FORECASTS ON THE GROWTH OF BRAZILIAN PUBLIC DEBT 2000-2026

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Abstract: A country's public debt is one of the main indicators of deficit control. In Brazil, the exponential growth of public debt in the 2000s, especially from 2016 onwards, has become the subject of extensive academic and institutional debate. In this sense, this study aims to predict the growth of Brazilian public debt using time-series econometrics. Tests indicated that the Autoregressive model. The Integrated Moving Average (ARIMA) (0,2,1), derived from an ETS function, is the most parsimonious for forecasting. The results indicated forecasts with Mean Absolute Percentage. The error (MAPE) was 1.76 in the training dataset and 3.82 in the test dataset. The forecasts made from the training datasets and validated on the test datasets indicate that, for the months of October 2023 to June 2026, Brazil's net public sector debt trajectory is upward.

Keywords: public debt. forecasts. time series.

Resumo: A dívida pública de um país é um dos principais indicadores de controle do déficit. No Brasil, o crescimento exponencial da dívida pública nos anos 2000, sobretudo a partir de 2016, tem se tornado objeto de amplo debate acadêmico e institucional. Nesse sentido, este estudo visa fazer previsões sobre o crescimento da dívida pública brasileira por meio de econometria de séries temporais. Os testes indicaram que o modelo Autoregressive Integrated Moving Average (ARIMA) (0,2,1), a partir de uma função ETS, é o mais parcimonioso para previsões. Os resultados indicaram previsões com Mean Absolute Percentage Error (MAPE) de 1,76 na base de treino e de 3,82 na base de teste. As previsões realizadas a partir das bases de treino e validadas nas bases de testes, mostram que para os meses de outubro de 2023 a junho de 2026 a trajetória da dívida liquida do setor público brasileiro é ascendente.

Palavras-chave: dívida pública. previsões. séries temporais.

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1 Initial Considerations

The growth of Brazilian public debt is attracting increasing attention, not only in academia but also among policymakers. This issue becomes even more relevant given the debt's behavior over the last few decades, which has shown upward trends. The evolution of public debt, in addition to reflecting the dynamics of fiscal accounts, is closely related to factors such as levels of public and private investment and the sustainability of the country's economic growth.

In the Brazilian context, challenges related to public debt have gained prominence since the 2000s, with periods of intense oscillation between fiscal stability and a significant increase in indebtedness. These changes reveal both the economy's vulnerability to external and internal shocks and the impacts of political and economic decisions. Since 2016, a more pronounced increase has been observed, underscoring the importance of analyses that account for long-term dynamics.

Given this scenario, the use of advanced analytical tools, such as time-series analysis, becomes essential to explore public debt behavior and to make robust forecasts that support more effective public policies. The time series approach not only allows us to describe the historical behavior of debt but also to understand the impacts of underlying economic variables and predict future trajectories.

This article aims to predict Brazil's net public sector debt growth from 2000 to 2026 using econometric time-series models. Among the main results obtained, the identification of a peak shift in net public sector debt from 2016 onwards stands out. This shift may be associated with political and economic factors that shape debt behavior, as well as with projections of increasing trajectories, which can inform strategies focused on fiscal sustainability.

The article's structure is organized as follows: the second section presents the methodological aspects that underpin the analyses, highlighting the data and models used. The third section reviews international and national literature; the fourth presents the results and related discussions. Finally, the concluding remarks summarize the main conclusions and suggest practical implications and avenues for future studies.

2 Methodological Procedures

In general terms, the methodological aspects are outlined by the type of research, the resources to be used, and the necessary procedures relevant to the object of study that are required for scientific investigation. Thus, the investigation was carried out using secondary data imported from the BACEN website and subsequently using R 4.3.1 to estimate the database. It is evident that the nature of the investigation was applied research, adopting the hypothetical-deductive method, through the establishment of relationships between variables, that is, the levels of impact between them, and is therefore classified as applied quantitative research. Regarding the research procedure, it was carried out through action research, since this method guides the investigative field in defining the variables studied, given the temporal periodicity. From there, the database was extracted from statistical sources, and finally, the data was analyzed, and the results were disseminated.

2.1 Area and Scope of the Data

The data used were extracted from the website of the Central Bank of Brazil (BACEN), subsequently entered into a spreadsheet, and then all its analytical content was estimated using R software to determine the impacts of public debt on investment levels and national economic growth.

2.2 Temporal and Spatial Delimitation

Regarding the period analyzed, the study begins in 2000, with monthly periodicity for all variables under study, making it the first year with data on Brazilian public debt and its impacts on investment levels and the Brazilian economy's growth rate over twelve months.

2.3 Univariate Model

2.4 Unit Root Tests

The objective of time series, in its analytical aspect, consists of constructing models with specific purposes that involve investigating the generating mechanism, making predictions, describing the behavior of the series, and searching for relevant periodicity in the data (Nomelini). et al., 2017). According to Almeida et al. (2008), historical series, in practice, exhibit trend and/or seasonality components and, in most cases, are considered non-stationary. To guarantee the invertibility of the process, it is necessary to meet the stationarity condition of the series. Latorre and Cardoso (2001) add that, to obtain a simpler model, the historical series must be free of any trend and seasonality components to prove stationarity. Stationarity of a series is a primary factor in its development over a time interval around a constant average (Nomelini). et al., 2017). Therefore, Bueno (2012) specifies that in the econometric field, there is convergence of residuals, given the ease in obtaining statistical inferences, and there is also a noticeable constancy in both the average value and the dispersion of the data. It is relevant that the unit root tests accept the alternative hypothesis, whereas they do not corroborate any indication of this econometric violation in the time series. The Dick-Fuller test equation considers the following model:

$$Y_t = \rho Y_{t-1} + \varepsilon_t, \quad -1 \leq \rho \leq 1, \quad t = 1, 2, \ldots, N \tag{1}$$

where Y_t represents the series; ρ the coefficient of $Y_(t-1)$; and ϵ_t, the white noise.

In difference form, for the purpose of performing the test, eq. (1) can be expressed as follows:

$$Y_t - Y_{t-1} = \rho Y_{t-1} - Y_{t-1} + \varepsilon_t \tag{2}$$

Therefore, the Dick-Fuller test equation is expressed as follows:

$$\Delta Y_t = \delta Y_{t-1} + \varepsilon_t \tag{3}$$

Where, Δ is the first difference operator and $\delta = \rho - 1$.

Dickey -Fuller (1981) demonstrates that when = 0, the test follows the δ statistic. The decision rule for detecting the unit root occurs when the null hypothesis is accepted, where $\delta = 0$, therefore $\rho = 1$ and, consequently, there is detection of a unit root, which indicates the non-stationarity of a series. In short:

$H_0 : \delta = 0$ (there is a unit root, therefore the series is not stationary)

$H_1 : \delta < 0$ (there is no unit root, therefore the series is stationary)

The persistence of a unit root in a series is tested using the Augmented Dickey-Fuller (ADF) test, which considers lagged values of the dependent variable in the estimated model. From there, the lag in the differences is defined, first by choosing a high value and then by verifying the significance of the last lag. (Silveira; De Mattos; Konrath, 2016).

The ADF (Augmented Dickey-Fuller) test assists in this decision-making process by considering models in which the variables are generated by an autoregressive process of order p. Including the lagged difference of the variable in the model preserves the white-noise condition of the error. The test consists of estimation using three equations:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \varepsilon_t \tag{4}$$

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \varepsilon_t \tag{5}$$

$$\Delta Y_t = \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \varepsilon_t \tag{6}$$

The KPSS test also aims to test the stationarity hypothesis for a given series, seeking to determine whether there are indications of a unit root. The null hypothesis supports the possibility of the series being stationary, in contrast to the Augmented Dickey-Fuller (ADF) test (Sibin, Da Silva Filho Ballini, 2016).

