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Do Tax Expenditures Contribute to the Increase in Total Factor Productivity in Brazil?

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ABSTRACT

The effectiveness of tax expenditures as a public policy instrument is a central issue in both Brazil and the global context, given their expansion and the significant indirect costs imposed on public budgets. Despite their relevance, further debate is needed in Brazil, where tax expenditures have exceeded the combined budgets of Health and Education since 2006 and have grown at a faster rate since 1996, without clear evidence of returns. This study aims to evaluate the dynamic effects of tax expenditures on total factor productivity in Brazil. To this end, a Bayesian Vector Autoregression (BVAR) model was employed, using deflated, per capita, and log-transformed variables, suitable for short macroeconomic time series. Holding other factors constant, an increase in tax expenditures leads to a reduction of 0.006331 in total factor productivity. These findings highlight the need for periodic and robust evaluations of such policies to ensure their effectiveness and to promote sustainable economic growth.

Keywords: Tax Expenditures; Fiscal Policy; Total Factor Productivity (TFP); Bayesian VAR; Public Policy Evaluation.
JEL Classification: H25, O47, E62, C32

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SUMMARY

1. INTRODUCTION

The relationship between fiscal policy and economic performance has been debated in the literature when referring to indirect instruments of state intervention on productivity. Within this context, tax expenditures—defined as revenue forgone due to differential treatment in the tax system—play a significant role, as they constitute an alternative form of public policy, often used with the ultimate goal of stimulating specific sectors, correcting market failures, or promoting economic development.

However, there remains little consensus on the effects of tax expenditures on productivity, particularly in emerging economies. In the case of Brazil, there has been a significant expansion of these instruments over the past few decades, accompanied by a scenario of low national productivity growth. This coexistence raises questions about the effectiveness of these policies, as well as about possible allocative distortions generated by misdirected tax incentives.

The international literature suggests that fiscal policies based on tax breaks can generate both positive and negative effects by introducing inefficiencies and favoring sectors that end up being less productive (Heady and Mansour, 2019; Beer et al., 2022). In Brazil, however, empirical evidence is limited and, in many cases, concentrated in sectoral analyses or descriptive studies (Corcelli, 2021; Oliveira et al., 2024; Renzio et al., 2024; Nery, 2025), highlighting the need for a more comprehensive quantitative approach.

In light of the above, an important question arises: have GTs, in fact, contributed to increased productivity in Brazil, or is this instrument distorting the efficiency of resource allocation and negatively affecting productivity? For example, the study by Ma et al. (2023) shows that government subsidies have a significant negative effect on firms' total factor productivity, especially in those at an early stage of growth, where such incentives can lead to complacency or inefficient resource allocation.

The overall objective of this study is to analyze the impact of tax expenditures on total factor productivity in the Brazilian economy during the post-Real Plan period. In terms of specific objectives, a Bayesian Vector Autoregressive (BVAR) model is estimated, which allows for capturing the dynamic interrelationships among macroeconomic variables and assessing effects over time, contributing to a more robust analysis of the transmission mechanisms associated with indirect fiscal policy. In other words, this approach allows us to capture the dynamic interdependencies among macroeconomic variables, in addition to addressing overparameterization issues common in traditional VAR models, especially in relatively small samples.

Thus, this study aims to analyze whether tax expenditures have contributed to increased productivity in Brazil in the recent period. It also aims to identify tax expenditures implemented in Brazil between 1995 and 2024, empirically assess the relationship between tax expenditures and total factor productivity (TFP), compare the effects of tax incentives on productivity over time, and discuss public policy implications based on the results obtained.

The Federal Court of Accounts (TCU), through an analytical report on tax expenditures in Brazil published in 2025, reinforced the view that projected federal tax expenditures for the year 2025 exceed R$ 544.5 billion, far surpassing the budgets of various public policies considered strategic. The agency highlights the absence of robust evaluation and monitoring mechanisms, even though the federal constitution and budgetary legislation already provide for the need for periodic analysis of the effectiveness of these tax benefits.

The main contribution of this study is to provide empirical evidence on the relationship between tax expenditures and total factor productivity in Brazil, broadening the debate on the efficiency of this economic policy instrument. In doing so, the article seeks to provide a basis for the formulation of more effective public policies, especially in the context of fiscal constraints and the need to increase productivity as a condition for sustainable economic growth.

2. THEORETICAL FRAMEWORK

2.1 Assessment of tax expenditures and the need for transparency

Within the IMF framework, Beer et al. (2022) highlight the great importance of systematic evaluations of tax expenditures to ensure continuous improvement in public policy formulation, thereby bringing increasing benefits to society. The authors argue that when tax expenditures deviate from a benchmark tax system, they end up providing financial support to various sectors of the economy, but simultaneously reduce public revenues, representing on average about 4% of the Gross Domestic Product (GDP) of the countries analyzed in the study's data.

According to Beer et al. (2022), these systematic evaluations are essential for mitigating the influence of narratives promoted by groups with vested interests or those benefiting from such incentives, thereby aligning decisions more closely with the public interest.

Building on this perspective, Heady and Mansour (2019) propose a roadmap for developing countries on how tax expenditure reports should be prepared and how they should be used in fiscal management. According to the authors, tax expenditures should be given the same level of importance and relevance as budgetary expenditures, since both ultimately generate costs for the government.

Heady and Mansour (2019) argue in this study that the production of tax expenditure reports should be a legal obligation, and that these reports should be submitted to parliament to assist in fiscal policy decision-making. The foregone revenue method is the authors' recommendation for estimating the costs of tax expenditures, even while acknowledging that data availability and the institutional specificities of each country can pose significant challenges. And like Beer et al. (2022), they emphasize that the systematic disclosure of these reports is fundamental for improving fiscal governance and increasing transparency.

2.2 The Trajectory of Tax Expenditures in Brazil

In the Brazilian context, Oliveira et al. (2024) offer a comprehensive analysis of much of the trajectory of tax expenditure policy between 1996 and 2023, showing the role this fiscal policy played in economic growth. The study reveals a very significant increase in tax expenditures, particularly since 2005, with projections indicating spending exceeding R$ 400 billion in 2022. Furthermore, since 2006, the volume of tax expenditures has exceeded the combined budgets of the Ministries of Education and Health.

The analysis by Oliveira et al. (2024) examines the impact of these tax subsidy policies on GDP and total tax revenue from a historical perspective. The study also identifies certain periods in which tax expenditures show moderate growth, but which are followed by sharp increases, often associated with changes in government and, consequently, in the country's macroeconomic policies. Thus, the authors conclude that there is indeed a need to assess the costs of these policies, given that the direct benefits to society are limited and the potential to further exacerbate economic inequalities.

Corroborating this critical perspective, Corcelli (2021) assesses the impact of tax expenditures on Brazil's economic growth between 2004 and 2015, using a panel model inspired by Devarajan et al. (1996). This study shows that a 1% increase in the ratio of tax expenditures to GDP generates a 0.013% reduction in annual per capita growth, suggesting a negative linear relationship between the variables. Corcelli further argues that since tax expenditures require few offsets in investment and employment, this ultimately limits their positive impact on long-term economic growth.

The author's analysis of the expansion of this fiscal policy during the Lula and Dilma administrations highlights that even with significant growth in spending, there was no correlation with economic growth. This demonstrates that this phenomenon is attributed to the lack of requirements for investment and job creation linked to the incentives granted. Finally, Corcelli (2021) suggests that tax expenditure policies be reassessed in order to align them properly with the goal of economic growth.

In the same vein, Nery (2025) notes that Brazil already has a tax burden nearly equal to that of developed countries, and that the trend for the coming years is for it to increase further, making tax expenditures a much greater challenge. In the study, the author advocates for the creation of a General Tax Expenditure Law, with provisions regarding duration, clear offsets, and periodic evaluations, similar to the example of the Special Regime for the Chemical Industry (Reiq), which links incentives to performance targets.

Renzio et al. (2024) also highlight that in 2023, federal tax expenditures accounted for 4.78% of the country's GDP, potentially reaching 7.2% when state expenditures are included. Despite the existence of the Statement of Tax Expenditures (DGT) and the initiatives of the Council for Monitoring and Evaluation of Public Policies (CMAP), the effectiveness of tax expenditure evaluations remains limited, and thus the recommendations produced have little influence on the policies adopted in the country.

2.3 Government Subsidies, Productivity, and Rent-Seeking Behavior

Ma et al. (2023) broaden the debate on the effects of fiscal policies by investigating the relationship between these government subsidies and firms' total factor productivity (TFP), taking into account rent-seeking activities and the business life cycle. Using a panel dataset from the Chinese equipment industry, the authors report that subsidies have a negative impact on TFP, particularly in firms in the growth stage of their life cycle, by inducing unproductive rent-seeking behavior.

