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FORECASTS ON THE EVOLUTION OF HUMAN RESOURCES IN THE HEALTH SYSTEM IN ROMANIA USING THE ARIMA METHOD

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In this paper, forecasts are made regarding the number of employees in the public and private health sector in Romania for different professional categories such as: physicians, dentists, pharmacists, family physicians, medical assistants, auxiliary personnel. Using the Dickey-Fuller test, it was initially checked whether the time series were stationary and if not, the first or second difference was applied to make them stationary. Using the auto-regressive integrated moving average (ARIMA) method with the stages of identification, estimation, diagnosis and prediction, the forecasts for the period 2023-2025 together with the associated confidence intervals were determined, using data provided by the National Institute of Statistics. Regarding the public sector health personnel, a decrease is expected, in general, for the period 2024-2025. Instead, the private sector continues its previous trend of constant growth in the number of employees. Thus, authorities can use these forecasts to adjust strategies for training and recruiting medical personnel according to the estimated need. Forecasts are an essential tool to ensure the balance between demand and supply in the health sector, thus contributing to the improvement of medical services and the long-term sustainability of the health system.

Keywords: **Forecast, Health system, Human resources, ARIMA method.**

JEL Classification: **C53, C32, I18**

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1. Introduction

The health system in Romania was and remains a subject of maximum importance, both from the perspective of public health and socio-economic development policies. In a global context marked by major health challenges, such as the COVID-19 pandemic, the efficiency and capacity of health systems are essential to ensure the well-being of the population and to manage health crises.

The medical system in Romania went through a series of transformations and challenges after 1990, reflecting the social, economic and political changes of the post-communist period. After 1990, Romania began to implement reforms in the health sector, including the decentralization of the medical system. This change involved the transfer of responsibilities to local authorities, which led to significant differences in the quality and accessibility of medical services in different regions of the country (Iacobuță, Asandului, Gavrilovici and Oprea, 2013). Also, the Romanian medical system has been affected by chronic underfunding and limited resources. The budget allocated for health was often insufficient to cover the real needs of the population, which led to shortages in equipment, medicines and medical personnel.

Human resources are fundamental to the efficient functioning of any health system. The analysis of the health personnel in Romania, both in the public and private sectors, is crucial to understand the challenges related to the unequal distribution of medical personnel, the exodus of doctors and the shortage of personnel in certain regions or specializations. Forecasts made by statistical methods are necessary to anticipate future developments and to propose viable solutions. In this paper we will make forecasts on the number of employees in the public and private health system in Romania, for the different categories of personnel, using the ARIMA method. A forecast of the health personnel, but using analytical functions, is carried out in the work of Mirescu and Popescu, 2024.

Accurate forecasts help policymakers understand future trends in health workforce needs. Depending on the expected increase or decrease in the number of employees, authorities can take proactive measures to adjust the allocation of human and material resources, such as staff training, recruitment or policy development to attract and retain medical staff. Forecasts can help identify potential staff shortages in different areas of the health system early. This allows for prompt interventions to ensure that there are enough doctors, nurses and support staff to meet the needs of the population. Using forecasting to anticipate staffing fluctuations allows managers to optimize scheduling and improve operational efficiency in hospitals and other healthcare facilities. This can reduce costs and improve the quality of medical services provided. Health authorities can use forecasts to estimate future staffing expenditure and budget accordingly. Accurate forecasts help avoid unexpected expenses and efficiently allocate funds to areas of greatest need.

Forecasts can be used to assess the effect of current or future public policies on the number of employees. For example, a policy to increase wages or improve working conditions for medical personnel could positively influence the number of employees, and ARIMA forecasts can help estimate this impact. Thus, the use of ARIMA forecasts for the number of employees in the healthcare system in Romania can help improve management and planning in the healthcare field, thus contributing to ensuring quality medical services for the population.

Determining confidence intervals for forecasts of health personnel in Romania is useful because it provides essential information about the precision and uncertainty associated with these forecasts. Confidence intervals provide a measure of the uncertainty associated with the predictions made. Rather than relying on just a point value, confidence intervals indicate a range of values where the actual number of employees is expected to lie, with some probability, usually 95%. This is important for decision makers because it allows them to take into account the variability and uncertainty inherent in forecasts. If the confidence interval is very wide, this suggests a large uncertainty in the forecast, which may require a more conservative approach to recruitment planning and resource allocation. Confidence intervals can be used to assess the risks associated with different scenarios. Thus, if there is a significant probability that the number of physicians will fall below a certain critical threshold (based on the lower confidence interval), preventive measures can be taken to avoid staff shortage. This allows for proactive risk management, thereby reducing potential staffing crises in the future.

Confidence intervals facilitate the communication of uncertainty to decision makers and other stakeholders. This helps to adjust expectations and understand that all forecasts have a degree of uncertainty. Thus, managers and decision makers are better prepared to respond to different possible outcomes. The use of confidence intervals allows authorities to monitor actual results against forecasts and adjust policies and strategies accordingly. If the actual results deviate systematically from the confidence intervals, this may indicate the need for a review of the forecast model or of applied policies.

In conclusion, the determination of confidence intervals for forecasts of health personnel in Romania is essential for effective planning and management, allowing a more realistic assessment of the future and preparation for various scenarios. This leads to better informed decisions and to the more efficient use of resources in the health system.

The present work is structured as follows. In the second section, the research methodology and the review of the specialized literature are presented. The third section contains the novelty of the scientific research in which forecasts are presented regarding the evolution of the number of employees in the health sector for different professional categories. We use the ARIMA method, we will make forecasts for the period 2023-2025. The aim is to evaluate the changes, developments and trends in the number of employees in the health sector. The available data corresponds to the period 1990-2022 for the public sector and 1997-2022 for the private sector and are obtained from the National Institute of Statistics (INS).

2. Literature Review

The autoregressive integrated moving average (ARIMA) model has been widely applied in various fields of public health, including epidemiology, health resource management, drug price analysis or health systems performance evaluation. Held, Höhle and Hofmann (2005) used ARIMA to monitor the temporal dynamics of infectious disease cases in Germany. Their study demonstrates how ARIMA can be used to predict the future number of cases based on historical data.

Forecasting the demand for medical resources, such as hospital beds and medical personnel, is essential for effective planning. ARIMA can help anticipate needs based on historical trends. Janssen et al. (2020) used ARIMA models to forecast the need for beds in intensive care units during the COVID-19 pandemic in the Netherlands. This study is useful for resource allocation in crisis conditions. ARIMA is used to analyze and forecast trends in drug prices and health spending. These forecasts are crucial for health policy-making and budget planning. Schuetz et al. (2018) investigated generic drug price fluctuations in Europe using ARIMA models to assess long-term trends. The results of their study provided valuable insights into the factors that influence drug prices. Assessing the performance of health systems by analyzing time series of health indicators can reveal changes over time and support policy decisions. Penasso et al. (2019) used ARIMA to assess the impact of health reforms in different EU countries. The study analyzed the evolution of key indicators, such as mortality and accessibility of medical services, to determine the effectiveness of implemented policies.

To forecast the demand for medical workers from 2014 to 2020 in Sichuan Province, the authors He, Wang, Liu et al. (2014,) used the ARIMA(1,2,1) model with the selection of medical workers from the data from 1995-2013. The results showed that the demand for medical workers in this province of China was going to increase to 649,700 in the year 2020. In the work of Duarte and Faerman (2019), a prediction was made of some performance indicators of the emergency department in chronological series that can benefit hospital planning, improving the quality of care and optimizing resources. It motivates the analysis of models, which can forecast relevant performance indicators, by identifying future pressure. This paper uses the ARIMA method compared to Prophet analysis, an autoregressive forecasting model based on recurrent neural networks. The analyzed data set consists of hospital indicators evaluated hourly, consisting of: waiting time in the emergency room to see a patient, number of major attendances in the emergency service, patients not assigned to the emergency room and number of beds available in the medical unit. Each model was designed to provide better predictions for different characteristics of the time series, and the metrics of the best prediction for each indicator are based on the indicator's precision, confidence intervals, and other information.

Kam, Sung and Park (2010) evaluated time series models to predict the daily number of patients arriving at the Emergency Department of a Korean hospital. Data were collected from the hospital's IT system database and to develop a forecasting model, they used 2 years of data from January 2007 to December 2008. The multivariate ARIMA model was the best fit for forecasting the daily number of patients visiting the emergency department. As healthcare costs remain an ongoing challenge for policymakers, forecasting healthcare inflation as accurately as possible has become crucial in the European Union. Erker's (2024) study aimed to provide insights into the medical inflation trend in the EU using the ARIMA model and verify whether this model is an effective tool for prediction. The study's findings have significant implications across sectors, with medical inflation forecasts helping policymakers to proactively address challenges, insurers to determine appropriate premiums and develop innovative models, and healthcare entities to strategically allocate resources to ensure financial stability and quality care.

The work of Sevim and Ağırbaş (2024) aimed to estimate and evaluate the trends of public health expenditure and total expenditure in the sphere of public financial management. The study uses the ARIMA model, using monthly data covering 202 periods from January 2006 to October 2022. The forecast period spans from November 2022 to December 2024. The results show a notable upward trend in both public health expenditure and total expenses. The study also highlights a strong link between policy, planning and budgeting, and draws conclusions to enhance the potential for effective and efficient use of resources. Accurate predictions of life expectancy at birth are crucial for governments and organizations to make informed decisions and effectively plan for future demographic changes. Forecasting life expectancy at birth has become central to demographic research because of its central role in planning and policy formulation. The study by Kittipittayakorn (2024) addresses this gap by examining the performance of two main econometric models, namely the autoregressive integrated moving average (ARIMA) and the vector error correction (VEC) model, in predicting future life expectancy at birth in Europe. The results showed that the ARIMA model better predicted future life expectancy at birth for half of the European countries in this study, while the VEC model was more accurate for the other half.

