBC-BR variation parameter. Once more, this finding is aligned to the result reported by Rubaszek and Serwa (2014). They report a positive role played by real GDP per capita for a panel with developed economies. In the opposite direction, the lagged variation in the R$/US$ exchange rate parameter is negative throughout the period in both credit equations. This negative value is more potent in earmarked credit (from -1.05 to -1.15).

The other macroeconomic variables do not show significant effects at any time. However, some results are still not statistically significant at 10% but are intuitive, in line with economic theory. These include the negative value of non-earmarked credit interest rates and earmarked credit default. On the other hand, we see the positive value of the parameters associated with the variation in the consumer confidence index, demand deposit, and physical money held by the public.

[3] See Carrielo et al. (2016) for a discussion on the trade-off between using a more general Bayesian VAR model, giving up on using the information available in a large dataset, and using a model nested in the first specification and computationally manageable for large datasets such as the typical macroeconomic dataset of 15–20 variables.

Table 3. Summary of the most relevant Bayesian Time-varying coefficient VAR estimates

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 — period	time-varying coefficient range	pattern over time	Real variation of nonearmarked credit granting operations — 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	2011 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 (6) 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

Brazil is an emerging bank-based economy with a private credit market characterized by a larger share of household credit since 2016. There is the leading role of this credit issued to families in cross-state growth [e.g., Matos et al. (2024)], and according to Matos et al. (2025a), in non-recession periods, household credit leads out-of-phase growth cycles, while enterprise credit plays a positive role during recessions. Our finding on the statistical significance of the variation of economic activity (IBC-BR) in explaining both types of household credit adds to this discussion.

This variable is also crucial to grasp some other mechanisms. From a demand perspective, it is essential to monitor the dynamics of banks' credit granting to households and how these agents' decisions react to changes in interest rates over time. In this monetary context, our finding that interest rates do not seem to drive short-run time-varying credit behavior is a key element in understanding and measuring the effectiveness of controlling basic interest rates as a monetary policy instrument in combating inflation in an emerging country with a history of hyperinflation. Since 1999, the observed official inflation has not respected the upper bound in eight years, and the most recent market forecasts still point to inflation of 5.68% in 2025, therefore, once again above the target, even with SELIC rates higher than 14% per year.

Regarding financial stability, Matos et al. (2025b) improve the experiment suggested by Hansen and Sulla (2013) on the effects of a gap in private credit on the gap in the banking index in Brazil. Their Bayesian TVP-VAR results show a differentiated role for disaggregated credit, whether household or entrepreneurship, as well as earmarked or non-earmarked.

To summarize, it is essential to understand the time-varying role of the determinants of banks' and families' decisions to offer and demand credit, considering both earmarked and non-earmarked credit, because this credit can influence growth, financial stability, and monetary policy channels in Brazil.

We also offer methodological contributions. Allowing for time-specific parameters enables us to find interesting results, and 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.

In practice, our exercise can be replicated for other developing countries. To extend this research agenda, the exercise can be revisited using a 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 credit into personal credit, vehicle purchases, and credit cards.

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 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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Appendix