The study develops hypotheses regarding the correlation between the cost of rent-seeking and subsidies, suggesting that this behavior harms firm productivity. Furthermore, it analyzes how different phases of the business life cycle influence this relationship, highlighting that firms in the growth phase are much more vulnerable to the negative effects of subsidies. The authors then argue that these incentives can stifle innovation as well as productive activities, emphasizing that there is a great need for adjustments to fiscal policies so that they promote firm productivity.

The literature review highlights the complexity of tax expenditures as fiscal policy instruments, revealing various dimensions that must be considered when they are formulated and evaluated. On the one hand, Beer et al. (2022) and Heady and Mansour (2019) point out in their studies that there is a great need for systematic and transparent evaluations of tax expenditures. On the other hand, the experience we have had in Brazil, which was analyzed by Oliveira et al. (2024), Corcelli (2021), Nery (2025), and Renzio et al. (2024), highlights various risks associated with the growing expansion of tax expenditures without clear offsets, including revenue losses, increased inequality, and ineffective growth stimulation.

Furthermore, Ma et al. (2023) suggest that subsidies and tax benefits can generate adverse effects, such as rent-seeking behavior and a disincentive to productivity.

3. METHODOLOGY

3.1 Stationarity Analysis

The modified Dickey-Fuller (ADF^{GLS}) and Phillips-Perron $\left(\overline{MZ}_{\alpha}^{GLS}\right)$ tests, proposed by Elliot, Rottemberg, and Stock (1996), and Ng and Perron (2001), are applied to test the stationarity of the series because they overcome the problems of low- , statistical power, and size bias in the traditional tests of Dickey and Fuller (1979, 1981), Said and Dickey (1984), and Phillips and Perron (1988).

The modifications to the unit root test by Dickey and Fuller (1979, 1981) and Said and Dickey (1984) are based on two central aspects: (a) trend extraction in time series using ordinary least squares (OLS) is inefficient; and (b) the importance of an appropriate choice of lag order for the augmented term, in order to obtain a better approximation of the true data-generating process.

In the first case, (a), Elliot, Rottemberg, and Stock (1996) propose using generalized least squares (GLS) to extract the stochastic trend from the series. The standard procedure is employed to estimate the ADF^{GLS} statistic as the t-statistic for testing the null hypothesis $H_0 : \beta_0 = 0$, indicating the presence of a unit root, from the following regression estimated by ordinary least squares:

$$\Delta\tilde{y}_t = \beta_0\tilde{y}_{t-1} + \sum_{j=1}^{k}\beta_j\Delta\tilde{y}_{t-j} + e_{tk} \qquad (1)$$

against the alternative hypothesis $H_A : \beta_0 < 0$, that the series is stationary. In (1), $\tilde{y}_t$ is the trend-removed series using generalized least squares, Δ is the first-difference operator, and e_{tk} is the non-autocorrelated and homoscedastic residual.

Regarding the second aspect, (b), Ng and Perron (2001) demonstrate that the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) tend to select low values for the lag *k* when there is a large negative root (close to -1) in the moving average polynomial of the series, leading unit root tests to significant distortions. This motivated the development of the modified Akaike information criterion (MAIC) for selecting the autoregressive lag, in order to minimize the distortions caused by inappropriate lag selection in equation (1). The MAIC is designed to select a relatively long lag length in the presence of a moving-average root close to unity, in order to avoid distortions, and a shorter lag length in the absence of such a root, so that the test's power is not compromised. The ADF^{GLS} test uses the OLS *t-statistic* corresponding toβ_0 in equation (1).

Ng and Perron (2001) propose that the same modifications be applied to the traditional Phillips and Perron (1988) test as well, resulting in the $\left(\overline{MZ}_{\alpha}^{GLS}\right)$test. Through simulations, Ng and Perron (2001) show that the combined application of GLS to extract the deterministic trend and the MAIC lag selection criterion produces tests with greater power but lower statistical size distortions when compared to the traditional ADF and PP tests. The critical values of the ADF^{GLS} and $\left(\overline{MZ}_{\alpha}^{GLS}\right)$statistics are reported in Ng and Perron (2001), Table 1.

Researchers need to be aware of the impact of structural breaks because they are characterized by a permanent change in the behavior of the time series and may correspond to a change in the trend slope, the trend intercept, or both. Given that traditional unit root tests have low power in the presence of structural breaks, these tests become biased toward failing to reject the null hypothesis of a unit root even in the absence of a unit root. Thus, when a structural break is suspected, certain modifications to unit root tests are recommended to avoid this bias.

Perron and Vogelsang (1998) formulated an additive model (Additive Outlier – AO) with breaks in the intercept and trend. The choice of the shock time point was made by minimizing the Student's *t-statistic* of the autoregressive component, a procedure similar to that in previous studies. This model would be capable of capturing abrupt changes.

In turn, the innovative model (Innovational Outlier – OI) was also used, and, again, the assumption is made that shocks occur around the alternative hypothesis. This model would be capable of capturing gradual changes.

The models are estimated assuming that the macroeconomic series have only one structural break. The date of the break can be denoted as T^c_b, where $T^c_b < T$, and T is the sample size.

The additive model assumes that the structural break occurs instantaneously and is therefore not affected by the dynamics of the series. The equations of this model are given by

$$y_t = \mu + \beta t + \theta DU^c_t + \xi^1_t \tag{2}$$

$$y_t = \mu + \beta t + \theta DU^c_t + \gamma DT^c_t + \xi^2_t \tag{3}$$

$$y_t = \mu + \beta t + \gamma DT^c_t + \xi^3_t \tag{4}$$

Where $DU^c_t = 1$ for $t > T^c_b$, $DT^c_t = t - T^c_b$ for $t > T^c_b$. The parameters θ and γ measure the magnitude of the possible structural break.

The unit root test procedure for the additive model consists of two steps. The first step involves removing the trend from the series by estimating equations (2), (3), and (4) using ordinary least squares. In the second step, the unit root hypothesis is tested using Student's *t-statistic* and $\alpha = 1$ in the following regressions:

$$\xi^j_t = \sum_{i=1}^{k} \omega_i D(T_b)_{t-j} + \alpha \xi^j_{t-1} + \sum_{i=1}^{k} c_i \Delta \xi^j_{t-i} + u_t \tag{5}$$

$$\xi^j_t = \alpha \xi^j_{t-1} + \sum_{i=1}^{k} c_i \Delta \xi^j_{t-i} + u_t \tag{6}$$

For $t = k + 1, \ldots, T$; where ξ^j_t are the residuals from regressions (2), (3), and (4), and $D(T_b) = 1$ for $t = T_b + 1$. According to Volgesang and Perron (1998), the inclusion of $k + 1$ dummy variables $D(T_b)_{t-i}$, $i = 0, \ldots, k$ in equation (5) is necessary to ensure that the distribution of the statistic t of α is invariant to the correlation structure of the errors. The Student's *t-statistic* for testing $\alpha = 1$ is denoted by $t_\alpha(j, OA, T_b, k)$.

The innovative model is best applied in cases where it is more reasonable to expect a break to occur over time. The unit root test for this type of model follows the procedure of Dickey and Fuller (1979):

$$y_t = \mu + \beta t + dD(T_b) + \theta DU_t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + u_t \tag{7}$$

$$y_t = \mu + \beta t + dD(T_b) + \theta DU_t + \gamma DT_t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + u_t \quad (8)$$

$$y_t = \mu + \beta t + \gamma DT_t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + u_t \quad (9)$$

The choice of the optimal number of lags k is made through a significance test of the last coefficient of the lag parameter. The procedure for choosing T_b is based on minimizing $t_\alpha(j,m,\text{-}T_b,k)$, where $m = OA$ *or* OI. Therefore, the choice of the time of the structural break corresponds to a specific instant, which makes it more likely to reject the null hypothesis. Mathematically, $t_\alpha[\lambda_{inf}] = \inf t_\alpha(\lambda)$, where $\lambda = \frac{T_b}{T}$. Thus, λ can vary between $\frac{2}{T}$ and $\frac{(T-1)}{T}$

Saikkonen and Lütkepohl (2002), as well as Lanne, Lütkepohl, and Saikkonen (2002, 2003), propose that structural breaks can occur over a number of periods and exhibit a smooth transition to a new level. Therefore, a level-switching function, which is known by the general nonlinear form $f_t(\theta)'\gamma$, is added to the deterministic term μ_t of the data-generating process. Thus, the model is expressed by the following regression:

$$q_t = \mu_0 + \mu_1 t + f_t(\theta)'\gamma + v_t \quad (10)$$

where θ and γ are unknown scalar parameters (or parameter vectors); t is a time trend; and v_t are residual error terms generated by an AR(p) process with a possible unit root. In addition to the possibility of modeling a structural break with a impulse dummy variable, the shift in the function $f_t(\theta)'\gamma$ can be:

(i) A simple shift dummy variable with a shift date T_b (*shift dummy*):

$$f_t^{(1)} = d_{1,t} := \{0,\ t < T_b \quad 1,\ t \geq T_b \quad (11)$$

This function does not involve any additional parameters θ. In the shift term $f_t^{(1)}\gamma$, the parameter γ is a scalar, and differentiating this shift function yields a impulse dummy variable.

