

Private credit gaps: a driver of banking instability in Brazil?

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Abstract

Although there is a well-documented positive relationship between credit market depth and economic growth, rapid credit expansion may threaten financial stability due to vulnerabilities in banks' balance sheets. This paper examines the relationship between the banking sector index (IFNC, from B3) and private credit in Brazil, revisiting Hansen and Sulla (2013) for Latin America. The study contributes by using a sector-specific banking index instead of a general one and by distinguishing between earmarked and non-earmarked credit for households and firms. The empirical analysis isolates the role of credit gaps by controlling for instability transmission through bank assets, liabilities, and economic overheating. Methodologically, it applies a vector error correction model with exogenous variables (VECX) and estimates impulse-response functions following Otero (2020). Using data from March 2011 to October 2025, the results identify when signs of banking instability may arise and which credit types can act as leading indicators.

Keywords: Household and Firms · Banking Sector Index · Short-run and Long-run relationships · Banking instability.

JEL classification: C11 · G21 · G51.

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Abstract

Although there is a well-documented positive relationship between credit market depth and economic growth, rapid credit expansion may threaten financial stability due to vulnerabilities in banks' balance sheets. This paper examines the relationship between the banking sector index (IFNC, from B3) and private credit in Brazil, revisiting Hansen and Sulla (2013) for Latin America. The study contributes by using a sector-specific banking index instead of a general one and by distinguishing between earmarked and non-earmarked credit for households and firms. The empirical analysis isolates the role of credit gaps by controlling for instability transmission through bank assets, liabilities, and economic overheating. Methodologically, it applies a vector error correction model with exogenous variables (VECX) and estimates impulse-response functions following Otero (2020). Using data from March 2011 to October 2025, the results identify when signs of banking instability may arise and which credit types can act as leading indicators.

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1. Introduction

Understanding household credit behavior in emerging markets is essential for understanding how monetary policy transmission, asset pricing, banking, and trade. Regarding the first topic, some central banks control inflation by adjusting benchmark interest rates, and the pass-through to lower demand depends on household credit. In asset pricing, Matos (2019) incorporates household debt and delinquency decisions into a lifecycle consumption, saving, and investment model, thereby helping explain the cross-sectional behavior of domestic assets. For trade, see Fanelli and Medhora (2002). Allen and Gale (2000) and Demirgüç-Kunt and Levine (2001) are key studies on macroeconomic and financial stability issues.

Furthermore, credit expansion can stimulate economic growth by increasing supply and encouraging capital buildup and productivity. Acemoglu and Zilibotti (1997) propose a model linking the level of market incompleteness with capital accumulation and growth, arguing that during early development stages, indivisible projects limit risk diversification, and the inability to spread unique risks creates significant uncertainty in the growth process. Additionally, private credit from deposit money banks can channel savings toward investors, which is crucial for understanding growth in emerging countries. It provides access to financial resources for lower-income families or those with limited savings, as well as for smaller firms that face more restrictions in capital markets. In this discussion, Levine (1997) contends that developing the financial system reduces information and transaction costs, thereby improving resource allocation, facilitating risk diversification and savings mobility, and ultimately strengthening financial institutions, which, in turn, influence economic growth through greater efficiency.

On one hand, whether finance influences growth and other macroeconomic variables depends on the financial structure, which is the mix of financial markets and institutions like banks and other intermediaries. On the other hand, although credit can positively impact economic activity, its rapid growth can also pose macroeconomic risks and financial instability, especially in emerging economies.

At the macroeconomic level, excessive credit expansion can weaken aggregate demand, leading to inflation and external imbalances. In the financial context, this rapid growth can increase vulnerabilities in assets and liabilities, reduce the quality of bank credit, and hinder banks' ability to diversify their loan portfolios. In the related literature, Bordo and Jeanne (2002) argue that cycles and fluctuations in asset prices, along with increased credit, amplify macroeconomic fragility, complicating monetary policy. Borio and Lowe (2002) note that rapid credit growth, combined with significant rises in asset prices, raises the risk of a financial instability episode, sometimes requiring a monetary response to credit and asset markets to maintain financial and monetary stability.

Borio and Drehmann (2009) improve this approach by using credit gaps and asset prices as early warning signs of potential financial instability. Therefore, credit is an essential variable, along with asset and real estate prices, for assessing the risk of banking crises. Drehmann et al. (2011) show that the difference between the credit-to-

GDP ratio and its long-term trend is a more effective indicator of capital buildup, as it exposes systemic vulnerabilities that often lead to banking crises. Matos et al. (2021) find that mortgage credit influences stock indices before a crisis, whereas delinquency can signal an upcoming economic recession.

A significant milestone in this empirical literature is Hansen and Sulla (2013). They investigate whether the expansion of bank credit in the private sector was driven by financial growth or by an economic cycle that causes instability in Latin America. In their model, they use credit indicators and macroeconomic variables, including income, interest rates, inflation, and external conditions. This paper revisits the empirical analysis of financial structure conducted by Hansen and Sulla (2013) by exploring the relationship between private credit and the financial market. The goal is to empirically determine whether excess resources allocated to households and firms can influence the performance of the banking sector's financial index, potentially leading to banking instability.

This paper specifically examines the Brazilian case, an emerging economy among the world's top 10 largest economies. Brazil has a bank-based system and, from a credit market perspective, stands out from other Latin American countries. According to Matos et al. (2013), there is no global convergence of private credit across Brazilian states, with two regional clusters forming. Additionally, private credit has an unusual composition. The monthly historical series shows that after the 2016 fiscal crisis, household lending surpassed business lending, and this trend continues. Based on credit portfolio stocks, household credit overtook corporate credit at the end of 2016. By the end of 2025, both stocks reached R\$ 4.4 trillion and R\$ 2.7 trillion, respectively. Considering non-earmarked household credit, default rates range between 4% and 7%, higher than in earmarked cases. It is concerning that household debt increased from 16% in 2005 to 50% by 2025. Credit to firms also raises concerns, as the gap to trend for this corporate credit reaches excessively high levels during recessions.

Further findings emerge regarding household credit in Brazil. Matos and Correia (2017) propose a panel model to explore the relationships between real per capita household credit and a set of social, economic, and financial variables over the same period, with results indicating that demand for credit is more influential than supply.

As a preliminary analysis, this paper provides an update on the warning signs of potential financial instability proposed by Borio and Drehmann (2009), based on thresholds of 40%-60% for real asset price gaps and 4%-6% for credit-to-GDP gaps. In the second step, rather than trying to identify causality, the exercise estimates a long-run relationship between the trend of the banking index (IFNC) and the trends of the types of private credit-to-GDP, controlling for a set of variables that capture the transmission channels in this literature. While a non-stationary variable can affect the long-run level of IFNC if it cointegrates with this sectoral index, if the explanatory variable is stationary, it will oscillate around a constant mean, allowing it to affect the variation of IFNC in the short-run relationship, but not the level of IFNC in the long-run relationship. This motivates the third and final step, which provides results based on VAR estimates and (endogenous and exogenous) impulse response functions.

In the main part of the study, four key innovations are introduced compared to the related papers. First, the empirical analysis uses a banking-sector-specific index (IFNC) rather than a general index such as the Ibovespa. Second, it disaggregates earmarked and non-earmarked credit issued to households and firms. Third, the analysis isolates the role of credit gaps by controlling for channels of instability transmission through bank assets and liabilities, economic overheating, the monetary side, and foreign influence. Lastly, this paper enhances the methodology by employing the traditional vector error correction model with an exogenous variable (VECX) and Vector Autoregressive (VAR) to examine short- and long-term relationships, as well as estimating an impulse-response function based on Otero (2020) to analyze the effect of a shock to an exogenous variable on the endogenous variable.

The main results, covering March 2011 to October 2025, offer insights into when and if signs of potential banking instability appear and which credit type could act as a leading indicator in the short or long run.