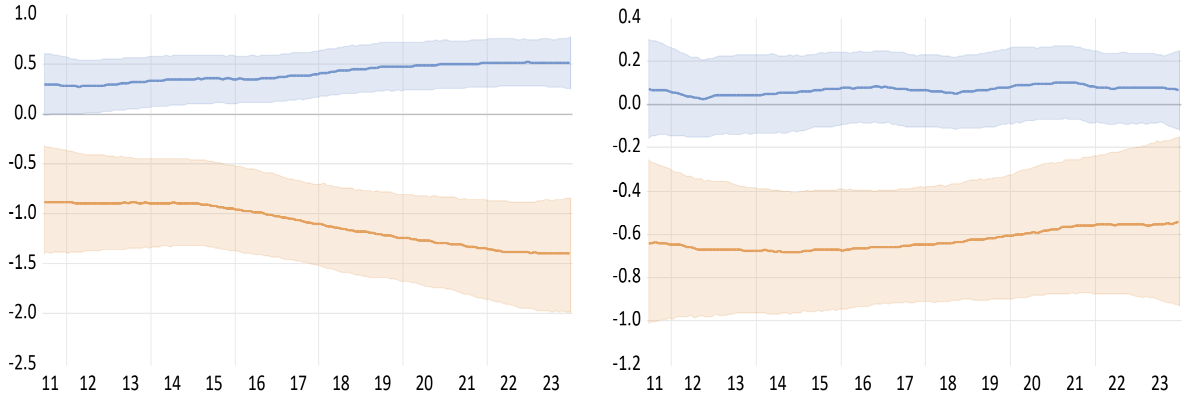

Fig. A.1. BTVCVAR equation coefficients of the lagged ($t-1$) real variation of earmarked (blue) and non-earmarked (red). Endogenous: Real variation in t of earmarked (left) and non-earmarked (right) credit grant. Posterior medians, 80% CIs. Monthly series from April 2011 to December 2023. Data source: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

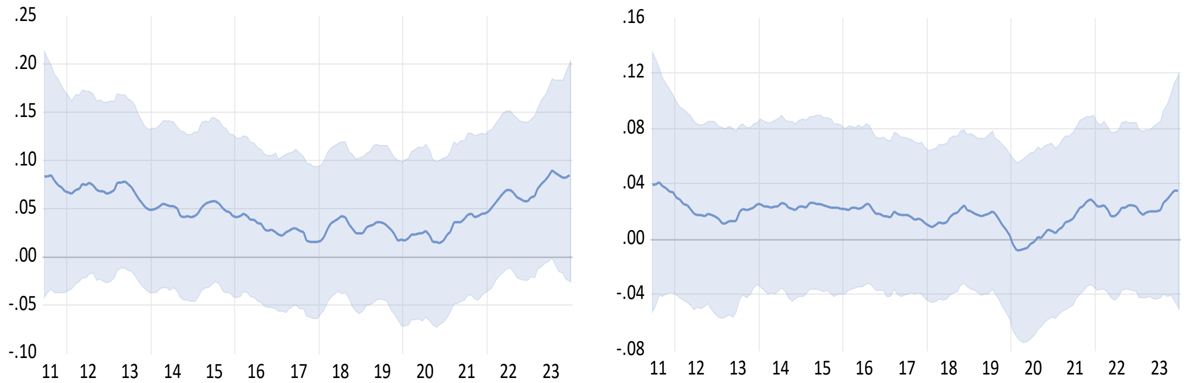

Fig. A.2. BTVCVAR equation constant. Endogenous: Real variation in t of earmarked (left) and non-earmarked (right) credit grant. Posterior medians, 80% CIs. Monthly series from April 2011 to December 2023. Data source: Central Bank of Brazil.

