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INSS Social Security Expenditures and Fiscal Sustainability: An Application of the SARIMA Model

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ABSTRACT

The Brazilian social security system for private sector workers is organized under the General Social Security Regime (RGPS), administered by the National Institute of Social Security (INSS). In the context of accelerated demographic transition, pension expenditures have increased, posing challenges to the actuarial sustainability and financial balance of the system. This article analyzes the behavior of the time series of INSS expenditures and proposes a forecasting model based on the SARIMA methodology, contributing to the debate on the dynamics of Brazilian social security. The study adopts a quantitative approach, using secondary data from the Social Security Information Technology Company (Dataprev) and econometric modeling techniques. The results indicate that pension expenditures are expected to grow above the inflation target in the coming years and are influenced by complex macroeconomic and institutional factors, which limits the performance of purely autoregressive models and suggests the need for complementary approaches.

Keywords: Social Security; INSS; Time Series; SARIMA Modeling.
JEL Classification: H55, C22, C53.

SUMMARY

1. INTRODUCTION

The purpose of Social Security is to protect workers and their dependents in situations of loss or reduction of work capacity, ensuring the maintenance of family livelihood. It is a public, contributory system with mandatory enrollment, in which contributors acquire the right to receive benefits based on the amount and duration of their contributions, as provided for in Article 201 of the Federal Constitution.

The INSS is the agency responsible for administering the RGPS and implementing the Continuous Cash Benefit (BPC). The Brazilian social security system is based on the pay-as--you-go model, in which active workers finance the benefits paid to retired workers. In parallel, there is the welfare dimension, represented by the BPC, which guarantees a minimum income to the elderly and people with disabilities in vulnerable situations, regardless of prior contributions, and is financed by taxes (Afonso; Sidone, 2025).

The RGPS's heavy reliance on the *pay-as-you-go* financing method makes the system highly sensitive to demographic changes and labor market dynamics, increasing its exposure to population aging, a shrinking contributor base, and informality, with direct impacts on the social security deficit. In this context, estimates from the General Social Security System Secretariat (SRGPS), released in 2023, indicate that the need for public financing of benefits paid by the INSS is expected to grow from 2.59% of Gross Domestic Product (GDP) in 2023, to 10.41% in 2100, highlighting the deepening fiscal imbalance and the structural challenges to the long-term sustainability of public accounts.

In the demographic context, the 2024 projections from the Brazilian Institute of Geography and Statistics (IBGE) indicate a profound shift in the age structure, compromising the sustainability of the RGPS. The ratio of contributors to beneficiaries, which in 2000 was 10.63 to 1, is projected to fall to 1.84 by 2070, highlighting unprecedented pressure on the social security system. Furthermore, according to Dataprev data, between 2002 and 2023 the number of active benefits grew by 88%, while actual spending on these benefits—adjusted by the Broad National Consumer Price Index (IPCA) at 2023 prices—increased by 215%, revealing that expenditures have been growing at a much faster rate than the expansion of the number of beneficiaries and inflation itself.

Given this context, the use of econometric tools to inform the debate on public policies aimed at the sustainability of the social security system becomes essential. In this regard, this article investigates whether the trajectory of INSS expenditures exhibits fiscally sustainable behavior, in light of its temporal dynamics observed over the past decades. The subject of study consists of the historical series of INSS social security expenditures for the period from 2000 to 2024, constructed using data from Dataprev.

As a general objective, this study proposes modeling this series using a seasonal autoregressive integrated moving average (SARIMA) model, seeking to capture its trend and seasonal patterns and provide forecasts that aid in understanding the evolution of social security expenditures in the short term.

2. THEORETICAL FOUNDATION AND EXPLORATORY ANALYSIS

2.1 Exploratory Analysis of the Time Series

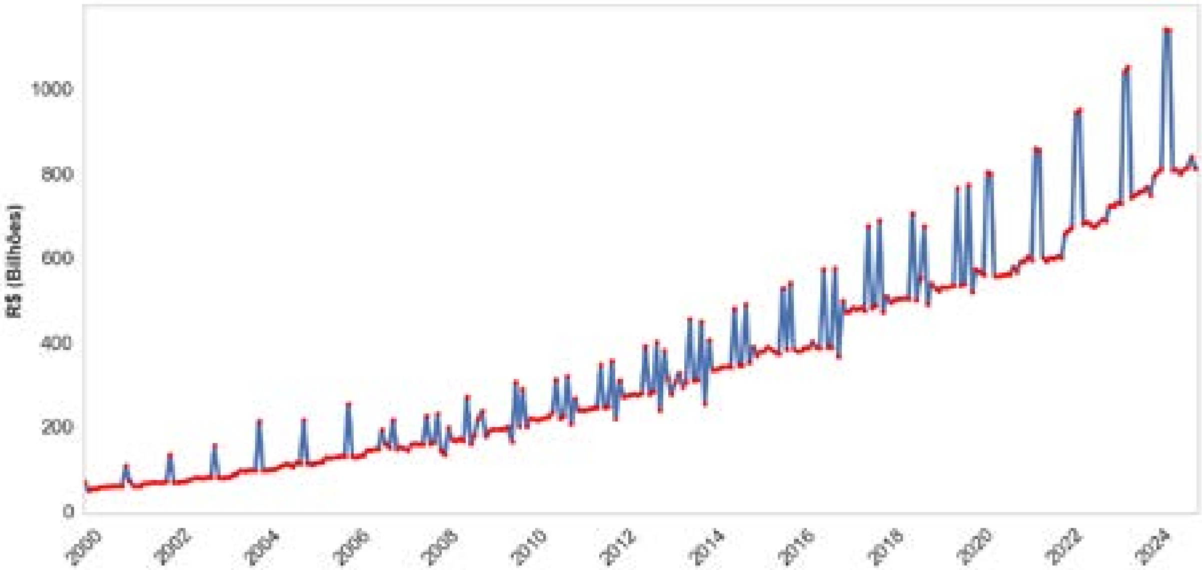
According to Morettin and Toloi (2006), a time series corresponds to a set of observations ordered chronologically. In this sense, the data obtained from Dataprev regarding INSS expenditures, organized monthly from January 2000 through December 2024, constitute a time series.