This paper proceeds as follows. Section 2 briefly shows the econometric techniques used. Section 3 presents the data and results. Section 4 offers the concluding remarks.

2. Methodology

2.1 Long-term analysis

The dataset includes endogenous variables IFNC and the four credit types, while the exogenous dataset includes macroeconomic variables such as real GDP, exchange rates, deposits, inflation, and overall default by credit line.

The first step in the methodology relies on the Hodrick–Prescott filter, as used by Bordo and Jeanne (2002), Borio and Drehmann (2009), Drehmann et al. (2011), and Hansen and Sull (2013). Following these authors, we use the Hodrick–Prescott filter to separate each time series into its trend and gap components. According to this approach, any time series can be decomposed into two components:

$$Y_t = C_t + \tau_t \quad (1)$$

where C_t is the cyclical component and τ_t is the trend extracted from the original series. Here, we use the trend for the long-term analysis by performing the Johansen cointegration test and estimating the Vector Error Correction Model (VECM). Based on the Phillips-Perron test, one cannot reject the hypothesis that all trends are $I(1)$, as expected. Next, we perform the Johansen cointegration test, and after identifying the number of cointegration vectors, we estimate the Vector Error Correction Model (VECM), given by this general version:

$$\Delta Y_t = \alpha - BA'Y_{t-1} + \sum_{i=1}^{P-1} \theta_i \Delta Y_{t-i} + \varepsilon_t; \varepsilon_t \sim N(0, \Omega) \quad (2)$$

where α is the error cointegration vector, indicating the fit of the variables to long-term equilibrium. $BA'Y_{t-1}$ is the long-term cointegration ratio between the variables in the Y_t vector. $\sum_{i=1}^{P-1} \theta_i \Delta Y_{t-i}$ is the sum of the effects of the lags of the variables that capture short-term dynamics. ε_t is the model error. These long-term results are reported in [subsection 3.3](#).

2.2 Short-term analysis

To address short-run relationships, we need to define a new variable, Z_t , known as gap to trend, given by

$$Z_t = C_t / \tau_t \quad (3)$$

Once more, as expected, gaps to trend series are stationary, based on a usual test, Kwiatkowski-Phillips-Schmidt-Shin (KPSS). Next, we estimate a common Vector Autoregressive (VAR) model, developed by Sims (1980). In this approach, the variables are determined jointly; that is, each variable uses its own data and time-delayed information. The equation can be written as:

$$Y_t = \mu + A_{1,t}Y_{t-1} + \dots + A_{k,t}Y_{t-k} + u_t \quad (4)$$

where μ is a vector that portrays the constant terms, A_i is the coefficient matrix, and u_t is the error term, in which $u_t \sim N(0, S)$. The model helps elucidate the dynamics among variables, capturing the interrelationships among endogenous variables and evaluating the effects of shocks. However, the traditional VAR framework does not allow for the analysis of the effects of shocks to exogenous variables on endogenous variables through Impulse Response Functions (IRFs). To address this limitation, an additional estimation using a Vector Autoregression with Exogenous variables (VARX) model is conducted. These short-term results are reported in [subsection 3.4](#).

2.3 Exogenous-source impulse response function (IFR) analysis

To estimate an impulse-response function, considering that a shock was given in an exogenous variable, this study follows Otero (2020). A new VAR specification needs to be used in RATS® to generate impulse-response functions via Monte Carlo simulations. Considering the following model:

$$X_t = F(L)X_{t-1} + G(L)Z_{t-1} + \xi_t \quad (5)$$

where X_t is an endogenous variable vector, $F(L)$ is an $n \times n$ polynomial, $G(L)$ is an $n \times 1$ polynomial vector, L is a lag operator, Z_t is an exogenous variable vector, and ξ is a classical error vector such that $\xi_t \sim (0, \Sigma)$, where Σ is a covariance matrix. The model is given by the respective vectors of endogenous and exogenous variables:

$$X_t = [X_{1,t} \ X_{2,t} \ X_{3,t} \ X_{4,t} \ X_{5,t}] \quad (6)$$

$$Z_{it} = [z_{1t} z_{2t} z_{3t} z_{4t} z_{5t} z_{6t} z_{7t} z_{8t}] \quad (7)$$

where $X_{1,t}$ is the IFNC, $X_{2,t}$ is the enterprise earmarked stock credit/GDP, $X_{3,t}$ is the enterprise non-earmarked stock credit/GDP, $X_{4,t}$ is the household earmarked stock credit/GDP, $X_{5,t}$ is the household non-earmarked stock credit/GDP, z_{1t} is the GDP, z_{2t} is the exchange rate, z_{3t} is the deposit rate, z_{4t} is the inflation rate, z_{5t} is the enterprise earmarked delinquency, z_{6t} is the enterprise non-earmarked delinquency, z_{7t} is the household earmarked delinquency, z_{8t} is the household non-earmarked delinquency. In the inference process, a simulation was constructed in which a fictitious equation was created, with only the shock of interest as the dependent variable and no other variables. This approach helps create a provisional element (a placeholder) useful for Monte Carlo simulations and for calculating impulse response functions. The effect of exogenous variables on endogenous variables is given by a unitary shock to the exogenous variables, which is then transmitted to the endogenous variables as recorded in the impulse-response functions. For each endogenous variable in the model, a VAR was estimated using the corresponding exogenous variables. This results in $5 \times 8 = 40$ models. After estimation, impulse-response functions were generated over a 12-month period. 10,000 results from the coefficient vector estimation were obtained via Monte Carlo simulations. To quantify the uncertainty, in odd-order Monte Carlo simulations, the covariance matrix was obtained via the inverse Wishart distribution given by:

$$\Sigma \sim IW(\Sigma_S, T - k) \quad (8)$$

where Σ_S is the true covariance matrix, T is the number of time observations, k is the number of lags of the endogenous variables included in the model (the order of the VAR), and $T - k$ is the number of degrees of freedom. The inverse Wishart distribution applied to the covariance matrix emerges as the distribution resulting from the adoption of *Jeffrey's prior*, a neutral (non-informative) Bayesian distribution with respect to a set of parameters, whose density function corresponds to the square root of the determinant of Fisher's information matrix (SUN; NI, 2004). This function is given by:

$$\pi(S) \propto |\Sigma|^{-\frac{n+1}{2}} \quad (9)$$

where n is the number of equations in the VAR. This distribution is applied when it is desired to avoid incorporating prior assumptions about the model parameters. After drawing the Σ matrix, the choice of odd coefficients for the Monte Carlo simulations is performed using the multivariate normal distribution, in order to estimate the parameter ϕ via OLS and adding the white noise, u_d .

$$\phi_d = \hat{\phi} + u_d \quad (10)$$

where $u_d \sim N(0, \Sigma_S)$ and $\hat{\phi}$ is the OLS estimate. The estimators will be drawn from a multivariate normal distribution given by $\phi_d | \Sigma \sim N(\hat{\phi}, \Sigma \otimes (X'X)^{-1})$. For even values of the Monte Carlo simulations, the Σ matrix is kept at its original value, and the values of the model parameter estimates are equal to:

$$\phi_d = \hat{\phi} - u_d \quad (11)$$

The coefficients ϕ_d are adjusted around the OLS estimate, following a unit shock applied to the placeholder. The VAR model is estimated and incorporated into this new result. The shock to the exogenous variable propagates and affects the endogenous variable, as reflected in the IRF. To obtain this function, it is necessary to represent, in a graph, the impact multipliers of one variable of the model on the other, as a function of t . To achieve this result, it is important to transform the VAR of order n into a finite moving average vector (VMA), which is possible through a stable VAR or when the eigenvalues of the polynomial are outside the unit circle ($I - \sum_{i=1}^p \Phi_i L^i$). To obtain the VMA, it is necessary to impose $\frac{1}{n}(n^2 - n)$ constraints on the matrix, which capture the simultaneous interactions among the endogenous variables, allowing the identification of the model. Through Cholesky decomposition, which allows the covariance matrix to be decomposed into the following structure:

$$W_t = B_0 + \sum_{i=1}^n B_i W_{t-i} + \rho_t \quad (12)$$

where ρ_t is a column vector whose elements are equal to $\sigma_j \varepsilon_{x_{j-i}}$ where $\varepsilon_{x_{j-i}}$ is a shock (referring to the endogenous variable X_j) with variance σ_j . Converting to a VMA(∞), we have the following:

$$W_t = \bar{W} + \sum_{i=0}^{\infty} \Phi^i \rho_{t-i} \quad (13)$$

where \bar{W} is the long-term average vector. Writing (13) in terms of the ε_t shocks, we have:

$$W_t = \mu + \sum_{i=0}^{\infty} \Psi_i \varepsilon_{t-i} = \begin{bmatrix} W_{1,t} \\ W_{2,t} \\ \vdots \\ W_{3,t} \end{bmatrix} = \begin{bmatrix} \bar{W}_1 \\ \bar{W}_2 \\ \vdots \\ \bar{W} \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \Psi_{11}(i) & \Psi_{12}(i) & \dots & \Psi_{1n}(i) \\ \Psi_{21}(i) & \Psi_{22}(i) & \dots & \Psi_{2n}(i) \\ \vdots & \vdots & \ddots & \vdots \\ \Psi_{n1}(i) & \Psi_{n2}(i) & \dots & \Psi_{nn}(i) \end{bmatrix} \begin{bmatrix} \varepsilon W_{1t-i} \\ \varepsilon W_{2t-i} \\ \vdots \\ \varepsilon W_{nt-i} \end{bmatrix} \quad (14)$$

where Ψ_{ij} are the impact multipliers of the exogenous variable shock on the endogenous variable of the model.

This technique allows the measurement of the effects of macroeconomic variable shocks on IFNC and credit variables. These exogenous-source impulse response results are reported in [subsection 3.5](#).

3. Empirical Exercise

3.1. Data

The database covers the period from March 2011 to October 2025, with 176 monthly observations, due to the limited availability of longer time series in Brazil. All series were obtained from the Central Bank of Brazil, except for the Banking Sector Index (IFNC), which is available at the Brazilian Stock Exchange (B3).

In addition to the Banking Sector Index (IFNC), the other endogenous variables include: earmarked and non-earmarked stock credit issued to both firms and households, expressed as a ratio of GDP. The macroeconomic set includes variables or proxies to account for: i) economic activity (monthly real GDP), ii) the monetary channel through official inflation¹, iii) the liabilities side of banking based on aggregate deposits, including demand, time, and savings deposits, iv) the external sector (the exchange rate), and v) the asset side measured by the portfolio “quality” (delinquency rates of earmarked and non-earmarked credit issued to enterprises and households).

[Table 1](#) shows the main descriptive statistics and identification codes for the variables from the Central Bank of Brazil (BCB). For the summary statistics, we include these measures for both the gap-to-trend and trend of each variable, as they are needed for short- and long-term analyses, respectively. The results of the stationarity tests for both series (gap-to-trend and trend) are shown in [Table A.1 \(appendix\)](#). Initially, the IFNC sector index stands out, with its trend (already adjusted for inflation during the period) doubling. However, its gap-to-trend remains negative, and it exhibits significant monthly standard deviation. The trend series for the credit market indicates that household credit has a higher stock than enterprise credit, and both show greater fluctuations in earmarked credit. Based on the gap-to-trend, the high values in the earmarked enterprise credit statistics are notable.

Regarding the variables used as channels for transmitting shocks between the credit market and the banking sector index, the monthly real GDP generally shows a trend of economic growth, except during the fiscal crisis between 2014 and 2016 and at the beginning of 2020 during the pandemic. The exchange rate trend remains steady and consistently increases over the period, with peaks after the fiscal recession and at the end of the pandemic.

It is important to emphasize the rise in the deposit-to-GDP ratio, which has ranged from 23% to 40%. This source of funds is among the most stable and secure, which helps reduce risk from banking liabilities. The average monthly inflation rate of around 0.46%, equivalent to an annual rate of over 5.6%, is concerning. This is notable because the country adopted an inflation-targeting monetary policy in 1999, yet by 2025, it had missed the target 8 times. Finally, regarding the quality of the bank's portfolio, default rates are consistently higher when credit is issued to households, as expected, and this behavior is even more pronounced in non-earmarked portfolios. The analysis of the time series of the endogenous variables, along with their cyclical and trend components, continues in the next section. The graphs of the variables used as a transmission channel are included in the appendix.

¹ The results reported by [Bamea et al. \(2015\)](#) indicate that in a banking economy, monetary policy aimed at restoring price stability should consider as well its effect on financial stability and vice versa.

Table 1. Summary statistics

Variables	Series code	Gap to trend				Trend			
		Mean	S.D	Min.	Max.	Mean	S.D	Min.	Max.
Endogenous variables									
Banking market index (IFNC)	-	-0.19%	9.85%	-26.15%	26.52%	11.481,92	2.687,02	7.478,66	15.123,77
Enterprise earmarked stock credit to GDP	20594	-0.10%	3.95%	-10.77%	14.11%	10.17%	2.42%	7.32%	13.82%
Enterprise non earmarked stock credit to GDP	20543	-0.08%	2.97%	-5.76%	8.19%	13.03%	0.88%	11.25%	14.07%
Household earmarked stock credit to GDP	20570	-0.02%	1.31%	-2.92%	3.52%	11.77%	2.45%	5.71%	15.52%
Household non earmarked stock credit to GDP	20606	-0.01%	1.27%	-2.60%	3.09%	15.01%	1.86%	12.95%	18.78%
Transmission channels									
Real GDP (R\$ billion)	4380	-0.01%	3.24%	-11.25%	8.72%	R\$ 904,21	R\$ 76,71	R\$ 808,04	R\$ 1.085,38
Foreign exchange (R\$/US\$)	3697	-0.11%	7.66%	-15.05%	26.13%	3.83	1.30	1.54	5.63
Deposit to GDP	1835; 27790; 27805	-0.06%	4.09%	-11.44%	15.13%	30.72%	5.39%	23.74%	39.06%
Inflation	433	-2.07%	74.11%	-223.07%	324.45%	0.46%	0.10%	0.29%	0.63%
Enterprise earmarked delinquency	21133	-0.90%	19.25%	-65.18%	42.63%	1.16%	0.44%	0.50%	1.84%
Enterprise non earmarked delinquency	21086	-1.01%	10.61%	-21.22%	30.10%	3.28%	0.91%	1.75%	4.85%
Household earmarked delinquency	21145	-0.12%	9.20%	-19.69%	43.29%	1.80%	0.22%	1.41%	2.21%
Household non earmarked delinquency	21112	-0.11%	7.35%	-14.74%	18.84%	5.62%	0.58%	4.65%	6.57%

Data source: Central Bank of Brazil. Monthly variation series from March 2011 to October 2025 (176 observations). The Banking Sector Index was obtained from the official website of B3. Savings deposits, demand deposits, and time deposits were aggregated into a single deposit variable, which was then expressed as a ratio to GDP, the corresponding codes follow the same order as these series.