The Phillips-Perron test is like the Dickey-Fuller test in both its mathematical and interpretive approaches. Consistency is essential because even with dependent lags and the presence of serial autocorrelation in the errors, a non-parametric correction is applied to the Dickey -Fuller test (Bueno, 2012). The interpretation, based on the hypotheses, highlights any indication of a unit root, since the non-rejection of the null hypothesis indicates non-stationary behavior, explained by the fact that the statistical test exceeds the critical value at a certain significance level. The mathematical model of the PP test is explained below.

$$\Delta Y_t = \gamma Y_{t-1} + \varepsilon_t \rightarrow z_t \tag{7}$$

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \varepsilon_t \rightarrow z_t \tag{8}$$

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \varepsilon_t \rightarrow z_t \tag{9}$$

The model proposed by Zivot and Andrews applies when a breakpoint is chosen so that the structural break receives greater weight in accepting the stationary trend model (Bueno, 2012). The disadvantage of the test is that its critical values are based on the null hypothesis of a unit root, making it invalid if the break occurs due to nonstationarity. This leads to divergence in the test statistics, which can result in spurious rejection (De Medeiros Braga, 2014).

The application of the DF-GLS test , proposed by Elliot, Rothenberg, and Stock (1996), provides a more robust view of the Augmented Dickey-Fuller (ADF) test applied to the series, preliminarily filtered of its deterministic components. The test aims to identify possible indications of a unit root, as indicated by the non-rejection of the null hypothesis (Caldarelli & Bacchi, 2012).

2.5 Univariate ARIMA Model

The Box and Jenkins (1994) methodology used for forecast estimation was based on the Autoregressive Integrated Moving Average (ARIMA) model.

Detzel et al. (2013) state that, generically, the method is represented by the orders (p, d, q), respectively defined by the autoregressive order (AR); the integrated part, defined by the number of differences (I); and the moving average component (MA), which, according to Gonçalves and Pandolfi (2024), the ARIMA model is a diffusion of the ARMA model, however applied to series that presented roots inside the unit circle, that is, the stationarity conditions were not satisfied for the level series. Therefore, in stochastic processes, the use of different series is necessary to ensure unbiased analysis in the face of spurious regressions.

$$(1 - \phi_1 B - \cdots - \phi\prime_p B^p)(1 - B - \cdots - B^d)z_t = (1 - \theta_1 B - \cdots - \theta_q B^q)\varepsilon_t \qquad (10)$$

As expressed above, the predictive model mathematically emphasizes ARIMA modeling in its generalized form, as well as the incorporation of autoregressive orders, the integrated part, and moving average orders. The left side of the equation denotes that the first term, defined by , $(1 - \phi_1 B - \cdots - \phi\prime_p B^p)$ demonstrates the polynomial of the autoregression term, accompanied by the coefficients $\phi_1, \ldots, \phi_(p)$, followed by the differentiation term $(1 - B - \cdots - B^d)z_t$, where drepresents the number of times the series needs to be differentiated to make it stationary; the term z_t represents the stationary time series, the entire structure of the historical series, along with its lags. The second member of the equation, in turn, expresses the polynomial referring to the moving average term, being, respectively, $\theta_1, \ldots, \theta_q$ and qthe coefficients and the order relative to the MA model. ϵ_t represents the error term of the original series, while Bdenotes the difference operator.

Traditionally, according to Gonçalves and Pandolfi (2024), the technique used to determine the ordering of the autoregressive (AR) and moving average (MA) parts is defined, respectively, by the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), whose ordering parameters are visually defined by finding the number of lags that exceed the critical value, considered insignificant. For this work, however, an automatic method was used to optimize the predictive model, determined by the auto.arima function from the forecast package in R. The predictive model resulting from the function described above aims to identify, among several model options, the one that minimizes the information criterion, in a combination of different orders p, deq, with the lowest reference value among the criteria.

According to Bueno (2012), information criteria determine the number of parameters or regressors in the model, aiming to balance the exclusion of errors and the incorporation of new regressors, assigning a degree of penalty to the addition of parameters. In other words, the incorporation of new parameters determines the penalty, with the goal of minimizing errors. If the penalty exceeds the sum resulting from the reduction of residuals, this additional regressor would bring more costs than benefits, resulting in the loss of degrees of freedom, a less parsimonious model, and, evidently, inconsistencies in the estimations. Therefore, it is necessary to adhere to the most parsimonious model, i.e., the one with the fewest parameters, aiming to obtain estimates with the minimum degree of imprecision. In general, the specification criterion presents the following expression:

$$C = \ln\left(\hat{\sigma}^2\right)(T) + c_T\,\varphi(T) \tag{11}$$

where σ^2 represents the estimated variance of the residuals, mathematically expressed as

$$\hat{\sigma}^2 = T^{-1}\sum_{i=1}^{T}\varepsilon_T^2 \tag{12}$$

is c_T the number of parameters; and is $\varphi(T)$ the model's ordering, which checks for possible parsimony violations. The value of T represents the number of observations.

Akaike (AIC), Bayesian Information (BIC), and Hannan–Quinn (HQ) criteria are expressed, respectively, by the following expressions:

$$AIC(p,q) = \ln\left(\hat{\sigma}^2\right) + 2\left(\frac{n}{T}\right) \tag{13}$$

$$BIC(p,q) = \ln\left(\hat{\sigma}^2\right) + \left(\frac{n}{T}\right)\ln T \tag{14}$$

$$HQ(p,q) = \ln\left(\hat{\sigma}^2\right) + 2\left(\frac{n}{T}\right)\ln T \tag{15}$$

Where $\hat{\sigma}^2$ represents the variance of the residuals, explicit in equation (12), as well as $n = p + q$ when there is no constant and $n = p + q + 1$ when there is a constant.

Once the model that best fits the predictions is defined, its robustness is subsequently verified, one aspect of which is established by accuracy, measured by the Mean Absolute Percent Error (MAPE). Finally, the model's quality is analyzed using the Ljung–Box test, which, according to Yasmin and Moniruzzaman (2024), requires the p-value to indicate insignificance at a certain level in order to validate the absence of autocorrelation of the residuals; that is, there must be evidence to accept the null hypothesis that the residuals are identically distributed.

3 Review of international and national literature

3.1 Application of exponential smoothing models to time series on public debt: an empirical approach in international studies

Given the global context, this subsection reviews the international literature on time-series forecasting models for the exponential smoothing method. This econometric model predicts using weighted averages based on past and more recent information, where the weight decreases as time goes back and increases as time goes forward, unlike more recent observations. Therefore, the global context of various economic variables is expanded upon in this exponential smoothing time-series model.

The observations put forth by Dumičić, Čeh Časni, and Žmuk (2015) aim to select the best forecasting model to improve the credibility of unemployment rate predictions for selected European countries. To this end, the authors used various time-series forecasting techniques that include a trend component. The most viable models were those using double-exponential smoothing, which considers trends without seasonality, and the Holt-Winters method, which considers trends with seasonality. According to the mean percentage error (MAPE), the viable model for forecasting time series is determined by the low percentage error obtained. Therefore, based on the results obtained, the optimal model for predicting the unemployment rate in Greece was the Holt-Winters additive method, with an MAPE of 3.684%. The greater viability of the forecasting models for Portugal and Spain was due to the use of double exponential smoothing, with a percentage error of approximately 3.933%. In the case of Italy and Croatia, both used the multiplicative Holt-Winters model, with MAPEs of 4.679% and 4.695%, respectively.

Jere and Siyanga (2016) examined Zambia's inflation behavior using monthly data from 2010 to 2014 on the General Consumer Price Index (CPI). To obtain the best fit for the time series, the ARIMA (12, 1, 0) model is viable for both the CPI and the Zambian inflation level, respectively. In addition to ARIMA, the optimal model was also observed when applying Holt's exponential smoothing, which, like ARIMA, considers low indices of the mean absolute percentage error and the mean squared error. Consequently, the inflation rates for April and May 2015 in Zambia differed by only 0.4 percentage points, with predictions of 7% and 6.6%, respectively.