(ii) A second shift function is based on the exponential distribution function, which allows for a gradual nonlinear shift to a new level starting in the period T_b (*exponencial shift*):

$$f_t^{(2)}(\theta) = \{0,\ t < T_b \quad 1 - exp\{-\theta(t - T_b + 1)\}\ t \geq T_b \quad (12)$$

(iii) A third function can be viewed as a rational function in the lag operator applied to a shift dummy variable d_{1t} (*rational shift*):

$$f_t^{(3)}(\theta) = \left[\frac{d_{1,t}}{1-\theta L} \ \frac{d_{1,t-1}}{1-\theta L} \right] \tag{13}$$

Here, the actual transformation function will be $[\gamma_1(1\text{-}\theta L)^{-1} + \gamma_2(1\text{-}\theta L)^{-1} L]d_{1,t}$, where θ is a scalar parameter between 0 and 1, and $\gamma = (\gamma_1,\gamma_2)'$ is a two-dimensional parameter vector. An alternative way to write this transformation function is:

$$f_t^{(3)}(\theta) = \left\{ 0, t < T_B \ \gamma_1, t = T_B \ \gamma_1 + \sum_{j=1}^{t-T_B} \theta^{j-i}\left(\theta\gamma_1 + \gamma_2\right), t > T_B \right\} \tag{14}$$

Both $f_t^{(2)}$ $(\theta)\gamma$ and $f_t^{(3)}$ $(\theta)'\gamma$ can generate sharp changes over a period of time T_B for appropriate values of θ. Therefore, these two terms are more general than $f_t^{(1)}$

Saikkonen and Lütkepohl (2002) and Lanne, Lütkepohl, and Saikkonen (2002, 2003) proposed a unit root test for equation (10) based on estimating the first deterministic term by generalized least squares (GLS) under the null hypothesis of the presence of a unit root, and the subtraction of this trend from the original series. Next, an ADF test is conducted on the adjusted series using critical values tabulated in Lanne et al. (2002), since in the case of the statistical ADF, the asymptotic null distribution is not standard. When conducting the test, one must decide on the AR order and the break date T_B. Since the tests are conducted with an unknown break date, Lanne et al. (2001) recommended choosing a reasonably large AR order in a first step and then selecting the break date that minimizes the GLS objective function used to estimate the parameters of the deterministic term. If a model with a linear and offset term is assumed, the relevant parameters $\eta = (\mu_0, \mu_1, \gamma)'$ are estimated by minimizing the generalized sum of the model's quadratic errors in first differences:

$$\Delta y_t = \mu_1 + \Delta f_t(\theta)'\gamma + v_t \ (t = 2, \dots, T) \tag{15}$$

Where $v_t = \alpha^*(L)^{-1}u_t$ In other words, the estimation is performed under the null hypothesis of the presence of a unit root by minimizing $Q_p\left(\eta, \theta, \alpha^*\right) = (Y - Z(\theta)\eta)'\Sigma\left(\alpha^*\right)^{-1}(Y - Z(\theta)\eta)$, where α^* is the vector of coefficients in $\alpha^*(L)$. $\Sigma\left(\alpha^*\right) = \frac{COV(V)}{\sigma_u^2}$, $V = \left(v_1, \dots, v_T\right)$ is the model error vector, $Y = [y_1,\Delta y_2, \dots ,\Delta y_T]'$ e $Z = [Z_1,Z_2,Z_3]$, with $Z_1 = [1,0,\dots,0]'$, $Z_2 = [1,1,\dots,1]'$, and $Z_3 = [f_1(\theta), \Delta f_2(\theta), \dots,\Delta f_T(\theta)]'$. Although the adjusted series $\hat{\varepsilon}_t$ could be used in the ADF approach, Lanne et al. (2002) also proposed a slightly different procedure that adjusts the error estimates in the parameters, and this procedure performed very well in small-sample simulations. The unit root test statistic is again obtained as the usual t-statistic of the estimator based on ordinary least squares estimation of the model. As in the case of the ADF statistic, the asymptotic null hypothesis in this case is not standardized, and the critical values are tabulated in Lanne et al. (2002).

3.2 Bayesian Multivariate Analysis

The specification of the econometric model in this study is based on a Bayesian Autoregressive Vector Model, with the aim of estimating the dynamic effects of tax expenditures on productivity in Brazil. After analysis, it was found that the optimal number of lags was two, as the *Final Prediction Error* (FPE), *Akaike Information Criterion* (AIC), and *Hannan-Quinn Information Criterion* (HQ) tests indicated this result. This choice ensures an appropriate balance between the model's complexity and its explanatory power, which guarantees that the time series used are appropriately capturing the intertemporal dynamics among the variables, as presented in Appendix A.

The estimation was performed using *Eviews* software, employing the BVAR model function, which allows for the incorporation of *priors* well-established in the literature, such as the Minnesota prior. This *prior* is particularly effective in avoiding the problem of overparameterization, imposing mild informational constraints on the model coefficients and contributing to greater precision in the estimates.

The year variable was used solely for temporal indexing purposes and was not included as an explanatory variable in the model, given that it carries no relevant endogenous informational content in the context of the model.

The analysis is based on the estimation of a Bayesian VAR model involving all the variables mentioned above. The reduced-form BVAR model of order q will be represented by the following equation:

$$Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_i Y_{t-i} + \epsilon_t \tag{10}$$

Where Y_t is a vector $p\times1$ containing the observations of the p time series at time t; c is the vector of constants $p\times1$; $A_1, A_2, \ldots, A_q$ are matrices $p\times p$ of coefficients associated with the lagged terms of the time series; and finally, ϵ_t is a vector $p \times 1$ of random residuals, typically assuming that the residuals follow a multivariate normal distribution.

4. DESCRIPTION OF VARIABLES AND DATA PROCESSING

The data used in this study are annual and cover the period from 1995 to 2024. All variables were selected to capture the relationship between productivity in Brazil and tax expenditures, drawing on various reliable sources that are widely used and recognized in the economic literature.

The dependent variable will be Total Factor Productivity (TFP), which measures the efficiency with which capital and labor are combined in production. An increase in TFP indicates that the country is producing more using the same amount of inputs, which aligns perfectly with the research question of this study. The data were obtained from the database available at the FGV Productivity Observatory. The calculations took into account the TFP variable adjusted for human capital based on the year 1995. This variable was chosen over TFP without human capital adjustment because one of the objectives of tax expenditures is to stimulate investment, innovation, and productive modernization; thus, their effects are better captured by TFP adjusted for human capital.

The Tax Expenditures variable will be the key independent variable in this study. Its data were extracted from the Tax Expenditure Statements (DGT), which are made available annually by the Brazilian Federal Revenue Service (RFB).

The country's productivity can be influenced by the overall performance of the economy, where during periods of strong economic growth, firms tend to invest more and utilize productive capacity more efficiently, which can increase productivity. On the other hand, during recessions, productivity may decline—the inclusion of this variable can generate endogeneity, a point that highlights another reason for choosing a BVAR model. For this reason, nominal GDP will be added to the equation as a control variable to isolate the effect of tax expenditures, ensuring that the observed impact is not merely a reflection of the country's current economic conditions. The data are annual and were obtained from the database available on the IPEADATA website.

General Government Gross Debt will also be included in the equation as an independent control variable. The inclusion of this variable may help determine whether the country's fiscal sustainability, in addition to tax expenditures, has an effect on productivity . An increase in tax expenditures may have a positive effect on productivity, but if this increase causes unsustainable debt growth, the final effect ends up being negative. The data for this variable were taken from the Time Series Management System (SGS) of the Central Bank of Brazil (BCB).

The final independent control variable will be real interest rates. With this variable, we can control for the effect of inflation, which during periods of high inflation can generate uncertainty and consequently discourage investment. Additionally, we can control for the effect of interest rates, where during periods of higher interest rates, credit becomes more expensive, which can also hinder corporate investment. The data for this variable were obtained from the database available on the IPEADATA website.

Furthermore, all monetary values in the tax expenditure time series were adjusted to constant prices to eliminate the effects of cumulative inflation over the years studied. Deflation was performed based on the IPCA to bring historical values to constant prices for the base year of 2024. After this, the values were expressed in per capita terms; with these adjustments, the analysis avoids spurious trends and brings the series closer to stationarity. Thus, with these changes, the variables become comparable across periods.