The chosen time frame is justified by the fact that the year 2000 marked the beginning of a new phase of the three-pillar macroeconomic framework in Brazil, which brought significant changes in inflation dynamics (Afonso; Araújo; Fajardo, 2016), a variable that, according to Giambiagi (2025), exerts a direct influence on the values of social security benefits. Thus, with the aim of constructing a series that is more consistent and representative of recent economic reality, the year 2000 was defined as the starting point, using the most up-to-date data available from Dataprev.

Thus, with the aim of building an efficient projection tool, it is justified to conduct an exploratory analysis of the INSS expenditure series. According to Dataprev, the composition of the INSS expenditure category in 2024 consists mainly of benefit payments (89.51%) and Personnel and Social Charges (8.49%). This analysis aims to extract relevant information about the main characteristics of the series, such as trends, seasonality, peculiarities, and atypical behaviors, as well as to understand how economic and social events that occurred throughout the analyzed period influenced its dynamics. These elements are essential for guiding the process of specifying and estimating the econometric model, contributing to the definition of more consistent methodological strategies and to the improvement of the predictive and interpretive capacity of the results obtained (Hyndman; Athanasopoulos, 2021).

As can be seen in Figure 1, INSS expenditures show a clear upward trend throughout their historical series. This behavior preliminarily indicates that the series is non-stationary, since it does not behave in a purely random manner but rather exhibits a systematic upward trajectory over time. This characteristic is consistent with economic and financial time series, based on demographic and macroeconomic factors and, especially, the social security reforms implemented during this period.

Figure 1 – Time series of INSS expenditures

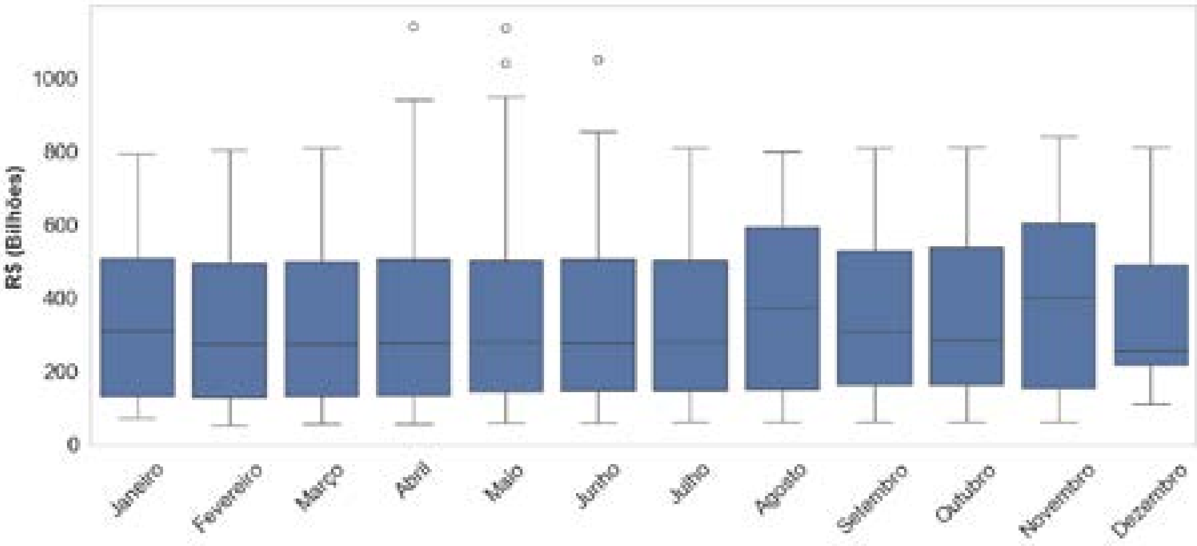


Source: Prepared by the authors using data provided by Dataprev.

Analysis of the dispersion of annual INSS expenditures reveals a consistent pattern throughout the time series, characterized by low variability of values within each fiscal year, combined with the recurring presence of outliers. These *outliers* are mainly associated with the seasonality inherent in the payment of benefits related to the 13th-month bonus, which occurs in installments throughout the year. In general, the second installment is concentrated in December, while the first is usually paid around the middle of the year, generating occasional spikes in monthly expenditures. This behavior highlights the existence of a significant seasonal pattern, which must be considered when modeling social security expenditures.