3.2. Preliminary results

Fig. 1 shows the credit-to-GDP ratio during 2011-2025, along with the respective trends and gaps estimated using the HP filter. Across both types of firm credit, there is a common pattern of rapid growth at the beginning of the sample, followed by a reduction associated with the national fiscal crisis. As part of a policy to combat the effects of the pandemic, both earmarked and non-earmarked credit to GDP grew, but the latter expanded faster. In the last years of the sample, enterprise earmarked credit stabilized at almost 8%, while non-earmarked credit is close to 13%. The most concerning aspect is that, in only a few moments in 2015 and 2016, the stock of earmarked credit exceeded that of non-earmarked credit

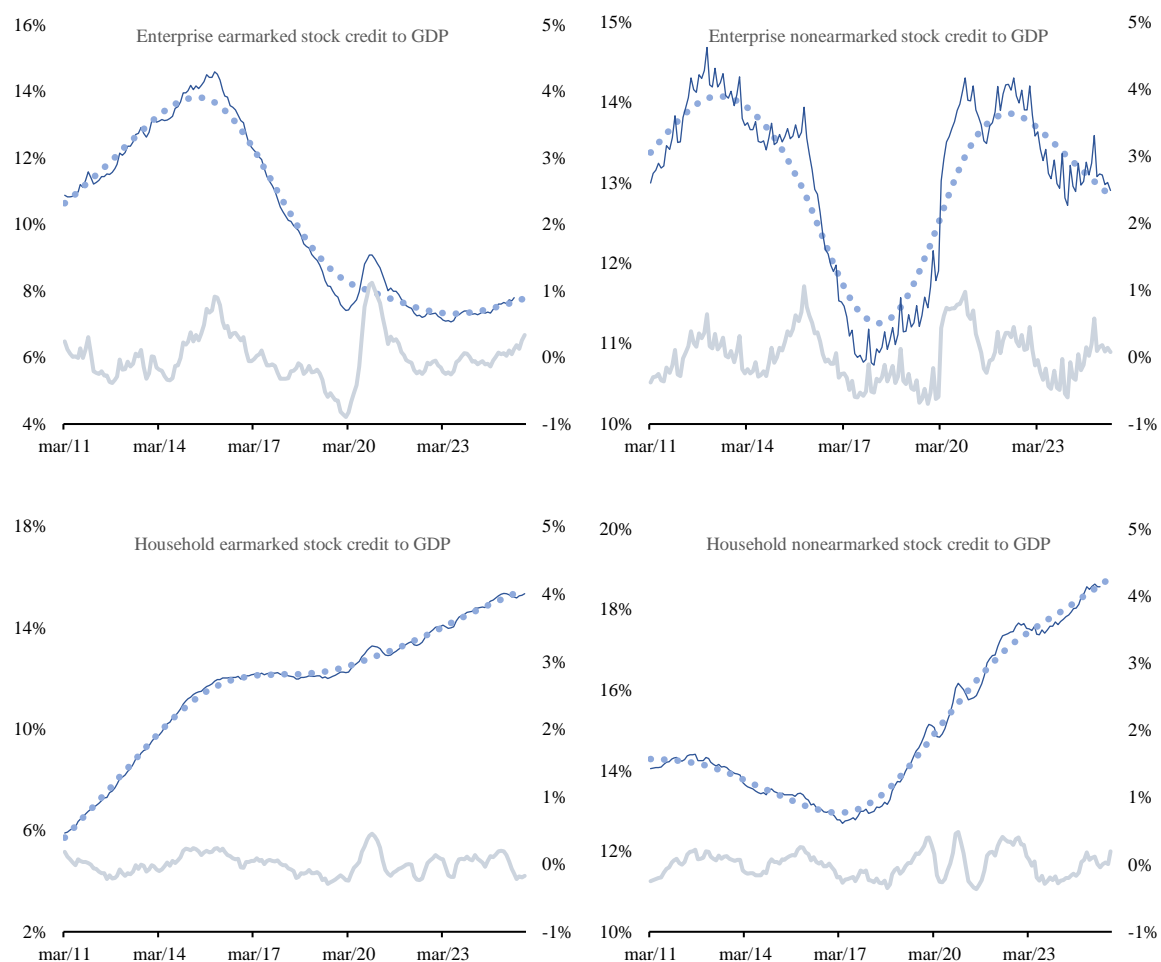


Fig. 1. Credit stock to GDP (blue), respective trend (dotted blue) and gap (light blue – right axis). Monthly series from March 2011 to October 2025. Notes: ^a Gap and trend constructed using HP filter ($\lambda = 14.400$). Data source: Central Bank of Brazil.

Based on the credit portfolio stock, households overtook enterprise credit at the end of 2016. The gap between the two stocks has been widening in recent years. By the end of 2025, both stocks reached R\$ 4.4 trillion and R\$ 2.7 trillion, respectively. According to Fig. 1, different types of household credit show very distinct patterns over time. Earmarked credit grew rapidly until the fiscal crisis, stagnated during the recession, and then resumed near-linear growth, though at a slower pace. It exceeded 15% of GDP by the end of 2025. Conversely, non-earmarked credit declined until 2016, reaching its lowest point at 13% of GDP. From 2017 onward, this stock steadily increased, reaching 19% of GDP by the end of 2025.

In summary, this credit growth is uneven, with credit to households being more vigorous than corporate credit. For both firms and families, non-earmarked credit remains the dominant form. Is there a significant gap between credit and deposits, indicating potential imbalances on the liability side, given that heavy reliance on non-deposit

funding often precedes banking instability? What can be said about the concentration of such credit across markets, sectors, currencies, maturities, and lenders? Could these issues be considered vulnerabilities?

According to this literature, the buildup of financial imbalances is often indicated by large, positive gaps in credit-to-GDP ratios and real asset prices relative to their long-term trends. Borio and Lowe (2002) propose a vulnerability indicator using these components of credit to GDP and real asset prices, applying the HP filter. Borio and Drehmann (2009) demonstrate that, with appropriate threshold choices, the indicator has historically provided relatively effective warning signals before banking crises. They suggest thresholds of 40% - 60% for real asset price gaps and 4% - 6% for credit-to-GDP gaps. To explore this topic, one might determine whether such credit is excessive through a simple analysis. Fig. 2 shows the gap to trend series for both earmarked and non-earmarked credit issued to firms and households. While the gap in household credit never came close to reaching the lower limit of 4%, earmarked and non-earmarked corporate credit exceeded the lower limit several times. Furthermore, this credit consistently exceeded the upper limit of 6% for consecutive months, both during the fiscal crisis and after the start of the pandemic. The most pronounced and prolonged evidence occurs in earmarked corporate credit between September 2020 and April 2021, when this ratio reaches 14% at its peak.

