Financial Conditions and Economic Activity in Brazil: Supervised Machine Learning

Francisco Alves de Oliveira Filho – alveschico@ymail.com
Banco do Nordeste do Brasil (BNB)
Rogério Sobreira - rogeriosb@bnb.gov.br
Banco do Nordeste do Brasil (BNB)
Allisson David de Oliveira Martins - allisson@bnb.gov.br
Banco do Nordeste do Brasil (BNB)
Marcos Falcão Gonçalves - marcosfalcao@bnb.gov.br
Banco do Nordeste do Brasil (BNB)
Sávio Medeiro Viana - saviomviana@gmail.com
Banco do Nordeste do Brasil (BNB)

ABSTRACT

This paper constructs a Financial Conditions Index (FCI) for Brazil using a supervised factor approach and evaluates its predictive power for economic activity. The index is built using grouped Principal Component Analysis and economically informed weights derived from predictive regressions of future economic growth. Monthly data from March 2014 to December 2024 are employed. The predictive performance of the FCI is evaluated using Random Forest and XGBoost algorithms under a rolling-origin out-of-sample framework. Results indicate that financial conditions contain persistent and economically meaningful information about future economic activity, particularly for the IBC-Br index. Random Forest systematically outperforms XGBoost across forecast horizons. The findings highlight the importance of non-linear transmission channels and reinforce the relevance of composite financial indicators for macroeconomic monitoring in emerging markets.

JEL classifications: E44, C53, G01, E32

Keywords: Financial Conditions Index; Economic Forecasting; Machine Learning; Brazil; Nonlinear Dynamics; Growth-at-Risk

1 Introduction

The measurement of financial conditions occupies a central position in modern macroeconomic analysis, particularly in emerging economies characterized by high exposure to external shocks, exchange rate volatility, abrupt capital flow fluctuations, and oscillations in sovereign risk premia. Unlike the simple observation of the policy interest rate, the concept of financial conditions encompasses multiple dimensions of the financial environment, including credit spreads, country risk, global monetary conditions, stock market dynamics, exchange rate movements, and commodity prices.

In this context, Financial Conditions Indices (FCIs) have emerged as synthetic instruments capable of summarizing, in a single indicator, the degree of financial tightening or accommodation prevailing in the economy. Such indices are particularly useful for macro-financial monitoring, systemic risk assessment, and forecasting economic activity.

The international literature presents different approaches to constructing FCIs. Hatzius et al. (2010) emphasize the importance of economically informed weighting schemes for financial variables, while Brave and Butters (2011) propose high-dimensional factor-based methodologies. Aramonte et al. (2019) introduce the growth-at-risk framework, demonstrating that adverse financial conditions increase the probability of negative economic growth in future horizons. In the Brazilian context, Gaglianone and Areosa (2016) show that a principal component-based index possesses significant predictive power for the IBC-Br, reinforcing the role of the financial channel in domestic macroeconomic dynamics.

The underlying theoretical framework is rooted in the monetary transmission channels discussed by Bernanke and Gertler (1995) and Mishkin (1996). Financial shocks affect real activity through the cost of capital, credit constraints, balance sheet deterioration, and amplification mechanisms associated with the financial accelerator. In emerging economies, financial frictions and external vulnerabilities tend to intensify these mechanisms, making the aggregate measurement of financial conditions particularly relevant.

This study constructs a Financial Conditions Index for Brazil covering the period from March 2014 to December 2024 and evaluates its predictive ability for two economic activity indicators: the Economic Activity Index (IBC-Br) and Industrial Production (PIM). The methodological innovation lies in combining a supervised factor approach for index construction with machine learning models to generate multi-horizon forecasts of economic activity.

2 Methodology

2.1 Conceptual Framework

Let $X^t \in \mathbb{R}^N$ denote a vector of financial variables observed at time t, and let ΔY_{t+h} represent the h-step-ahead growth rate of economic activity. The objective is to construct a Financial Conditions Index (FCI), denoted ICF_t, that maximizes predictive content for future economic activity.

Two main approaches dominate the literature. The first relies on economically calibrated linear aggregations of financial variables (Hatzius et al., 2010). The second employs statistical dimension-reduction techniques, particularly factor models and Principal Component Analysis (PCA), to extract common variation from high-dimensional financial datasets (Stock & Watson, 2002; Brave & Butters, 2011).

While PCA efficiently captures shared variance across correlated financial variables, it does not guarantee that the extracted factors are informative about future real activity. To address this limitation, we adopt a supervised factor approach, in which financial factors are weighted according to their predictive relevance for economic growth (Kelly, Pruitt & Su, 2019; Aramonte et al., 2019). This aligns index construction with its economic objective.

2.2 Data

The dataset consists of monthly observations from March 2014 to December 2024. Financial variables are obtained from Bloomberg to ensure consistency and international comparability.

The financial system is organized into seven economically meaningful groups:

1. Domestic Interest Rates
2. International Interest Rates
3. Sovereign and Global Risk
4. Exchange Rates
5. Oil Prices
6. Broad Commodity Prices
7. Capital Markets

Domestic financing conditions are proxied by Brazilian DI swap rates (1-year and 5-year maturities). Global monetary conditions are captured by sovereign yields from the United States, Germany, the United Kingdom, and Japan. Risk perception is measured by Brazil's 5-year CDS spread and the VIX index. Exchange rate conditions include the BRL/USD rate and broad U.S. dollar indices. Commodity exposure is represented by Brent, WTI, and CRB indices. Financial wealth channels are captured by MSCI indices and the Ibovespa.

Economic activity is measured using:

I. The Brazilian Central Bank Economic Activity Index (IBC-Br)
II. Monthly Industrial Production (PIM)

2.3 Factor Extraction

2.3.1 Standardization

To ensure comparability across variables with different units and volatility scales, each financial variable $X_{i,t}$ is standardized:

$$Z_{i,t} = \frac{X_{i,t} - \mu_i}{\sigma_i}$$

where μ_i and σ_i denote the sample mean and standard deviation of variable iii, respectively. Let $Z_{g,t}$ denote the vector of standardized variables belonging to financial group g.

2.3.2 Principal Component Analysis

For each financial group g, the first principal component is extracted:

$$F_{g,t} = w_g' Z_{g,t}$$

where w_g' is the eigenvector associated with the largest eigenvalue of the covariance matrix of $Z_{g,t}$.The first principal component captures the dominant common variation within each financial segment and is interpreted as the latent factor representing that financial channel.