It is worth noting that the timing of these additional payments may change due to public policies aimed at income support, as observed during the COVID-19 pandemic, a period in which payments were brought forward. This behavior introduces a significant seasonal component into the series, clearly identified in Figure 2 with a monthly *box plot*. The latter highlights significant variations between months, showing greater dispersion in those directly impacted by the payment of the first installment of the 13th-month bonus. This seasonal volatility poses additional challenges in building a predictive model, hindering the accuracy of forecasts.

Figure 2 - Monthly box plot of the INSS historical expenditure series



Source: Prepared by the authors using data provided by Dataprev

It can therefore be observed that the INSS time series exhibits various complexities throughout its history, characterized by non-stationary behavior and a strong seasonal component. Given this context, the use of the SARIMA model is appropriate, as it allows for the capture of these structural characteristics of the series.

2.2 SARIMA Model

The exploratory analysis of the INSS expenditure time series data revealed its non-stationary nature, marked by a growth trend over the analyzed period, associated with a recurring seasonal pattern, strongly influenced by the payment of the 13th-month bonus installments.

In this context, as guided by the methodology proposed by Morettin and Toloi (2006), when working with univariate time series, it is essential to adopt an adjustment process that simultaneously accounts for both trend and seasonality, avoiding an approach restricted to only one of these components. Thus, to model the time series of INSS expenditures, the SARIMA methodology, formalized by Box and Jenkins (1976), was employed, which is the most suitable given the characteristics identified in the preliminary exploratory analysis of the data.

Thus, the SARIMA model is autoregressive and uses the values of the monthly observations from the series itself to estimate new values and make forecasts, in order to simultaneously address issues of trend and constant seasonality. The model's parameters are divided into two parts: the non-seasonal component, represented by (p, d, q), and the seasonal component, represented by $(P, D, Q)_s$.

In the non-seasonal component (p, d, q): Autoregressive (p) refers to the order of the autoregressive polynomial (ϕ_p) and indicates the number of past observations from the series included in the model to predict the current value; Integrated (d): integration, indicates the number of differencing applied to make the series stationary, that is, with constant mean and variance over time; Moving Average (q): This is the order of the moving average polynomial (θ_q) and specifies the number of past forecast errors that influence the current observation, modeling unanticipated random shocks.

As for the seasonal component $(P,D,Q)_s$, this component models the periodic dependence of the series, where s represents the seasonal frequency. Seasonal Autoregression (P): This is the order of the seasonal autoregressive polynomial (Φ_P) that uses observations from past seasonal cycles to forecast the current observation; Seasonal Differencing (D), the number of seasonal differencing required to remove seasonality from the series; Seasonal Moving Average (Q): The order of the seasonal moving average polynomial (Θ_Q) that incorporates forecast errors from previous seasonal periods.

The combination of these components results in the general SARIMA model equation shown below, which additively integrates the effects of trend, short-term autocorrelation, and seasonal cycles into a single predictive equation (Morettin; Toloi, 2006).

General SARIMA model equation:

$$\phi_p(B) \cdot \Phi_P\left(B^S\right) \cdot (1 - B)^d \cdot \left(1 - B^S\right)^D \cdot y_t = \theta_q(B) \cdot \Theta_Q\left(B^S\right) \cdot \varepsilon_t \qquad (1)$$

Breaking down each part of this equation:

y_t : corresponds to the value of the series at time t;

ε_t : represents the error term (white noise).

Non-seasonal components:

$\phi_p(B) = \left(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p\right)$: a non-seasonal autoregressive polynomial of order p. The coefficients $\phi_1,\ldots,\phi_p$ are the parameters of the AR model.

$(1 - B)^d$: non-seasonal differencing operator of order d.

$\theta_q(B) = \left(1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q\right)$: non-seasonal moving average polynomial of order q. The coefficients $\theta_1, \ldots, \theta_q$ are the parameters of the MA model.

Seasonal components:

$\Phi_P(B^s) = \left(1 - \Phi_1 B^s - \Phi_2 B^{2s} - \cdots - \Phi_P B^{Ps}\right)$: seasonal autoregressive polynomial of order P. The coefficients Φ1,…,ΦP are the parameters of the SAR model, and the operator Bs applies the lag corresponding to the seasonal period s.

$\left(1 - B^s\right)^D$: seasonal differencing operator of order D, applied to remove the seasonal component from the series.

$\Theta_Q(B^s) = \left(1 + \Theta_1 B^s + \Theta_2 B^{2s} + \cdots + \Theta_Q B^{Qs}\right)$: seasonal moving average polynomial of order Q. The coefficients Θ1,…,ΘQ are the parameters of the SMA model.

In summary, the SARIMA model proves to be methodologically suitable for modeling the INSS expenditure time series, since its structure allows for the integrated capture of the growth trend, the short-term time dependence, and the recurring seasonality observed in the data, ensuring greater statistical consistency in the estimates and greater robustness in the long-term projections, in line with the classical time series analysis approach proposed by Box and Jenkins (1976) and systematized by Morettin and Toloi (2006).