One of the most notable macroeconomic indicators globally is the unemployment rate. Considering this, Nor et al. (2018) predicted the Malaysian unemployment rate for 2016. The prediction methods were based on Naïve, Simple Exponential Smoothing, and Holt's method, using five sets of Malaysian unemployment data. The results emphasize the viability of Holt's model in the face of global unemployment rates, the annual male rate, and the overall quarterly rate. Furthermore, the Simple Exponential Smoothing method will apply to the female unemployment rate and the overall monthly unemployment rate. Based on the above, the predictions for Malaysia's unemployment rate in 2016 resulted in almost 3% (2.9%), while 3.4% is projected for the second half of the same year, based on quarterly and monthly data. The percentages obtained for predicting global data for men and women were 2.9% and 3.4%, respectively.

In summary, this subsection will focus on explaining the application of exponential smoothing methods to time series, in relation to studies on the predictive behavior of various economic series, as reported in the external literature.

3.2 Application of exponential smoothing models to time series on public debt: an empirical approach in national studies

Analyzing the tourism potential of Brazilian cities, Costa, Santos, and Yamashita (2008) describe, based on statistical errors, the analytical procedures for forecasting demand in the tourism sector, specifically in air transport. Methodologically, the authors relied on 2006 data to analyze demand forecasts for air transport via simple exponential smoothing and potential regression, with each model applied to "sun and beach" and "business and events" tourism, respectively. It is important to emphasize that one of the peculiar assumptions of statistical analysis is the choice of the model with the smallest possible margin of error, as the authors evidently apply it to the simple exponential smoothing and exponential regression models for forecasting demand in the air sector. Furthermore, in this study, the Congonhas and Galeão airports were excluded because they exhibited discrepancies in error relative to the others, given the differences in economic capacity between the airports in the two forecasting models.

Also, from a demand forecasting perspective, Veríssimo et al. (2013) seek to predict sales demand planning for a specific company located in the north of the state of Santa Catarina, aiming to make optimized decisions within the administrative scope of this company in the metal-mechanical sector. Notably, the authors omit information about the establishment under analysis, citing ethical considerations in scientific research. Methodologically, the study used sales time series for two product categories, whose behavior exhibits seasonality and is significant for costs and investments. The projections for the series were based on the Holt-Winters exponential smoothing model, which accounts for prevailing seasonality. Due to the seasonal behavior, the Holt-Winters Seasonal Multiplicative and Additive methods were applied. The results, therefore, are based exclusively on historical sales demand series, to which the forecasting analyst must pay attention regarding model accuracy, as well as to monitor possible predictive errors when necessary.

Bastos (2016) evaluated the performance of national diesel oil production using a time-series forecasting approach between January 2000 and August 2014. The author used different methods, including Basic Decomposition, Trend-corrected Exponential Smoothing (Holt), Trend-corrected and Seasonality-corrected Exponential Smoothing (Holt-Winters), and the ARIMA model, aiming to choose the one that yielded the lowest possible error. After analyzing the feasibility of the predictive methods, the author concluded that Holt-Winters Exponential Smoothing yielded the lowest error rate among the methodologies mentioned.

At the end of this subsection, it becomes clear that national studies on exponential smoothing methods have been included, given the absence of studies specifically on public debt in the national context that use this method.

3.3 Application of ARIMA models to time series on public debt: an empirical approach in international studies

This subsection reviews the international literature on studies that apply ARIMA models to time series and forecast certain economic indicators from an external perspective.

Frequently debated in economic and political spheres, the unemployment rate is one of the indicators discussed in the literature below, with the aim of making predictions through econometric time-series modeling. In view of this, the study proposed by Adenomon (2017) used annual data from 1972 to 2014 to predict the evolution of unemployment rates in Nigeria between 2015 and 2017. Before applying the forecasting model, any indications of a unit root were first investigated using the Augmented Dickey-Fuller (ADF) test, which confirmed stationarity in first differences. Subsequently, the ideal prediction model for this economic indicator was verified, offering greater credibility to the inferences, and was therefore confirmed by the ARIMA model with two lags considered in the forecast, along with an applied differentiation and two past residuals, synthetically represented by ARIMA (2, 1, 2). Regarding the results, the author concluded that the forecast for the Nigerian unemployment rate for 2015 to 2017 had followed an upward trajectory; however, in 2018, the trend would reverse, with a substantial decline.

Ramli et al. (2018) predicted unemployment behavior in Malaysia between 2017 and 2026. The study aimed to identify factors contributing to Malaysia's unemployment rate and to identify an optimal model for predicting this economic indicator. Methodologically, the research used the following variables: inflation rate, population, and economic growth, and the results corroborate the possible significance of unemployment, determined by inflation rates and population. Considering the ideal model for data prediction, ARIMA (2, 1, 2) proved to be the best option for the estimation. Therefore, unemployment rates are expected to increase between 2017 and 2026. However, according to the authors, this possible increase is not expected to be a critical factor for the Malaysian economy over the next ten years.

In the Turkish context, Uğur and Erkal (2021) analyzed the perspective on economic growth and unemployment. Therefore, the resulting models from this dual database, involving two macroeconomic indicators, were based on the ARIMA (2, 1, 1) forecasting method for the unemployment level and on the ARIMA (1, 1, 0) model for the growth of the Turkish economy. The forecasting period was based on historical data, specifically from 1988 to 2017. Thus, the forecasting power will be evaluated, resulting in successful projections. In view of this, predictions were made for the two-year period (2018 and 2019) and for the period between 2020 and 2025 (ex-ante). Finally, the analytical approach concludes with a fluctuating acceleration of unemployment rates in subsequent years. Regarding growth, it follows a constant upward trend.

To explain the Tanzanian unemployment rate, the study proposed by Tengaa, Maiga, and Mwasota (2023) used the ARIMA model and the Box-Jenkins methodology. ADF, PACF, and stationarity tests served as a guide for choosing the ideal model for forecasting data. The unit root test detects the absence of stationarity, which is one of the violations of econometric assumptions. Thus, the adoption of differentiation is sufficient to smooth the data and make the series stationary, removing the effects of trend and seasonality. The adoption of the ARIMA (3, 1, 4) model reveals superior performance for the Tanzanian unemployment rate, and the residuals are white noise, confirming its viability. Regarding the forecast of the unemployment rate in Tanzania, the results reveal a consistent trend over 9 years.

Given the above, the unemployment rate will be examined in the context of international literature, from the perspectives of different countries. It is observed that there is methodological variability and divergences in the results obtained by the authors.

3.4 Application of ARIMA models to time series on public debt: an empirical approach in national studies

The real exchange rate is one of the relevant indicators for the economy, which, together with foreign trade, identifies the impacts arising from such transactions with the rest of the world. It is a determining factor in the foreign exchange market, as it records supply and demand relationships for foreign currency, with the impacts arising from these transactions defined by the trade balance, determined by the difference between exports and imports, and, above all, by the Balance of Payments, which analyzes the financial-transactional situation between nations. In the study by De Oliveira, Franchini, and Rodrigues (2019), the Brazilian real exchange rate and its time-series modeling for predictability were evaluated. Monthly data from 2010 to 2018, extracted from Ipeadata, were used. The general objective was to estimate the real exchange rate in Brazil using two predictive models: Holt and ARIMA. Consequently, the predicted values were compared with the actual data, thereby identifying the one that exhibits greater predictability, i.e., greater proximity to the actual values. Thus, the Holt model will fit the predictive series, as evidenced by the smaller sum of squared errors.

In Southern Brazil, specifically the state of Rio Grande do Sul, Dos Santos Nunes et al. (2022) sought to model the demand for electricity in the industrial, commercial, and residential sectors using the Autoregressive Moving Average (VAR) model, complemented by Vector Error Correction (VEC). Furthermore, information on GDP, electricity tariffs, and prices for household appliances, materials, and electrical equipment was included. The study will gather data from 1971 to 2010 and will be validated from 2011 to 2017. Regarding the predictive methodology, it will be compared to the Box-Jenkins model, especially the ARIMA model. Finally, regarding the results of the analyzed forecast, the viability of the method applies to the Autoregressive Moving (ARIMA) model, with emphasis on the three consumer sectors (industrial, commercial, and residential). However, the other methods already tested and analyzed by the authors are not disregarded, since, based on this, they conclude that the findings obtained are predictions one step ahead.