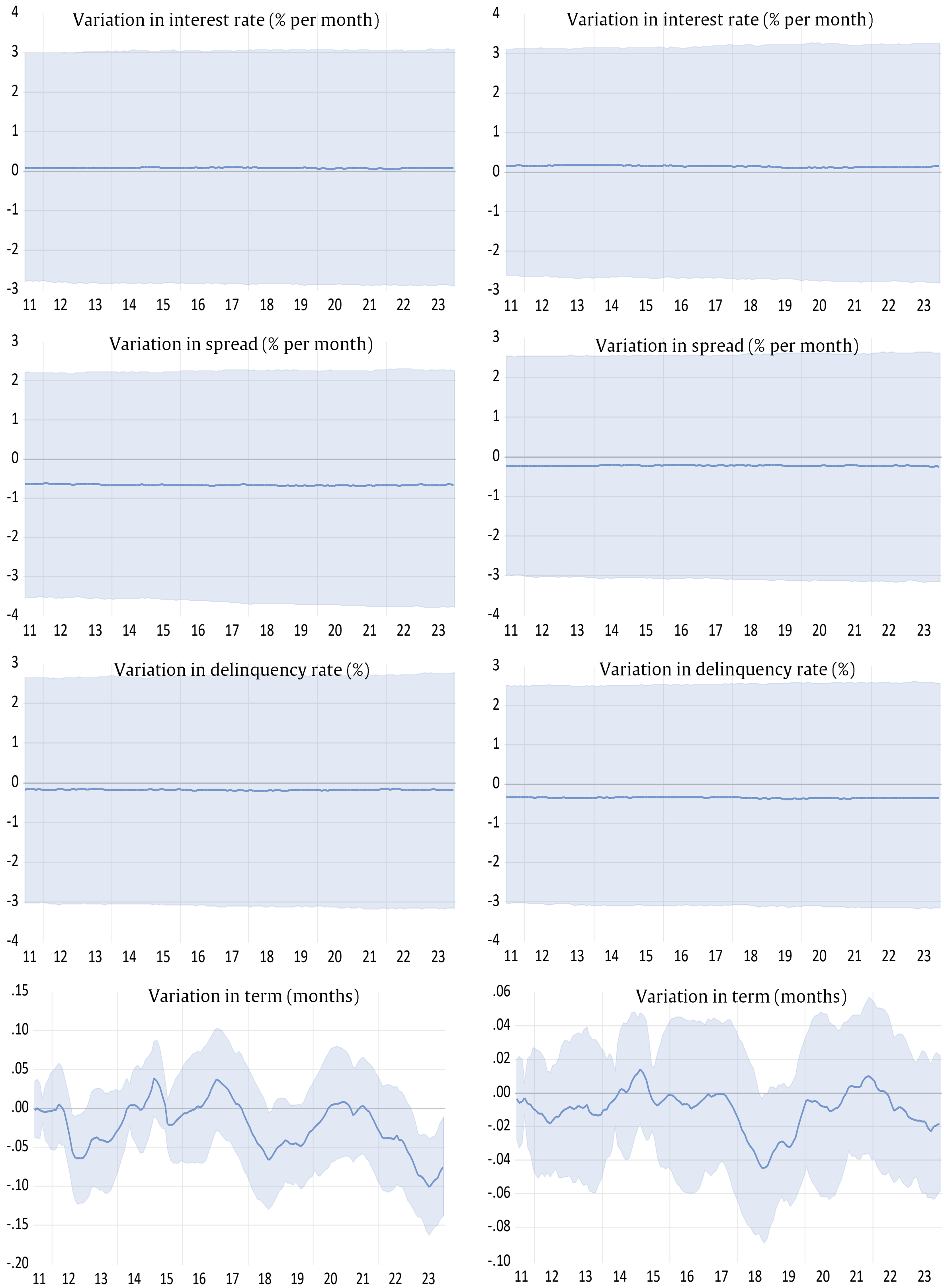

Fig. A.3. BTVCVAR equation coefficients of the earmarked credit variables in t. Endogenous: Real variation in t of earmarked (left) and non-earmarked (right) credit grant. Posterior medians, 80% CIs. Monthly series from April 2011 to December 2023. Data source: Central Bank of Brazil.