2.4 Supervised Aggregation

To align factor aggregation with predictive content, we estimate the following regression:

$$\Delta Y_{t+h} = \alpha + \sum_{g=1}^{G} \beta_g F_{g,t} + \varepsilon_{t+h}$$

where ΔY_{t+h} denotes the h-step-ahead growth rate of economic activity.

The estimated coefficients β_g are then used as economic weights to construct the Financial Conditions Index:

$$ICF_t = \sum_{g=1}^{G} \widehat{\beta_g}\, F_{g,t}$$

This structure ensures that financial groups with greater predictive relevance receive proportionally larger weights. Unlike traditional PCA aggregation, which maximizes explained variance, the supervised approach maximizes predictive covariance with future economic activity.

3. Machine Learning Models

3.1 Random Forest

Following Breiman (2001), Random Forest constructs an ensemble of regression trees.

Given training data $\{(X_t, y_t)\}_{t=1}^{T}$, each tree $T_b(\cdot), b = 1, \ldots, B$ is estimated on a bootstrap sample.

At each split, a random subset of predictors is considered (feature subsampling), reducing correlation across trees.

The h-step-ahead forecast is:

$$\hat{g}t + h^{RF} = \frac{1}{B}\sum b = 1^B T_b(X_t)$$

As $B \to \infty$, prediction error converges to a limit determined by tree strength and correlation. Random Forest captures nonlinearities and interaction effects without imposing parametric structure.

3.2 XGBoost

XGBoost (Chen & Guestrin, 2016) builds trees sequentially using gradient boosting.

The forecast is:

$$\hat{g}t + h^{XGB} = \sum m = 1^M f_m(X_t)$$

where each $f_m(\cdot)$ is a regression tree.

The objective function minimized is:

$$\mathcal{L} = \sum_{t=1}^{T}(y_t - \hat{y}t)^2 + \sum m = 1^M \Omega(f_m)$$

The regularization term is:

$$\Omega(f) = \gamma K + \frac{1}{2}\lambda \sum_{j=1}^{K} w_j^2$$

where:

- K = number of terminal nodes
- w_j = leaf weights
- γ = structural penalty
- λ = L2 regularization parameter

Regularization mitigates overfitting in relatively short macroeconomic samples.

4. Out-of-Sample Evaluation

Forecast performance is evaluated using a rolling-origin scheme.

Let the initial estimation window be T_0. For each forecast origin $\tau \geq T_0$:

1. Estimate model using data $1, \dots, \tau$
2. Generate forecast $\widehat{g_{\tau+h}}$

Accuracy is measured using:

$$RMSE = \sqrt{\frac{1}{H} \sum_{t=1}^{H} (y_t - \widehat{y_t})^2}$$

$$MAE = \frac{1}{H}\sum_{t=1}^{H} |y_t - \widehat{y_t}|$$

Model comparison uses the Diebold-Mariano (1995) test and Clark-West (2007) adjustment for nested models.

5. Level Reconstruction

Predicted growth rates are converted back to levels using multiplicative accumulation:

$$Yt + h = Y_t \prod j = 1^h \left(1 + \frac{\widehat{g_{t+J}}}{100}\right)$$

This ensures dynamic consistency between predicted growth rates and reconstructed index levels.

4.1 Estimated Weights and Financial Transmission Channels

Table 1 reports the estimated supervised weights for the seven financial groups composing the Financial Conditions Index (FCI). The weights are obtained from predictive regressions in which the dependent variable is the future growth rate of the IBC-Br. The magnitude and sign of the coefficients provide insight into the relative importance of distinct financial transmission channels in the Brazilian economy.

Table 1 – Groups, Series and Supervised Weights of the Financial Conditions Index

Group	Name	Weight
1	Domestic Interest Rates	0,26
2	International Interest Rates	0,04
3	Risk	-0,28
4	Exchange Rates	-0,08
5	Oil	0,07
6	Commodities	0,15
7	Capital Markets	-0,11

Source: Author's calculations based on research results.

The **Risk** group exhibits the largest absolute weight (−0.28-0.28−0.28), indicating that sovereign risk perception and global volatility represent the dominant financial transmission mechanism. This group includes variables such as Brazil's 5-year CDS spread and the VIX index, which capture fluctuations in investor confidence and global risk appetite. The magnitude of this coefficient suggests that variations in risk premia exert stronger predictive influence on future economic activity than traditional monetary instruments. This result is consistent with the financial accelerator framework of Bernanke and Gertler (1995), in which deteriorating balance sheets and rising risk premia amplify real economic fluctuations. It also aligns with the growth-at-risk literature (Aramonte et al., 2019), which emphasizes that adverse financial conditions primarily operate through tightening risk channels rather than interest rate levels alone.

The **Domestic Interest Rate** group presents the second largest weight (0.260.260.26), confirming the central role of domestic monetary policy in shaping financial conditions. The positive sign is theoretically coherent: higher interest rates increase the cost of capital and signal financial tightening. The close proximity between the coefficients of the Risk and Domestic Interest groups (0.280.280.28 and 0.260.260.26, respectively, in absolute value) suggests a dual structure of financial transmission in Brazil. While monetary policy operates through the price of credit, risk perception acts through expectations and balance sheet channels. This duality reinforces Mishkin's (1996) view that monetary transmission encompasses both interest rate effects and broader credit conditions.

The **Commodities** group exhibits a positive weight of 0.150.150.15, reflecting Brazil's structural position as a commodity-exporting economy. Interestingly, the positive sign indicates that commodity price increases are associated with financial tightening in the estimated model. This effect likely operates through the exchange rate channel: periods of strong commodity appreciation often coincide with currency appreciation, which may reduce external competitiveness and generate contractionary pressures in tradable sectors. This interpretation is consistent with open-economy transmission models in which terms-of-trade shocks affect domestic financial conditions through exchange rate adjustments.

The **Capital Markets** group carries a negative weight (−0.11-0.11−0.11), in line with theoretical expectations. Stock market appreciation reduces firms' cost of external finance and generates positive wealth effects, thereby easing financial conditions. This result aligns with the asset-price channel emphasized in macro-finance literature and is consistent with the factor-based evidence documented by Brave and Butters (2011), who highlight the importance of equity markets in composite financial indicators.