3. METHODOLOGY

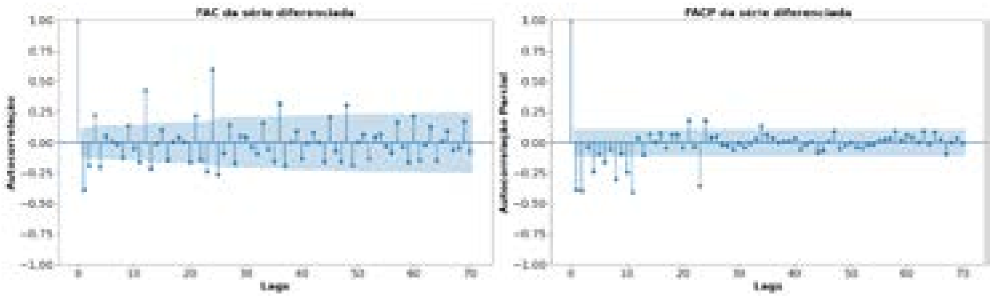
Methodologically, the study adopts an applied quantitative approach based on the econometric modeling of time series of INSS expenditures using official secondary data from Dataprev. The analytical strategy focuses on estimating seasonal autoregressive integrated moving average (SARIMA) models, which allow for the capture of trend, cycle, and seasonal patterns present in the dynamics of social security expenditures over time.

This procedure enables the systematic analysis of expenditure behavior and the assessment of its temporal evolution, being particularly suitable for studies aimed at monitoring and analyzing the sustainability of public social security policies, in line with the applied quantitative approach discussed by Creswell (2018) and with the perspective of empirical analysis of social phenomena grounded in consolidated statistical bases, according to Gil (2019).

Based on the definition of the quantitative approach and the choice of the SARIMA model as the central analytical tool, the next methodological step consisted of the empirical operationalization of the model, involving the identification, estimation, and selection of the most appropriate specifications for the INSS expenditure time series. This procedure followed the classical methodology of time series analysis, in which the choice of parameters is guided by both statistical criteria and performance evaluations and residual diagnostics, ensuring the robustness of the estimated model and the reliability of the generated projections. In this context, the analysis of the time-dependence structures of the series became a fundamental element for defining the autoregressive and moving average orders, both seasonal and non-seasonal, as detailed below (Hyndman; Athanasopoulos, 2021).

The selection of the model's optimal parameters was performed through the analysis of Autocorrelation Functions (ACF) and Partial Autocorrelation Functions (PACF), applied to the previously stationarized series, using a 5% significance level, with the aim of adequately identifying the orders of the autoregressive and moving average components, both seasonal and non-seasonal. For this purpose, *Python* software, version 3.13.2, was used in conjunction with the *Statsmodels* statistical library.

Figure 3 - ACF and PACF after differencing the series



Source: Prepared by the authors using data provided by Dataprev

The parameters selected for conducting the tests based on the ACF and PACF in Figure 3 were: q = (1, 2, 3, 4), d = 1, p = (1, 2, 4), Q = (1, 2, 3, 4, 5), D = 1, and P = (1, 2, 3, 4). Following this selection, random combinations of the aforementioned parameters were generated, resulting in a total of 240 tested models. It is important to note that, given the extensive time series, the use of multiple parameter combinations with high degrees became a computationally complex task. For this reason, it was necessary to resort to parallel processing to make the analysis feasible, which also required hardware with adequate minimum processing capacity.

After running the model combinations, the *Akaike Information Criterion* (AIC), *Bayesian Information Criterion* (BIC), and *Log-Likelihood* metrics were adopted as the initial selection criteria, thereby selecting the three models that performed best according to these indicators.

In the next step, a more thorough evaluation was conducted using the Shapiro-Wilk normality test and the following residual evaluation metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Mean Percentage Error (MPE) (Bueno, 2011). The mathematical formulations of the metrics used are provided in Appendix A of this article.

Finally, the model that demonstrated the highest efficiency was selected—that is, the one with the lowest levels of systematic error and bias—and this configuration was then used to perform projections for the next 36 months.

4. ANALYSIS OF RESULTS

After testing various combinations of parameters to explore a wide range of specifications and identify those with the best performance, the three models with the highest scores according to the AIC, BIC, and *Log-Likelihood* criteria were selected. These indicators allow for measuring the relative quality of the models, penalizing excessively complex configurations.

Table 1 – Results of the SARIMA model selection

Model	p	d	q	P	D	Q	AIC	BIC	*Log-Likelihood*
SARIMA 1	4	1	4	5	1	1	4,512.58	4,563.69	-2,241.29
SARIMA 2	4	1	4	5	1	2	4,513.85	4,568.36	-2,240.93
SARIMA 3	4	1	4	5	1	3	4,514.27	4,572.19	-2,240.13

Source: prepared by the authors using data provided by Dataprev

In general, preference was given to models with better performance according to the AIC and BIC criteria, since, according to Akaike (1974) and Schwarz (1978), the log-likelihood function, when used in isolation, tends to favor overparameterized models, increasing the risk of *overfitting* — a situation in which the model fits the historical data excessively, capturing noise and random variations at the expense of the series' structural patterns, which compromises its predictive ability. The specifications and metrics of the selected models are presented in Table 1.