In summary, all variables included in the model are represented by TFP, which, as previously mentioned, is total factor productivity adjusted for human capital (1995 as the base year, = 1); GDP, which is Brazil's annual gross domestic product; GT, which shows the total value of tax expenditures; DBGG, which refers to General Government Gross Debt; and finally, JR, which is the real interest rate;

5. ANALYSIS OF RESULTS

The first crucial step in applying a time series model, such as the BVAR, is to ensure the stationarity of the variables. To this end, four distinct unit root tests were conducted. As can be seen in Table 1, considering the last Saikkonen and Lütkepohl test, the results show that almost all time series used in the model are stationary at the 1% significance level, with the remaining portion being significant at the 10% level. This result is fundamental because, as previously mentioned, stationarity is a basic premise that the series must follow in order to avoid spurious regression probleThe first crucial step in applying a time series model, such as the BVAR, is to ensure the stationarity of the variables. To this end, four distinct unit root tests were conducted. As can be seen in Table 1, considering the last Saikkonen and Lütkepohl test, the results show that almost all time series used in the model are stationary at the 1% significance level, with the remaining portion

being significant at the 10% level. This result is fundamental because, as previously mentioned, stationarity is a basic premise that the series must follow in order to avoid spurious regression problems, ensuring the statistical validity of the estimates.

The two unit root tests, which include structural breaks, identified key dates in Brazil's economic history marked by major shocks that may have altered the behavior of the time series used. To capture these shocks and prevent the estimates from becoming biased, four structural breaks were incorporated into the BVAR model, with the first referring to the year 1999. This year marked the transition from a fixed exchange rate regime to a floating exchange rate, an event that redefined the country's monetary policy as well as the dynamics of the Brazilian macroeconomy. The second break relates to the year 2003, notable for the start of President Lula's first administration, which brought radical changes to the country's economic policies. The third break is linked to the year 2008, the year of the global subprime financial crisis—an external shock that originated in the United States and ultimately affected the entire world, with significant repercussions for the Brazilian economy. Finally, the last—and most recent—period refers to the year 2020, the exogenous shock caused by the COVID-19 pandemic crisis, which imposed unprecedented restrictions on global economic activity. The inclusion of these structural breaks increases the model's robustness, allowing it to better account for the major changes that occurred in the trajectory of the variables.

Table 1 - Results of unit root tests

Variável	Modelo	Sem quebra estrutural			Com quebra estrutural					
					Vogelsang e Perron (1998)			Saikkonen e Lütkepohl (2002)		
		ADF^{GLS}	MZ_T^{GLS}	*Lags*	Tipo de quebra	Data de Quebra	Estatística do teste	Tipo de quebra	Data de Quebra	Estatística do teste
PTF	C	0,50	0,96	-	*Innovational Outlier*	2020	-5,78[illegible]	*Rational Shift*	2021	-2,86 (3 *lags*)[illegible]
PTF	C, T	-1,37	-1,30	-	*Innovational Outlier*	2009	-4,49	*Rational Shift*	2021	-4,61 (3 lags)[illegible]
ΔPTF	C	-2,01[illegible]	-1,50	2	*Innovational Outlier*	2003	-5,75[illegible]	*Rational Shift*	2021	-3,78 (4 lags)[illegible]
ΔPTF	C, T	-2,14	-1,56	2	*Innovational Outlier*	2003	-5,63[illegible]	*Rational Shift*	2021	-3,27 (5 lags)[illegible]
GT	C	0,68	0,73	1	*Innovational Outlier*	2022	-5,39[illegible]	*Exponential Shift*	2008	-1,67 (2 lags)
GT	C, T	-2,11	-1,78	-	*Innovational Outlier*	2007	-5,82[illegible]	*Rational Shift*	2008	-3,98 (2 lags)[illegible]
ΔGT	C	-0,94	-0,51	2	*Innovational Outlier*	2005	-13,52[illegible]	*Rational Shift*	2017	-3,69(0 lags)[illegible]
ΔGT	C, T	-5,22[illegible]	-2,29	-	*Innovational Outlier*	2005	-13,01[illegible]	*Rational Shift*	2017	-2,82(0 lags)[illegible]
PIB	C	-0,23	-0,02	1	*Innovational Outlier*	2023	-3,69	*Rational Shift*	2021	-3,61 (7 lags)[illegible]
PIB	C, T	-1,10	-1,07	-	*Innovational Outlier*	2009	-4,61	*Rational Shift*	2021	-3,86 (6 lags)[illegible]
ΔPIB	C	-2,42[illegible]	-2,08[illegible]	1	*Innovational Outlier*	2014	-5,08[illegible]	*Rational Shift*	2015	-3,57 (6 lags)[illegible]
ΔPIB	C, T	-2,48	-2,13	1	*Innovational Outlier*	2012	-4,96[illegible]	*Rational Shift*	2015	-4,28 (6 lags)[illegible]
DBGG	C	-0,48	0,73	-	*Innovational Outlier*	2016	-4,51	*Rational Shift*	2006	-3,05 (0 lags)[illegible]
DBGG	C, T	-2,11	-1,12	-	*Innovational Outlier*	2020	-3,88	*Rational Shift*	2006	-4,09 (5 lags)[illegible]
ΔDBGG	C	-2,24[illegible]	-1,17	2	*Innovational Outlier*	2002	-6,06[illegible]	*Rational Shift*	2003	-4,35 (2 lags)[illegible]
ΔDBGG	C, T	-2,43	-1,41	2	*Innovational Outlier*	2006	-7,75[illegible]	*Rational Shift*	2003	-4,09 (2 lags)[illegible]
JR	C	-2,15[illegible]	-1,82[illegible]	-	*Innovational Outlier*	2022	-5,89[illegible]	*Rational Shift*	2001	-5,50 (3 lags)[illegible]
JR	C, T	-3,19[illegible]	-2,35	-	*Innovational Outlier*	2022	-5,71[illegible]	*Exponential Shift*	2001	-3,47 (2 lags)[illegible]
ΔJR	C	-3,22[illegible]	-2,07[illegible]	2	*Innovational Outlier*	1999	-9,03[illegible]	*Rational Shift*	2020	-5,06 (2 lags)[illegible]
ΔJR	C, T	-5,47[illegible]	-2,64	-	*Innovational Outlier*	2000	-10,27[illegible]	*Rational Shift*	2020	-4,40 (2 lags)[illegible]

Source: Author's own calculations. Use of the econometric software Eviews and JMULTI.

Note:

NOTE: 1 – "Lags" refers to time lags. Δ represents the variable in first differences. Model types: "C" stands for constant; "T" stands for deterministic trend. Maximum initial count of 7 lags. Note that (a), (b), and (c) indicate that the estimated coefficients are statistically significant or rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. Annual observations included: 30 (sample: 1995 to 2024).

2 – The critical values of the [(ADF)]^GLS test are (Elliot, Rothenberg, and Stock, 1996): (i) model with a constant: -2.65 (1%), -1.95 (5%), and -1.61 (10%). (ii) model with constant and deterministic trend: -3.77 (1%), -3.19 (5%), and -2.89 (10%). Selection of the optimal number of lags using the modified Akaike information criterion.

3 – The asymptotic critical values of the MZ_α^GLS test are (Ng and Perron, 2001): (i) model with constant:

-2.58 (1%), -1.98 (5%), and -1.62 (10%); (ii) model with constant and deterministic trend: -3.42 (1%), -2.91 (5%), and -2.62 (10%); Spectral estimation method: AR GLS-detrended. Selection of the optimal number of lags using the modified Akaike information criterion.

4 – The critical values of the Vogelsang and Perron (1998) test are: (i) model with constant/intercept break: -5.35 (1%), -4.86 (5%), and -4.61 (10%); (ii) model with constant and deterministic trend/break in intercept and trend: -5.72 (1%), -5.18 (5%), and -4.89 (10%). Break type: innovational outlier. Selection of the structural break: minimized Dickey-Fuller t-statistic. Selection of the optimal number of lags: Akaike Information Criterion.

5 – The critical values of the Saikkonen-Lütkepohl test are (Lanne et al., 2002): (i) model with constant: -3.48 (1%), -2.88 (5%), and -2.58 (10%); (ii) model with constant and deterministic trend: -3.55 (1%), -3.03 (5%), and -2.76 (10%). Types of structural breaks: Rational Shift.

As can be seen in Table 2, the BVAR estimation results demonstrate an excellent fit to the data, since all variables are statistically significant at a level of at least 5%, indicating a robust relationship between tax expenditures and productivity, as well as among the other variables included in the model. It presents a coefficient of determination R^2 of 0.9482 and an adjusted coefficient of determination R^2 of 0.8924. These values, which are notably high, indicate that this econometric model is well-adjusted to the data, explaining, respectively, approximately 94.82% and 89.24% of the total variation in the dependent variable (TFP).

Analyzing the results obtained, the coefficient vector provides the direct answer to the research question, where the estimated coefficient value for tax expenditures on productivity ( ) shows that tax expenditures have a negative impact on the country's productivity. In practical terms, *ceteris paribus*, when there is an increase in tax expenditures, productivity would decline. With this finding, we can infer that tax benefits or revenue waivers may be misdirected, distorting resource allocation rather than stimulating innovation or efficiency gains that could increase aggregate productivity.