Despite the importance of accurate demand forecasting for the registered nurse (RN) workforce, few studies have evaluated prior forecasts. Thus, Jeong's (2024) paper examined the accuracy of previous forecasting studies and explored its determinants of the accuracy of demand forecasts. Data was collected through systematic review of national reports or articles on RN demand forecasts. The mean absolute percentage error (MAPE) was measured for the forecast error by comparing the forecast with the actual demand. Nonparametric, Mann–Whitney and Kruskal–Wallis tests were used to analyze differences in MAPE according to variables, which are methodological and research factors. Luo, Chen, Liu, and Weng's (2024) research aimed to provide a reference point for relevant departments to improve resource allocation for the elderly and formulate policies accordingly. Data from the Office for National Statistics and the Ministry of Civil Affairs on adults aged over 60 from 2000 to 2022 and care beds from 1978 to 2022 were analyzed. ARIMA modeling and Monte Carlo simulation were used to predicts the growth of care beds per 1000 elderly people in China for the years 2023–2025. Thus, from 2023 to 2025, China is projected to experience further growth in its aging population, with an average annual growth rate of 3.1%. In addition, there will be an increase in the number of care beds, with an average annual growth rate of 1.9%.

The study by Zheng et al. (2020) aimed to forecast changes in total health expenditure (THE), government health expenditure (GHE), social health expenditure (SHE) and health out-of-pocket expenditure (OOP) in China from 2018 to 2022 and provide a theoretical assessment as a basis for health policy adjustment. Based on the health expenditure data from the time series from 1978-2017, the following ARIMA (3.3.0), ARIMA (1.3.1), ARIMA (2.4.0), ARIMA (2.2.2) models were validated. According to the simulation results, in 2022, China's THE is expected to reach 8473.00 billion yuan, and the constituent rates in GHE, SHE and OOP will be 25.49%, 51.25% and 23.26% respectively %. The ratio of THE to GDP will continue to increase during 2018-2022 at a reasonable rate, while the THE itself will grow rapidly.

The work of Boghicevici (2023) aimed to carry out a diagnosis of the health system in Romania, the analyzes being carried out on a database with specific indicators for the medical infrastructure for the period 2014-2021. The research carried out analyzes the resources allocated to the healthcare system in Romania, for the mentioned period, from the point of view of efficiency, effectiveness and economy and makes forecasts with the ARIMA model, including the healthcare staff. The results of the research revealed a direct link between the allocation of resources in the health system and the sustainability of the system. The study by Klazoglou and Dritsakis (2018) presents the practical steps to consider in using autoregressive integrated moving average (ARIMA) time series models to forecast total health spending as a percentage of GDP for the US using data annually from the period 1970–2015. The purpose of this study was to identify the appropriate type of model based on the Box-Jenkins methodology. The results of this study showed that the ARIMA(0,1,1) model is suitable for forecasting US health expenditures during this period. Nyoni (2023) uses annual Neonatal Mortality Rate (NMR) time series data for Italy from 1960 to 2019 to predict future NMR trends from 2020 to 2030. The optimal model found was ARIMA (2,2,2). The findings of this study indicate that neonatal mortality will remain very low throughout the out-of-sample period.

The paper by Choudhury and Urena (2020) discusses the use of hourly time series forecasting to help improve emergency department management by predicting future patient arrivals. Data were obtained from the emergency department from January 2014 to August 2017 and were retrieved from one hospital in Iowa. Auto-regressive integrated moving average (ARIMA), Holt-Winters, TBATS, and neural network methods were implemented and compared to forecast patient hourly arrivals. ARIMA (3,0,0) and (2,1,0) model was selected as the best fit model with Akaike minimum information criterion and Schwartz Bayesian criterion. The model was stationary and qualified under the Box-Ljung correlation test and the Jarque-Bera test for normality. Mean error and root mean square error were selected as performance measures. A mean error of 1.001 and a root mean square error of 1.55 were obtained. Thus, the auto-regressive integrated moving average can be used to provide hourly forecasts for emergency department arrivals and can be implemented as a decision support system to assist staff in scheduling and adjusting emergency department arrivals.

Accurate forecasting of outpatient hospital visits is beneficial for planning and reasonable allocation of healthcare resources to meet medical demands. Regarding multiple attributes of daily outpatient visits, such as randomness, cyclicity, and trend, ARIMA time series methods may be a good choice for forecasting outpatient visits. On the other hand, outpatient visits are also affected by physician scheduling, and the effects are not purely random. The work of Luo, Luo, Zhang et al. (2017) formulate a seasonal ARIMA (SARIMA) model on a daily time series and then a single exponential smoothing (SES) model on the weekday time series and establish a combinatorial model by modifying them. The models are applied to 1 year of daily visit data in two internal medicine departments of a hospital in Chengdu to forecast daily outpatient visits approximately 1 week in advance. The proposed model is applied to forecast data for 7 consecutive days of daily outpatient visits over an 8-week period based on 43 weeks of observational data over a year. The results show that the two traditional single models and the combinatorial model are suitable for short-term forecasting horizons. In addition, the combinatorial model can better capture the comprehensive features of the time series data.

The main objective of the study by Earnest, Chen et al. (2005) was the application of type (ARIMA) models to make real-time predictions of the number of occupied beds in a hospital in Singapore. The ARIMA(1,0,3) model was found to be able to describe and predict well the number of occupied beds during the SARS outbreak. To continuously promote the rational clinical application of antibacterial drugs and provide decision-making support to the scientific management of hospitals, the work of Xie, Zhang et al. (2020) assessed the ambulatory antibiotic use rate from 2010 to 2018. The (ARIMA) model was established and verified and predicted trends in the ambulatory antibiotic use rate from November 2018 to March 2019. Thus, the average monthly rate of outpatient antibiotic use in 2010–2013 decreased from 13.04 to 12.28% in 2014–2018 (p = 0.002). The verification results show that the model can accurately predict the change trend. The mean absolute error of the actual value and the adjusted value of the antibiotic use rate was 0.76% from January to October 2018. The model can be applied to the short-term prediction and dynamic analysis of the antibiotic use rate in the outpatient setting, helping hospitals reasonably assess and monitor clinical antibiotic use and provide decision-making services for hospital management.

The purpose of the study by Zhang, Luo, Yang et al. (2019) was to investigate and evaluate the use of a hybrid ARIMA-SVR approach to forecast daily radiological emergency patient flow. Due to the fact that the flow of emergency patients is highly uncertain and dynamic, the problem of forecasting is considered a complicated task. Since emergency patient flow can have both linear and nonlinear patterns, this paper presents a hybrid ARIMA-SVR approach, which hybridizes the autoregressive integrated moving average (ARIMA) model and the support vector regression (SVR) model to predict arrival emergency of patients. The proposed model is applied to 4 years of daily emergency visit data in the radiology department of a large hospital to justify the performance of the hybrid model against individual models. The experimental results indicated that the proposed hybrid ARIMA-SVR approach is a promising alternative for emergency patient flow forecasting. These findings are beneficial for effectively managing patient flow and optimizing scheduling decisions.

Examining how to properly allocate the limited supply of medical resources is a crucial issue in the management of a medical facility. Based on time series data for all outpatients visiting a hospital in Seoul from January 2, 2017 to December 31, 2017, the study by Kim, Park, and Jang (2020) used autoregressive integrated moving average (ARIMA) models and seasonal autoregressive integrated moving averages (SARIMA) to build an ambulatory prediction model. ARIMA (3,0,2) and SARIMA (2,0,1) (1,0,0) models were established. Comparing the predicted accuracy of outpatient visits, the SARIMA model was found to be relatively more accurate than the ARIMA model. In the work of Dubrovina et al. (2021) three of the most popular indicators used for the macroeconomic description of health care financing are analyzed: total government health expenditure as a percentage of GDP, total government health expenditure as a percentage of total general public expenditure and total government health expenditure per capita of resident. The purpose of this research was to study the trends for the main indicators of health financing at the macroeconomic level and to develop models based on ARIMA time series methods for the analysis of trend characteristics and the prediction of values for the next period.

The study by Ceylan, Bulkan and Elevli (2020) evaluated the performance of different mathematical modeling methods to forecast medical waste generation. Autoregressive integrated moving average (ARIMA) analysis, support vector regression (SVR), Gray (1,1) modeling and linear regression (LR) were used to estimate annual medical waste generation from 2018 to 2023 using data on 23 years from 1995 to 2017. Various performance measures such as mean absolute deviation (MAD), mean absolute percentage error (MAPE), root mean square error (RMSE) and coefficient of determination (R2). The ARIMA(0,1,2) model with the lowest RMSE (763.6852), MAD (588.4712) and MAPE (11.7595) values and the highest R2 value (0.9888) showed a performance of superior prediction compared to SVR, Gray (1, 1) modeling, and LR analysis. Results from the models indicated the total amount of annual medical waste to be generated increased from approximately 26,400 tonnes in 2017 to 35,600 tonnes in 2023. The purpose of the study by Tekindal et al. (2016) was to forecast the number of people per doctor through the ARIMA method, exponential smoothing methods and trend models, but also to make a comparison between these models for the best estimates. Data on the number of persons per physician were obtained for the period 1928 to 2010. The ARIMA model was found to have the best values except for the mean absolute percentage error (MAPE) and the mean absolute error (MAE).