Equation 2 presents the specification of the SARIMA 1 $(4,1,4)(5,1,1)_{12}$ model, while Equation 3 corresponds to the SARIMA 2 $(4,1,4)(5,1,2)_{12}$ model. In turn, Equation 4 describes the formulation of the SARIMA 3 $(4,1,4)(5,1,3)_{12}$ model.

$$\left(1-\Phi_1 L^{12}-\Phi_2 L^{24}-\Phi_3 L^{36}-\Phi_4 L^{48}-\Phi_5 L^{60}\right)\cdot\left(1-\phi_1 L-\phi_2 L^2-\phi_3 L^3-\phi_4 L^4\right)\cdot(1-L)(1-L^{12})\cdot y_t=\left(1+\Theta_1 L^{12}\right)\cdot\left(1+\theta_1 L+\theta_2 L^2+\theta_3 L^3+\theta_4 L^4\right)\cdot\varepsilon_t$$

$$\left(1-\Phi_1 L^{12}-\Phi_2 L^{24}-\Phi_3 L^{36}-\Phi_4 L^{48}-\Phi_5 L^{60}\right)\cdot\left(1-\phi_1 L-\phi_2 L^2-\phi_3 L^3-\phi_4 L^4\right)\cdot(1-L)(1-L^{12})\cdot y_t=\left(1+\Theta_1 L^{12}+\Theta_2 L^{24}\right)\cdot\left(1+\theta_1 L+\theta_2 L^2+\theta_3 L^3+\theta_4 L^4\right)\cdot\varepsilon_t$$

$$\left(1-\Phi_1 L^{12}-\Phi_2 L^{24}-\Phi_3 L^{36}-\Phi_4 L^{48}-\Phi_5 L^{60}\right)\cdot\left(1-\phi_1 L-\phi_2 L^2-\phi_3 L^3-\phi_4 L^4\right)\cdot(1-L)(1-L^{12})\cdot y_t=\left(1+\Theta_1 L^{12}+\Theta_2 L^{24}+\Theta_3 L^{36}\right)\cdot\left(1+\theta_1 L+\theta_2 L^2+\theta_3 L^3+\theta_4 L^4\right)\cdot\varepsilon_t$$

Table 2 – Error metrics and residual diagnostics

Model	MAE	MAPE (%)	MSE	MPE (%)	Shapiro-Wilk	ARCH
SARIMA 1	3,423.50	8.28	29,860,717.69	-0.38	1.02×10^{-11}	2.30×10^{-3}
SARIMA 2	3,418.68	8.24	29,781,228.79	-0.30	8.96×10^{-12}	2.39×10^{-3}
SARIMA 3	3,397.77	8.27	29,508,394.30	-0.50	6.28×10^{-12}	1.51×10^{-3}

Source: prepared by the authors using data provided by Dataprev

It is observed that, among the three models evaluated, the most complex specification showed slightly superior performance in the assessment of predictive performance based on error metrics and residual diagnostic tests, as shown in Table 2. This result suggests that incorporating a greater number of parameters may contribute to a better *in-sample* fit of the series. However, such gains proved marginal when compared to the increase in model complexity. It should be noted that the residual diagnostics and performance metrics were evaluated exclusively from the period following the *burn-in*, as determined by the Kalman filter in the estimation process via *Statsmodels*, with the aim of avoiding distortions resulting from the diffuse initialization of states in the integrated model.

Initially, it should be noted that none of the models fully satisfied the assumptions of normality in the *Shapiro-Wilk* test and homoscedasticity in the *Autoregressive Conditional Heteroskedasticity* (ARCH) test. Additionally, the models were unable to adequately capture the exogenous impact caused by the pandemic, which significantly altered the pattern of 13th-month bonus benefit payments.

Another relevant finding was the continuous growth of the error over time, particularly marked by an underestimation of the model starting in 2016, which became even more pronounced during the pandemic period. However, after the pandemic ended, the error returned to levels close to those observed previously, in 2016.

One possible explanation for this phenomenon lies in the increase in benefits granted due to the 2019 social security reform (Constitutional Amendment 103/2019), which spurred a rush to retire before the new rules took effect. This exogenous factor continuously increased social security expenditures, representing an additional challenge that the analyzed models were unable to estimate or address adequately.

Finally, when analyzing the error measures, it is observed that the evaluated models exhibit very similar performance, with relative advantages distributed among the different specifications. The SARIMA 3 model presented the lowest MAE and MSE values, indicating a smaller mean error and a lower penalty for deviations of greater magnitude. In turn, the SARIMA 2 model presented the lowest MAPE and the MPE closest to zero, suggesting a lower average percentage error and less systematic bias in the forecasts. The SARIMA 1 model, although it did not stand out individually in any error metric, performed comparably to the other models.

In summary, considering the balance between fit quality and complexity, the SARIMA 1 model is chosen as the final specification for making forecasts. This choice is based on its relatively lower complexity, as indicated by the information criteria, and on the fact that the differences observed in the error metrics relative to the alternative models are marginal, not justifying the adoption of a more parameterized structure, following the principle of parsimony advocated by Box and Jenkins (1976).