This subsection will address national studies concerning predictions via ARIMA modeling in the context of different economic variables, as well as other methods used by authors for the predictive estimation of the exchange rate and the demand for electricity, respectively highlighted by De Oliveira, Franchini, and Rodrigues (2019) and Dos Santos Nunes et al. (2022).

4 Results and discussion

4.1 Validation and selection tests

The graph below shows the behavior of the net debt of the Brazilian public sector, using data from January 2000 to September 2023, totaling 285 observations. The x-axis corresponds to the time, in months, while the y-axis highlights the monetary quantity (in millions of reais).

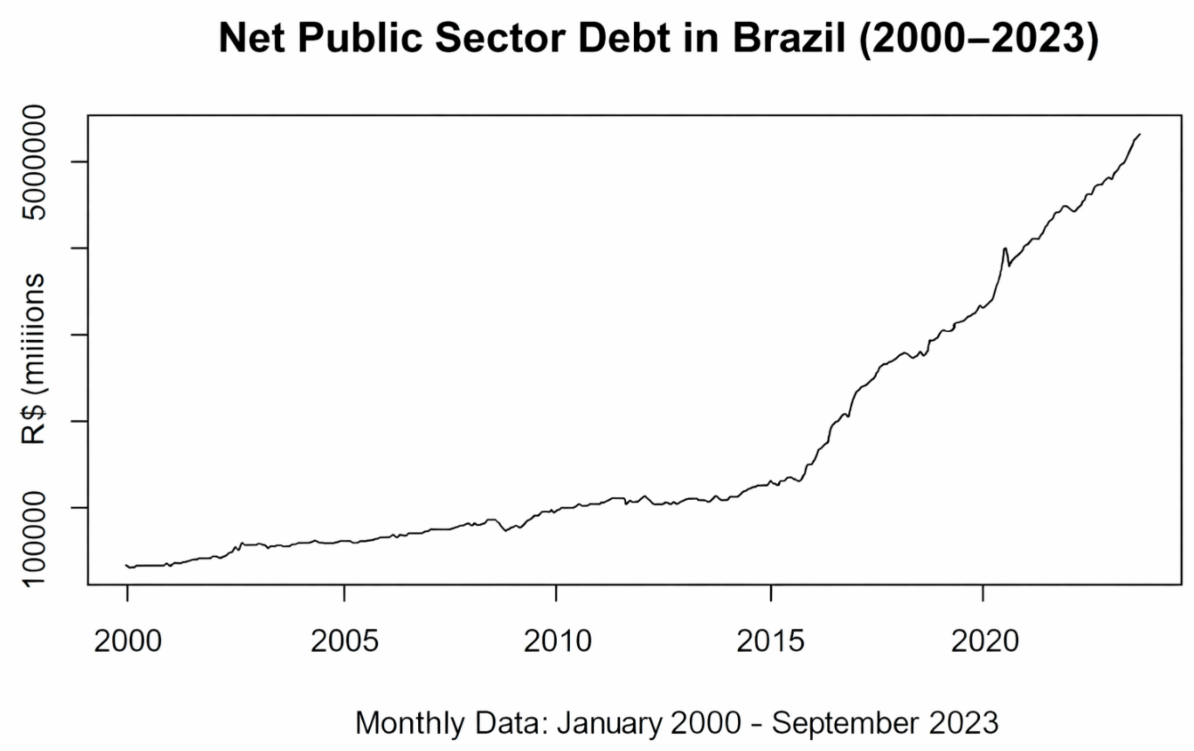

Chart 1: Net debt of the Brazilian public sector from January 2000 to September 2023 (in millions of reais).

Conceptually, net public sector debt is an indicator that reflects the non-financial obligations of the public sector, as well as those of the Central Bank, the private sector, the financial sector, and external relations. Furthermore, a more comprehensive definition of net public sector debt incorporates the three levels of government (federal, state, and municipal), the Central Bank, social security, and state-owned enterprises (Brazil, National Congress, 2023).

Indeed, the accumulated increase in the net debt of the Brazilian public sector exceeded 1,500%, considering the extreme points of the series presented above. Next, it will be subjected to econometric tests using time-series analysis to identify a forecasting model that aligns with the analytical procedures. Following this, the series is divided into two categories, highlighted in yellow and purple; these represent, respectively, training and test data.

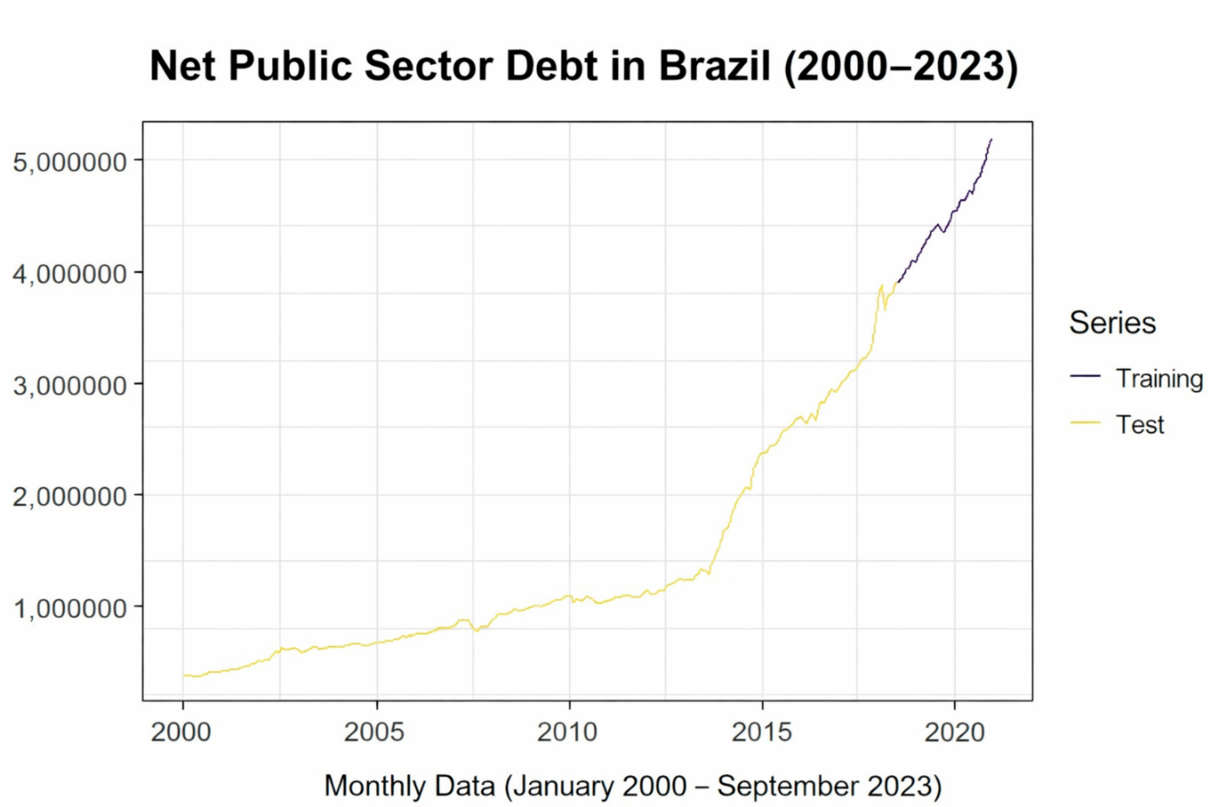

Figure 1: Series divided into a training set with 252 observations and a test set with 33 observations.

The division of the series into two categories, as observed in the figure above, serves as the basis for predictive analyses, since it is through the training series that it will be subjected to econometric tests. Furthermore, the forecast of the Brazilian public sector's level of indebtedness over the subsequent 33 months will also be modeled using the training series.

A necessary condition to avoid analytical bias and compromise the credibility of the research is the elimination of possible violations of econometric assumptions, which in the time-series model are the presence of a unit root and residual autocorrelation. Next, the Dickey-Fuller, Augmented Dickey-Fuller, KPSS, Phillips-Perron, and DF-ERS tests are applied to the Brazilian public sector debt series to detect the possible presence of a unit root. These tests were applied to the series at the level relative to the net public sector debt.