Table2 - Econometric Results

Variável dependente: Produtividade Total dos Fatores (PTF)		
Metodologia: BVAR		
Variável	**Coeficiente**	**Valor-p**
Gastos Tributários (GTs)	-0,006331[(b)]	0,01156
Produto Interno Bruto (PIB)	0,000353[(b)]	0,04124
Dívida Bruta (DBGG)	-0,003873[(b)]	0,02013
Juros Real (JR)	-7,02E-06[(a)]	0,00030
Constante (C)	0,164605	0,57766
D 1999	-0,001071[(b)]	0,02661
D 2003	-0,019371[(b)]	0,02587
D 2008	0,009990[(b)]	0,02501
D 2020	0,043163[(b)]	0,02537
R2	0,948200	-
R2 ajustado	0,892415	-

Erro-padrão da regressão	0,022145	-
Média da Variável Dependente	4,499059	-
Desvio Padrão da Variável Dependente	0,067516	-
Soma dos Quadrados do Resíduos	0,006375	-

Source: Author's own calculations. Using the econometric software Eviews.

Note:

1. Observations included: 28 after adjustments.

2. Note that (a), (b), and (c) indicate that the estimated coefficients are statistically significant or reject the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

To validate the reliability of the results, diagnostic tests were performed alongside the estimation. The first was the stationarity test, in which the model satisfied the stationarity condition. In a BVAR model, this indicates that all the inverse roots of the characteristic polynomial lie within the unit circle, ensuring that the Impulse Response Functions (IRFs) and the variance decomposition are valid, and th ly, the model is capable of returning to equilibrium after a shock, as shown in Appendix B. Next, the Cholesky (Lütkepohl) normality test for the residuals was performed, in which the residuals were found to have a normal distribution, according to the results presented in Appendix C. This property is desirable in statistical inferences and indicates that the shocks are not excessively asymmetric. Subsequently, it was determined that the residuals are homoscedastic using White's heteroscedasticity test, which is presented in Appendix D. This means that the variance of the errors is constant over time, fulfilling an essential condition for the efficiency of the estimators. Finally, the autocorrelation of the residuals was verified, and the result shows that they are autocorrelated, which is the only specification problem detected, as shown in Appendix E. Although this autocorrelation does not invalidate the consistency of the BVAR estimators, it indicates that the standard errors of the coefficients may be biased; consequently, the significance tests and impulse-response functions may not be optimal. However, given the Bayesian framework of this study, this impact is mitigated by the use of *prior* distributions.

To complete the analysis of the dynamic impact, the decomposition of the variance of the forecast errors was examined, as shown in Table 3; and, upon analyzing the impacts on total factor productivity, shocks to the variable itself dominate the explanation of the variance. The contribution of tax expenditure shocks becomes significant starting in the fifth period, when it reaches a share of over 1%, a figure that rises to approximately 3.9% in the tenth period. This share, though small, echoes the concern expressed by Ma et al. (2023) that government subsidies negatively impact TFP.

Table3 —Decomposition of Forecast Error Variance

Decomposição da Variância da PTF		
Período	**Produtividade Total dos Fatores**	**Gastos Tributários**
1	100,00	0,00
2	99,92	0,06
5	98,67	1,01
7	97,18	2,06
10	94,39	3,89

Source: Author's own calculations. Use of the econometric software Eviews

Along with variance decomposition, a classical historical decomposition was performed, which breaks down the trajectory observed for each variable into its baseline and the specific contribution of tax expenditure shocks (see Appendix G).

Generalized Impulse Response Functions (GIRFs), proposed by Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), are essential tools in the analysis of VAR and BVAR models, precisely because they describe the time-series evolution of a system's variable following an exogenous shock of one standard deviation in one of the variables, with the order of the variables being invariant. In the present study, the focus is on the impact of a shock to tax expenditures on other macroeconomic variables.

In the Bayesian approach, there are at least two types of VAR models. On the one hand, there is the standard Bayesian VAR model, which assumes that the coefficients are fixed—that is, constant—throughout the entire time series. Although these are less flexible models, they can perform well in short-term forecasts but may be less accurate in volatile environments if the underlying dynamics change. In short, they are less complex to estimate and interpret.

In turn, Bayesian VAR models with Time-Varying Coefficients (BVAR-TVC) allow the coefficients (and often the variances/covariances of the errors) to change over time, modeling them as stochastic processes (specifically, as random walks). These are more flexible models, as they adapt to changes in relationships and to possible structural breaks or regime shifts in the data. Often, these models produce more accurate long-term forecasts as the amount of available data increases, capturing the evolution of relationships, especially during periods of structural change. In short, these are more complex models, involving a larger amount of data and advanced techniques such as Bayesian inference with Markov Chain Monte Carlo (MCMC) methods to handle the growing number of parameters and uncertainties.

The absence of confidence intervals (CI) in impulse response functions (IRF) generated by Bayesian VAR models is generally related to how uncertainty is treated in the Bayesian context.

In Bayesian models, we do not work with point estimators and CIs in the classical (frequentist) sense. Instead, we have *posterior* distributions for the parameters and for the IRFs. Uncertainty is represented by the entire distribution, not by a fixed interval with a confidence level. Instead of CI, it is common to present **credibility bands**, which are intervals derived from the posterior distribution. These bands indicate regions where the impulse response function is likely to lie, given the

Unlike the frequentist approach, BVAR-TVC models do not use confidence intervals, but rather credibility intervals. This distinction arises because, in Bayesian statistics, model parameters are not treated as fixed values— —but as random variables with their own probability distributions. While the confidence interval describes the uncertainty of the sampling process, the credibility interval quantifies the uncertainty regarding the parameter itself.

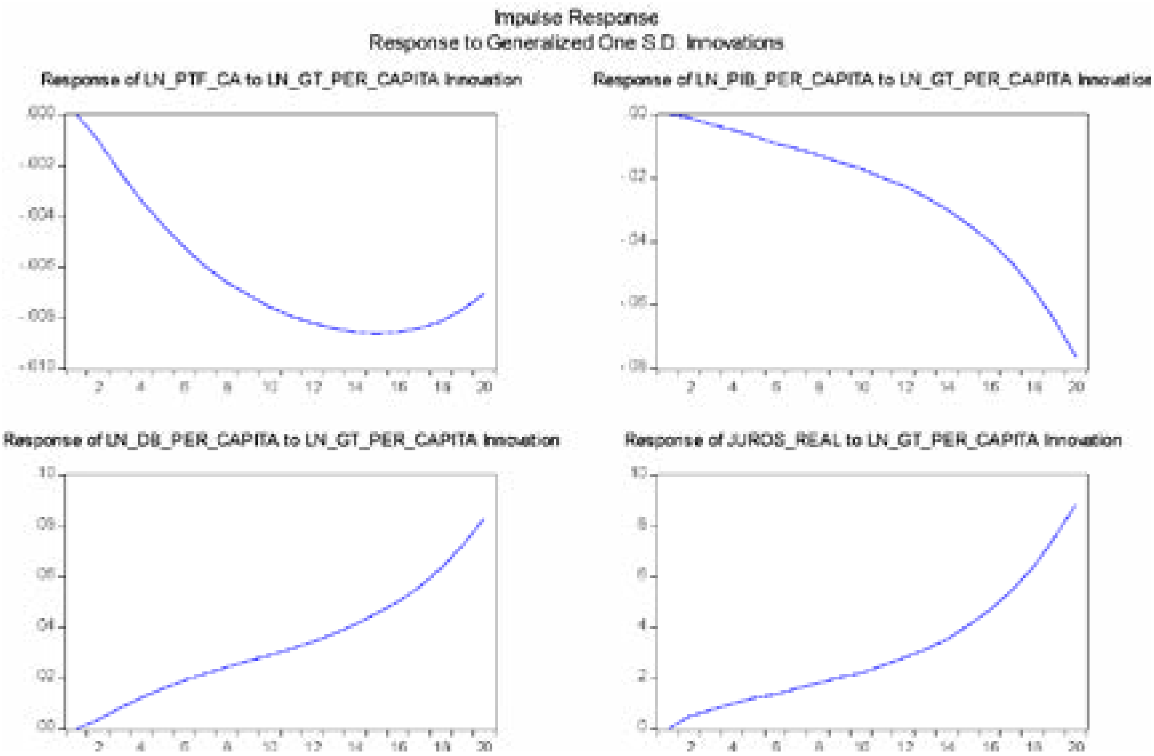
In this study, credibility intervals for the impulse-response functions were not generated because they are characteristic of BVAR models with time-varying coefficients (TVP–BVAR), in which the dynamics of the parameters allow for capturing structural changes and additional uncertainties over the analyzed period.