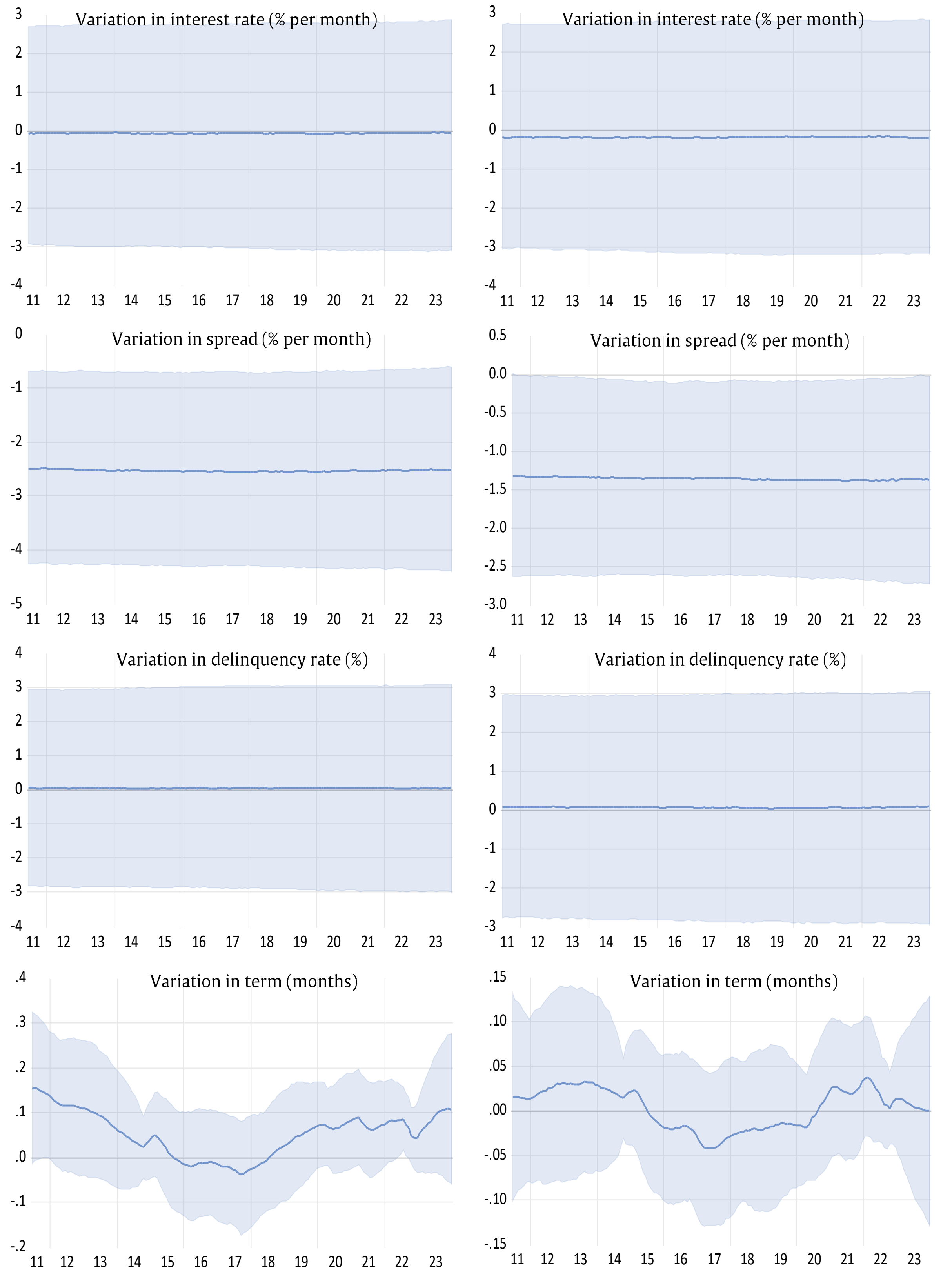

Fig. A.4. BTVCVAR equation coefficients of the non-earmarked credit variables in t. Endogenous: Real variation in t of earmarked (left) and non-earmarked (right) credit grant. Posterior medians, 80% CIs. Monthly series from April 2011 to December 2023. Data source: Central Bank of Brazil.