3. Methodology

The Dickey-Fuller test (Dickey and Fuller, 1979) is a statistical test used to determine whether a time series is stationary or not. Stationarity is an important property of time series, meaning that the statistical properties of the series, such as mean and variance, do not change over time. A time series is considered stationary if it does not have a long-term upward or downward trend and if its variability does not vary over time. The Dickey-Fuller test checks for the existence of a unit root in an autoregressive (AR) model, which indicates non-stationarity of the time series. If there is a unit root, it means that the time series is non-stationary and has a tendency to move over time, either increasing or decreasing, without returning to a constant mean value. The Augmented Dickey-Fuller (ADF) test assumes that the series may have a deterministic trend or a constant (intercept) and allows the addition of lag terms to correct for autocorrelation of the residuals. This test is more robust and is usually preferred in practice because adding lags solves the problem of autocorrelation of residuals, which can lead to erroneous results in the case of the simple Dickey-Fuller test. The basic mathematical model of the augmented Dickey-Fuller test can be expressed as follows:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \epsilon_t, \tag{1}$$

Where,

- y_t is the analyzed time series
- Δy_t is the first-order differentiation, i.e. $y_t - y_{t-1}$
- α is the constant term (intercept)
- βt is the linear trend term
- γy_{t-1} is the autoregressive coefficient for the first-order lag
- $\delta_1, \delta_2 \dots, \delta_p$ are the coefficients for the additional lag terms
- ϵ_t is the error, called white noise

The Dickey-Fuller test verifies the null hypothesis H0: the time series has a unit root (is non-stationary), respectively the alternative hypothesis H1: the time series does not have a unit root (is stationary). The interpretation of the test results is done by comparing the value of the test statistic (attached probability) with predefined critical values (at significance levels of 1%, 5%, 10%). If the value of the test statistic is less than the critical value, the null hypothesis is rejected, indicating that the time series is stationary. The test also generates an attached probability and if this is less than 0.05 then the series is stationary at a 5% significance level. The Dickey-Fuller test is frequently applied in time series analysis to determine whether a series is stationary or requires differentiation to become stationary. Stationarity is an essential condition for many prediction and estimation models, such as ARIMA (autoregressive integrated moving average) models.

The t-Student statistical test is used to test the null hypothesis H0: the coefficients are not significantly different from 0, respectively the alternative hypothesis H1: the coefficients are significantly different from 0. If the probability attached to the t-Student test is lower than the chosen significance threshold (usually 0.05), then the null hypothesis is rejected and the hypothesis H1 is accepted, i.e. the coefficients are significantly different from zero.

The Durbin-Watson test is used to check whether there is first-order autocorrelation of the residuals, or whether they are independent, and the Breusch-Godfrey test is useful for checking for higher-order autocorrelation of the errors. Autocorrelation of errors occurs when the errors (residuals) of a regression model are correlated with each other, that is, the value of an error at a given time depends on the values of previous errors. This violates one of the basic assumptions of linear regression, which assumes that the residuals are independent. The presence of autocorrelation can lead to underestimation of standard errors of coefficients and incorrect interpretations of significance tests. The Durbin-Watson test generates a scored test statistic (DW) based on the difference between the residuals between two consecutive points in time defined by (Durbin and Watson, 1950):

$$DW = \frac{\sum_{i=2}^{n}(\hat{\varepsilon}_i - \hat{\varepsilon}_{i-1})^2}{\sum_{i=1}^{n}(\hat{\varepsilon}_i)^2}, \quad (2)$$

where *n* represents the number of observations. The *DW* statistic varies between 0 and 4, and the closer it is to 0, the greater the positive autocorrelation, and the closer it is to 4, the greater the negative autocorrelation. Conversely, a value close to 2 indicates no autocorrelation. The null hypothesis H0: there is no first-order autocorrelation (errors are independent), respectively the alternative hypothesis H1: there is first-order autocorrelation (positive or negative). For verification, the *DW* value is compared to the lower limit d_L and upper limit d_U from the Durbin-Watson table for a certain significance threshold, usually 5%.

- $DW < d_L$, the null hypothesis is rejected, indicating the existence of positive autocorrelation.
- $d_L \leq DW \leq d_U$, the result is inconclusive (cannot reject or accept the null hypothesis with a
- certain level of confidence).

- d_U < *DW* < 4 - d_U, the null hypothesis is accepted, indicating the absence of autocorrelation.
- 4 - $d_U \leq DW \leq$ 4 - d_L, result inconclusive (but for negative autocorrelation).
- *DW* > 4 - d_L, the null hypothesis is rejected, indicating the existence of negative autocorrelation.
- In conclusion, if *DW* is in the interval (d_U, 4-d_U) then the null hypothesis H0 is accepted, which means that the errors are not autocorrelated.

The Breusch-Godfrey test (Breusch, 1978 and Godfrey, 1978) is a statistical test used to check for the presence of higher-order autocorrelation (i.e., autocorrelation of errors at multiple lags) in the residuals of a regression model. This test is an extension of the Durbin-Watson test, which is limited to detecting first-order autocorrelation (i.e. between consecutive residuals). An auxiliary regression is constructed in which the square of the estimated residuals is the dependent variable and the original explanatory variables and the lags of the residuals as the dependent variables:

$$\hat{\varepsilon}_i^2 = \alpha_0 + \alpha_1 X_{1i} + \alpha_2 X_{2i} + \cdots + \alpha_k X_{ki} + \rho_1 \hat{\varepsilon}_{i-1} + \rho_2 \hat{\varepsilon}_{i-2} \ldots + \rho_p \hat{\varepsilon}_{i-p} + \epsilon_i, \quad (3)$$

where

- $\hat{\varepsilon}_i$ are the estimated residuals from the original model,
- $X_{1i}, X_{2i}, \ldots X_{ki}$ are the original explanatory variables,
- $\hat{\varepsilon}_{i-1}, \hat{\varepsilon}_{i-2}, \ldots, \hat{\varepsilon}_{i-p}$ are the lags of the residuals,
- p is the maximum lag order for which autocorrelation is checked,
- ϵ_i is the error of the auxiliary model.

The F (Fisher) statistic is used to test the global significance of the lag coefficients of the residuals $(\rho_1, \rho_2, .., \rho_p)$. Test if all coefficients are zero. The null hypothesis H0: there is no autocorrelation at any order (all lag coefficients are zero) is checked, respectively the alternative hypothesis H1: there is autocorrelation at least one order (at least one of the lag coefficients is different from zero). If the value of the F-test statistic is greater than the corresponding critical value for some level of significance (typically 5%), the null hypothesis is rejected, indicating the presence of higher-order autocorrelation. The Breusch-Godfrey test also generates an attached probability. If this probability is greater than 0.05 then the hypothesis H0 is accepted, and there is no autocorrelation, at a chosen significance threshold of 5%.

The ARCH test (Engle, 1982) is a statistical test used to detect the presence of conditional heteroscedasticity in time series. Heteroscedasticity occurs when the variance (dispersion) of a regression model's errors is not constant. In a conditional context, this means that the variance of the errors depends on the prior values of the errors. The ARCH test is based on estimating a regression model and analyzing its residuals to check whether there is dependence in the squared errors, that is, whether the errors have an autoregressive pattern. It starts by estimating a standard regression model and obtaining the residuals (errors). The squares of the residuals obtained from the regression model are calculated. This is important for the ARCH test because the goal is to see if these squared residuals (which represent the conditional variance of the errors) are correlated over time. An auxiliary regression of the squared residuals on their own lags (lags) is performed. The test uses the R2 statistics from the auxiliary regression to calculate a test statistic, which is then compared to a chi-square distribution to determine whether there is significant conditional heteroscedasticity. The test statistic is:

$$LM = T \times R^2 \tag{4}$$

where T is the number of observations and R^2 is the coefficient of determination from the auxiliary regression. The null hypothesis H0: there is no conditional heteroscedasticity, which means that the variance of the residuals is constant over time, respectively the alternative hypothesis H1: there is conditional heteroscedasticity, that is, the variance of the residuals depends on their previous values. If the value of the test statistic exceeds a certain critical threshold (determined by the chi-square distribution with the number of degrees of freedom equal to the number of lags), the null hypothesis of homoscedasticity is rejected (i.e. conditional heteroscedasticity is accepted). The test also generates an attached probability. If this probability is greater than 0.05 then the null hypothesis is accepted and we do not have heteroscedasticity, at a significance level of 5%.

The ARIMA or auto-regressive integrated moving average method (Box and Jenkins, 1976) is one of the most widely used time series modeling and forecasting techniques. This method is able to model and predict values in time series that exhibit autocorrelation, that is, dependent relationships between past and future values of a variable. The ARIMA model consists of three main parts (Wooldridge, 1999; Maddala, 2001):

- *Auto-regressive* (AR). This part of the model assumes that the values in the series depend linearly on the previous values. In an AR(p) model, "p" represents the number of prior terms that are used to predict the current value. The general formula for the AR component is:

$$X_t = c + \phi_1 X_{t-1} + \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + \epsilon_t, \tag{5}$$

where $\phi_1, \phi_1, \ldots, \phi_p$ are the autoregressive coefficients, c is a constant, and ϵ_t is the random error at time t.

- *Integrated* (I). The integrated component refers to the number of differentiations required to transform a non-linear (non-stationary) time series into a stationary one. A stationary series is a series whose statistical properties do not change over time. If *d* is the order of differentiation, the transformed series can be obtained as:

$$Y_t = (1-B)^d X_t, \tag{6}$$

where *B* is the lag operator and *d* is the number of differentiations.