Similarly, the **Exchange Rate** group displays a negative weight (−0.08-0.08−0.08), suggesting that currency depreciation is associated with financial easing within the index construction. This may reflect improved external competitiveness and higher export revenues during depreciation episodes, partially offsetting tightening effects from other financial channels.

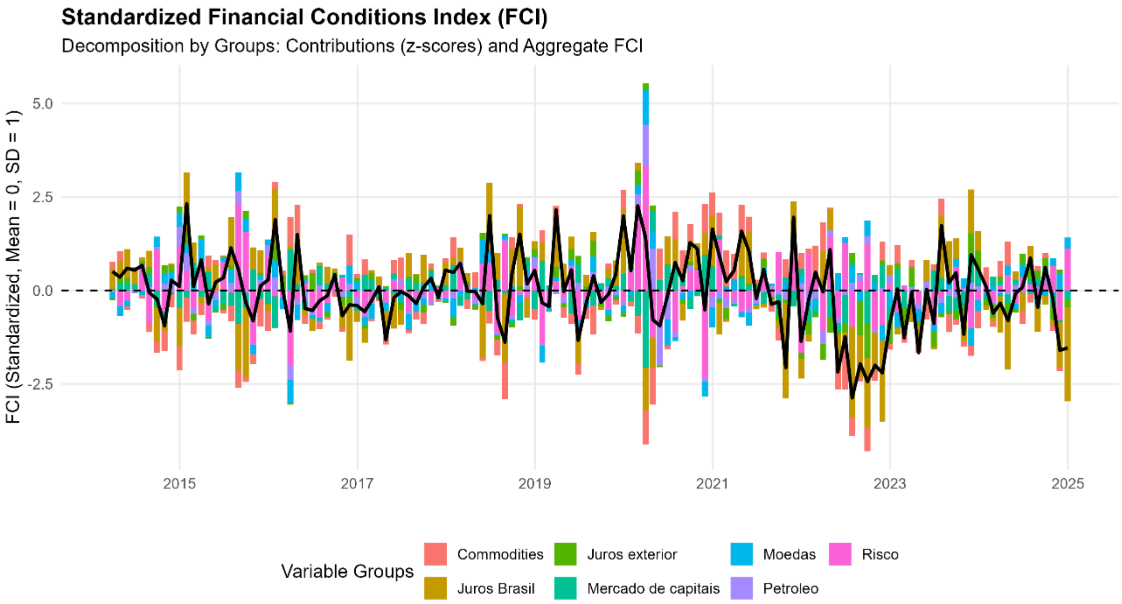
The **Oil** group presents a modest positive weight (0.070.070.07), capturing the relevance of oil price dynamics for domestic cost structures and inflationary pressures. Finally, the **International Interest Rate** group exhibits the smallest weight (0.040.040.04), indicating that the direct impact of global rate levels on Brazilian activity is limited once risk premia and exchange rate channels are accounted for. This finding suggests that global monetary spillovers operate primarily through risk and currency adjustments rather than through direct yield transmission, consistent with emerging market spillover literature.

Overall, the supervised aggregation produces economically interpretable weights that reflect Brazil's macro-financial structure: risk premia and domestic monetary conditions dominate transmission, while external variables affect activity mainly through indirect channels. The results reinforce the argument that composite financial indices provide a more comprehensive representation of macro-financial conditions than policy rates alone.

4.2 Dynamics and Decomposition of the Financial Conditions Index

Figure 1 displays the evolution of the standardized Financial Conditions Index (FCI) together with its group-level decomposition. The index exhibits substantial dispersion over the sample, fluctuating between −2.87 and 2.32 standard deviations. This amplitude highlights its capacity to capture both episodes of acute financial stress and periods of pronounced financial accommodation.

Figure 1 – Financial Conditions Index (FCI) and Its Decomposition by Financial Groups



Source: Author's calculations based on research results.

The early part of the sample (2015–2016) is characterized by persistent financial tightening, with the index remaining consistently above +1.0 standard deviation. This episode coincides with Brazil's domestic crisis, marked by fiscal deterioration, rising sovereign risk premia, and political instability. The behavior of the index during this period suggests that idiosyncratic domestic factors were the primary drivers of financial tightening, consistent with the view that emerging market financial cycles can be heavily influenced by sovereign risk dynamics and credibility shocks.

Between 2018 and 2019, the index displays lower-amplitude fluctuations, reflecting heightened volatility associated with electoral uncertainty and external market oscillations. However, the most pronounced spike occurs in 2020, when the index reaches its historical maximum (2.32) during the COVID-19 pandemic. This peak reflects the simultaneous freezing of credit markets, a sharp increase in global risk aversion, and significant exchange rate depreciation. The rapid propagation of financial stress across multiple channels is consistent with the contagion and uncertainty transmission mechanisms documented in the macro-financial literature (Bluedorn and Bowdler, 2011). The dominance of risk factors during this episode aligns with the growth-at-risk framework (Aramonte et al., 2019), which emphasizes that financial stress episodes are primarily driven by abrupt increases in risk premia rather than gradual interest rate adjustments.

In contrast, the period 2022–2023 exhibits a pronounced reversal, with the FCI reaching values close to −2.9 standard deviations. This strong easing phase coincides with compressed sovereign spreads, improved terms of trade driven by the commodity cycle, and elevated liquidity in capital markets. Notably, this financial accommodation occurs despite a tightening monetary cycle. This divergence reinforces the argument that policy rates alone do not fully characterize aggregate financial conditions, echoing the findings of Hatzius et al. (2010) and Brave and Butters (2011), who show that composite financial indices often diverge from short-term policy rates.

4.3 Group-Level Decomposition

The decomposition of the FCI in Figure 1 allows for identification of the relative contribution of each financial channel. The **Domestic Interest Rate** group displays the highest volatility over the entire sample and constitutes the primary tightening force during the 2015–2016 crisis. Its contribution closely mirrors the domestic monetary policy cycle, confirming the central role of the Selic rate in shaping financial conditions during periods of internal imbalance. This result is consistent with traditional interest rate transmission models (Mishkin, 1996).