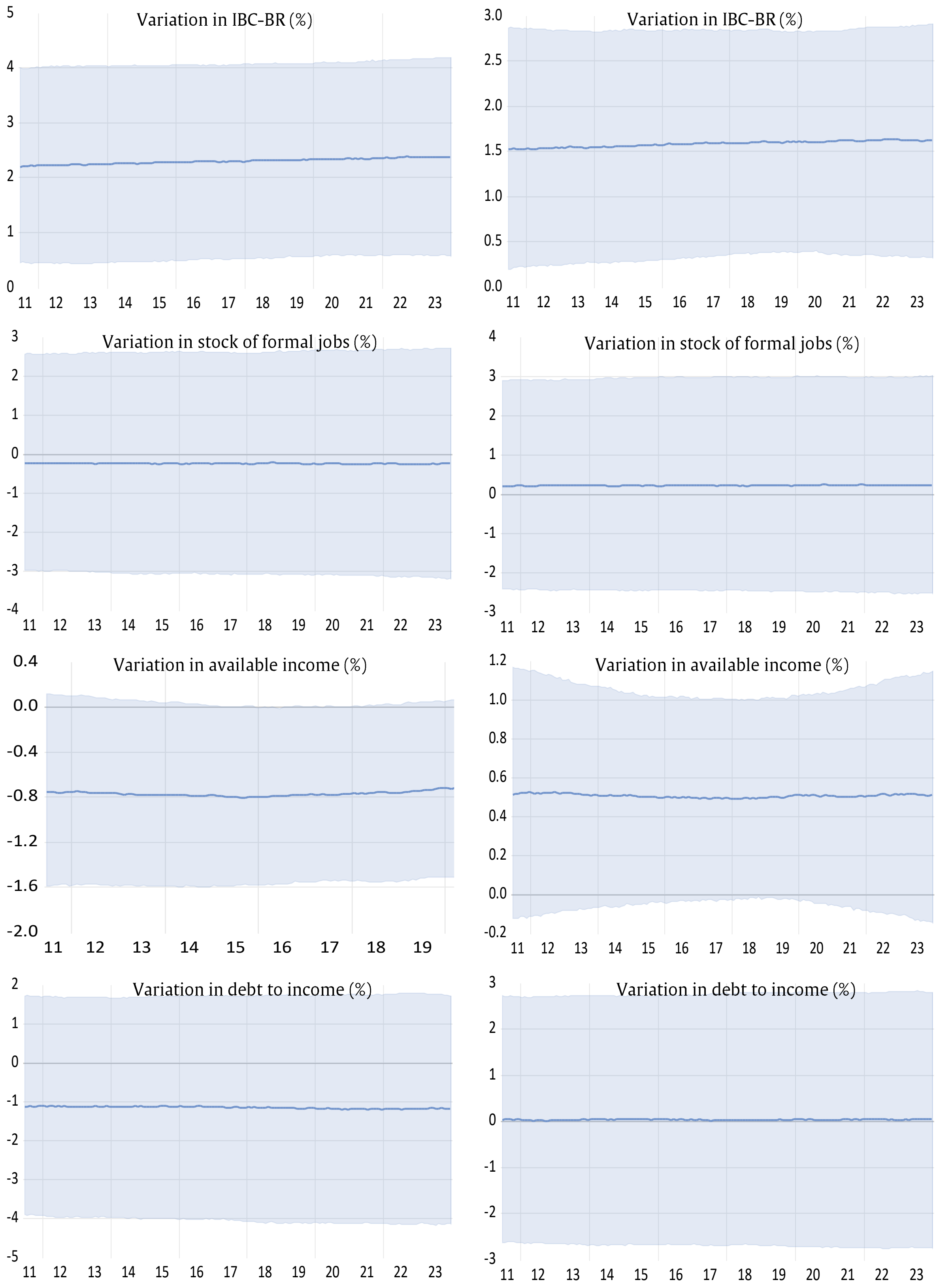

Fig. A.5. BTVCVAR equation coefficients of the macroeconomic variables in $t-1$. Endogenous: Real variation in t of earmarked (left) and non-earmarked (right) credit grant. Posterior medians, 80% CIs. Monthly series from April 2011 to December 2023. Data source: Central Bank of Brazil.