- *Moving average* (MA). The MA component assumes that the current value of the time series can be expressed as a sum of past random error terms. In an MA(q) model, "q" represents the number of prior errors included in the model. The general formula for the MA component is:

$$X_t = c + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q X_{t-q}, \tag{7}$$

where $\theta_1, \theta_2, \dots, \theta_q$ are the coefficients of the moving average.

An ARIMA(p, d, q) model is defined by three parameters:

- p: the order of the autoregressive component (AR)
- d: order of differentiation (I)
- q: the order of the moving average component (MA).

The ARIMA model combines these three components into a general model that can be written as:

$$X_t = c + \phi_1 X_{t-1} + \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q X_{t-q}, \tag{8}$$

where the X_t series has been differentiated *d* times to make it stationary.

In order to build an ARIMA model, four stages are followed (Davidson and Mackinnon, 2004):

Identify:

- stationarity: it is checked if the series is stationary and if so, an ARMA(p,q) model results. Otherwise, differencing is performed to make it stationary, and an ARIMA(p,d,q) model is obtained.
- autocorrelation: the autocorrelation functions (ACF) and partial autocorrelation functions (PACF) are analyzed using the correlogram of the stationary series to identify possible values

corresponding to p and q. Autocorrelation determines the MA(q) component and partial correlation determines the AR(p) component.

Estimation:

- the estimation of the parameters p, d and q can be done by the method of least squares or the method of maximum likelihood. Among several possible and validated models, the one for which the values of the Akaike and Schwartz criteria are the lowest is chosen. The coefficient of determination R^2 is also taken into account, to have a higher value.
- *Evaluation*:
- the model is evaluated to check that the residuals (errors) are white noise (random series without autocorrelation). This can be done by checking the correlogram of the residuals. Attached probabilities (p-values) greater than 0.05 mean that the residuals are not autocorrelated, at a 5% significance level (they are not white noise). This hypothesis can also be verified by applying the Breusch-Godfrey test or the Ljung-Box test.
- it is verified that the estimated ARMA process is stationary: the roots of the AR component are inside the unit circle.
- it is verified if the estimated ARMA process is invertible: the roots of the MA component are inside the unit circle.
- If all the previous conditions are met, you can move on to forecasting. Otherwise, another ARIMA model is estimated and conditions are checked.

Forecast:

- after the model has been validated, it can be used to forecast future values of the time series

4. Results

4.1 Forecasts for public sector health personnel

4.1.1 Physicians (excluding dentists)

In Figure 4.1.1.1 we have the graphic representation of the number of physicians (excluding dentists) from 1990-2022. A sharp decrease was observed in the period 2014-2015, due to low wages and problems in the health system, followed by an increase starting in 2016, due to wage increases. For prediction we used the ARIMA model and initially checked if the series was stationary by applying the Dickey-Fuller test, with constant and trend. Since the probability attached to the test is 0.9383, which is greater than 0.05, it follows that the null hypothesis is accepted and the series is not stationary (Table 4.1.1.1), at a significance level of 5%. We apply the first difference to the series and check for stationarity. As the probability attached to the test 0.0045, which is less than 0.05 results in rejecting the null hypothesis and the new series is stationary (Table 4.1.1.2).

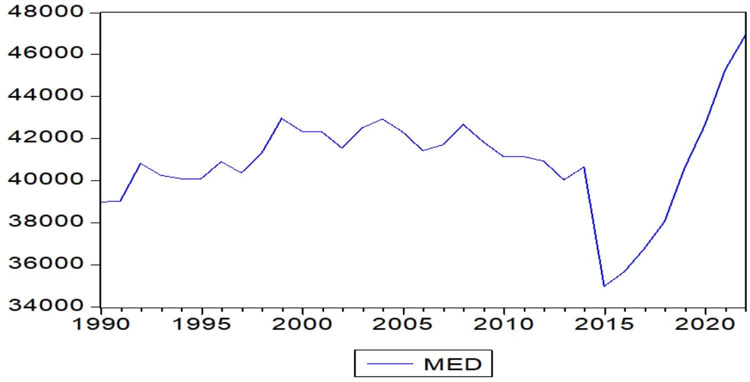

Figure 4.1.1.1. Physicians (excluding dentists) in the public sector

Table 4.1.1.1. Dickey-Fuller test at MED in the public sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-0.941821	0.9383
Test critical values:	1% level	-4.273277	
	5% level	-3.557759	
	10% level	-3.212361	

Source: Authors' calculations with Eviews software

Table 4.1.1.2. Dickey-Fuller test at D(MED) in the public sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-4.618669	0.0045
Test critical values:	1% level	-4.284580	
	5% level	-3.562882	
	10% level	-3.215267	

Source: Authors' calculations with Eviews software

From the analysis of the correlogram of the different series we can test several ARIMA models of the type (p,1,q). Several valid models resulted, and we selected the ARIMA (9,1,2) model which has the lowest Akaike and Schwarz criteria values and the highest coefficient of determination. It is found that all the estimated coefficients are significant (Table 4.1.1.3), having the probabilities attached to the t-Statistic test lower than 0.05. Also, the residuals of the model are not autocorrelated, a fact confirmed by the Durbin-Watson tests with the value 1.69 and Breusch-Godfrey with the attached probability 0.35. The ARCH test confirms the lack of heteroscedasticity, the probability attached to the test being 0.25. The ARIMA(9,1,2) model is stationary and invertible. The predictions are found in Table 4.1.1.4 and are plotted in Figure 4.1.1.2 with the confidence interval.

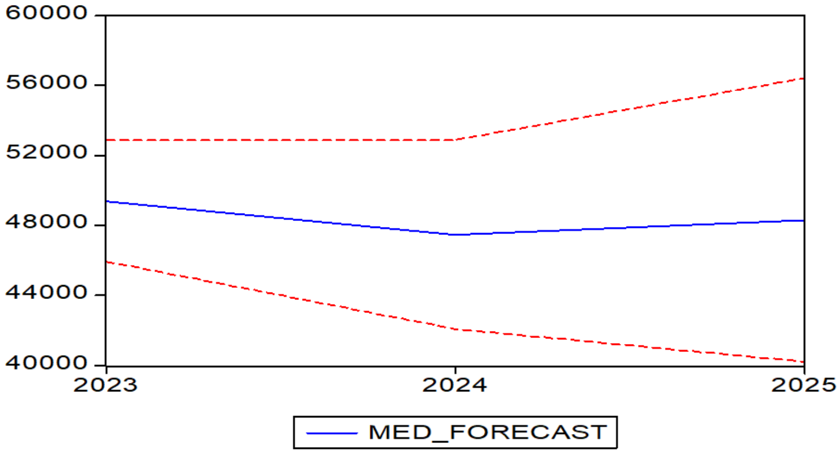

Figure 4.1.1.2. Prediction of physicians in the public sector with the ARIMA (9,1,2) model

Table 4.1.1.3. **ARIMA (9,1,2) model to D(MED) in the public sector**

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	1118.391	2025.938	0.552036	0.5870
AR(9)	0.673041	0.201687	3.337057	0.0033
MA(2)	0.842537	0.115859	7.272112	0.0000
R-squared	0.172722	Mean dependent var		171.5652
Adjusted R-squared	0.089994	S.D. dependent var		1677.834
S.E. of regression	1600.557	Akaike info criterion		17.71520
Sum squared resid	51235663	Schwarz criterion		17.86331
Log likelihood	-200.7248	F-statistic		2.087836
Durbin-Watson stat.	1.693958	Prob(F-statistic)		0.150146
Inverted AR Roots	.96	.73 -.62i	.73+.62i	.17+.94i
Inverted MA Roots	.17 -.94i			
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	1.087315	Probability		0.358263
Obs*R-squared	2.479142	Probability		0.289508
ARCH Test:				
F-statistic	1.364460	Probability		0.256502
Obs*R-squared	1.405050	Probability		0.235880

Source: Authors' calculations with Eviews software

Table 4.1.1.4. Predictions for physicians in the public sector with the ARIMA (9,1,2) model

Model	*Forecast 2023*	*Forecast 2024*	*Forecast 2025*
ARIMA (9,1,2)	49.384	47.445	48.284

Source: Authors' calculations with Eviews software

4.1.2 Dentists

The graphic representation of the number of dentists is given in Figure 4.1.2.1 where a decreasing trend can be seen from 1993 to 2015, followed by a period with a relatively constant number until 2019 and then an increasing trend until 2022. By applying the Dickey-Fuller test, with constant and trend, it was found that the initial series (STOM) is not stationary, having the probability attached to the test of 0.9991, accepting the null hypothesis of non-stationarity (Table 4.1.2.1). We apply the first difference to the series and obtain a stationary series, denoted D(STOM), the probability attached to the Dickey-Fuller test being 0.0282 (Table 4.1.2.2). From the analysis of the correlogram of the differentiated series and the verification of several possible models, we chose the ARIMA(5,1,6) model with the lowest values of the Akaike and Schwarz criteria (Table 4.1.2.3). The estimated coefficients are significant at the 5% threshold, as the probabilities attached to the t-Statistic test are less than 0.05. The residuals of the model are not autocorrelated, as confirmed by the Durbin-Watson test with a value of 1.58 and the Breusch-Godfrey test with an attached probability of 0.41. The ARCH test with the attached probability 0.79 confirms the lack of heteroscedasticity of the model. The ARIMA(5,1,6) model is stationary and invertible. The predictions are found in Table 4.1.2.4 and are plotted in Figure 4.1.2.2 with the confidence interval.