The **Risk** group (CDS and global volatility) emerges as the dominant driver during the 2020 pandemic shock. The surge in sovereign spreads and global volatility (VIX) is immediately reflected in the index, indicating that risk perception was the principal transmission channel of the pandemic crisis into domestic financial conditions. This behavior is fully consistent with financial accelerator models (Bernanke and Gertler, 1995), where balance sheet deterioration and rising risk premia amplify real shocks.

The **Exchange Rate** and **Capital Markets** groups also contribute to tightening during episodes of abrupt currency depreciation, such as in 2020, reflecting higher hedging costs and increased external debt servicing burdens. Conversely, during the recovery phase (2022–2023), the **Capital Markets** group acts as a stabilizing force, as rising equity prices contribute negatively to the index, thereby generating financial easing through wealth and collateral channels.

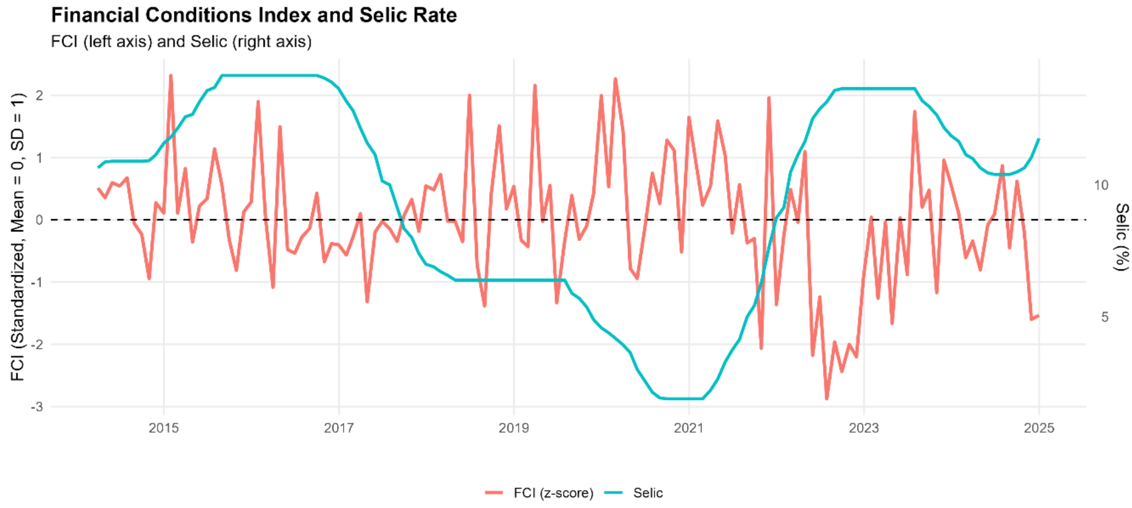
The **Commodities** and **International Interest Rate** groups play a more moderate but still economically meaningful role. Commodity price increases consistently generate expansionary contributions during favorable terms-of-trade episodes, reinforcing the external channel of transmission typical of commodity-exporting economies. This is consistent with open-economy macro-finance models in which commodity cycles influence financial conditions through exchange rate and income effects.

The **International Interest Rate** group exhibits smaller but perceptible contributions, particularly during episodes of anticipated monetary tightening in the United States. This suggests that global spillovers operate primarily through expectations and risk premia adjustments rather than through direct yield transmission, in line with the emerging market spillover literature.

4.4 Comparative Analysis: Financial Conditions Index versus the Selic Rate (2014–2024)

Figure 2 compares the standardized Financial Conditions Index (FCI) with the twelve-month Selic policy rate between March 2014 and December 2024. The joint evolution of the two series highlights the complexity of Brazil’s macro-financial dynamics and shows that monetary policy, while central, does not fully determine aggregate financial conditions.

Figure 2 – Financial Conditions Index (FCI) and the Selic Interest Rate



Source: Author's calculations based on research results.

During the 2014–2016 domestic crisis, the trajectories of the Selic rate and the FCI are closely aligned. The policy rate increased from approximately 10.65% in early 2014 to 14.15% in 2015, remaining at elevated levels throughout much of 2016. The FCI moved in tandem, reaching 2.31 standard deviations in January 2015 and 1.89 in January 2016, signaling significantly tighter-than-average financial conditions. This co-movement is consistent with a conventional monetary tightening cycle reinforced by fiscal deterioration, rising sovereign spreads, and declining confidence.

However, even within this period of alignment, temporary reversals in the FCI occurred despite stable policy rates, suggesting that variations in risk premia and capital market conditions contributed independently to financial tightening. This indicates that monetary transmission operated jointly with broader credit and risk channels.

From 2017 onward, the Selic entered a pronounced easing cycle, declining from above 13% to 6.4% by 2018 and remaining near that level through much of 2019. The FCI partially reflected this easing, recording negative values such as −1.31 standard deviations in April 2017. Nevertheless, the relationship between the two series was neither linear nor perfectly synchronized.

Two episodes illustrate this dissociation. In June 2018, the FCI reached 2.00 standard deviations despite a stable Selic at 6.4%, and in March 2019 the index rose again to 2.15. These divergences suggest that political uncertainty, external volatility, and risk shocks generated tightening independently of the policy rate. Such episodes underscore the importance of non-monetary transmission channels, particularly risk premia and expectations.

The most pronounced decoupling occurred during the COVID-19 shock in 2020. In February 2020, the FCI reached 2.26 standard deviations while the Selic was already declining toward 4.19%. Monetary easing coincided with the sharpest financial tightening in the sample. This episode highlights the dominance of risk and uncertainty channels during systemic crises, consistent with financial accelerator models in which rising risk premia temporarily overwhelm conventional interest rate transmission.

Subsequently, as the Selic fell to historically low levels near 2%, the FCI exhibited substantial volatility, alternating between tightening and easing phases. This pattern suggests that expansionary monetary policy was at times offset or amplified by fluctuations in exchange rates, sovereign spreads, and asset prices.

The 2021–2022 period provides further evidence of dissociation. Despite a sharp policy reversal, with the Selic increasing from 2% to 13.65%, the FCI recorded strongly negative values, reaching −2.06 in October 2021 and −2.87 in July 2022—the lowest reading in the sample. This indicates markedly accommodative financial conditions despite aggressive rate hikes. Commodity price appreciation, improved terms of trade, equity market recovery, and spread compression appear to have offset the contractionary impulse of monetary policy.