Table 1: Unit root tests (Dickey-Fuller)

Unit root tests (Dickey-Fuller) H_0: the series has a unit root. H_1: the series is stationary.		
	Estimated	**p-value**
Dickey–Fuller	0.011842	0.0000
ADF with trend and intercept	0.011064	0.0381*
ADF with intercept	0.013500	0.0000
ADF without intercept and trend	0.011842	0.0000

Notes: * indicates statistical significance at the 5% level.
Source: Author's elaboration based on research data.

Based on the results of the explicit tests in Table 1, which emphasize the Dickey-Fuller and ADF tests, the p-values provide sufficient evidence to reject the null hypothesis, making them highly significant. In terms of statistical significance, the exception applies to the addition of a trend and intercept using the Augmented Dickey-Fuller test. Furthermore, the KPSS test (which is contrary to the ADF test) and the Phillips-Perron test were also performed, and their results indicated a violation of the time-series stationarity assumption.

Table 2: KPSS Test

KPSS Test H_0: the series has a unit root. H_1: the series is stationary.	
Statistic	**Value**
KPSS test statistic	3.4161
Critical value (1%)	0.7390

Source: Author's elaboration based on research data.

Table 2, relating to the KPSS test, shows evidence of non-stationarity, as the test statistic exceeds the critical value at the 1% level; therefore, the alternative hypothesis of a unit root is accepted. The same result is observed in the Phillips-Perron test, as the null hypothesis of a unit root is rejected because the p-value exceeds the significance level. (P-value of the Phillips- Perron test = 0.99; therefore, 0.99 > 0.01, which corroborates the existence of a unit root in the training series).

Table 3: DF–ERS test applied to the training series

DF-ERS Test H_0: the series has a unit root. H_1: the series is stationary.		
Specification	**Estimated**	**p-value**
With intercept	0.015663	0.0000
With trend	0.006345	0.18917

Source: Author's elaboration based on research data.

Like the previous tests, the DF-ERS test aims to detect evidence of a unit root in the training series. Based on this, DF-ERS tests with trend removal were performed for the series with an intercept, and the evidence of rejection of the null hypothesis is at a very small p-value, closer to zero, indicating statistical significance of less than 1%. However, for the test with trend removal for the series with intercept and trend, the results indicate acceptance of the null hypothesis, as the p-value (0.18917) exceeds the significance level and is not statistically significant, suggesting a non-stationary series.

Table 4: Structural break tests applied to the training series (Zivot and Andrews)

Structural Break Tests (Zivot and Andrews)			
Inclusion	**I Estimated**	**p-value**	**Break position**
Intercept	0.98580	0.0000	189
Trend	0.89046	0.0000	177
Intercept and trend	0.88132	0.0000	189

Source: Author's elaboration based on research data.

Given the explicit results in Table 4, the rejection of the null hypothesis of non-stationarity is confirmed when adding the three features (intercept, trend, or both), with p-values below 1%. Consequently, for each of the features incorporated into the test, the existence of a level change position in the series is palpable.

The training series related to DLSP was subjected to all tests aimed at assessing its stationarity, and, based on these results, some indicated a violation in the context of time series. It is important to emphasize that, after the differentiation process, the series is called an "integrated series," which determines one of the components of the ARIMA forecasting model, as discussed in the subsequent sub-item. If the series is differentiated n times, it is denoted by I(n). Therefore, two differences were applied, making it an integrated series of order 2 (I(2)).

4.2 Results of the forecasts

This subsection discusses the results of the univariate model's forecasts for public sector net debt. In univariate time series modeling, the requirements for obtaining a stationary series must be met. Therefore, the predictive model that best fits the data is selected; in this case, the ARIMA family. Thus, the auto.arima function available in analysis software facilitates the process by using the ARIMA methodology to autonomously find the model that best suits the predictive modeling of a time series, as stated by Machado (2022). As with any univariate series, it is important that the chosen model yields the smallest possible MAPE (Maximum Permissible Exposure) and that predicted values are as close as possible to the actual data.

It is important to note that predictions from the Autoregressive Integrated Moving Average model exploit any indications of serial autocorrelation in the residuals, which is defined as the degree of association between a given observation and its lagged values (Camilo et al., 2019).

Thus, using the auto.arima function, a more robust model for predictive analyses, was found, with the DLSP series being added to the first-order moving average component (MA(1)), and integrated into two differences. In short, the predictive model is denoted by ARIMA(0, 2, 1) and is then used to forecast net public sector debt over the next 33 months.

Table 5 below presents forecasts for the DLSP test dataset, covering data from January 2021 to September 2023. Using the forecast package, it is possible to obtain point estimates of the forecasts, along with their 80% and 95% confidence intervals.

Table 5: Forecasts in the test base of net public sector debt (millions of reais) made by ARIMA (0,2,1) using the ETS function

Month	Year	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan	2021	4,058,459.0	4,013,053.0	4,103,865.0	3,989,017.0	4,127,901.0
Feb	2021	4,114,838.0	4,048,357.0	4,181,319.0	4,013,164.0	4,216,512.0
Mar	2021	4,150,432.0	4,066,202.0	4,234,661.0	4,021,614.0	4,279,250.0
Apr	2021	4,188,987.0	4,088,457.0	4,289,517.0	4,035,239.0	4,342,734.0
May	2021	4,237,176.0	4,121,096.0	4,353,256.0	4,059,646.0	4,414,706.0
Jun	2021	4,300,704.0	4,169,480.0	4,431,928.0	4,100,014.0	4,501,393.0
Jul	2021	4,351,270.0	4,205,114.0	4,497,425.0	4,127,744.0	4,574,795.0
Aug	2021	4,382,754.0	4,221,758.0	4,543,750.0	4,136,531.0	4,628,976.0
Sep	2021	4,424,751.0	4,248,925.0	4,600,576.0	4,155,849.0	4,693,653.0
Oct	2021	4,470,822.0	4,280,124.0	4,661,521.0	4,179,174.0	4,762,471.0
Nov	2021	4,506,047.0	4,300,392.0	4,711,702.0	4,191,525.0	4,820,569.0
Dec	2021	4,563,077.0	4,342,354.0	4,783,799.0	4,225,511.0	4,900,643.0
Jan	2022	4,602,906.0	4,366,982.0	4,838,829.0	4,242,092.0	4,963,720.0
Feb	2022	4,659,285.0	4,408,013.0	4,910,556.0	4,274,999.0	5,043,570.0
Mar	2022	4,694,878.0	4,428,100.0	4,961,657.0	4,286,876.0	5,102,881.0
Apr	2022	4,733,433.0	4,450,979.0	5,015,888.0	4,301,457.0	5,165,410.0
May	2022	4,781,622.0	4,483,316.0	5,079,929.0	4,325,402.0	5,237,842.0
Jun	2022	4,845,150.0	4,530,811.0	5,159,489.0	4,364,410.0	5,325,890.0
Jul	2022	4,895,716.0	4,565,160.0	5,226,272.0	4,390,174.0	5,401,258.0
Aug	2022	4,927,200.0	4,580,239.0	5,274,161.0	4,396,569.0	5,457,832.0
Sep	2022	4,969,197.0	4,605,642.0	5,332,753.0	4,413,187.0	5,525,208.0
Oct	2022	5,015,269.0	4,634,927.0	5,395,610.0	4,433,587.0	5,596,951.0
Nov	2022	5,050,493.0	4,653,174.0	5,447,813.0	4,442,846.0	5,658,141.0
Dec	2022	5,107,523.0	4,693,034.0	5,522,012.0	4,473,616.0	5,741,430.0
Jan	2023	5,147,352.0	4,715,499.0	5,579,206.0	4,486,889.0	5,807,815.0
Feb	2023	5,203,731.0	4,754,322.0	5,653,140.0	4,516,420.0	5,891,042.0
Mar	2023	5,239,325.0	4,772,169.0	5,706,481.0	4,524,871.0	5,953,778.0
Apr	2023	5,277,880.0	4,792,785.0	5,762,975.0	4,535,991.0	6,019,769.0
May	2023	5,326,069.0	4,822,844.0	5,829,294.0	4,556,453.0	6,095,685.0
Jun	2023	5,389,597.0	4,868,051.0	5,911,142.0	4,591,962.0	6,187,231.0
Jul	2023	5,440,163.0	4,900,108.0	5,980,217.0	4,614,220.0	6,266,105.0
Aug	2023	5,471,647.0	4,912,894.0	6,030,399.0	4,617,108.0	6,326,185.0
Sep	2023	5,513,644.0	4,936,006.0	6,091,282.0	4,630,223.0	6,397,065.0

Source: Author's elaboration based on research data, 2023.