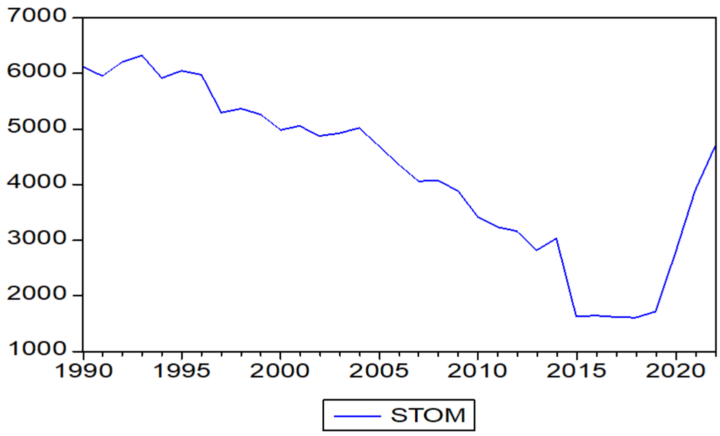

Figure 4.1.2.1. Dentists in the public sector

Table 4.1.2.1. Dickey-Fuller test at STOM in the public sector

	Level	*t-Statistic*	*Prob.*
Augmented Dickey-Fuller test statistic		0.571461	0.9991
Test critical values:	1% level	-4.273277	
	5% level	-3.557759	
	10% level	-3.212361	

Source: Authors' calculations with Eviews software

Table 4.1.2.2. Dickey-Fuller test at D(STOM) in the public sector

	Level	*t-Statistic*	*Prob.*
Augmented Dickey-Fuller test statistic		-3.829821	0.0282
Test critical values:	1% level	-4.284580	
	5% level	-3.562882	
	10% level	-3.215267	

Source: Authors' calculations with Eviews software

Table 4.1.2.3. ARIMA (5,1,6) model to D(STOM) in the public sector

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	-117.4016	35.44948	-3.311799	0.0029
AR(5)	-0.722936	0.257061	-2.812312	0.0096
MA(6)	-0.858638	0.058789	-14.60551	0.0000
R-squared	0.422983	Mean dependent var		-50.6666
Adjusted R-squared	0.374898	S.D. dependent var		491.2295
S.E. of regression	388.3825	Akaike info criterion		14.86630
Sum squared resid	3620184.	Schwarz criterion		15.01028
Log likelihood	-197.6950	F-statistic		8.796621
Durbin-Watson stat.	1.585395	Prob(F-statistic)		0.001362
Inverted AR Roots	.76 -.55i -.94	.76+.55i	-.29+.89i	-.29 -.89i
Inverted MA Roots	.97 -.49+.84i	.49 -.84i -.97	.49+.84i	-.49 -.84i
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.910530	Probability		0.416944
Obs*R-squared	0.979856	Probability		0.612671
ARCH Test:				
F-statistic	0.068317	Probability		0.796034
Obs*R-squared	0.073800	Probability		0.785883

Source: Authors' calculations with Eviews software

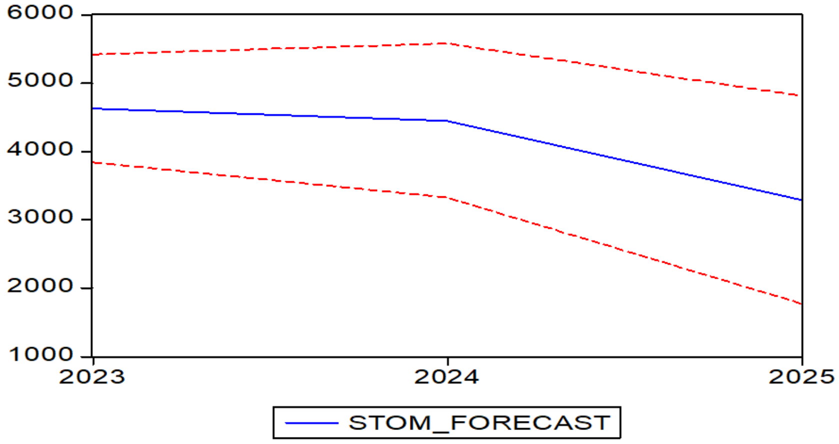

Figure 4.1.2.2. Prediction of dentists in the public sector with the ARIMA(5,1,6) model

Table 4.1.2.4. Predictions for dentists in the public sector with ARIMA(5,1,6)

Model	***Forecast 2023***	***Forecast 2024***	***Forecast 2025***
ARIMA (5,1,6)	4.626	4.446	3.289

Source: Authors' calculations with Eviews software

4.1.3 Pharmacists

For pharmacists, a downward trend was observed until 2009, followed by an upward trend, which was accentuated after 2018, with the salary increases in the system. To use the ARIMA model for prediction, we initially applied the Dickey-Fuller test with constant, without trend, and it is found that the initial FARM series is not stationary, because the probability attached to the test is 0.1013, accepting the null hypothesis of non-stationarity (Table 4.1.3.1). Applying the first difference to the series yields a stationary series, denoted D(FARM), with the probability attached to the Dickey-Fuller test being 0.0485, which is less than 0.05 (Table 4.1.3.2). From the analysis of the correlogram of the differentiated series and after checking several possible models, a valid ARIMA(1,1,3) model resulted, with the lowest values of the Akaike and Schwarz criteria (Table 4.1.3.3). The estimated coefficients are significant at a 5% threshold, with the probabilities attached to the t-Statistic test lower than 0.05 and the residuals of the model are not autocorrelated, which results from the Durbin-Watson tests with the value of 2.18 and the Breusch-Godfrey tests with the probability attached 0.27. The ARCH test confirms the homoscedasticity of the model. The ARIMA (1,1,3) model is stationary and invertible. The predictions are given in Table 4.1.3.4 and are plotted in Figure 4.1.3.2 with the confidence interval.

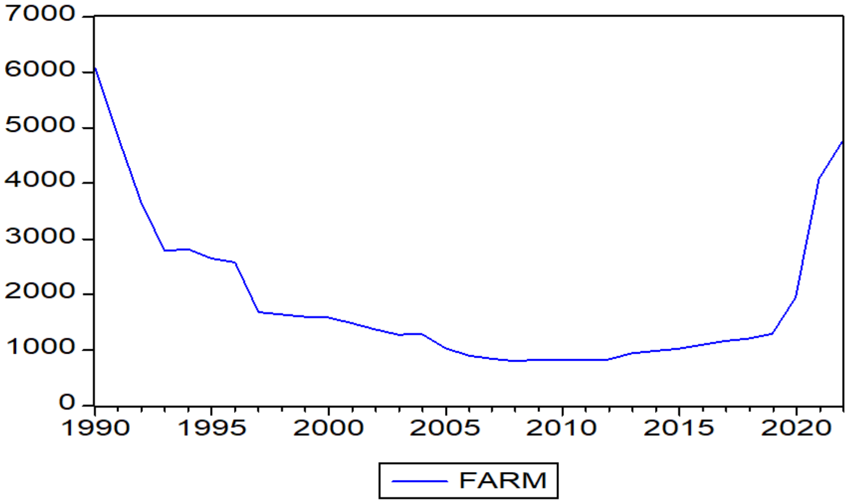

Figure 4.1.3.1. Pharmacists in the public sector

Table 4.1.3.1. Dickey-Fuller test at FARM in the public sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-2.610922	0.1013
Test critical values:	1% level	-3.653730	
	5% level	-2.957110	
	10% level	-2.617434	

Source: Authors' calculations with Eviews software

Table 4.1.3.2. Dickey-Fuller test at D(FARM) in the public sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-2.974219	0.0485
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

Source: Authors' calculations with Eviews software

Table 4.1.3.3. ARIMA(1,1,3) model to D(FARM) in the public sector

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	60.87283	84.95858	0.716500	0.4796
AR(1)	0.650748	0.135469	4.803665	0.0000
MA(3)	-0.824367	0.085391	-9.654053	0.0000

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R-squared	0.459887	Mean dependent var		-2.93548
Adjusted R-squared	0.421308	S.D. dependent var		536.1082
S.E. of regression	407.8274	Akaike info criterion		14.95133
Sum squared resid	4657048.	Schwarz criterion		15.09010
Log likelihood	-228.7456	F-statistic		11.92050
Durbin-Watson stat.	2.185836	Prob(F-statistic)		0.000180
Inverted AR Roots	.65			
Inverted MA Roots	.94	-.47 -.81i	-.47+.81i	
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	1.352694	Probability		0.276140
Obs*R-squared	2.534832	Probability		0.281558
ARCH Test:				
F-statistic	0.417818	Probability		0.523291
Obs*R-squared	0.441080	Probability		0.506602

Source: Authors' calculations with Eviews software

Table 4.1.3.4. Forecasts for pharmacists in the public sector with ARIMA(1,1,3)