This episode represents the most pronounced divergence between policy rates and aggregate financial conditions in the sample. It reinforces the argument that the policy rate alone is insufficient to characterize macro-financial conditions, particularly in commodity-exporting emerging markets exposed to global liquidity cycles.

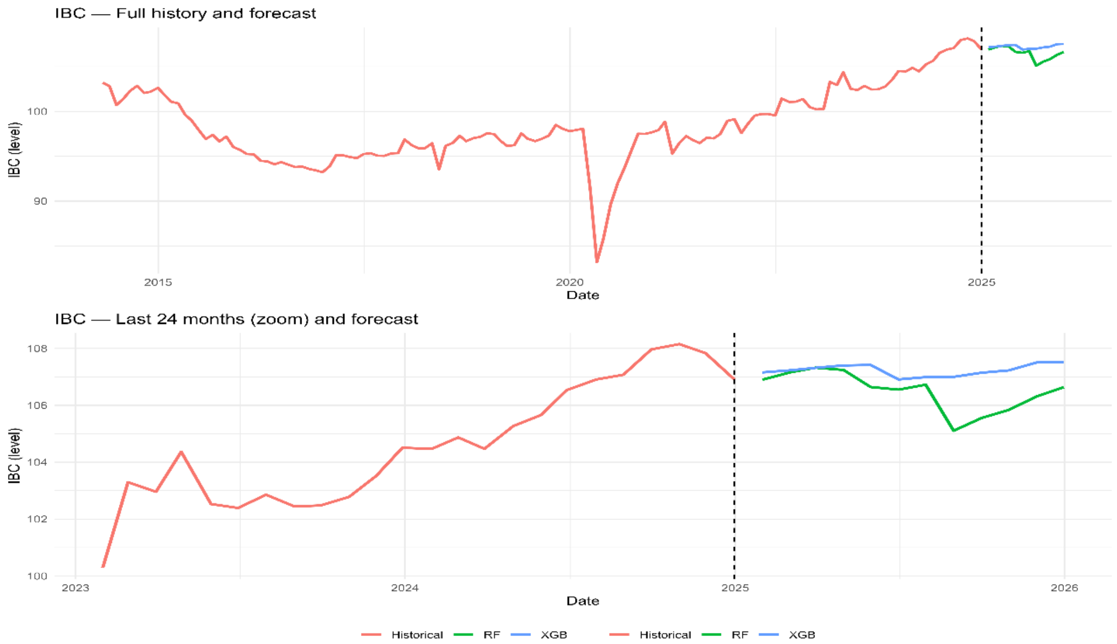
In 2023–2024, the Selic remained elevated for an extended period before beginning gradual reductions. During this phase, the FCI oscillated around zero, with moderate tightening in mid-2023 and more pronounced easing toward late 2024 (approximately −1.53 in December). This pattern suggests gradual normalization and reduced volatility relative to earlier crisis episodes.

Three main conclusions emerge from the comparative analysis. First, positive correlation between the Selic and the FCI is observed during conventional domestic tightening cycles, particularly in 2015–2016. Second, significant divergences occur during external shocks and commodity-driven cycles, when non-monetary channels dominate. Third, the evidence supports the use of composite financial indicators: while the Selic is influential, it represents only one dimension of aggregate financial conditions. The FCI, by incorporating risk premia, exchange rates, asset prices, and global conditions, provides a broader and more accurate measure of effective financial tightness or accommodation.

4.5 IBC Forecasts and the Informational Content of Financial Conditions

Figure 3 presents the historical trajectory of the Economic Activity Index (IBC) from March 2014 to December 2024 and the out-of-sample forecasts for 2025 generated by the Random Forest (RF) and XGBoost (XGB) models. The upper panel displays the full sample, while the lower panel zooms into the final 24 months to emphasize the transition from observed data to forecasts.

Figure 3 – Out-of-Sample IBC Forecasts Using the Financial Conditions Index: Random Forest and XGBoost Models



Source: Author's calculations based on research results.

The historical evolution of the IBC reveals three distinct macroeconomic regimes. The 2014–2016 period reflects a deep domestic recession, consistent with fiscal deterioration and rising sovereign spreads. The 2017–2019 interval shows gradual recovery, though fragile and volatile. The 2020 pandemic shock is clearly visible, characterized by abrupt contraction followed by partial recovery. From 2021 onward, activity exhibits a relatively stable upward trajectory, culminating in elevated levels by end-2024.

The dashed vertical line marks the beginning of the out-of-sample forecasting window. Beyond this point, both RF and XGB generate broadly similar projections in terms of direction, though with differences in slope and short-run volatility. XGBoost projects continuation of moderate expansion throughout 2025, while Random Forest initially signals mild deceleration before converging to modest growth.

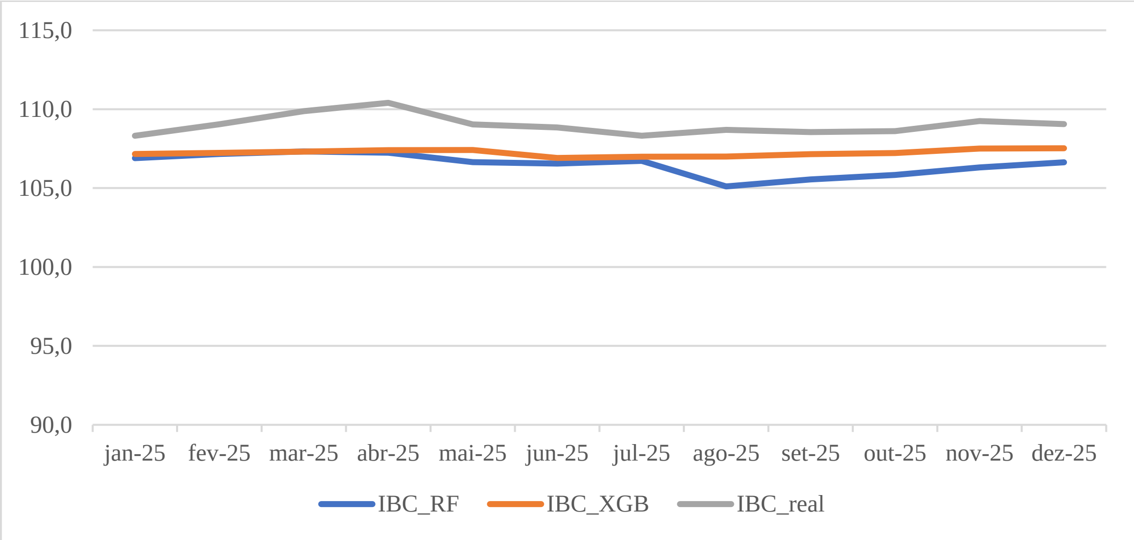
From a macro-financial perspective, neither model predicts abrupt cyclical reversal. This finding is consistent with the behavior of the Financial Conditions Index (FCI), which, despite tightening episodes in prior years, does not indicate systemic stress in the forecast window. The results align with Hatzius et al. (2010), who argue that composite financial indicators primarily signal downside tail risks rather than moderate cyclical fluctuations. Similarly, the growth-at-risk framework (Aramonte et al., 2019) suggests that financial conditions become especially predictive during stress episodes; in periods of relative stability, predictive power tends to moderate.