Table 3 presents the estimated parameters of the selected SARIMA 1 model. In the non--seasonal component, it is observed that the second-order autoregressive coefficient (AR(2)) is statistically significant at the 5% level ($p = 0.032$), indicating the presence of short-term time dependence, in which variations occurring in recent periods influence the behavior of the series with a lag of up to two months. The other non-seasonal autoregressive and moving average terms were not statistically significant individually, which is consistent with higher-order models and multiplicative structures.

In the seasonal component, the autoregressive term with a 60-month lag (AR.S(60)) stands out, being statistically significant at the 5% level ($p = 0.042$), suggesting the presence of long-term seasonal dependence in social security expenditures. Additionally, the AR.S(48) coefficient showed marginal significance at the 10% level ($p = 0.062$), reinforcing the evidence of multi-year cyclical patterns. These results are consistent with the institutional dynamics of INSS expenditures, influenced by periodic benefit adjustments and recurring components of the social security calendar.

Table 3 – Results of the estimation of the SARIMA 1 model parameters

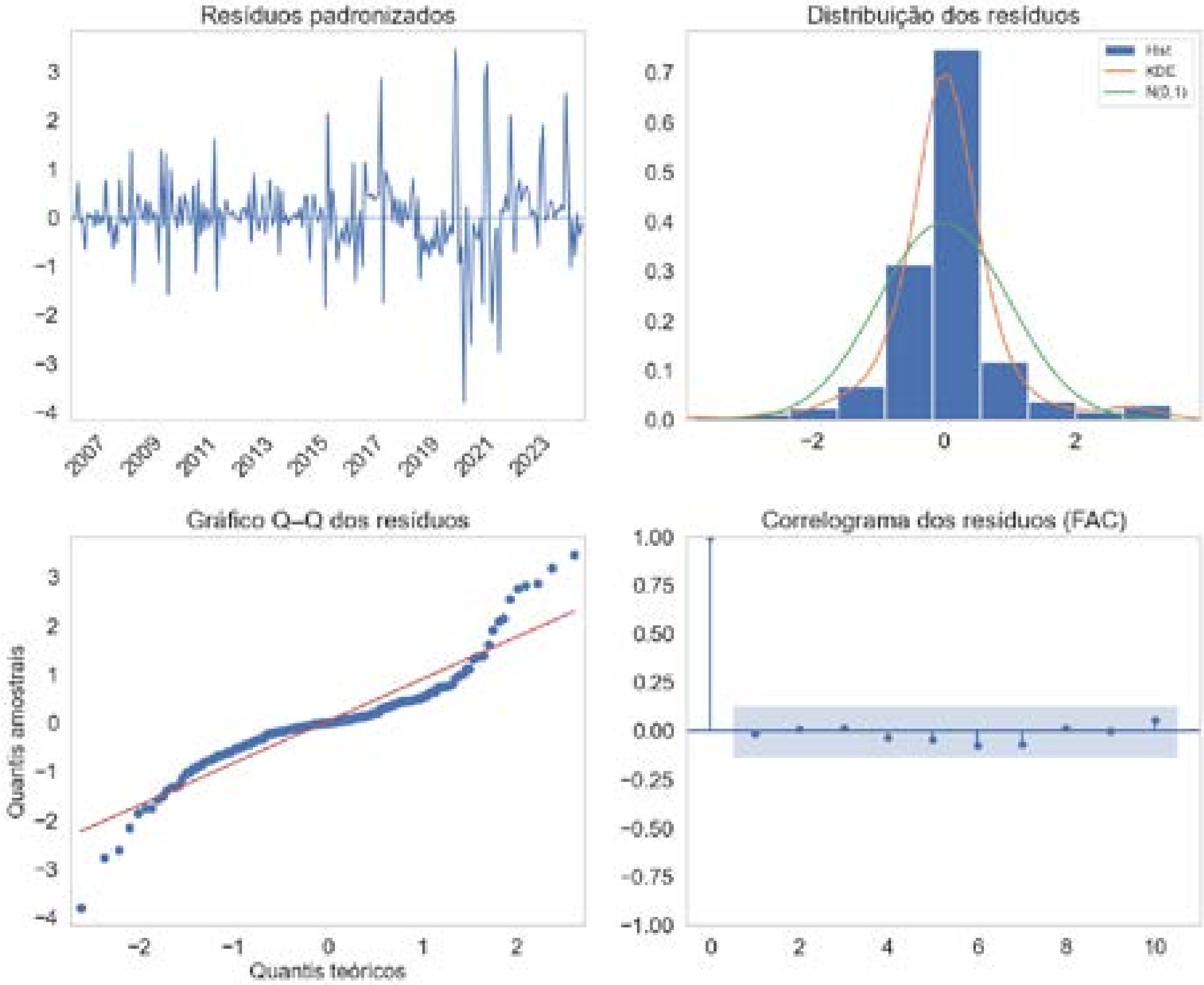
Parameters	Coefficient	Standard Error	Z	P>|z|	[0.025	0.975]
ar.L1	-0.3405	1.801	-0.189	0.85	-3,871	3,190
ar.L2	0.9663	0.45	2,145	0.032	0.083	1,849
ar.L3	0.4507	1,438	0.313	0.754	-2,368	3,270
ar.L4	-0.0702	0.142	-0.493	0.622	-0.349	0.209
ma.L1	-0.4733	1.795	-0.264	0.792	-3,991	3,044
ma.L2	-14,582	1,934	-0.754	0.451	-5,250	2,333
ma.L3	0.3749	1,474	0.254	0.799	-2,515	3,264
ma.L4	0.5577	1,610	0.346	0.729	-2,597	3,713
ar.S.L12	-0.9283	0.613	-1,514	0.13	-2,130	0.273
ar.S.L24	-0.1023	0.409	-0.25	0.803	-0.905	0.7
ar.S.L36	-0.11	0.139	-0.793	0.428	-0.382	0.162
ar.S.L48	-0.2185	0.117	-1.865	0.062	-0.448	0.011
ar.S.L60	-0.2543	0.125	-2.033	0.042	-0.5	-0.009
ma.S.L12	0.2828	0.637	0.444	0.657	-0.966	1.531
sigma2	3.95E+10	4.85E-07	8.14E+13	0	3.95E+07	3.95E+07