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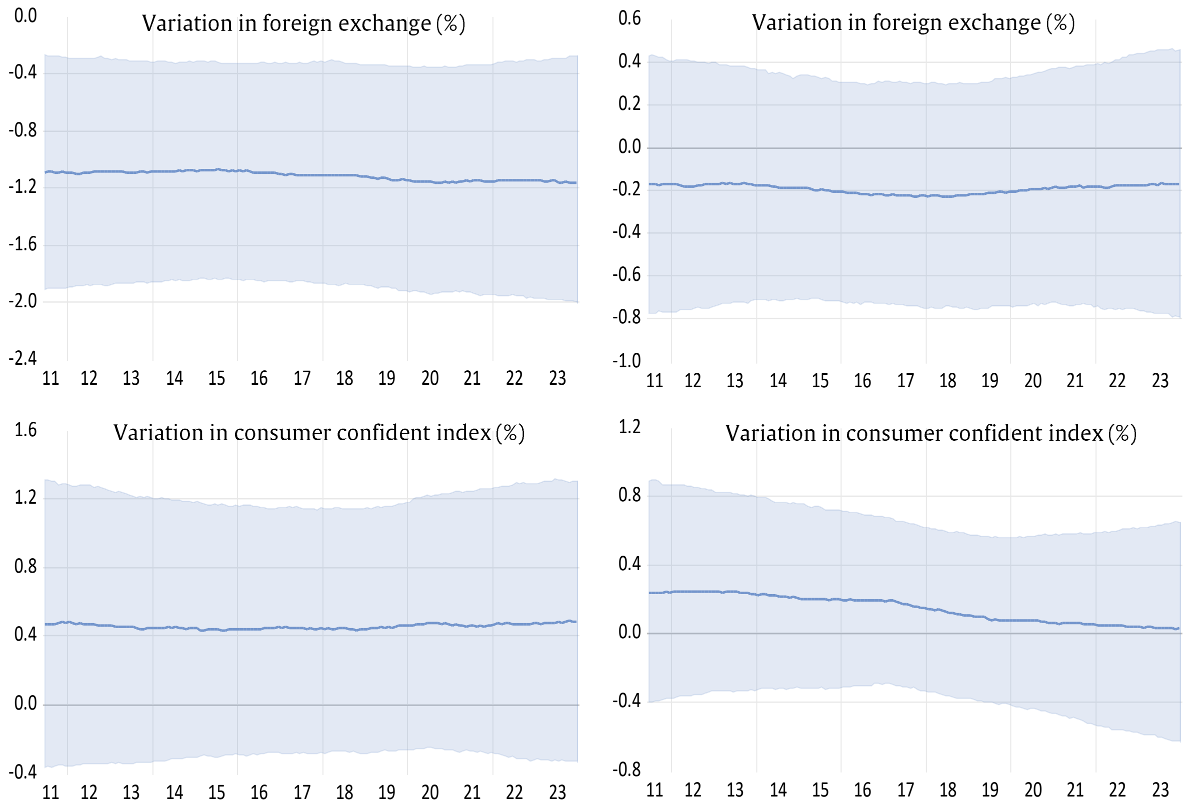

Fig. A.5. BTVCVAR equation coefficients of the macroeconomic variables in $t-1$. Endogenous: Real variation in t of earmarked (left) and non-earmarked (right) credit grant. Posterior medians, 80% CIs. Monthly series from April 2011 to December 2023. Data source: Central Bank of Brazil.