The relative smoothness of XGB forecasts compared to RF reflects differences in algorithmic structure. Random Forest, which aggregates independent recursive partitions, may overreact to historical nonlinearities embedded in the FCI, especially patterns associated with tightening episodes preceding slowdowns. XGBoost, through sequential boosting and explicit regularization (Chen and Guestrin, 2016), imposes smoother adjustments and may better handle macroeconomic persistence.

3.6 Out-of-Sample Accuracy and Economic Interpretation

Graph 1 reports monthly out-of-sample forecasts of the IBC for January–December 2025, comparing realized values with model projections.

Graph 1 – Out-of-Sample Forecasts and Realized Values of the IBC-Br for 2025



Source: Author's calculations based on research results.

Both models display systematic negative bias. In the first four months of 2025, the observed IBC rises steadily, reaching 110.4 in April, while forecasts remain clustered between 107.2 and 107.4. The early-year acceleration was therefore not fully captured by financial conditions and their lags.

This underestimation raises an important interpretative question: does it signal model failure, or reduced elasticity of real activity to financial variables? The literature suggests two complementary explanations.

First, financial conditions indices are typically more powerful predictors of downside risk than upside surprises (Aramonte et al., 2019). In tranquil periods, when risk premia remain contained and no abrupt tightening occurs, the predictive content of financial variables for incremental positive growth may diminish. This asymmetry is consistent with financial accelerator theory (Bernanke and Gertler, 1995), where amplification mechanisms are stronger during stress.

Second, macroeconomic activity may be temporarily driven by non-financial impulses,such as fiscal measures, supply-side normalization, or sectoral adjustments, that are not directly embedded in the FCI. If fiscal expansion or inventory rebuilding contributed to the observed growth, the divergence would not necessarily invalidate the financial signal but rather indicate partial decoupling between financial and real dynamics.

During the second quarter, forecast errors narrow modestly. XGBoost performs marginally better than Random Forest, remaining closer to realized values. From the second semester onward, divergence increases. RF projects sharper deceleration (105–106 range), while realized activity remains above 108. XGB maintains smoother predictions around 107–107.5, suggesting superior stability.

This pattern aligns with recent macro-ML evidence showing that boosting methods often outperform bagging approaches in small to medium macroeconomic samples when persistence dominates structural breaks. However, both models correctly capture the absence of recession or major cyclical reversal.

Three implications emerge, first, the FCI retains predictive relevance for broad cyclical direction but appears less informative for marginal positive deviations in stable environments. This asymmetry is consistent with the literature emphasizing financial conditions as indicators of stress rather than expansion magnitude.

Second, machine learning methods add value by capturing nonlinear interactions between financial groups, but their performance remains constrained by the informational content of the underlying financial variables. When financial tightening does not materialize, models naturally predict moderation rather than acceleration.

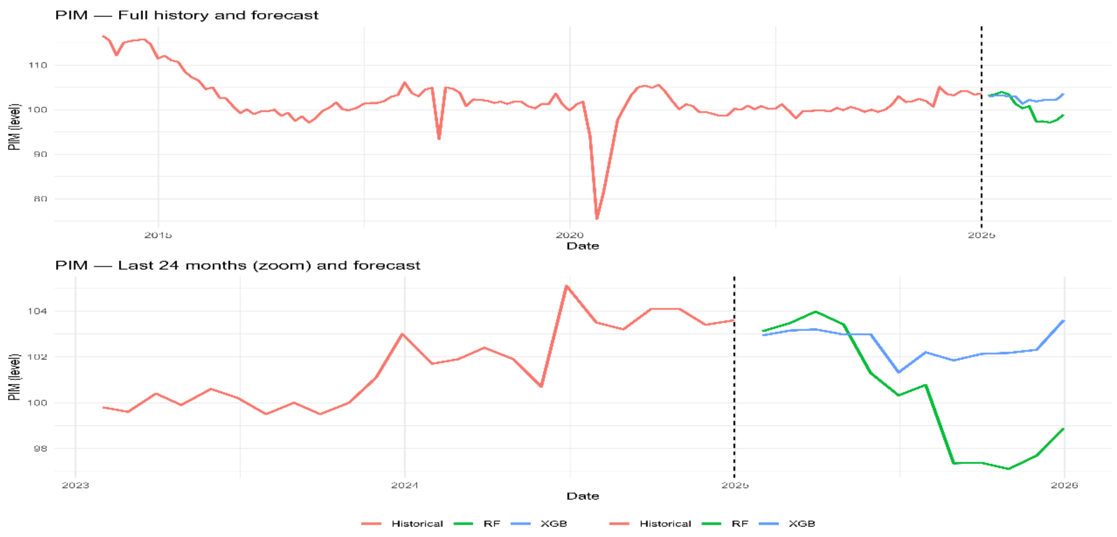
Third, the convergence of RF and XGB toward modest growth strengthens the robustness of the signal extracted from the FCI. Despite methodological differences, both algorithms indicate continuity rather than reversal in economic activity.

In sum, the out-of-sample evidence supports the view that the Financial Conditions Index contains forward-looking information about economic dynamics, particularly regarding downside risks. However, its short-run elasticity to activity may vary across regimes, being stronger during stress episodes and weaker during expansionary phases.

4.8 Forecasts of Monthly Industrial Production (PIM)

Figure 4 reports the historical trajectory of Monthly Industrial Production (PIM) from March 2014 to December 2024, together with out-of-sample forecasts for 2025 generated by the Random Forest (RF) and XGBoost (XGB) models. The upper panel displays the full sample, while the lower panel zooms into the last 24 months, emphasizing the transition from observed values to forecasts.