Source: prepared by the authors using data provided by Dataprev

Taken together, the results indicate that the model is capable of capturing both short-term dynamics and long-term seasonal components, even though not all individual parameters are statistically significant. This characteristic is common in multi-term SARIMA models, especially when model selection is based on information criteria and overall performance.

Figure 4 presents the analysis of the standardized residuals of the estimated SARIMA model, considering only the period after the *burn-in*, which allows for a more appropriate assessment of the quality of the fit and the behavior of the errors. It can be observed in the upper left graph that the residuals remain distributed around zero, with no apparent systematic trend and with approximately constant variance over time until 2015, indicating that the model captures the trend and seasonality well. However, it is noted that starting in 2015, the deviations become more pronounced, reflecting an increase in the discrepancy between observed and estimated values. This behavior may be associated with the institutional changes discussed earlier, which altered the dynamics of social security expenditures.

Figure 4 – Analysis of SARIMA 1 model residuals



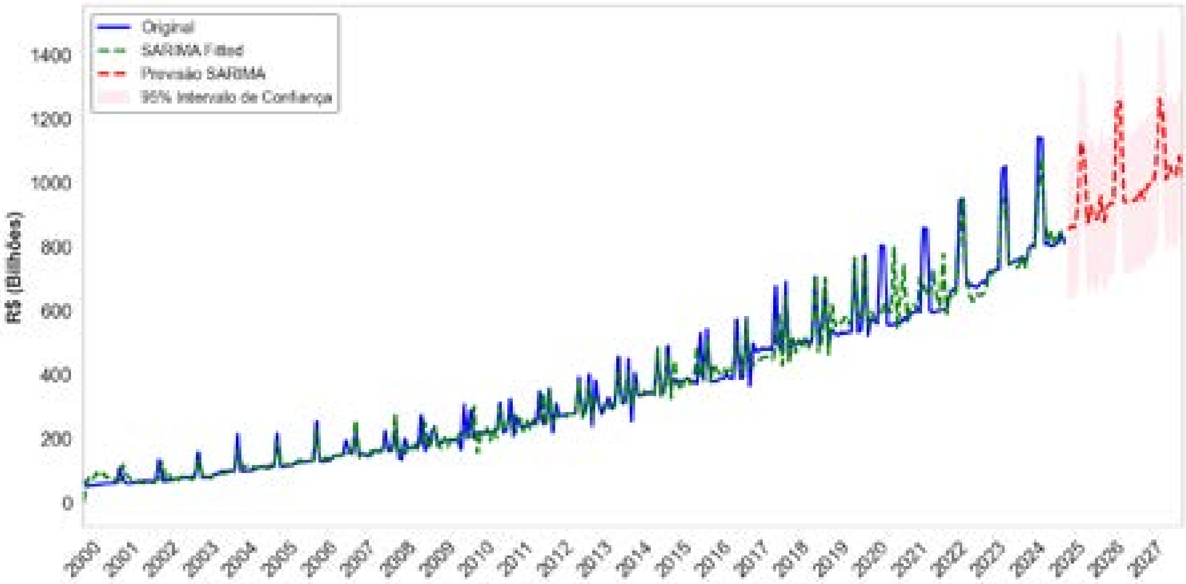
Source: prepared by the authors using data provided by Dataprev

The histogram (top right) shows that the distribution of the residuals is approximately normal, centered at zero, although it exhibits a slight concentration of values in the tails, suggesting the occurrence of larger-magnitude shocks. This characteristic is confirmed by the Q–Q plot (bottom left), where the points align well with the theoretical line, except at the ends, indicating modest deviations from normality. The correlogram (bottom right), on the other hand, reveals that all residual autocorrelations fall within the confidence limits, showing that the residuals behave like white noise, with no residual temporal pattern.

In substantive terms, it is important to note that the increase in residual variability after 2020 coincides with the context of the COVID-19 pandemic, a period marked by changes in the schedule and disbursement of the 13th-month bonus and a reduction in in-person services at the INSS, which delayed new retirement applications. These factors contributed to temporary structural breaks in the series, generating fluctuations not anticipated by the model. Despite this, the overall behavior of the residuals indicates that the model retains good explanatory power, adequately capturing the trend and seasonal cycles of social security expenditures, with occasional deviations consistent with exceptional shocks.