In general, Hyndamn and Athanasopoulos (2018) note that ARIMA predictions tend to increase with the predictive horizon. Applied to stationary series, these predictions converge, so that the confidence intervals for long horizons are essentially unchanged. However, in models where differentiation is necessary, these predictive intervals tend to widen over time.

The same authors cited earlier present further ideas regarding confidence intervals for an autoregressive integrated moving average (ARIMA) model, in which these intervals, in light of the ARIMA model, tend to narrow, as only the variation in errors is considered. Furthermore, according to the authors, there are variations in the parameter estimations, as well as in the model order, the latter being disregarded in the calculation. Moreover, these mathematical estimations assume that the historical patterns included in the model will continue throughout the predictive periods.

The table below (Table 6) presents the predicted values for the net public sector debt and their confidence intervals (80% and 95%) for the forecasts for the remaining months of 2023 (beginning in October of the same year) until June of 2026. For the end of 2024, the point forecast for indebtedness is R$ 6,196,416. Within the margin of error, it is possible to estimate that, with 95% confidence, the net public sector debt for this period will be between R$ 4,846,551 and R$ 7,546,281.

Table 6: Forward forecasts of net public sector debt (millions of reais) made by ARIMA (0,2,1) using the ETS function

Month	Year	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Oct	2023	5,559,715.0	4,963,006.0	6,156,425.0	4,647,127.0	6,472,304.0
Nov	2023	5,594,940.0	4,978,974.0	6,210,906.0	4,652,901.0	6,536,979.0
Dec	2023	5,651,970.0	5,016,562.0	6,287,377.0	4,680,198.0	6,623,741.0
Jan	2024	5,691,799.0	5,036,767.0	6,346,831.0	4,690,013.0	6,693,584.0
Feb	2024	5,748,177.0	5,073,340.0	6,423,015.0	4,716,102.0	6,780,253.0
Mar	2024	5,783,771.0	5,088,948.0	6,478,595.0	4,721,130.0	6,846,412.0
Apr	2024	5,822,326.0	5,107,337.0	6,537,315.0	4,728,845.0	6,915,808.0
May	2024	5,870,515.0	5,135,183.0	6,605,848.0	4,745,921.0	6,995,110.0
Jun	2024	5,934,043.0	5,178,190.0	6,689,897.0	4,778,065.0	7,090,021.0
Jul	2024	5,984,609.0	5,208,059.0	6,761,159.0	4,796,978.0	7,172,240.0
Aug	2024	6,016,093.0	5,218,672.0	6,813,514.0	4,796,543.0	7,235,644.0
Sep	2024	6,058,090.0	5,239,624.0	6,876,556.0	4,806,355.0	7,309,826.0
Oct	2024	6,104,162.0	5,264,479.0	6,943,845.0	4,819,978.0	7,388,346.0
Nov	2024	6,139,386.0	5,278,315.0	7,000,457.0	4,822,492.0	7,456,281.0
Dec	2024	6,196,416.0	5,313,787.0	7,079,045.0	4,846,551.0	7,546,281.0
Jan	2025	6,236,245.0	5,331,888.0	7,140,603.0	4,853,150.0	7,619,341.0
Feb	2025	6,292,624.0	5,366,371.0	7,218,876.0	4,876,043.0	7,709,205.0
Mar	2025	6,328,218.0	5,379,904.0	7,276,532.0	4,877,896.0	7,778,539.0
Apr	2025	6,366,773.0	5,396,231.0	7,337,314.0	4,882,458.0	7,851,088.0
May	2025	6,414,962.0	5,422,029.0	7,407,895.0	4,896,401.0	7,933,523.0
Jun	2025	6,478,490.0	5,463,001.0	7,493,978.0	4,925,434.0	8,031,546.0
Jul	2025	6,529,056.0	5,490,849.0	7,567,262.0	4,941,256.0	8,116,856.0
Aug	2025	6,560,540.0	5,499,454.0	7,621,626.0	4,937,749.0	8,183,331.0
Sep	2025	6,602,537.0	5,518,411.0	7,686,662.0	4,944,510.0	8,260,564.0
Oct	2025	6,648,608.0	5,541,284.0	7,755,933.0	4,955,101.0	8,342,115.0
Nov	2025	6,683,833.0	5,553,151.0	7,814,515.0	4,954,604.0	8,413,062.0
Dec	2025	6,740,863.0	5,586,665.0	7,895,060.0	4,975,670.0	8,506,055.0
Jan	2026	6,780,692.0	5,602,822.0	7,958,561.0	4,979,295.0	8,582,088.0
Feb	2026	6,837,070.0	5,635,374.0	8,038,767.0	4,999,234.0	8,674,907.0
Mar	2026	6,872,664.0	5,646,986.0	8,098,343.0	4,998,151.0	8,747,178.0
Apr	2026	6,911,219.0	5,661,405.0	8,161,033.0	4,999,794.0	8,822,644.0
May	2026	6,959,408.0	5,685,306.0	8,233,510.0	5,010,838.0	8,907,979.0
Jun	2026	7,022,936.0	5,724,394.0	8,321,478.0	5,036,987.0	9,008,885.0

Source: Author's elaboration based on research data, 2023.

Subsequently, in Graph 2, the interval estimates are summarized according to the predictive method mentioned at the beginning of this subsection. Predictions by confidence intervals are represented in blue, where the lighter color indicates intervals with 95% confidence, while the darker color indicates intervals with 80% confidence. It is important to highlight the predicted time because the longer it is, the longer the interval estimates will be (Machado, 2022). Given this condition, the Mean Absolute Percentage Error (MAPE) will be greater.

Subsequently, in graph 3, the predictive behavior is shown in comparison with the real data. It is noticeable that the predictions follow the real data in upward trajectories, and these predictions also demonstrate the robustness of the model, as confirmed by the graphical behavior (graphs 2 and 3). The accuracy of the results (Table 7), with emphasis on the Mean Absolute Percentage Error (MAPE), ratifies the robustness of the predictive model, with excellent percentages obtained in both the training and test series, of 1.76% and 3.82%, respectively.