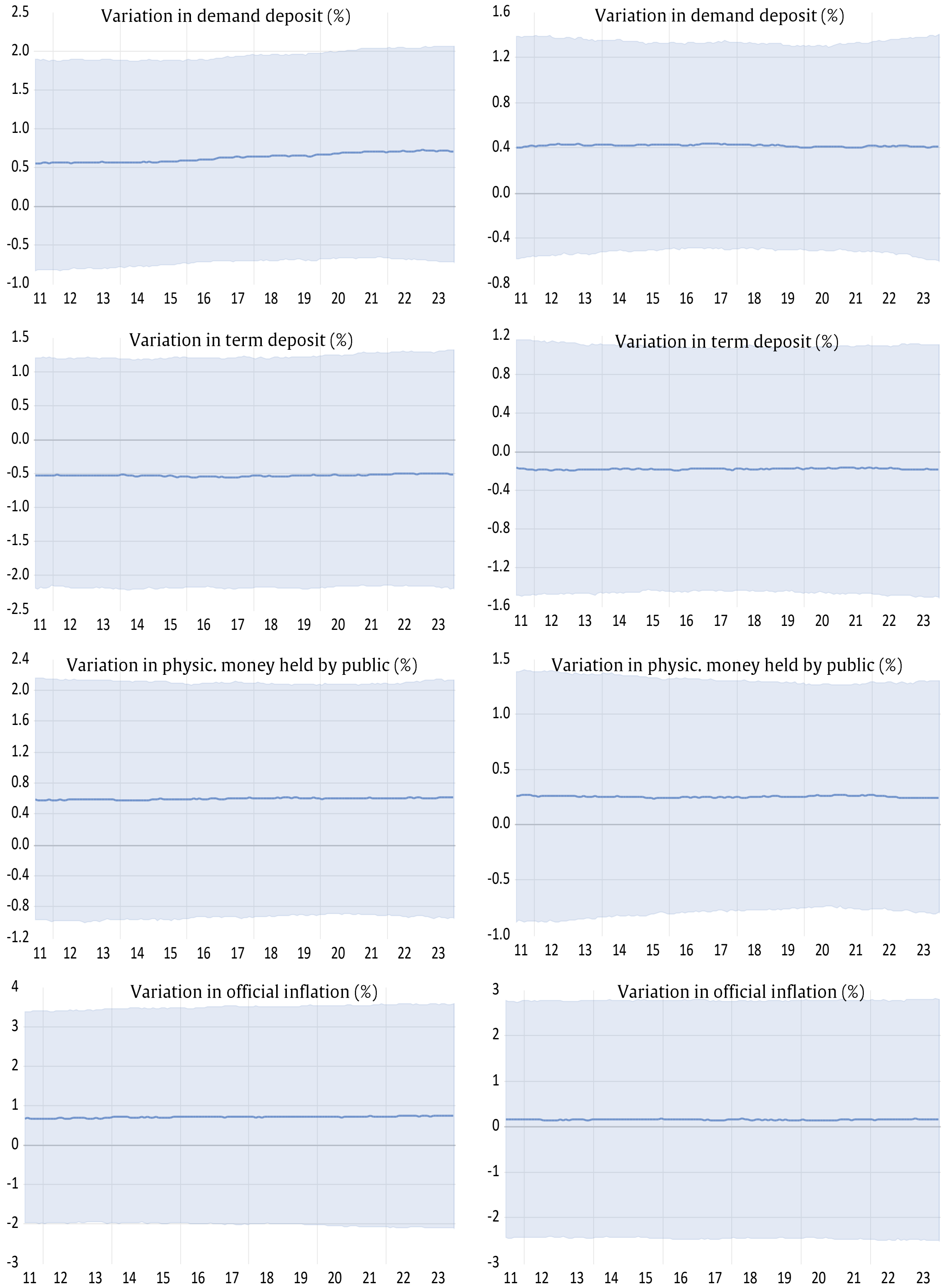

Fig. A.6. BTVCVAR equation coefficients of the monetary variables in $t-1$. Endogenous: Real variation in t of earmarked (left) and non-earmarked (right) credit grant. Posterior medians, 80% CIs. Monthly series from April 2011 to December 2023. Data source: Central Bank of Brazil.