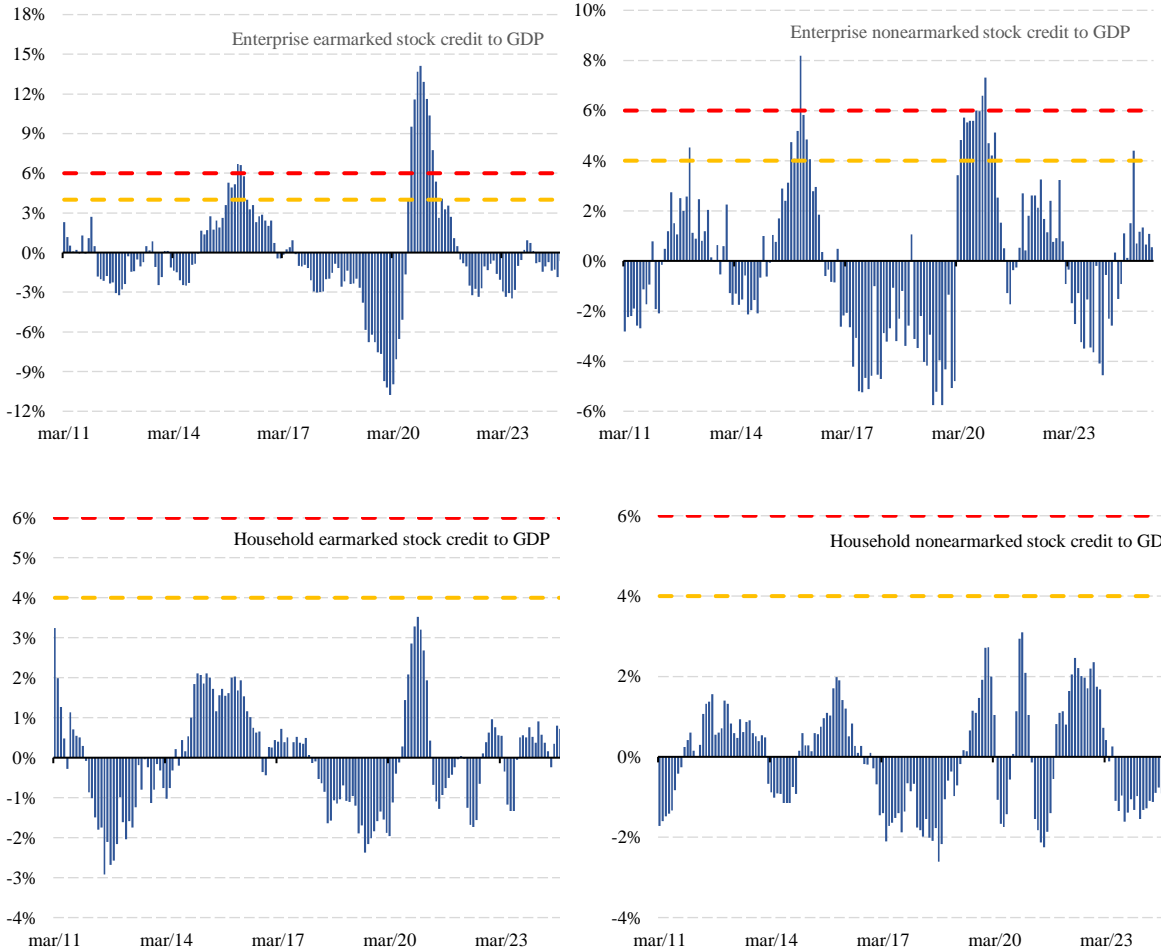


Fig. 2. Credit stock to GDP: gap to trend monthly series from March 2011 to October 2025. Notes: ^a Gap and trend constructed using HP filter ($\lambda = 14,400$). Data source: Central Bank of Brazil.

To complement this preliminary analysis, it is necessary to examine the evolution of the IFNC. Fig. 3 illustrates the real IFNC at its level, including its gap and trend components, as measured by the HP filter, from March 2011 to October 2025. The series demonstrates a sustained long-term growth trend, especially notable between 2016 and 2019, indicating a period of financial expansion. The index peaked in December 2019 at 18,303, with the trend component accelerating sharply after the 2015 Brazilian crisis. The cyclical component reflects fluctuations around the long-term trend, with more significant positive deviations between 2018 and 2019, signaling a period where

financial conditions exceeded their structural path. Conversely, a notable negative deviation appears in 2020, corresponding to the contractionary effects of the COVID-19 pandemic. The index then gradually recovers, resuming its upward movement in the post-pandemic period.

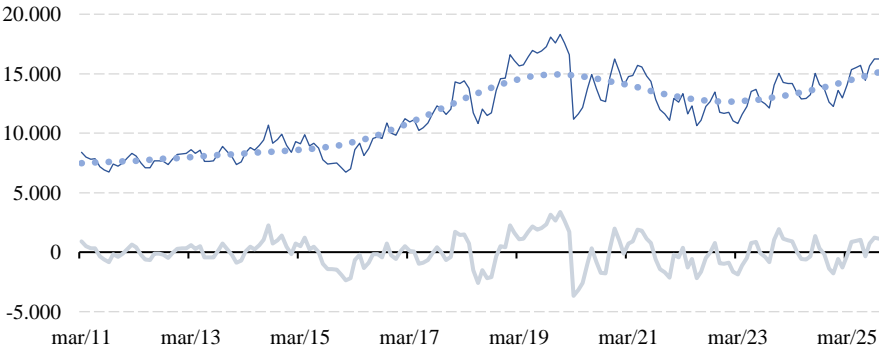


Fig. 3. Real IFNC (blue), respective trend (dotted blue) and gap (light blue). Monthly series from March 2011 to October 2025. Notes: ^a Gap and trend constructed using HP filter ($\lambda = 14.400$). Data source: Central Bank of Brazil.

Even more crucial is determining whether the gap to trend of the IFNC, a proxy for the banking sector index, breaches the 40% and 60% limits at any point. According to Fig. 4, this does not occur and is not even close to occurring in any month. The highest positive deviation was 26.52% in August 2014, while the lowest negative deviation was -26.15% in January 2015, following the Brazilian macroeconomic crisis. These figures highlight the significant cyclical swings in financial conditions during times of macro-financial stress.

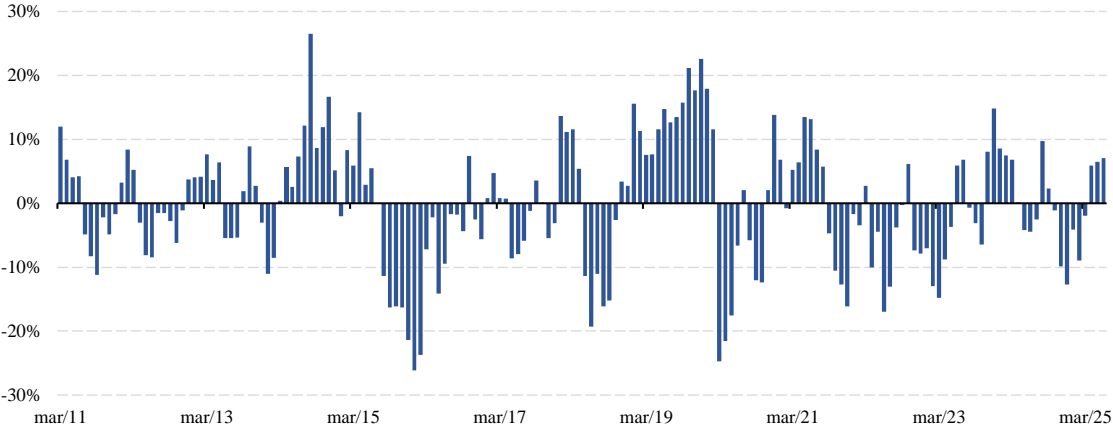


Fig. 4. IFNC: gap to trend monthly series from March 2011 to October 2025. Notes: ^a Gap and trend constructed using HP filter ($\lambda = 14.400$). Data source: Central Bank of Brazil.

3.3. Long-term analysis

The preliminary analysis, based on indicators that may signal a warning, whether from the perspective of excessive credit or a bubble in the financial market, is relevant, but it is unconditional and not based on statistical inference.

To complement the previous gap analysis and to support this relationship between credit and the banking index, the initial statistical analysis will focus on estimating the cointegrating vector. The Phillips-Perron stationarity test on the trend series of the credit-to-GDP variables, the IFNC (Banking Index), and the variables used as transmission channels indicates the presence of a unit root in all of them, as expected. The next step is to determine, using the maximum eigenvalue test, whether a cointegrating vector exists, considering the inclusion of the 8 variables (transmission channels) as instruments in the most parsimonious version of the VECX. Estimating the corresponding cointegrating vector without deterministic terms, based on a 4-lag specification selected by Schwarz's criterion, indicates that a long-term relationship is present. The results for the cointegration vector

indicate a structural relationship between the trends of IFNC and credit, characterized by significant negative parameter values, with greater intensity for household credit. From this result, it is clear that these variables exhibit a conditional long-term equilibrium relationship with adverse effects from all types of private credit.

$$\tau_{IFNC t} = -16.10^3 \cdot \tau_{ENT EAR t} - 43.10^3 \cdot \tau_{ENT NON t} - 77.10^3 \cdot \tau_{HH EAR t} - 186.10^3 \cdot \tau_{HH NON} \quad (15)$$

$$\begin{matrix} [-1.89] & [-2.50] & [-1.89] & [-6.50] \end{matrix}$$

3. 4. Short-term analysis: Var results and (endogenous) impulse response of IFNC

Table 3 reports the results of the Vector Autoregressive (VAR) estimation in its reduced form.