Model	Forecast 2023	Forecast 2024	Forecast 2025
ARIMA (1,1,3)	4.917	3.743	3.507

Source: Authors' calculations with Eviews software

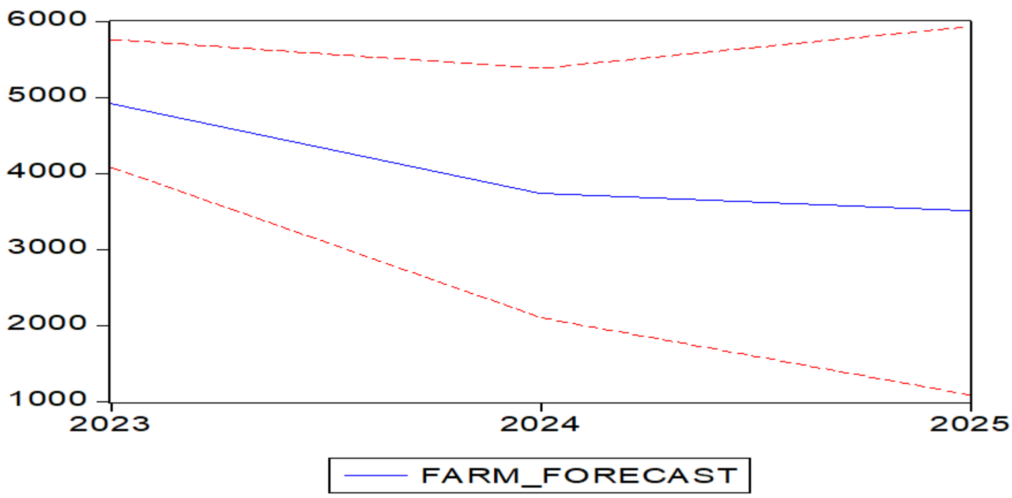

Figure 4.1.3.2. Prediction of pharmacists in the public sector with ARIMA(1,1,3)

4.1.4 Medical assistants

In the case of medical assistants, in general, a downward can be observed until 2015, followed by an upward trend (Figure 4.1.4.1). For ARIMA forecasting we initially checked if the series was stationary. Since the probability attached to the Dickey-Fuller test is 0.6808 (Table 4.1.4.1) it follows that the series (ASIST) is non-stationary. After the first difference performed on the data series, a stationary series D(ASIST) was obtained, a fact confirmed by the Dickey-Fuller test with the attached probability 0.0006 (Table 4.1.4.2). From the analysis of the correlogram of the differentiated series and after checking several possible models, a valid ARIMA(3,1,3) model resulted (Table 4.1.4.3) where the Akaike and Schwarz criteria have the lowest values. The coefficients estimated in the model are representative at a threshold of 5%, having the probabilities attached to the t-Statistic test lower than 0.05. Also, the model residuals are not autocorrelated, according to Durbin-Watson with value 1.88 and Breusch-Godfrey with probability attached 0.90. The model is found to verify the assumption of homoscedasticity, according to the ARCH test, with the attached probability 0.81. The ARIMA(3,1,3) model is stationary and invertible. The predictions are in Table 4.1.4.4 and are plotted in Figure 4.1.4.2 along with the confidence interval of the prediction.

Table 4.1.4.1. Dickey-Fuller test at ASIST in the public sector

	Level	***t-Statistic***	***Prob.***
Augmented Dickey-Fuller test statistic		-1.800729	0.6808
Test critical values:	1% level	-4.273277	
	5% level	-3.557759	
	10% level	-3.212361	

Source: Authors' calculations with Eviews software

Table 4.1.4.2. Dickey-Fuller test at D(ASIST) in the public sector

	Level	***t-Statistic***	***Prob.***
Augmented Dickey-Fuller test statistic		-5.426670	0.0006
Test critical values:	1% level	-4.284580	
	5% level	-3.562882	
	10% level	-3.215267	

Source: Authors' calculations with Eviews software

Table 4.1.4.3. ARIMA (3,1,3) model to D(ASIST) in the public sector

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
C	-788.7754	710.2131	-1.110618	0.2769
AR(3)	-0.643991	0.100336	-6.418317	0.0000
MA(3)	0.939392	0.050682	18.53506	0.0000
R-squared	0.382852	Mean dependent var		-762.5517
Adjusted R-squared	0.335379	S.D. dependent var		4189.352

Variable	Coefficient	Std. Error	t-Statistic	Prob.
S.E. of regression	3415.340	Akaike info criterion		19.20764
Sum squared resid	3.03E+08	Schwarz criterion		19.34908
Log likelihood	-275.5108	F-statistic		8.064637
Durbin-Watson stat.	1.884706	Prob(F-statistic)		0.001884
Inverted AR Roots	.43 -.75i	.43+.75i	-.86	
Inverted MA Roots	.49+.85i	.49 -.85i	-.98	
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.099351	Probability		0.905796
Obs*R-squared	0.072648	Probability		0.964328
ARCH Test:				
F-statistic	0.057999	Probability		0.811576
Obs*R-squared	0.062321	Probability		0.802864

Source: Authors' calculations with Eviews software

Table 4.1.4.4. Forecasts of medical assistants in the public sector with ARIMA(3,1,3)

Model	Forecast 2023	Forecast 2024	Forecast 2025
ARIMA (3,1,3)	98.873	97.224	95.286

Source: Authors' calculations with Eviews software

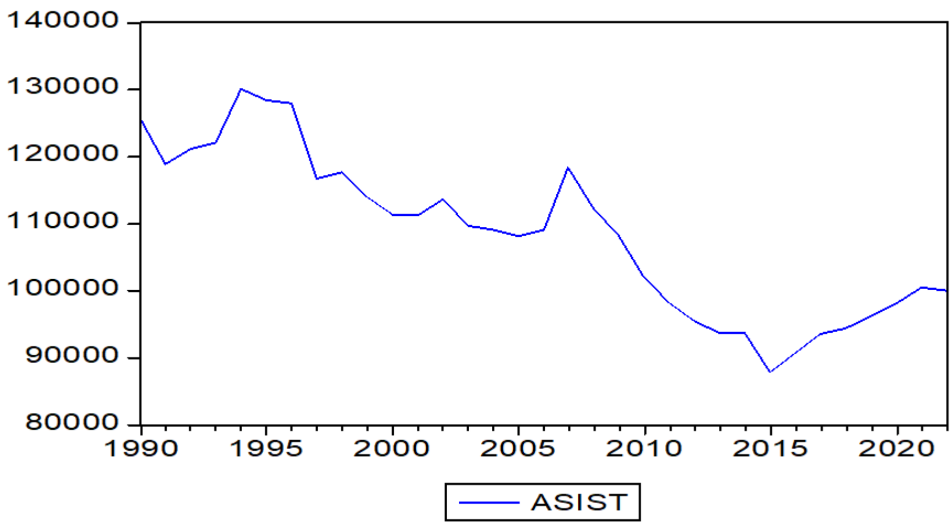

Figure 4.1.4.1. Medical assistants in the public sector

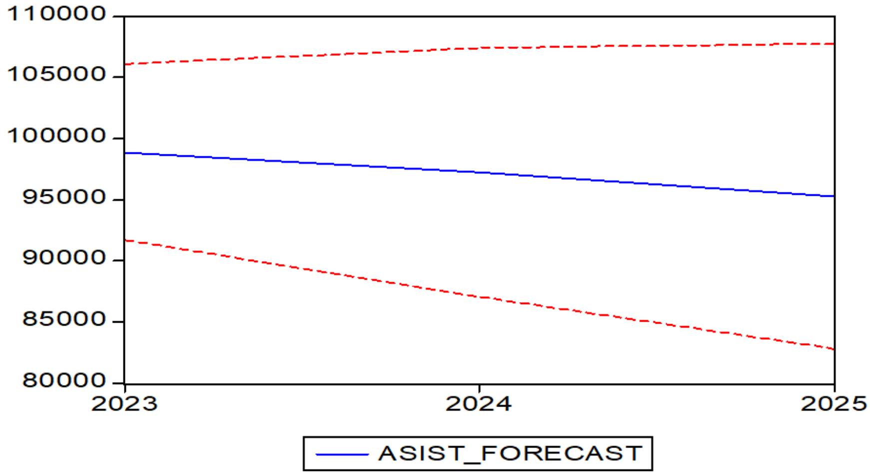

Figure 4.1.4.2. Prediction of medical assistants in the public sector with ARIMA(3,1,3)

4.1.5 Auxiliary health personnel

Fluctuations in the evolution of the number of employees can be observed for auxiliary health personnel, with a sharp decrease in the period 2008-2013, followed by an increase until 2021 (Figure 4.1.5.1). To be able to apply the ARIMA model for forecasting, we initially checked whether the series was stationary, using the Dickey-Fuller test (Table 4.1.5.1). It turned out that the original AUX series was non-stationary, the attached probability finding 0.8434. Applying the first difference to the data series and a stationary series D(AUX) was obtained, a fact confirmed by applying the Dickey-Fuller test with the attached probability 0.0007 (Table 4.1.5.2). Following the analysis of the correlogram of the differentiated series and after checking several possible models, a valid ARIMA(4,1,4) model was obtained (Table 4.1.5.3) where the Akaike and Schwarz criteria have the lowest values. Estimated model coefficients are representative at a 5% threshold, as probabilities attached to the t-Statistic test less than 0.05. Moreover, the residuals of the model are not autocorrelated, according to Durbin-Watson tests with value 1.69 and Breusch-Godfrey with attached probability 0.40. The ARCH test with probability attached 0.96 confirms the hypothesis of a homoscedastic model. Also, the ARIMA (4,1,4) model is stationary and invertible. The predictions are in Table 4.1.5.4 and are plotted in Figure 4.1.5.2 along with the confidence interval of the prediction.