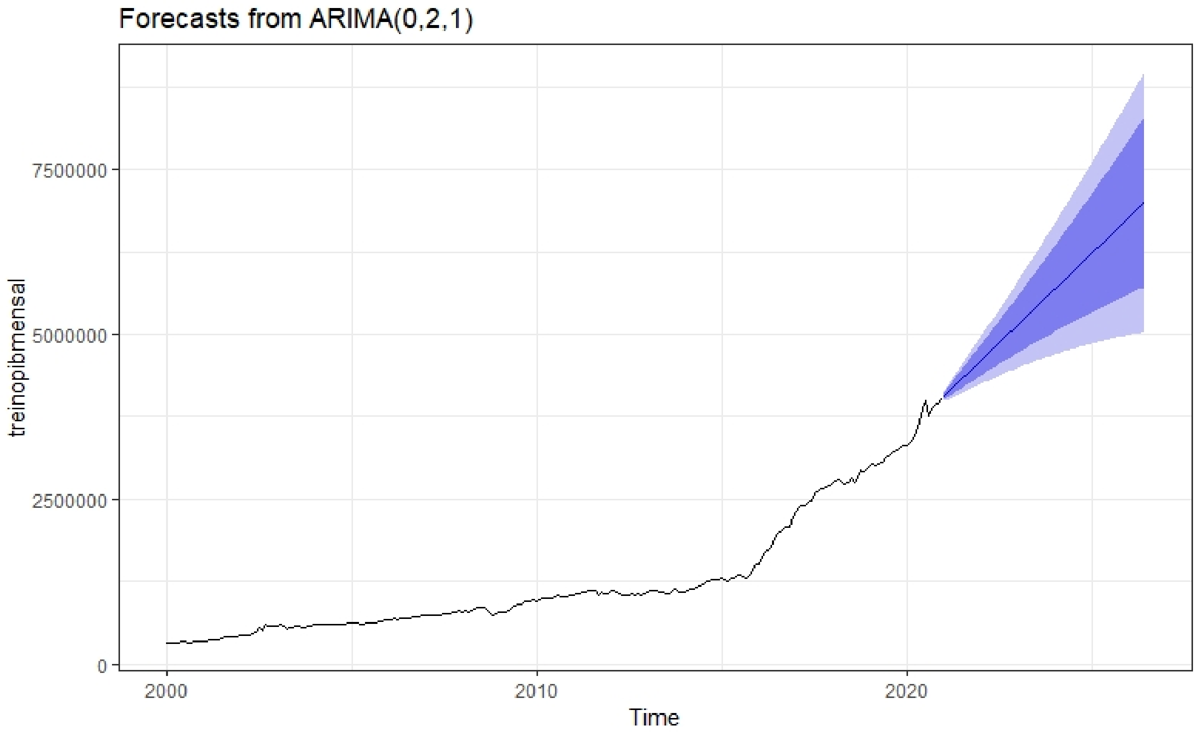

Figure 2: ARIMA (0, 2, 1) model forecasts using the ETS function for time series, considering 33 values ahead.

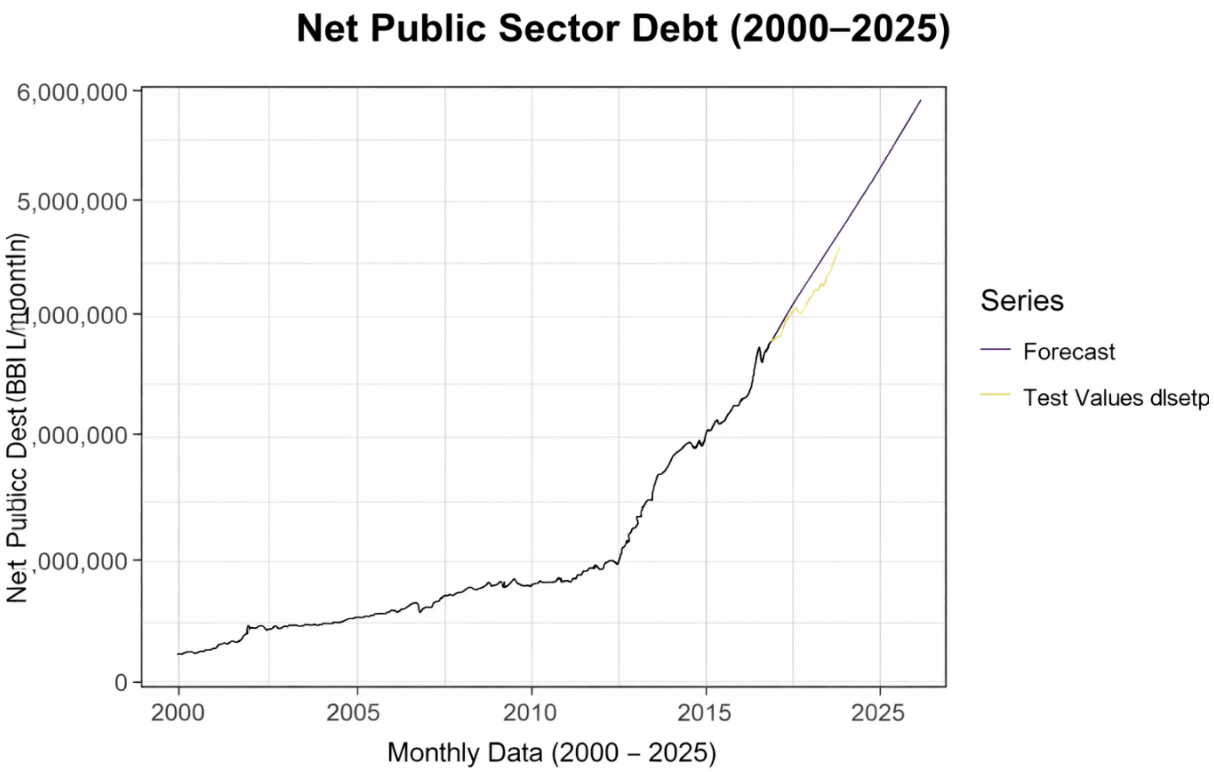

Figure 3: ARIMA (0 2 1) model forecasts using the ETS function for time series, considering training and test sets and 33 forward data points.

Table 7: Accuracy of forecast results using the ARIMA (0,2,1) model with the ETS function for training and test sets

Accuracy	ME	RMSE	MOTHER	MPE	MAP	BUT	ACF1
Accuracy based on training data	2,544.56	35,801.89	20,901.77	0.16	1.76	0.12	0.01
Accuracy in the test base	-180,700.94	208,380.84	180,700.94	-3.82	3.82	1.03	0.91

Source: Author's elaboration based on research data.

stationarity conditions to residual analysis. Finally, according to the ARIMA (0, 2, 1) model applied to the DLSP forecast, the Ljung -Box test was performed (Table 8), which, according to Yasmin and Moniruzzaman (2024), aims to verify if the model is accepted if there are no indications of significant autocorrelation in the residuals; that is, they should follow white noise. These conditions are established by the null and alternative hypotheses of the test, defined, respectively, by the absence and presence of autocorrelation. These hypotheses can also be stated, in other words, as conditions for whether the residuals are white noise or identically distributed.

Based on the definition of the Ljung-Box residual test, Table 8 presents the results. Given the above, there is sufficient evidence to accept the null hypothesis, according to which the residuals do not show any indication of residual autocorrelation, that is, they follow white noise, or in other words, the fact that they are identically distributed.

Table 8: Residual test results for the ARIMA (0,2,1) model: Ljung–Box test

Residuals from ARIMA(0,2,1)	
H_0: the residues are identically distributed	
H_1: The waste is not identically distributed	
Statistic	**Value**
Test statistic (Q^*)	26.32
Degrees of freedom (df)	23
p-value	0.286

Source: Author's elaboration based on research data, 2023.

Therefore, the tests performed on the univariate series for net public sector debt corroborate the forecasts for the period analyzed. Based on observations of the point forecasts, the net public sector debt tends to grow gradually over time. Crucially, monitoring public debt helps maintain fiscal sustainability, ensure stable fiscal management, and, evidently, prevent the compromise of funds allocated to public investments.

5 Final considerations

This study aimed to analyze the trajectory of Brazilian public debt between 2000 and 2022 and to make projections for the following years using the ARIMA (AutoRegressive Integrated Moving Average) econometric model. (Integrated Moving Average). The choice of this method was based on its ability to model time series, identify historical patterns, and generate forecasts based on historical data. This approach is particularly relevant in a context where fiscal sustainability has become one of Brazil's main economic concerns.

The methodology applied followed three main steps: identification, estimation, and validation of the ARIMA model. Criteria such as AIC (Akaike) were used. Information Criterion, and BIC (Bayesian Information Criterion) were used to select the most appropriate specification. Furthermore, residual analysis was performed to assess the absence of autocorrelation, confirming that the fitted model met the statistical requirements. The model proved to be effective in describing the historical evolution of public debt and predicting its future dynamics.

The results indicated a persistent upward trend in Brazilian public debt throughout the analyzed period, especially from 2016 onwards, when economic and political factors worsened the fiscal scenario. The ARIMA model accurately captured this trajectory, showing that increases in debt are closely associated with recurring primary deficits and the impact of economic shocks, such as global crises and rising interest rates. The forecast for the period 2023 to 2026 reinforces the continuation of this growth if structural measures are not adopted to contain indebtedness.

One of the most significant contributions of the ARIMA model was identifying a strong relationship between economic cycles and the rate of debt growth. During periods of economic expansion, the debt ratio declined, whereas during recessions or periods of moderate growth, debt increased rapidly. These results highlight the need for countercyclical policies that balance the public budget across economic cycles and mitigate the effects of prolonged fiscal crises.