Table 3. Vector Autoregression (VAR)

	Banking market index (IFNC)	Enterprise earmarked stock credit to GDP	Enterprise non-earmarked stock credit to GDP	Household earmarked stock credit to GDP	Household non-earmarked stock credit to GDP
Lagged endogenous variables					
Banking market index (IFNC)	0.496 *** [7.331]	0.039 *** [4.038]	0.019 * [1.405]	0.002 [0.338]	0.006 [1.169]
Enterprise earmarked stock credit to GDP	0.313 * [1.404]	0.834 *** [25.920]	-0.099 ** [-2.264]	-0.019 [-1.171]	0.015 [0.905]
Enterprise non-earmarked stock credit to GDP	0.536 * [1.752]	0.001 [0.0163]	0.368 *** [6.133]	-0.050 ** [-2.222]	0.018 [0.769]
Household earmarked stock credit to GDP	0.051 [0.093]	0.215 *** [2.737]	0.040 [0.376]	0.923 *** [23.076]	-0.003 [-0.081]
Household non-earmarked stock credit to GDP	0.129 [0.209]	-0.205 ** [-2.322]	0.585 *** [4.861]	0.030 [0.673]	0.823 *** [17.540]
Transmission channels					
Real GDP	0.070 [0.427]	0.028 [1.174]	0.031 [0.951]	-0.010 [-0.795]	0.043 *** [3.454]
Foreign exchange (R\$/US\$)	-0.598 *** [-6.033]	0.063 *** [4.404]	0.142 *** [7.327]	0.015 ** [2.132]	0.009 [1.150]
Deposit to GDP	-0.156 [-0.902]	0.153 *** [6.157]	0.255 *** [7.546]	0.048 *** [3.794]	-0.027 ** [-2.063]
Inflation	-0.014 * [-1.925]	0.000 [0.278]	0.002 [1.447]	-0.001 [-1.087]	0.001 [1.443]
Enterprise earmarked delinquency	0.036 [0.978]	0.000 [-0.009]	-0.002 [-0.316]	0.000 [-0.126]	0.003 [1.097]
Enterprise non-earmarked delinquency	-0.035 [-0.498]	-0.026 ** [-2.540]	-0.032 ** [-2.283]	-0.006 [-1.256]	-0.014 ** [-2.593]
Household earmarked delinquency	-0.024 [-0.386]	-0.010 [-1.148]	0.011 [0.873]	-0.011 ** [-2.465]	-0.014 *** [-2.982]
Household non-earmarked delinquency	-0.130 [-0.981]	0.078 *** [4.050]	0.031 [1.178]	0.014 [1.414]	0.020 * [1.998]
Complementary results					
Adjusted R2	0.601	0.949	0.845	0.885	0.871
F-statistic	21.121	248.926	67.650	95.029	83.466

Data source: Results based on the standard VAR approach applied to model (1) from March 2011 to October 2025. Notes: t statistic in []. Significance at: * 10%, ** 5%, *** 1%.

Focusing first on effects among endogenous variables, all parameters related to their lagged values are both significant and positive. Some parameters also show notable cross-effects between credit variables. The main finding is that positive parameters associated with corporate credit types explain the IFNC, with a stronger impact for non-earmarked credit. Additionally, it is important to note the positive and significant parameter associated with the IFNC in the equations for both types of corporate credit. Regarding transmission channels, the VAR estimation indicates that parameters related to foreign exchange and deposits to GDP are significant in nearly all endogenous equations. The modeling of the IFNC further emphasizes the importance of inflation, along with the exchange rate variable. To better illustrate these effects, Fig. 5 displays the impulse response functions.

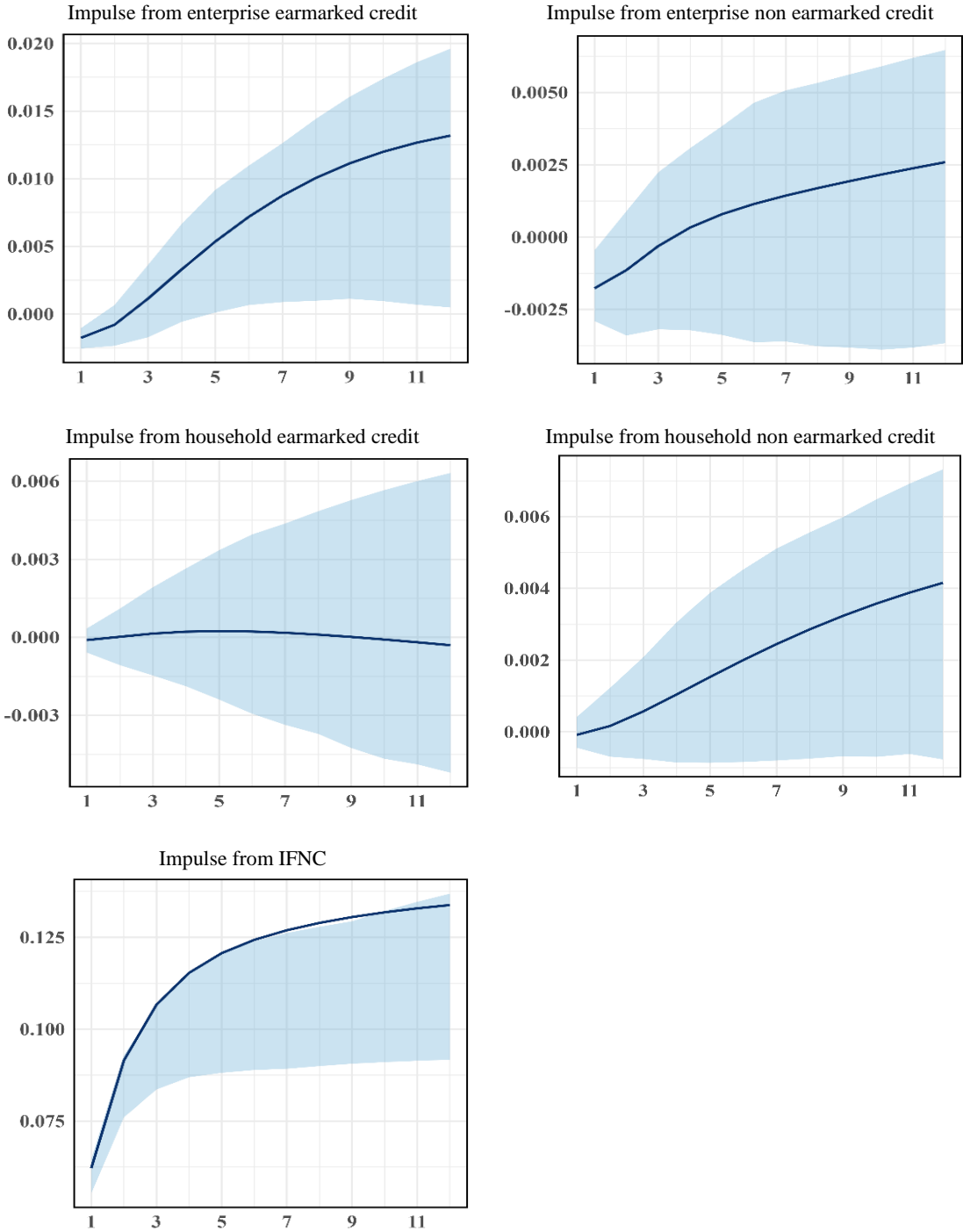


Fig. 5. Accumulated response of IFNC to Cholesky one S.D. innovation. 80% C.I. using Halls studentized bootstrap (999 bootstrap and 499 double bootstrap repetitions). Monthly series from March 2011 to October 2025.