Figure 3 – Out-of-Sample Forecasts of Monthly Industrial Production (PIM) Using the Financial Conditions Index: Random Forest and XGBoost Models



Source: Author's calculations based on research results.

The historical behavior of PIM confirms its well-documented sensitivity to macroeconomic shocks. The 2014–2016 period is marked by pronounced contraction associated with the domestic recession. A gradual recovery follows through 2019, interrupted by the abrupt collapse of 2020 and subsequent rapid rebound, consistent with the pandemic shock and policy response. From 2021 onward, industrial production stabilizes, fluctuating moderately within the 100–105 range.

The dashed vertical line indicates the beginning of the 2025 out-of-sample forecast window. Compared to the IBC results, model divergence is more pronounced for PIM, reflecting the intrinsically higher volatility of industrial activity.

XGBoost projects a relatively stable trajectory throughout 2025, with a mild upward slope toward the end of the horizon. The forecast suggests maintenance of industrial production near late-2024 levels, indicating no abrupt deceleration. In contrast, Random Forest produces a more volatile and predominantly downward path during the second semester, projecting industrial levels significantly below the historical endpoint.

The zoomed panel highlights this divergence. While XGB maintains a smooth trajectory, RF displays a marked decline in the third quarter followed by partial recovery. This pattern suggests that Random Forest is more responsive to historical episodes in which financial tightening preceded industrial contractions.

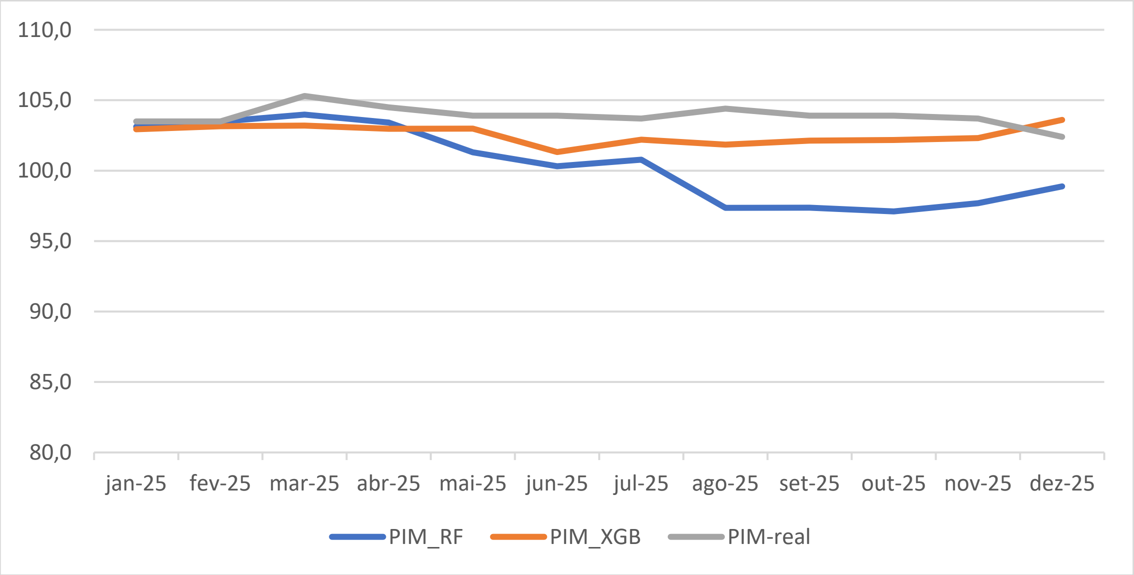
From an economic standpoint, greater divergence between models for PIM is consistent with the structural characteristics of industrial activity. The industrial sector is typically more sensitive to fluctuations in credit conditions, capital costs, and external demand than broader activity indicators. Empirical macro-finance literature frequently documents stronger credit-channel effects for investment-intensive sectors, implying that nonlinearities in financial transmission may be more pronounced for industrial output.

The relative stability of XGBoost forecasts likely reflects the algorithm's regularization mechanism, which reduces excessive extrapolation of past nonlinearities. By contrast, Random Forest,based on independent recursive partitions, may overfit historical stress episodes embedded in the Financial Conditions Index (FCI), generating overly pessimistic projections when similar stress does not materialize.

Overall, neither model predicts industrial collapse. However, forecast dispersion indicates greater uncertainty surrounding the magnitude of future industrial expansion. The divergence between models supports the hypothesis that the relationship between financial conditions and industrial production is nonlinear and potentially regime-dependent.

Graph 2 presents monthly out-of-sample forecasts for PIM during January–December 2025, comparing realized values with RF and XGB projections.

Graph 2 – Out-of-Sample Forecasts and Realized Values of Monthly Industrial Production (PIM) for 2025



Source: Author's calculations based on research results.

In the first four months of 2025, both models perform reasonably well. Forecasts for January and February are close to realized values, suggesting that contemporaneous financial conditions adequately captured the level of industrial activity. Minor underestimation emerges in March and April, particularly for XGBoost, though RF remains slightly closer to realized values in this subperiod.

From May onward, divergence becomes more substantial. Realized PIM remains stable within the 103–104 range, indicating resilience in industrial production. XGBoost tracks this trajectory with moderate variation, projecting values around 102–103 and maintaining relatively controlled errors. In contrast, Random Forest signals progressive deceleration during the second semester.

The divergence becomes especially pronounced between August and October, when RF projects levels below 98 while realized production remains consistently above 103. This gap suggests that Random Forest extrapolated historical patterns linking financial tightening to industrial contraction, even though such deterioration did not occur in the current macroeconomic environment.

XGBoost, by incorporating explicit regularization and sequential boosting, produces smoother projections and remains substantially closer to realized values. By December, convergence improves modestly: realized PIM declines to 102.4, while XGB projects 103.6 and RF 98.9. Although XGB retains slight positive bias, its absolute forecast error remains considerably smaller than that of RF.

Statistically, the results indicate greater intertemporal stability and lower predictive variance for XGBoost. Random Forest exhibits stronger sensitivity to financial signals embedded in the FCI but incurs overfitting when stress signals fail to materialize.