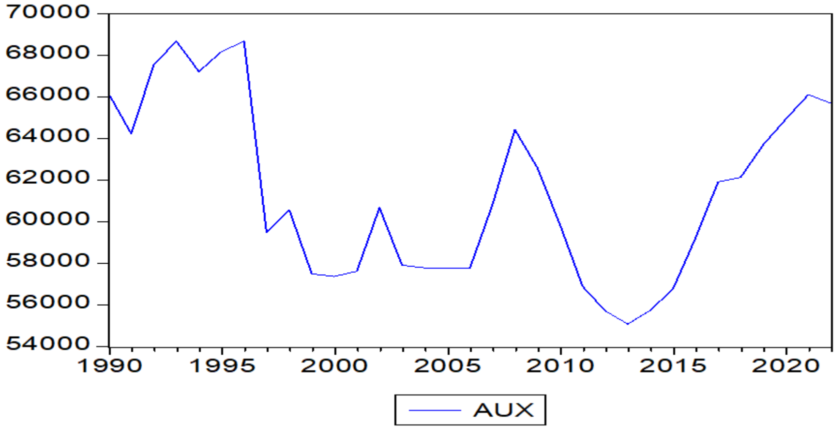

Figure 4.1.5.1. Auxiliary health personnel in the public sector

Table 4.1.5.1. Dickey-Fuller test at AUX in the public sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-1.391936	0.8434
Test critical values:	1% level	-4.284580	
	5% level	-3.562882	
	10% level	-3.215267	

Source: Authors' calculations with Eviews software

Table 4.1.5.2. Dickey-Fuller test at D(AUX) in the public sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-5.377501	0.0007
Test critical values:	1% level	-4.284580	
	5% level	-3.562882	
	10% level	-3.215267	

Source: Authors' calculations with Eviews software

Table 4.1.5.3. ARIMA(4,1,4) model to D(AUX) in the public sector

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	56.63471	456.3004	0.124117	0.9022
AR(4)	-0.520788	0.121349	-4.291638	0.0002
MA(4)	0.989987	0.079101	12.51542	0.0000
R-squared	0.365364	Mean dependent var		-54.39286
Adjusted R-squared	0.314593	S.D. dependent var		2570.372

Variable	Coefficient	Std. Error	t-Statistic	Prob.
S.E. of regression	2127.993	Akaike info criterion		18.26470
Sum squared resid	1.13E+08	Schwarz criterion		18.40744
Log likelihood	-252.7058	F-statistic		7.196320
Durbin-Watson stat.	1.693102	Prob(F-statistic)		0.003401
Inverted AR Roots	.60+.60i	.60+.60i	-.60 -.60i	-.60 -.60i
Inverted MA Roots	.71+.71i	.71+.71i	-.71 -.71i	-.71 -.71i
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.942311	Probability		0.404262
Obs*R-squared	2.119792	Probability		0.346492
ARCH Test:				
F-statistic	0.002547	Probability		0.960154
Obs*R-squared	0.002750	Probability		0.958177

Source: Authors' calculations with Eviews software

Table 4.1.5.4. Forecast of auxiliary health personnel in the public sector with ARIMA(4,1,4)

Model	Forecast 2023	Forecast 2024	Forecast 2025
ARIMA (4,1,4)	64.896	64.281	63.827

Source: Authors' calculations with Eviews software

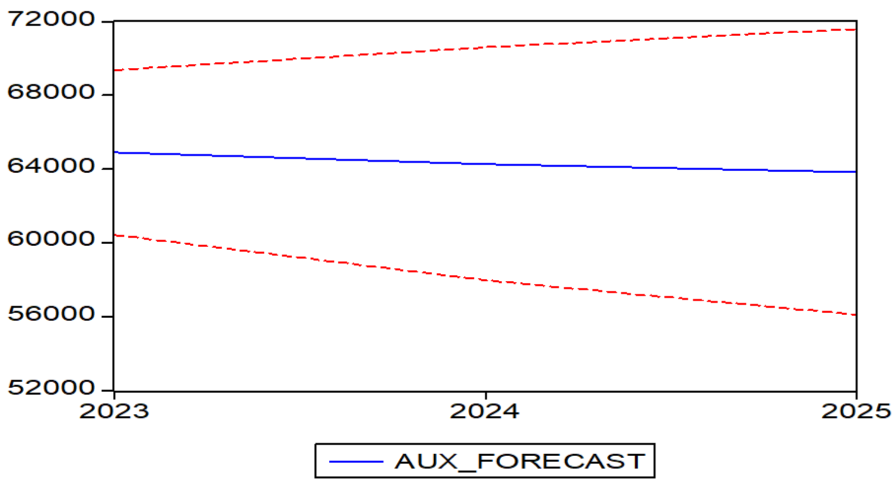

Figure 4.1.5.2. Prediction of auxiliary health personnel in the public sector with ARIMA(4,1,4)

4.1.6. Family physicians

For family physicians, a downward trend can be observed, in general, with a sharp decrease in the period 2010-2015, followed by a period of moderate growth. To apply the ARIMA method, it was found that the initial data series (FAM) was not stationary (Table 4.1.6.1), because the probability attached to the Dickey-Fuller with constant, non-trending test was 0.8464. After applying the first difference to the series, a new series D(FAM) was obtained, which became stationary according to the Dickey-Fuller test, with the attached probability 0.0029 (Table 4.1.6.2). From the analysis of the correlogram of the differentiated series and after testing several possible models, the ARIMA(3,1,3) model was chosen (Table 4.1.6.3) where the Akaike and Schwarz criteria had the lowest values. The estimated coefficients are significant at a threshold of 5%, having the probabilities attached to the t-Statistic test less than 0.05 and the residuals of the model are not autocorrelated, according to the Durbin-Watson tests with the value of 1.85 and the Breusch-Godfrey tests with the attached probability of 0, 75. The model is homoscedastic according to the ARCH test with probability attached 0.65. The ARIMA(3,1,3) model is stationary and invertible. Forecasts for GPs in the public sector can be found in Table 4.1.6.4 and are plotted in Figure 4.1.6.2 together with the confidence interval.

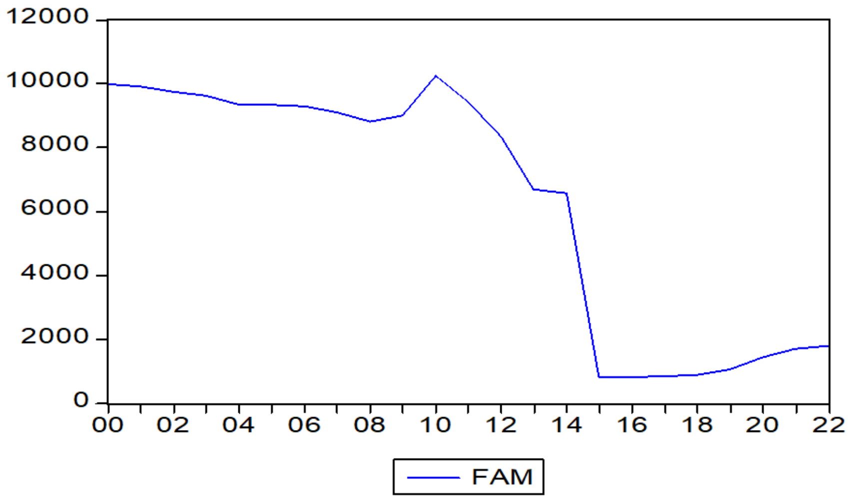

Figure 4.1.6.1. Family physicians in the public sector

Table 4.1.6.1. Dickey-Fuller test at FAM in the public sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-0.622018	0.8464
Test critical values:	1% level	-3.769597	
	5% level	-3.004861	
	10% level	-2.642242	

Source: Authors' calculations with Eviews software

Table 4.1.6.2. Dickey-Fuller test at D(FAM) in the public sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-4.355789	0.0029
Test critical values:	1% level	-3.788030	
	5% level	-3.012363	
	10% level	-2.646119	

Source: Authors' calculations with Eviews software

Table 4.1.6.3. ARIMA (3,1,3) model to D(FAM) in the public sector

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-133.6588	473.6733	-0.282175	0.7814
AR(3)	0.679675	0.210182	3.233751	0.0052
MA(3)	-0.992499	0.119496	-8.305686	0.0000
R-squared	0.170861	Mean dependent var		-411.0526
Adjusted R-squared	0.067219	S.D. dependent var		1421.697
S.E. of regression	1373.083	Akaike info criterion		17.43144
Sum squared resid	30165713	Schwarz criterion		17.58057
Log likelihood	-162.5987	F-statistic		1.648565
Durbin-Watson stat.	1.857235	Prob(F-statistic)		0.223366
Inverted AR Roots	.88	-.44 -.76i	-.44+.76i	
Inverted MA Roots	1.00	-.50 -.86i	-.50+.86i	
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.280034	Probability		0.759893
Obs*R-squared	0.096482	Probability		0.952904
ARCH Test:				
F-statistic	0.206241	Probability		0.655830
Obs*R-squared	0.229069	Probability		0.632215

Source: Authors' calculations with Eviews software

Table 4.1.6.4. **Forecast for family physicians with ARIMA (3,1,3) in the public sector**

Model	*Forecast 2023*	*Forecast 2024*	*Forecast 2025*
ARIMA (3,1,3)	1.999	2.144	2.152