Since the approach adopted in this study is based on a standard BVAR model with fixed coefficients, and given that the sample size is smaller, the impulse response functions (IRFs) are generated only as *posterior* means. To obtain credibility intervals in this type of model, it would be necessary, for example, to simulate FIRs for each draw from the posterior distribution and calculate quantiles (generally, for constructing the intervals, one can consider 16% and 84% for a 68% confidence level, or 5% and 95% for a 90% confidence level). Even so, this limitation does not compromise the relevance of the results obtained, since the estimates and tests conducted provide preliminary evidence on the dynamics of the relationships between tax expenditures and total factor productivity, consistently contributing to the understanding of the investigated problem and to the empirical debate in the literature.

As shown in Figure 2, when considering non-cumulative shocks (short-term response), the GT shock generates a negative and persistent response in TFP. Even though the effect is small—only approximately 0.01—we can see that the result runs counter to what economic theory suggests, where tax expenditures aim to increase productivity by directing resources toward more productive activities, innovation, or investment. This negative result may occur due to allocative inefficiency—GT being allocated to less productive areas or generating rent-seeking, as Ma et al. (2023) conclude in their work—or as a result of poor implementation that may depress productivity before generating benefits.

When analyzing how the GDP variable reacts to the GT shock, a negative response is observed with a magnitude of 0.08. This result is counterintuitive from a fiscal policy perspective, since tax expenditures are an economic stimulus. This confirms once again the finding by Corcelli (2021). The GT shock also leads to a positive and increasing response in Gross Debt. Since tax expenditures represent a revenue waiver, their increase directly leads to the accumulation of public debt. The effect of continuous growth, reaching approximately 0.08 by the end of the period, only confirms the pressure generated by GTs.

Chart 2 – Generalized Impulse-Response Function (non-cumulative shocks)

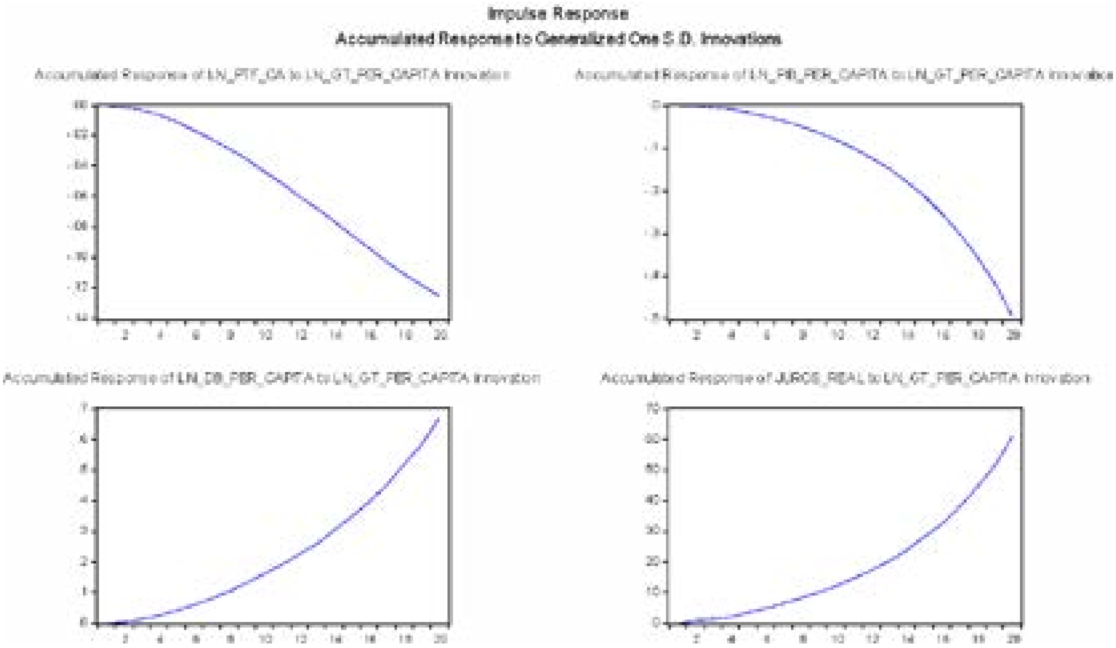


Source: Author's own work. Use of Eviews econometric software

In the analysis of cumulative shocks, as shown in Figure 3 (long-term response), productivity has a cumulative effect that reaches a negative peak of 0.14. This reinforces the fact that, in the long run, the increase in GT not only fails to boost productivity but also causes a significant net loss in TFP. The trajectories of GDP and General Government Gross Debt follow the same pattern, showing that the economic stimulus from tax grants is ineffective and leads to a large increase in government debt in the long run.

In summary, economic theory and the literature on fiscal efficiency are largely unfavorable to the expansion of tax expenditures. The main objective of this study is to identify the impact of tax expenditures on the PTF, and through impulse-response functions, we can infer that in the short and long term, the shock fails to achieve its objective of increasing productivity and GDP, while generating high monetary and fiscal costs that can stifle growth.

Chart 3 - Generalized Impulse-Response Function (cumulative shocks)



Source: Author’s own work. Using the econometric software Eviews

6. FINAL CONSIDERATIONS AND POLICY IMPLICATIONS

This study has demonstrated that Tax Expenditures, an essential tool within Brazilian fiscal policy, may be having a negative impact on the country’s Total Factor Productivity. Using the Bayesian Autoregressive Vector Model, this study aligns with the literature on the effectiveness of tax expenditures, supporting the view that tax breaks, in their current form, are not aligned with their primary objective, which is to provide incentives for sustainable economic growth. Its main contribution lies in the use of an advanced methodology to capture dynamic and intertemporal effects, filling a gap in the literature regarding the analysis of the relationship between tax breaks and TFP in Brazil.

The most significant finding revealed by the BVAR model is that the coefficient of tax expenditures on the PTF is negative and statistically significant. This finding suggests that these tax benefits are poorly targeted and may be distorting resource allocation rather than stimulating gains in efficiency and innovation. This result aligns with Corcelli’s (2021) view on the inefficiency of tax incentives in long-term growth, and with the international literature indicating the great need to evaluate these subsidies.

The dynamic analysis, through variance decomposition and impulse-response functions, indicates that the influence of tax incentives on productivity manifests itself in the medium to long- , with shocks in tax expenditures accounting for up to 3.9% of the variance in TFP in the tenth period. However, the result of a negative and cumulative impact in the long term may indicate that these incentives may be stifling innovation and inducing rent-seeking behavior on the part of firms, as further explored by Ma et al. (2023).

The implications of this study extend beyond the realm of fiscal policy and directly affect the sustainability of public finances and the fight against inequality. With GTs projected to exceed R$ 544.5 billion in 2025, representing nearly 5% of federal GDP in 2023, the ineffectiveness of this spending exacerbates Brazil's already high tax burden and diverts resources that could be allocated to strategic social areas that would yield greater benefits, such as health, education, and public safety. The results underscore the need to treat GTs with the same level of importance and rigor as budgetary expenditures. Instead of creating taxes to raise more revenue—thereby reducing people's purchasing power—as the current government has been doing, or implementing taxes on individuals considered ultra-wealthy—a measure that has proven ineffective in numerous cases, such as in France and Sweden, which suffered for many years from tax evasion and declining revenues— the government could utilize the misused and inefficient amounts of tax expenditures to increase its revenues.

To guide future research, we suggest conducting a disaggregated analysis of tax expenditures. A more precise analysis to determine the impact of each tax expenditure on productivity would be ideal for identifying which expenditures may be causing a decline in productivity due to poor targeting, and which expenditures yield effective returns and achieve the objectives of this fiscal policy.

In light of the above, this study recommends that policymakers enact a General Law on Tax Expenditures, establishing clear provisions and, above all, periodic and transparent effectiveness evaluations, ensuring that the state's tax waivers are, in fact, an investment and not merely another cost for which the population must foot the bill.

Appendix A - Selection of the Optimal Number of Lags

VAR Lag Order Selection Criteria

Endogenous variables: PTF PIB GT DBGG JR

Exogenous variables: C D1999 D2003 D2008 D2020

Date: 10/21/25 Time: 21:31

Sample: 1995 2024

Included observations: 28

Lag	LogL	LR	FPE	AIC	SC	HQ
0	19.13466	NA	1.07e-06	0.418953	1.608422	0.782586
1	172.0890	196.6556*	1.32e-10	-8.720646	-6.341709*	-7.993381
2	210.9265	36.06340	7.80e-11*	-9.709039*	-6.140634	-8.618142*

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Appendix B - Stability Condition of the VAR Model

Roots of Characteristic Polynomial

Endogenous variables: PTF

PIB

GT

DBGG

JR

Exogenous variables: C D1999 D2003

D2008 D2020

Lag specification: 1 2

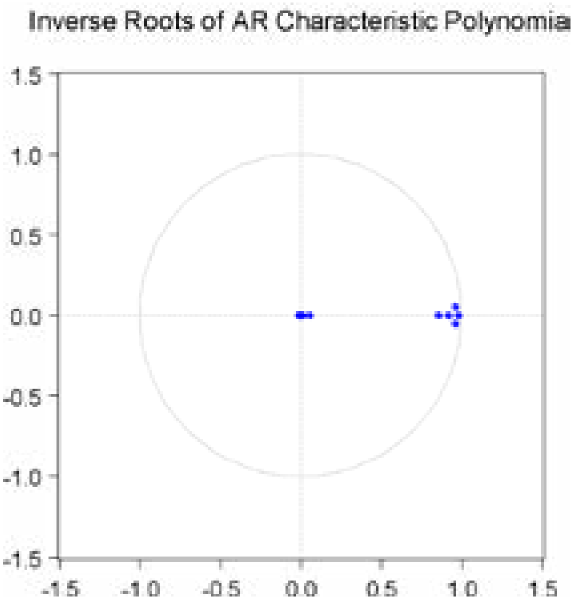
Date: 10/21/25 Time: 21:34

Root	Modulus
0.974162	0.974162

0.960668 - 0.048213i	0.961877
0.960668 + 0.048213i	0.961877
0.916462	0.916462
0.852250	0.852250
0.055066	0.055066
0.016735	0.016735
-0.010325	0.010325
-0.005911	0.005911
0.005315	0.005315

No root lies outside the unit circle.