Economically, the findings suggest that while financial conditions influence industrial production, the transmission intensity in 2025 was more moderate than implied by historical stress patterns. The persistence of industrial output despite prior financial tightening indicates that additional factors, such as resilient domestic demand or stable external conditions, may have mitigated potential contractionary effects.

In summary, out-of-sample evidence indicates that XGBoost outperforms Random Forest in forecasting PIM over the analyzed period, combining lower bias and greater stability. The Financial Conditions Index retains informational relevance;

however, the strength of its transmission to industrial activity appears to be state-dependent and weaker outside periods of systemic stress.

4.9 Out-of-Sample Predictive Performance

Table 2 reports the out-of-sample evaluation results for forecast horizons ranging from one to twelve months, using a rolling-origin procedure that preserves the temporal ordering of the data. Forecast accuracy is assessed using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) for both IBC growth and Monthly Industrial Production (PIM).

Table 2 – Out-of-Sample Forecast Errors for IBC and Monthly Industrial Production (PIM) Growth

Horizonte (h)	Variável	Modelo	RMSE	MAE
1	IBC	RF	0,996	0,708
1	IBC	XGB	1,141	0,843
1	PIM	RF	1,234	0,861
1	PIM	XGB	1,302	0,903
6	IBC	RF	0,887	0,636
6	IBC	XGB	1,208	0,887
6	PIM	RF	1,304	0,996
6	PIM	XGB	1,985	1,454
12	IBC	RF	0,848	0,621
12	IBC	XGB	1,190	0,979
12	PIM	RF	1,284	1,008
12	PIM	XGB	1,628	1,291

Source: Author's calculations based on research results.

The results indicate systematic superiority of the Random Forest (RF) model across most horizons and for both activity indicators. At the one-month horizon, RF achieves an RMSE of 0.996 for the IBC, compared to 1.14 for XGBoost (XGB). For PIM, the difference also favors RF, albeit with smaller magnitude at short horizons.

As the forecast horizon expands, an important pattern emerges: RF forecast errors remain relatively stable and, in some cases, decline moderately. At the twelve-month horizon for the IBC, RF records an RMSE of 0.848, substantially lower than the 1.19 observed for XGB. This behavior suggests that the ensemble structure of independent trees in RF captures persistence in macroeconomic dynamics more robustly. Such findings are consistent with evidence in macro-forecasting literature indicating that bagging-based methods perform well in environments characterized by moderate sample sizes and high temporal persistence.

For PIM, forecast errors are structurally higher across all horizons, reflecting the greater volatility of industrial production relative to the aggregate activity index. Nevertheless, RF maintains a consistent advantage. At the six-month horizon, for instance, RF yields an RMSE of 1.304, while XGB reaches 1.985, indicating a substantial loss of precision under boosting.

From a methodological perspective, the comparatively weaker performance of XGBoost is noteworthy. Despite incorporating explicit regularization and sequential learning (Chen and Guestrin, 2016), XGB appears more sensitive to local fluctuations in the training sample. In macroeconomic applications with relatively short samples, this sensitivity may generate residual overfitting, particularly when nonlinearities are regime-specific and not persistent.

By contrast, Random Forest combines multiple trees estimated on bootstrap subsamples and random feature selection, effectively reducing predictive variance. This variance-reduction property appears especially advantageous in macroeconomic contexts where structural breaks coexist with persistent dynamics. The results align with empirical findings suggesting that RF often outperforms boosting methods in medium-sized macro datasets.

Another important result is that the relative performance gap in favor of RF widens at medium and long horizons. This suggests that the Financial Conditions Index (FCI) contains forward-looking information about economic trajectories beyond contemporaneous effects. However, the way this information is extracted and aggregated by the forecasting algorithm materially affects forecast quality.

From an economic standpoint, the findings reinforce the hypothesis that financial conditions play a meaningful role in shaping Brazilian economic dynamics, particularly when modeled through nonlinear frameworks. The stability of forecast errors across horizons indicates that the FCI embodies persistent informational content rather than purely short-term correlations.

5. Conclusion

This paper constructs a Financial Conditions Index (FCI) for Brazil using a supervised factor approach and evaluates its predictive content for economic activity under nonlinear machine learning frameworks. By combining grouped principal components with economically informed weights derived from predictive regressions, the proposed index aligns statistical extraction with macroeconomic relevance.

The empirical results yield four main findings.

First, the supervised weighting scheme produces economically coherent transmission patterns. Risk premia emerge as the dominant channel in explaining future economic fluctuations, followed closely by domestic interest rates. This reinforces the relevance of the financial accelerator mechanism in emerging markets and supports the view that risk-based transmission channels may dominate conventional interest-rate channels during stress episodes.

Second, the dynamic analysis shows that the FCI captures major macro-financial episodes, including the 2015–2016 domestic crisis and the 2020 pandemic shock. Importantly, the index diverges from the Selic rate in several periods, demonstrating that policy rates alone do not fully summarize aggregate financial conditions. This finding corroborates the literature emphasizing the informational superiority of composite financial indicators over single policy instruments.

Third, out-of-sample forecasting results indicate that financial conditions contain persistent forward-looking information about Brazilian economic activity. For the IBC, both Random Forest and XGBoost predict continued moderate expansion in 2025, without signaling systemic stress. For industrial production (PIM), the predictive signal is more volatile and potentially regime-dependent, consistent with the higher cyclical sensitivity of industrial activity.

Fourth, in terms of predictive performance, Random Forest systematically outperforms XGBoost across most horizons and for both activity measures. The performance gap widens at medium and long horizons, suggesting that the ensemble variance-reduction mechanism of Random Forest is particularly well-suited to macroeconomic environments characterized by persistence and structural breaks. These results contribute to the growing literature on machine learning applications in macroeconomic forecasting, highlighting that algorithm choice materially affects predictive outcomes when nonlinear financial information is involved.

From a policy perspective, the findings underscore the importance of monitoring broad financial conditions rather than relying exclusively on the policy rate. In commodity-exporting emerging economies subject to global liquidity cycles and risk spillovers, financial conditions may ease or tighten independently of domestic monetary stance.

Finally, the results suggest that the elasticity of economic activity to financial conditions is state-dependent,stronger during stress episodes and weaker during expansionary regimes. Future research could formally model such nonlinear regime dependence and integrate quantile-based growth-at-risk approaches with machine learning frameworks.

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