Since VAR estimation is performed in reduced form, the interpretation of the effects is limited. Therefore, analyzing the impulse response between endogenous variables is essential. By examining the cumulative 12-month response of the gap-to-trend of the IFNC, based on a one standard deviation impulse in each type of credit, Fig. 5 shows a significant reaction at 10% of the banking index only when there is a shock in earmarked credit. This response is positive, statistically significant from the fifth month onward, and continues until the end of the year following the shock, oscillating between 0.5% and nearly 0.14% during this period.

IFNC cycles also react positively to shocks within themselves from the very first month. This response suggests inertial behavior in the banking index gap, with the response intensity increasing until it reaches almost 14% at the end of 12 months.

3.5. Short-term analysis: (exogenous) impulse response of IFNC

Hansen and Sulla (2013) assume that the banking index and credit market variables are endogenous, while the variables that address the transmission channels are exogenous, in both short- and long-term exercises. To estimate how IFNC cycles respond to shocks in exogenous variables—that is, an exogenous-source impulse-response function—this study follows Otero (2020). As explained in subsection 3.3, a new VAR specification must be used in RATS® to generate impulse-response functions via Monte Carlo simulations. Fig. 6 displays the responses of the IFNC to shocks in the model's macroeconomic variables over a 12-month period. Among the statistically significant results, the deposit shock appears to be the main macroeconomic variable positively influencing the IFNC in the short term, up to the fourth month, highlighting liquidity as a transmission mechanism for financial conditions. Regarding credit risk shocks, household earmarked delinquency negatively affects the IFNC from the second to the seventh month, with an impact of 9%. Meanwhile, household non-earmarked credit delinquency appears to positively influence it with a similar magnitude during the third and fifth months.

3.6. Summary and discussion of the results

The first step follows Borio and Lowe (2002) and Borio and Drehmann (2009), by proposing a simple and intuitive sign of vulnerability based on thresholds of 40% - 60% for real asset price gaps and 4% - 6% for credit-to-GDP gaps, and main findings reported here show that while the gap in household credit never came close to reaching the lower limit of 4%, earmarked and non-earmarked corporate credit exceeded the lower limit several times. Furthermore, this credit consistently exceeded the 6% upper limit for consecutive months, both during the fiscal crisis and after the start of the pandemic. The most pronounced and prolonged evidence occurs in earmarked corporate credit between September 2020 and April 2021, when this ratio reaches 14% at its peak.

In the second step, instead of trying to identify causality, the analysis estimates a long-term relationship between the trend of the banking index (IFNC) and the trends of different types of private credit-to-GDP, while controlling for a set of variables that capture the transmission channels discussed in this literature. The cointegration vector indicates that the trend in IFNC has a conditional long-term equilibrium relationship, with adverse effects from all types of private credit. These effects are characterized by significant negative parameter values, with greater severity for household credit, especially non-earmarked credit. Regarding the higher parameter values for household credit, it might be helpful to further explore this market by referring to Matos and Soares (2025). These authors contribute to the debate on access to finance by proposing an empirical analysis of 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.

It is well known that if the explanatory variable is stationary, it will oscillate around a constant mean, affecting only short-term variation in IFNC rather than its long-term level. This leads to the third and final step, which presents results based on VAR estimates and (endogenous and exogenous) impulse response functions. In the short term, VAR estimates show positive parameters for different types of corporate credit explaining IFNC, highlighting the importance of transmission channels driven by inflation and the foreign exchange rate. By examining the impulse-response function, the cycles of the IFNC respond only to shocks in the cycles of corporate earmarked credit, deposits to GDP, and delinquency rates for both types of household credit.

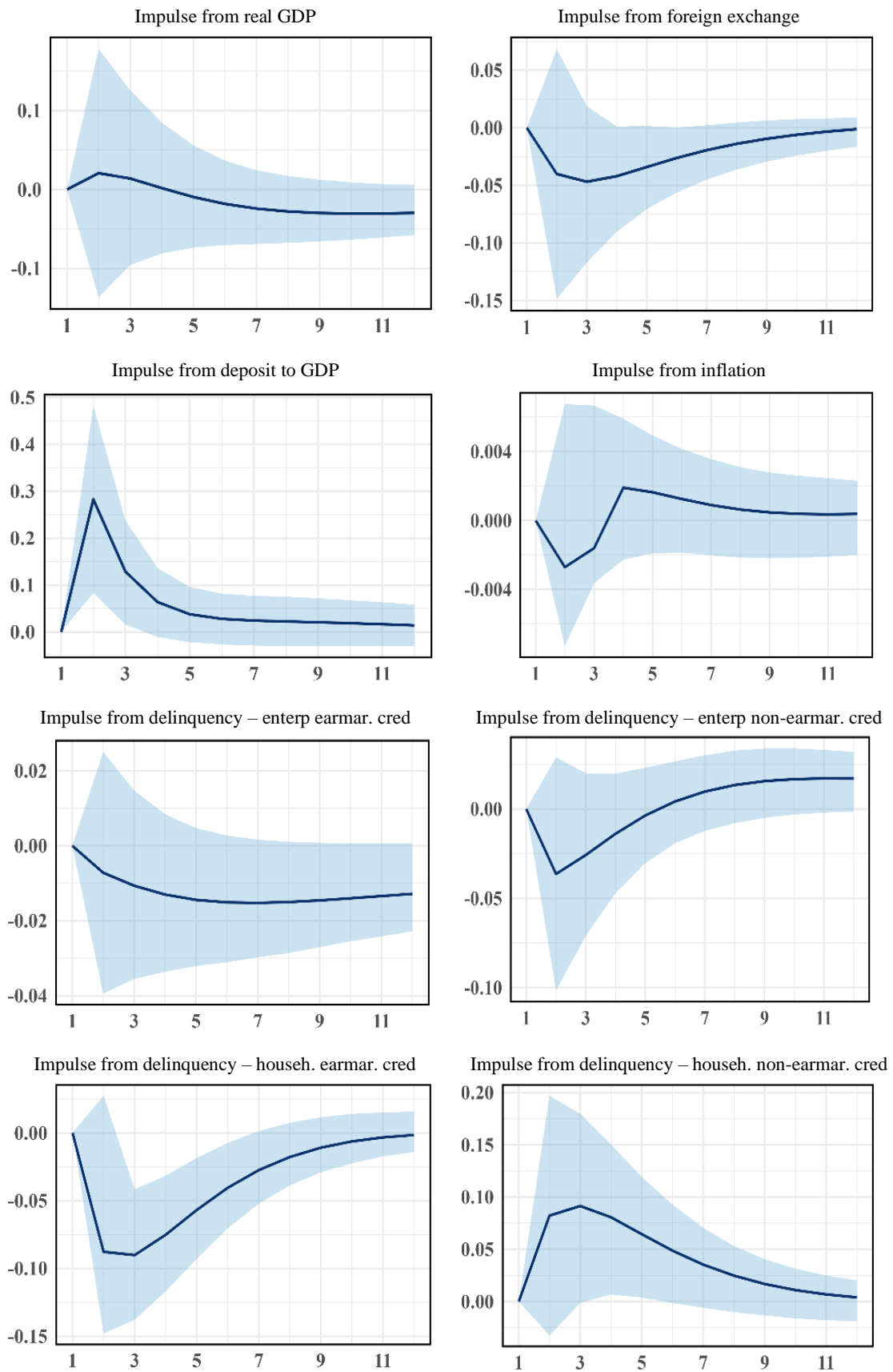


Fig. 6. IFNC response to shocks in the model's exogenous variables. 80% confidence interval. Monthly series from March 2011 to October 2025.

4. Conclusion

This paper examines the relationship between the banking sector index (IFNC, from B3) and private credit in Brazil, an emerging economy among the world's top 10 largest economies. Brazil has a bank-based system and, from a credit market perspective, stands out from other Latin American countries.