VAR satisfies the stability condition.



Appendix C – Normality of Residuals

VAR Residual Normality Tests

Orthogonalization: Cholesky (Lutkepohl)

Null Hypothesis: Residuals are multivariate normal

Date: 10/21/25 Time: 22:05

Sample: 1995 2024

Included observations: 28

Component	Skewness	Chi-sq	df	Prob.*
1	-0.199944	0.186561	1	0.6658
2	0.847431	3.351320	1	0.0672
3	-1.389527	9.010326	1	0.0027
4	-0.570651	1.519667	1	0.2177

5	0.561309	1.470315	1	0.2253
Joint		15.53819	5	0.0083

Component	Kurtosis	Chi-sq	df	Prob.
1	3.539823	0.339977	1	0.5598
2	5.946841	10.13118	1	0.0015
3	5.826770	9.322400	1	0.0023
4	5.478117	7.164576	1	0.0074
5	2.432263	0.376047	1	0.5397
Joint		27.33418	5	0.0000

Component	Jarque-Bera	df	Prob.
1	0.526539	2	0.7685
2	13.48250	2	0.0012
3	18.33273	2	0.0001
4	8.684243	2	0.0130
5	1.846362	2	0.3973
Joint	42.87237	10	0.0000

*Approximate p-values do not account for coefficient estimation

Appendix D - Heteroscedasticity of Residuals

VAR Residual Heteroskedasticity Tests (Levels and Squares)

Date: 10/21/25 Time: 22:08

Sample: 1995 2024

Included observations: 28

Joint test:		
Chiq-sq	df	Prob.
381.5767	360	0.2080

Individual components:					
Dependent	R-squared	F(24,3)	Prob.	Chi-sq(24)	Prob.
res1*res1	0.835420	0.634511	0.7789	23.39177	0.4968
res2*res2	0.825994	0.593364	0.8033	23.12782	0.5123
res3*res3	0.910325	1.268924	0.4876	25.48910	0.3796
res4*res4	0.947077	2.236902	0.2784	26.51814	0.3274
res5*res5	0.998008	62.62418	0.0028	27.94422	0.2624
res2*res1	0.892415	1.036874	0.5744	24.98762	0.4064
res3*res1	0.988061	10.34523	0.0389	27.66572	0.2744
res3*res2	0.901951	1.149872	0.5296	25.25463	0.3920
res4*res1	0.898640	1.108230	0.5455	25.16192	0.3970
res4*res2	0.875166	0.876332	0.6475	24.50466	0.4331
res4*res3	0.935021	1.798687	0.3508	26.18058	0.3441

res5*res1	0.958298	2.872445	0.2092	26.83234	0.3123
res5*res2	0.950667	2.408807	0.2563	26.61868	0.3225
res5*res3	0.989394	11.66044	0.0328	27.70302	0.2728
res5*res4	0.959713	2.977775	0.2004	26.87198	0.3105

Appendix E – Autocorrelation

VAR Residual Serial Correlation LM Tests

Date: 10/21/25 Time: 22:10

Sample: 1995 2024

Included observations: 28

Null hypothesis: No serial correlation at lag h						
Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	79.70325	25	0.0000	10.78148	(25, 16.4)	0.0000
2	68.21822	25	0.0000	6.918158	(25, 16.4)	0.0001
3	55.89732	25	0.0004	4.211755	(25, 16.4)	0.0020

Null hypothesis: No serial correlation at lags 1 to h						
Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	79.70325	25	0.0000	10.78148	(25, 16.4)	0.0000
2	NA	50	NA	NA	(50, NA)	NA
3	NA	75	NA	NA	(75, NA)	NA

*Edgeworth expansion corrected likelihood ratio statistic.

Appendix F - Variance Decomposition

Variance Decomposition of PTF:

Period	S.E.	PTF	PIB	GT	DBGG	JR
1	0.015089	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.021191	99.92323	0.006710	0.061616	0.008343	0.000105
3	0.025726	99.66488	0.059798	0.265639	0.009233	0.000449
4	0.029424	99.23470	0.162149	0.591356	0.010750	0.001044
5	0.032566	98.66152	0.307815	1.013123	0.015617	0.001921
6	0.035299	97.97064	0.491025	1.508497	0.026686	0.003155
7	0.037708	97.18250	0.707004	2.058485	0.047151	0.004857
8	0.039853	96.31374	0.951886	2.647100	0.080098	0.007171
9	0.041775	95.37818	1.222510	3.260894	0.128142	0.010272
10	0.043504	94.38763	1.516229	3.888550	0.193228	0.014359

Variance Decomposition of PIB

Period	S.E.	PTF	PIB	GT	DBGG	JR
1	0.029105	12.65162	87.34838	0.000000	0.000000	0.000000
2	0.040606	13.24517	86.68809	0.000568	0.046972	0.019200
3	0.048691	13.71216	85.98563	0.014811	0.219328	0.068071
4	0.054991	14.09187	85.22844	0.046960	0.490843	0.141877
5	0.060148	14.39483	84.44664	0.095334	0.827007	0.236186
6	0.064495	14.62910	83.66589	0.157363	1.200320	0.347328
7	0.068227	14.80199	82.90490	0.230401	1.590386	0.472329
8	0.071475	14.92029	82.17633	0.311933	1.982643	0.608799
9	0.074327	14.99031	81.48812	0.399648	2.367091	0.754827
10	0.076848	15.01789	80.84457	0.491466	2.737192	0.908880

Variance Decomposition of GT:

Period	S.E.	PTF	PIB	GT	DBGG	JR
1	0.096019	0.242480	17.48654	82.27098	0.000000	0.000000
2	0.130320	0.174189	18.03210	81.54001	0.251929	0.001772
3	0.153678	0.488258	18.22098	80.29792	0.985709	0.007130
4	0.171555	1.164717	18.26106	78.50320	2.052113	0.018917
5	0.186132	2.170071	18.21167	76.28220	3.296174	0.039884
6	0.198511	3.461152	18.10131	73.77238	4.592927	0.072223
7	0.209322	4.990193	17.94754	71.09439	5.850547	0.117329
8	0.218953	6.708729	17.76230	68.34604	7.007195	0.175732
9	0.227658	8.570201	17.55403	65.60284	8.025779	0.247149
10	0.235613	10.53152	17.32876	62.92078	8.888336	0.330604

Variance Decomposition of DBGG:

Period	S.E.	PTF	PIB	GT	DBGG	JR
1	0.056405	1.559539	11.12960	0.048617	87.26225	0.000000
2	0.074930	1.798322	11.17081	0.071169	86.87558	0.084121
3	0.085419	2.059249	11.01371	0.058284	86.57721	0.291549
4	0.091965	2.312719	10.79839	0.052565	86.21372	0.622600
5	0.096266	2.544180	10.56287	0.064274	85.75746	1.071221
6	0.099203	2.744269	10.32496	0.096303	85.20827	1.626200
7	0.101286	2.907328	10.09569	0.148417	84.57612	2.272447
8	0.102823	3.031073	9.882388	0.218534	83.87550	2.992507
9	0.104010	3.116252	9.689695	0.303426	83.12254	3.768086
10	0.104971	3.166137	9.520056	0.399239	82.33323	4.581340

Variance Decomposition of JR:

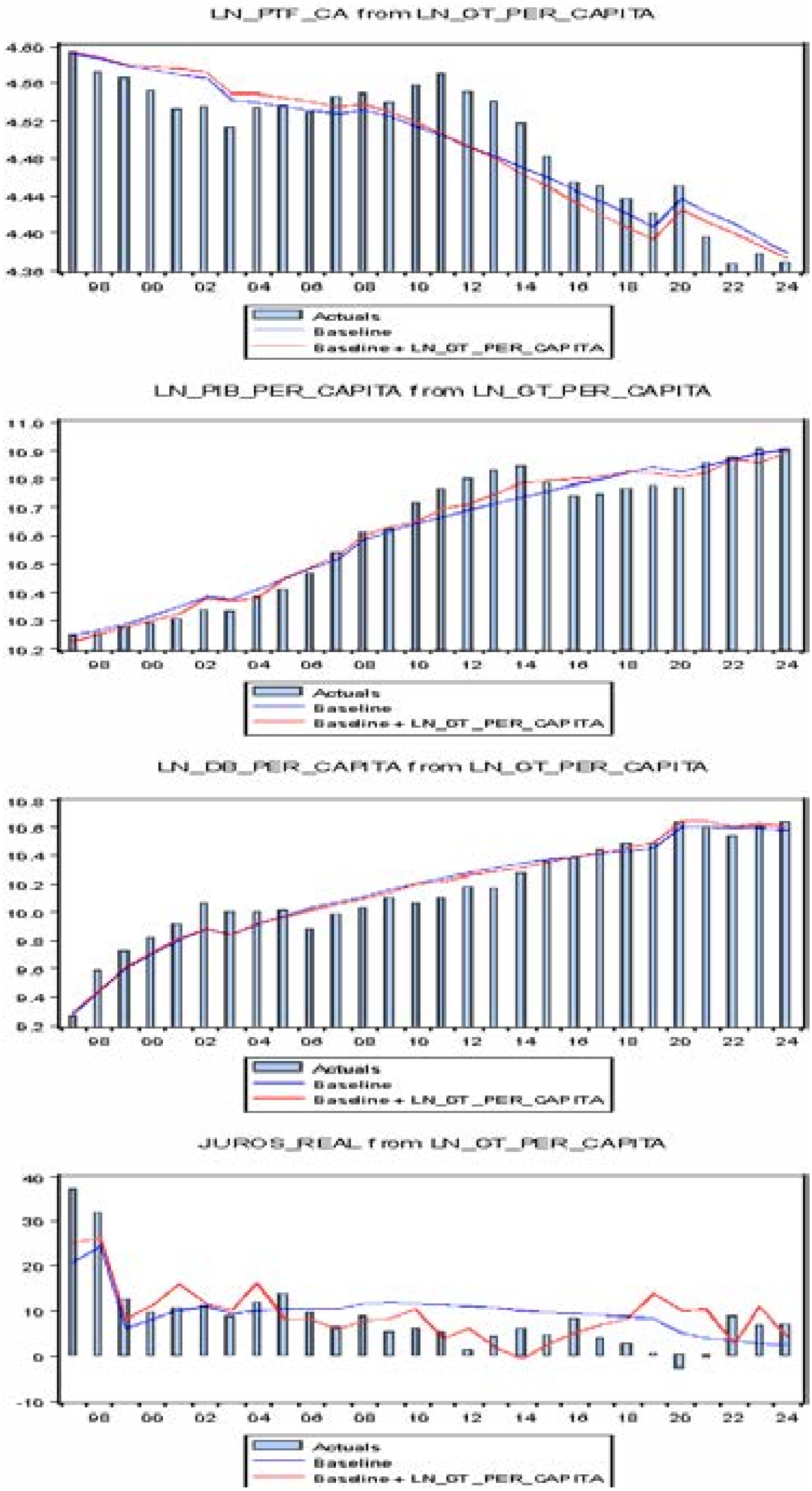
Period	S.E.	PTF	PIB	GT	DBGG	JR
1	4.538049	0.436152	0.331607	41.73969	10.83917	46.65338
2	6.227364	0.739248	0.498117	38.82513	12.70080	47.23670
3	7.435183	1.081786	0.633373	36.30700	14.74358	47.23426
4	8.381731	1.452903	0.754010	34.06074	16.69113	47.04122
5	9.154693	1.840896	0.862318	32.06100	18.46911	46.76667
6	9.800048	2.236111	0.959235	30.28824	20.05471	46.46171
7	10.34590	2.630783	1.045700	28.72270	21.44619	46.15463
8	10.81127	3.018694	1.122764	27.34460	22.65207	45.86187
9	11.21000	3.394877	1.191529	26.13486	23.68595	45.59278
10	11.55271	3.755384	1.253074	25.07560	24.56373	45.35221

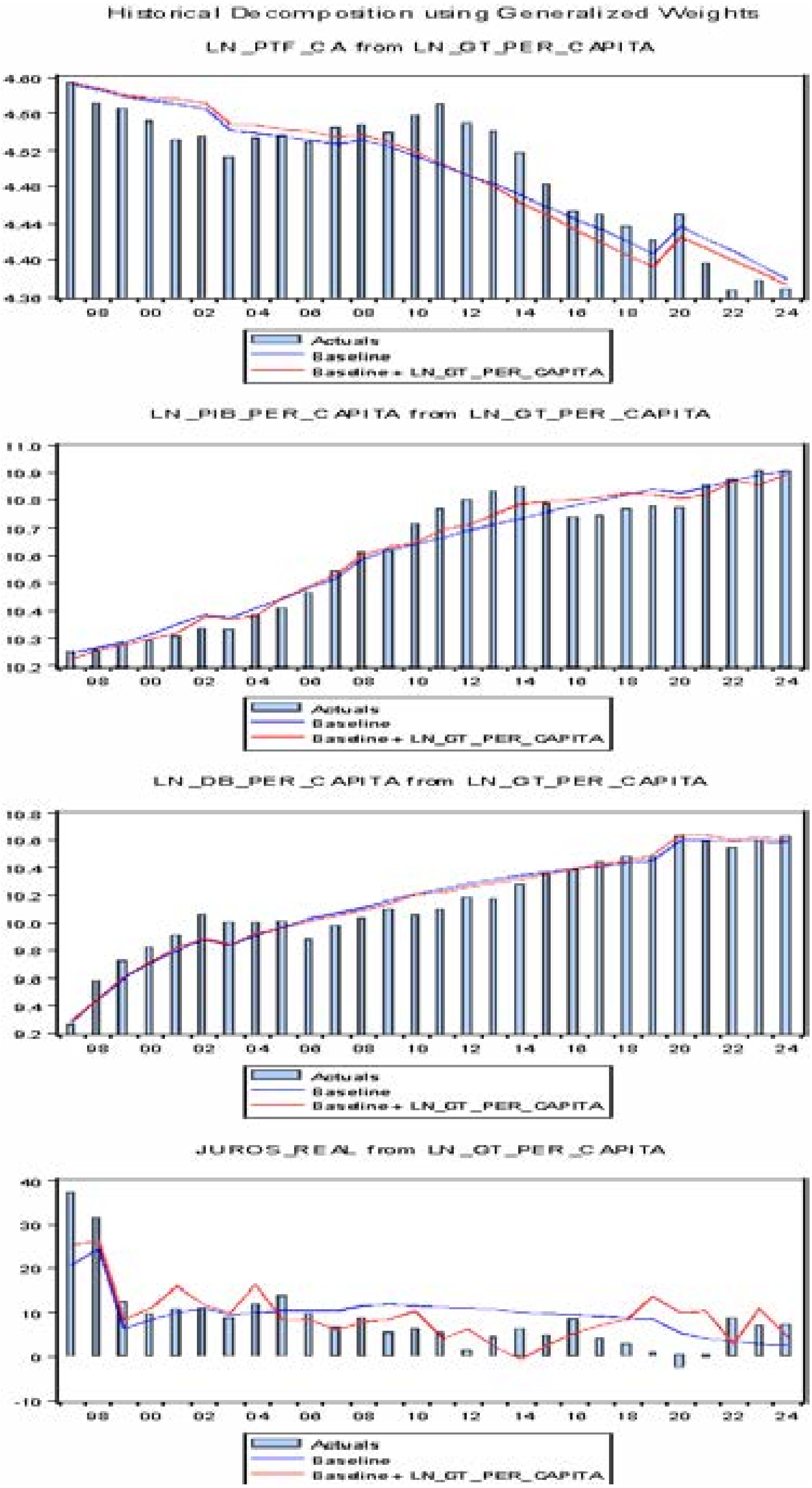
Cholesky One S.D. (d.f. adjusted) Innovations
Cholesky ordering: PTF PIB GT
DBGG JR

Appendix G – Classical Decomposition

Analysis of the impact of GT shocks on PTF indicates that, at various points in the historical series, the contribution of these shocks was below the baseline, suggesting a depressive effect on the productivity trajectory. This result aligns with the conclusion of Corcelli (2021), who found a negative linear relationship between the GT/GDP ratio and annual *per capita* growth. In addition, the tax expenditure shock contributes to a gradual increase in the trajectory of general government gross debt. This increase in debt only reinforces the argument by Renzio et al. (2024) and Nery (2025) regarding the fiscal challenge posed by general government entities, and how they require a reassessment of policies to ensure that they promote economic growth in a sustainable manner and do not merely cause an ever-increasing rise in government debt.

Historical Decomposition using Generalized Weights





Fonte: Elaboração própria. Uso do software econométrico Eviews

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