The projections for nominal INSS expenditures, shown in Figure 5, indicate a consistent growth trajectory in the coming years. Between 2024 and 2027, a cumulative increase of 22.63% is observed, a significant figure even over a relatively short time horizon. In annual terms, this result corresponds to a compound annual growth rate (CAGR) of 7.04% per year, a level significantly higher than the 3% inflation target set by the Central Bank of Brazil.

Figure 5 - Forecast of INSS Social Security Expenditures (2025–2027)



Source: prepared by the authors using data provided by Dataprev

Given that the analyzed period covers only 36 months, no significant demographic changes are expected to occur that could, on their own, explain real growth of this magnitude. In this sense, the projected behavior of expenditures is strongly linked to the policy of adjusting the minimum wage above inflation, since a significant portion of social security benefits is indexed to this parameter. This dynamic demonstrates that, even in the short term, real adjustments to benefits have significant impacts on the system's expenditure level, an aspect already highlighted by Giambiagi (2025) when discussing the effects of this policy on long-term social security sustainability.

5. FINAL CONSIDERATIONS

Therefore, it is concluded that the historical series of INSS nominal expenditures, in the short term, is influenced by a broad set of social security, political, and socioeconomic factors, as discussed throughout the article. These elements contribute to the persistence of expenditure growth and intensify the debate regarding the economic viability and sustainability of the Brazilian social security system.

In this context, the estimated SARIMA model proves suitable for short-term forecasting, showing that INSS expenditures continue to grow even after the implementation of social security reforms. This result underscores the need to deepen the debate on new structural reforms, as well as to improve the use of econometric tools to support the process of formulating and evaluating public policies.

Furthermore, the series exhibits, in the long term, high sensitivity to external explanatory variables, such as inflation, demographic dynamics, labor market conditions, and changes in social security rules. In this context, the incorporation of exogenous factors proves essential for making forecasts over longer time horizons.

From this perspective, it is important to highlight other classes of time-series models that can contribute to deepening this debate. Within the scope of univariate models, the possibility of extending SARIMA-type seasonal structures to include regression components with autocorrelated errors stands out, in accordance with the ARIMA regression treatment presented by Shumway and Stoffer (2017). This formulation constitutes the theoretical basis for models widely used in applied practice, such as SARIMAX (Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors).

In multivariate contexts, VARX (*Vector Autoregression with Exogenous Variables*) models are particularly suitable when multiple series exhibit dynamic interdependence, and are comprehensively formalized by Lütkepohl (2005). Furthermore, when there are long-term relationships between cointegrated variables, the *Vector Error Correction Model* (VECM) structure, also addressed by Lütkepohl (2005), offers an appropriate framework for capturing both short-term dynamics and long-term equilibria.

Thus, the objective of this article is to foster debate on the adoption of more advanced econometric tools capable of generating information that supports the formulation and evaluation of public policies aimed at the sustainability of the social security system.

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APPENDIX A – EVALUATION METRICS

Log – Likelihood:

$$l(\hat{L}) = -\frac{n}{2} l(2\pi) - \frac{n}{2} l\left(\hat{\sigma}^2\right) - \frac{1}{2\hat{\sigma}^2} \sum_{t=1}^{n} \left(y_t - \hat{y}_t\right)^2 \quad (5)$$

Where:

n is the number of observations,

y_t are the observed values,

$\hat{y}_t$ are the values predicted by the model,

$\hat{\sigma}^2$ is the estimated variance of the residuals.

$\hat{L}$ is the value of the maximized likelihood function.

Akaike Information Criterion (AIC):

$$AIC = 2k - 2 \ln ln \left(\hat{L}\right) \quad (6)$$

Where:

k is the number of model parameters,

Bayesian Information Criterion (BIC):

$$BIC = k \ln ln\ (n) - 2 \ln ln \left(\hat{L}\right) \quad (7)$$

Mean Absolute Error (MAE):

$$MAD = \frac{1}{n} \sum_{t=1}^{n} \left|y_t - \hat{y}_t\right| \quad (8)$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{n} \sum_{t=1}^{n} \left|\frac{y_t - \hat{y}_t}{y_t}\right| \quad (9)$$

Mean Percentage Error (MPE):

$$MPE = \frac{100}{n} \sum_{t=1}^{n} \left(\frac{y_t - \hat{y}_t}{y_t} \right) \tag{10}$$

Mean Square Error (MSE):

$$MSD = \frac{1}{n} \sum_{t=1}^{n} \left(y_t - \hat{y}_t \right)^2 \tag{11}$$

Shapiro–Wilk P-value Test:

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)} \right)^2}{\sum_{i=1}^{n} \left(x_i - \bar{x} \right)^2} \tag{12}$$

Where:

$x_{(i)}$ are the ordered residuals of the SARIMA model,

$\bar{x}$ is the mean of the residuals,

a_i are constant coefficients based on the normal distribution,

n is the number of observations (residuals).

ARCH Test (*Autoregressive Conditional Heteroskedasticity*):

$$LM = nR^2 \tag{13}$$

Where:

n is the number of observations,

R^2 is the coefficient of determination of the auxiliary regression.