From an economic policy perspective, the results suggest the urgency of fiscal reforms that prioritize reducing the primary deficit and controlling public debt relative to Gross Domestic Product (GDP). Measures such as tax reform, a review of public spending, and strategies to foster economic growth are essential to stabilize the debt trajectory. Furthermore, policies that promote greater efficiency in the use of public resources can help improve perceptions of fiscal sustainability and reduce government financing costs.

Despite its robustness, the ARIMA model has limitations inherent to its own structure. It relies exclusively on historical time series patterns and does not consider external explanatory variables, such as changes in public policies, unforeseen economic shocks, or institutional factors that may influence public debt. This implies that projections made with the model may not adequately capture unexpected events that alter the economic landscape in the short and medium term.

Another important limitation of the study was the absence of analyses integrating other econometric models that could complement the ARIMA results, such as VAR (Vector Autoregressive) models or spatial models that account for interactions between regions. Furthermore, qualitative factors, such as the political environment and the credibility of institutions, were not incorporated into the analyses, which limits a complete understanding of the determinants of Brazilian public debt.

In summary, the use of the ARIMA model has significantly contributed to understanding the trajectory of Brazilian public debt and has informed the formulation of better-informed economic policies. However, the effectiveness of these projections depends on the implementation of policies that promote fiscal stability and the continuous monitoring of economic and institutional variables that may affect indebtedness. Future studies can expand this analysis by integrating multivariate approaches and considering uncertainty scenarios to provide a more comprehensive view of the sustainability of public debt in Brazil.

REFERÊNCIAS

ALMEIDA, A. Q. et al. Enhanced Vegetation Index (EVI) na análise da dinâmica da vegetação da reserva biológica de Sooretama, ES. *Revista Árvore*, v. 32, p. 1099–1107, 2008. Disponível em: SciELO. Acesso em: 18 maio 2024.

BASTOS, R. F. Avaliação de desempenho de modelos de séries temporais para previsões da produção de óleo diesel nacional. In: *Simpósio de Pesquisa Operacional & Logística da Marinha (SPOLM)*, 18., 2016. Disponível em: Blucher. Acesso em: 3 set. 2023.

BOX, G. E. P.; JENKINS, G. M.; REINSEL, G. C. *Time series analysis: forecasting and control*. Englewood Cliffs: Prentice Hall, 1994.

BRASIL. Tesouro Nacional. O que é a dívida pública federal? Disponível em: Tesouro Nacional. Acesso em: 4 set. 2023.

BUENO, R. L. S. *Econometria de séries temporais*. 2. ed. São Paulo: Cengage Learning, 2012.

CALDARELLI, C. E.; BACCHI, M. R. P. Fatores de influência no preço do milho no Brasil. *Nova Economia*, v. 22, p. 141–164, 2012. Disponível em: SciELO. Acesso em: 18 maio 2024.

CAMILO, G. I. et al. Avaliação da precisão dos métodos ARIMA, suavização exponencial e redes neurais na previsão de séries temporais anuais brasileiras. Disponível em: UFU. Acesso em: 2 jun. 2024.

DE MEDEIROS BRAGA, J. Mudança estrutural e evolução da dinâmica intersetorial na economia brasileira no período de baixa inflação. *Ensaios FEE*, v. 35, n. 2, 2014. Disponível em: FEE. Acesso em: 29 nov. 2023.

DE OLIVEIRA, B. M.; FRANCHINI, A. A.; RODRIGUES, L. L. M. Análise do comportamento da taxa de câmbio real no Brasil no período de janeiro de 2010 a julho de 2018: uma aplicação em séries temporais. *Revista Debate Econômico*, v. 7, n. 1, p. 26–42, 2019. Disponível em: Unifal. Acesso em: 1 set. 2023.

DETZEL, D. H. M. et al. Preenchimento de dados limnimétricos horários via modelos ARIMA. *RBRH – Revista Brasileira de Recursos Hídricos*, v. 18, p. 281–292, 2013. Disponível em: ResearchGate. Acesso em: 18 maio 2024.

DICKEY, D. A.; FULLER, W. A. Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, p. 1057–1072, 1981.

DOS SANTOS NUNES, G. et al. Avaliação da capacidade preditiva de modelos ARIMA e VAR-VEC: o caso da demanda por energia elétrica no Rio Grande do Sul. *Exacta*, v. 20, n. 2, p. 307–335, 2022. Disponível em: Uninove. Acesso em: 4 set. 2023.

DUMIČIĆ, K.; ČEH ČASNI, A.; ŽMUK, B. Forecasting unemployment rate in selected European countries using smoothing methods. *World Academy of Science, Engineering and Technology: International Journal of Social, Education, Economics and Management Engineering*, v. 9, n. 4, p. 867–872, 2015. Disponível em: ResearchGate. Acesso em: 27 ago. 2023.

GONÇALVES, J. N.; PANDOLFI, A. S. Previsão da sinistralidade em seguros de vida utilizando modelos de séries temporais. *Revista ENIAC Pesquisa*, v. 13, n. 1, p. 3–28, 2024. Disponível em: ENIAC. Acesso em: 18 maio 2024.

HYNDMAN, R. J.; ATHANASOPOULOS, G. *Forecasting: principles and practice*. 2. ed. Melbourne: OTexts, 2018. Disponível em: OTexts. Acesso em: 2 jun. 2024.

INSTITUTO DE PESQUISA ECONÔMICA APLICADA (IPEA). Dívida pública total. Disponível em: Ipeadata. Acesso em: 18 maio 2024.

JERE, S.; SIYANGA, M. Forecasting inflation rate of Zambia using Holt's exponential smoothing. *Open Journal of Statistics*, v. 6, n. 2, p. 363–372, 2016. Disponível em: SCIRP. Acesso em: 26 ago. 2023.

LATORRE, M. R. D. O.; CARDOSO, M. R. A. Análise de séries temporais em epidemiologia: uma introdução sobre os aspectos metodológicos. *Revista Brasileira de Epidemiologia*, v. 4, p. 145–152, 2001. Disponível em: SciELO. Acesso em: 24 maio 2024.

MACHADO, N. S. Modelos de previsão via análise de séries temporais da produção de café no Brasil no período de 1960 a 2021. Disponível em: UFU. Acesso em: 2 jun. 2024.

NOR, M. E. et al. Forecasting of unemployment rate in Malaysia using exponential smoothing methods. *International Journal of Engineering and Technology*, v. 7, n. 4.30, p. 451, 2018. Disponível em: IJMTSS. Acesso em: 27 ago. 2023.

RAMLI, S. F. et al. Prediction of the unemployment rate in Malaysia. *International Journal of Modern Trends in Social Sciences*, v. 1, n. 4, p. 38–44, 2018. Disponível em: IJMTSS. Acesso em: 29 ago. 2023.

SIBIN, B. H.; DA SILVA FILHO, L. A.; BALLINI, R. Financiamento habitacional e seus impactos sobre os preços na construção civil brasileira. *Revista Espacios*, v. 37, n. 20, 2016. Disponível em: Espacios. Acesso em: 8 jul. 2023.

SILVEIRA, A. G.; DE MATTOS, V. L. D.; KONRATH, A. C. Avaliação da estacionariedade e teste de cointegração em séries temporais: o caso da demanda de energia elétrica residencial no Brasil. *RETEC – Revista de Tecnologias*, v. 9, n. 3, 2016. Disponível em: Fatec Ourinhos. Acesso em: 8 jul. 2023.

TENGAA, P. E.; MAIGA, Y. M.; MWASOTA, A. M. Modeling and forecasting unemployment rate in Tanzania: an ARIMA approach. *Journal of Accounting, Finance and Auditing Studies*, v. 9, n. 3, p. 270–288, 2023. Disponível em: ProQuest. Acesso em: 29 ago. 2023.

UĞUR, A. Y. I.; ERKAL, G. Forecasting of unemployment and economic growth for Turkey: ARIMA model application. *Turkish Journal of Forecasting*, v. 5, n. 1, p. 12–22, 2021. Disponível em: DergiPark. Acesso em: 29 ago. 2023.