According to the most relevant findings, the preliminary analysis—based on indicators that may signal a warning, whether from the perspective of excessive credit or a financial market bubble—is relevant, but it is unconditional and not based on statistical inference. Still, it suggests that there was only unconditional excess credit during recessions and that it did not coincide with excesses in the IFNC (National Financial System), so there is no reason to worry about banking instability in Brazil.

The long-term evidence indicates that excessive growth in private credit, whether earmarked or non-earmarked, granted to households or firms, could jeopardize the long-term stability of the banking sector and negatively impact the trend of the Brazilian banking sector index, the IFNC.

Finally, short-term evidence can be interpreted as showing that the positive impacts of earmarked corporate credit and deposits to GDP, and the negative effects of the delinquency rate of household earmarked credit, all follow the expected trend. If one type of private credit should be prioritized, it is real estate and rural credit granted to companies, as it is well known that when credit grows faster than deposits, which are the usual pool of funds, banks need to turn to other, potentially less stable, funding sources to sustain credit growth. In this specific case of the dispositif to GDP, it is opportune to examine the time-varying results for the period 2011-2015, when this variable fell from 30% to 23%. During the same period, non-earmarked household credit to GDP rose from 6% to 12%. Moreover, it is obviously essential to control for the quality of the asset side, especially given that earmarked household credit is a long-term loan capable of structurally stimulating the economy, with a stock size exceeding 15% of GDP. The delinquency rate for this portfolio rose from 1.35% (Dec/23) to 2.65% by the end of 2025.

This research agenda provides valuable insights into sources of instability and potential short- and long-term signals that could trigger alerts in financial markets, society, and among policymakers. It is empirical work that can be reproduced in other emerging economies. It is also important to highlight possible future developments of this research approach applied to Brazil. Methodologically, it is worth noting that the HP-filter methodology has limitations. First, such calculations do not account for the variable's initial level, and the gaps can be quite sensitive to the choice of starting point and smoothing parameter. In summary, the analysis above can offer useful warning signs, but there is a strong case for supplementing it with other methods. In this regard, using alternative time-series techniques instead of VECX or VAR could be beneficial. Regarding the data, it might be helpful to replicate this study at the individual bank level, which could help identify instability risks within a specific bank rather than across the entire system. It's worth remembering that Brazil experienced a banking crisis linked to issues at a small bank called Master. Another potential avenue is to explore sectoral spillovers in Brazil. According to Costa et al. (2022), contagion occurred between sectoral indices from B3 during the pandemic.

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

Table A.1. Phillips-Perron stationarity test

	Gap-to-trend	Trend
Banking market index (IFNC)	-5.29 *** [0.00]	2.16 [0.99]
Enterprise earmarked stock credit to GDP	-3.10 *** [0.00]	-0.97 [0.29]
Enterprise non-earmarked stock credit to GDP	-3.96 *** [0.00]	-0.40 [0.54]
Household earmarked stock credit to GDP	-3.75 *** [0.00]	4.29 [1.00]
Household non-earmarked stock credit to GDP	-3.56 *** [0.00]	2.83 [1.00]
Real GDP	-8.72 *** [0.00]	4.14 [1.00]
Foreign exchange (R\$/US\$)	-3.60 *** [0.00]	4.66 [1.00]
Deposit to GDP	-3.31 *** [0.00]	1.42 [0.96]
Inflation	-9.22 *** [0.00]	-0.68 [0.42]
Enterprise earmarked delinquency	-4.56 *** [0.00]	0.55 [0.83]
Enterprise non-earmarked delinquency	-3.21 *** [0.00]	-0.36 [0.55]
Household earmarked delinquency	-4.86 *** [0.00]	-0.57 [0.47]
Household non-earmarked delinquency	-3.42 *** [0.00]	-0.33 [0.57]

H0: The variable series from March 2011 to October 2025 has a unit root. Notes: p-value in []. Significance at: * 10%, ** 5%, *** 1%.

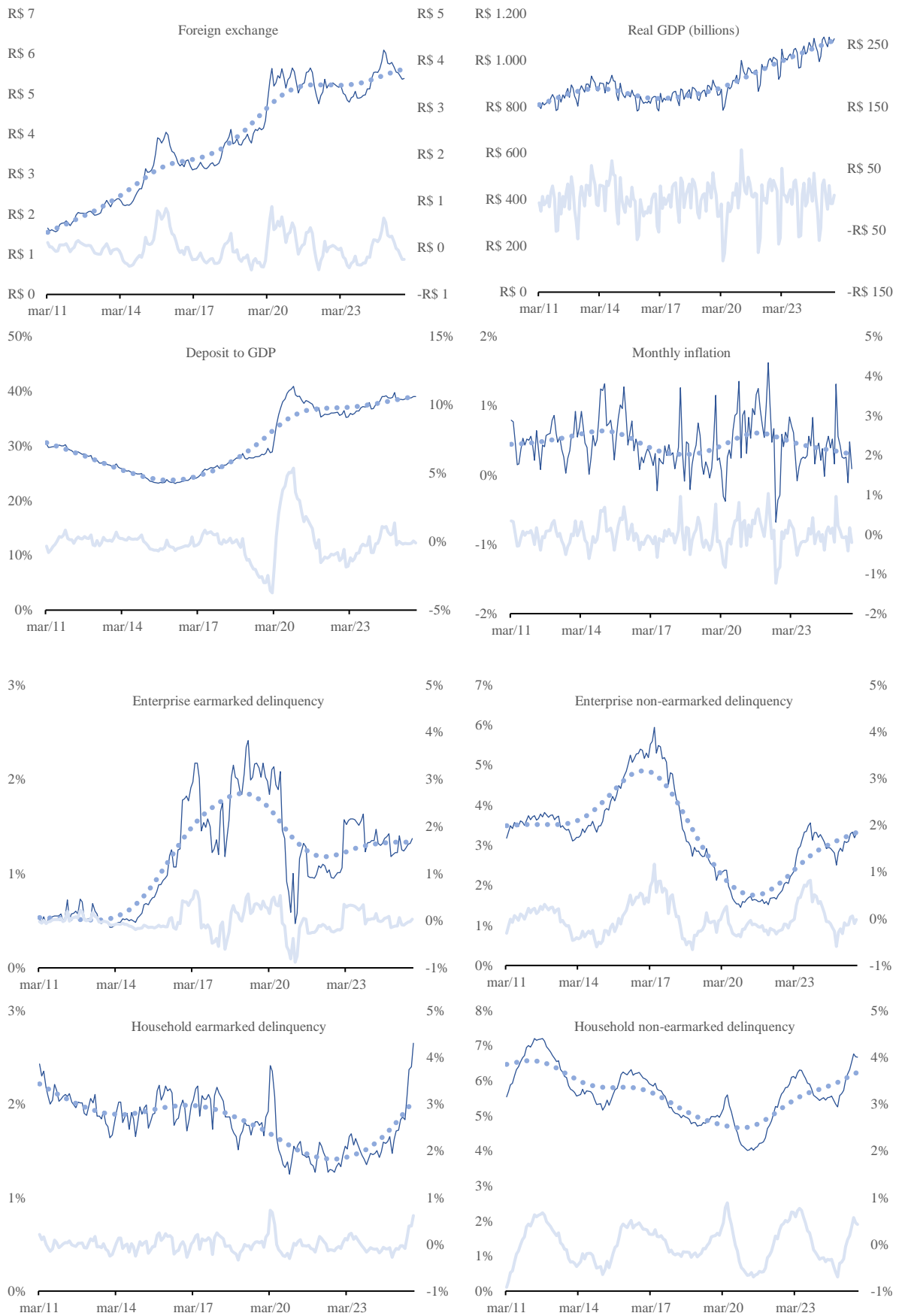


Fig. A.2. Original series (blue), respective trend (dotted blue), and gap (light blue – right axis). Monthly series from March 2011 to October 2025. Notes: ^a Gap and trend constructed using HP filter ($\lambda = 14,400$). Data source: Central Bank of Brazil.