Source: Authors' calculations with Eviews software

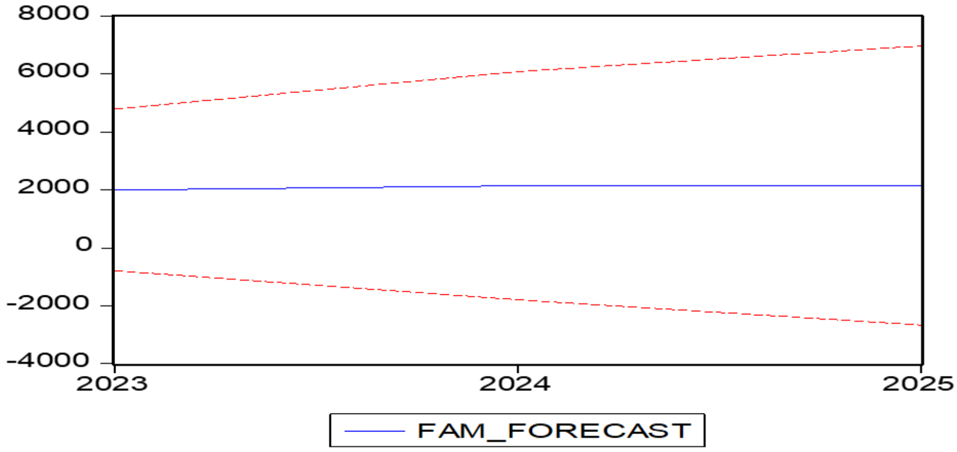

Figure 4.1.6.2. **Predictions for family physicians with ARIMA(3,1,3)**

4.2 Forecasts for health personnel in the private sector

4.2.1 Physicians (excluding dentists)

For physicians in the private sector (excluding dentists), an upward trend can be observed throughout the analyzed period (Figure 4.2.1.1). We initially checked whether the series was stationary, using the Dickey-Fuller test with constant and trend (Table 4.2.1.1) and it turned out that the original series (MED) was non-stationary, the attached probability finding 0.6007. Applying the first difference to the data series, a stationary series D(MED) was obtained, which was confirmed by the Dickey-Fuller test with the attached probability 0.0012 (Table 4.2.1.2). From the analysis of the correlogram of the differentiated series and by testing several possible models, a valid ARIMA(3,1,3) model was obtained, in which the Akaike and Schwarz tests have the lowest values (Table 4.2.1.3). Estimated coefficients from the model are significant at the 5% threshold, with t-Statistic attached probabilities less than 0.05 and model residuals are not autocorrelated, according to the Durbin-Watson with 2.04 and Breusch-Godfrey tests with attached probability 0.76. The model is homoscedastic, according to the ARCH test with attached probability 0.77, and the ARIMA(3,1,3) process is stationary and invertible. The predictions are in Table 4.2.1.4 and are plotted in Figure 4.2.1.2 with the confidence interval.

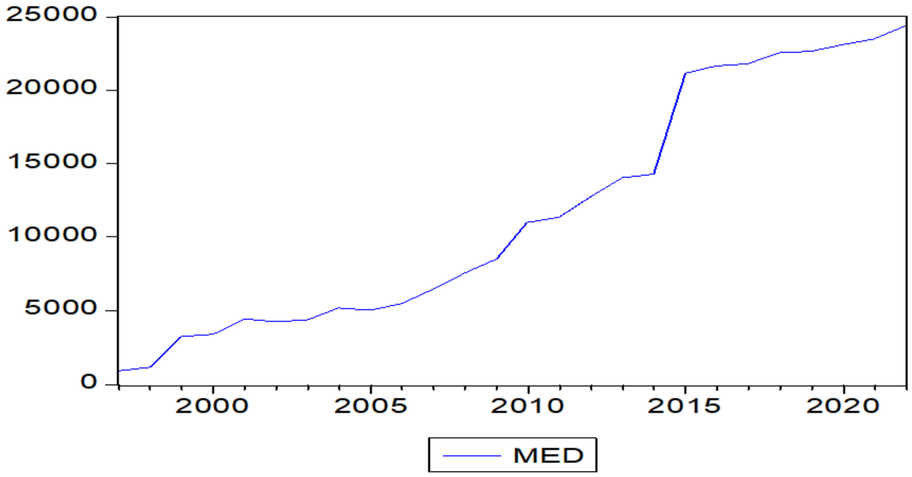

Figure 4.2.1.1. Physicians in the private sector

Table 4.2.1.1. Dickey-Fuller test at MED in the private sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-1.946563	0.6007
Test critical values:	1% level	-4.374307	
	5% level	-3.603202	
	10% level	-3.238054	

Source: Authors' calculations with Eviews software

Table 4.2.1.2. Dickey-Fuller test at D(MED) in the private sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-5.364767	0.0012
Test critical values:	1% level	-4.394309	
	5% level	-3.612199	
	10% level	-3.243079	

Source: Authors' calculations with Eviews software

Table 4.2.1.3. ARIMA (3,1,3) model to D(MED) in the private sector

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(3)	0.901267	0.071824	12.54821	0.0000
MA(3)	-0.992322	0.109009	-9.103123	0.0000
R-squared	0.085749	Mean dependent var		952.5909
Adjusted R-squared	0.040036	S.D. dependent var		1449.184

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Variable	Coefficient	Std. Error	t-Statistic	Prob.
S.E. of regression	1419.877	Akaike info criterion		17.44104
Sum squared resid	40321026	Schwarz criterion		17.54022
Log likelihood	-189.8514	Durbin-Watson stat		2.043295
Inverted AR Roots	.97	-.48+.84i	-.48 -.84i	
Inverted MA Roots	1.00	-.50 -.86i	-.50+.86i	
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.272630	Probability		0.764463
Obs*R-squared	0.642724	Probability		0.725161
ARCH Test:				
F-statistic	0.083544	Probability		0.775681
Obs*R-squared	0.091934	Probability		0.761733

Source: Authors' calculations with Eviews software

Table 4.2.1.4. Forecast for physicians in the private sector with ARIMA (3,1,3)

Model	Forecast 2023	Forecast 2024	Forecast 2025
ARIMA (3,1,3)	24.737	25.138	25.900

Source: Authors' calculations with Eviews software

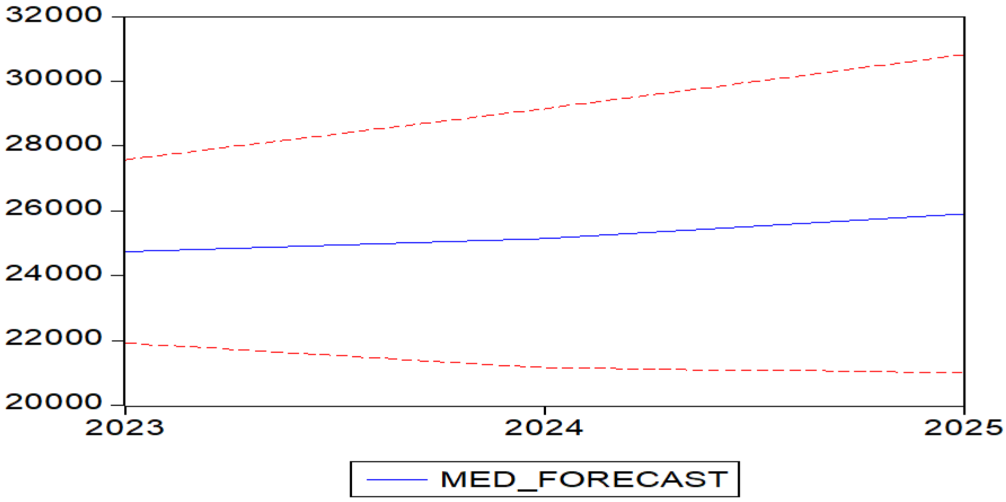

Figure 4.1.1.2. Predictions for physicians in the private sector with ARIMA (3,1,3)

4.2.2 Dentists

An upward trend was observed throughout the analyzed period (Figure 4.2.2.1). For prediction with the ARIMA model, we apply the Dickey-Fuller test for the original STOM series, which is non-stationary, with the probability attached to the test of 0.3038, and it follows that the null hypothesis of non-stationarity is accepted (Table 4.2.2.1). We apply the first difference to the series and a stationary series is obtained, D(STOM) having the probability attached to the Dickey-Fuller test of 0.0059 (Table 4.2.2.2). From the analysis of the correlogram of the differentiated series and after checking several possible models, a valid ARIMA(1,1,1) model resulted, where the Akaike and Schwarz tests have the lowest values (Table 4.2.2.3). The estimated coefficients are representative at a threshold of 5%, having the probabilities of the t-Statistic test lower than 0.05 and the residuals of the model are not autocorrelated, a fact confirmed by the Durbin-Watson tests with the value of 1.87 and the Breusch-Godfrey tests with the attached probability of 0,72. The ARCH test confirms the absence of heteroscedasticity, having the attached probability of 0.30. The ARIMA(1,1,1) model is stationary and invertible. The predictions are found in Table 4.2.2.4 with the graphical representation in Figure 4.2.2.2, together with the confidence interval.

Table 4.2.2.1. Dickey-Fuller test at STOM in the private sector

	Level	**t-Statistic**	**Prob.**
Augmented Dickey-Fuller test statistic		-2.549802	0.3038
Test critical values:	1% level	-4.374307	
	5% level	-3.603202	
	10% level	-3.238054	

Source: Authors' calculations with Eviews software

Table 4.2.2.2. Dickey-Fuller test at D(STOM) in the private sector

	Level	**t-Statistic**	**Prob.**
Augmented Dickey-Fuller test statistic		-4.668148	0.0059
Test critical values:	1% level	-4.416345	
	5% level	-3.622033	
	10% level	-3.248592	

Source: Authors' calculations with Eviews software

Table 4.2.2.3. ARIMA (1,1,1) model to D(STOM) in the private sector

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	648.0118	30.52999	21.22542	0.0000
AR(1)	0.563117	0.217634	2.587444	0.0172
MA(1)	-0.963763	0.068212	-14.12886	0.0000
R-squared	0.182040	Mean dependent var		628.6250
Adjusted R-squared	0.104139	S.D. dependent var		490.4196

Variable	Coefficient	Std. Error	t-Statistic	Prob.
S.E. of regression	464.1819	Akaike info criterion		15.23490
Sum squared resid	4524762.	Schwarz criterion		15.38216
Log likelihood	-179.8188	F-statistic		2.336806
Durbin-Watson stat.	1.872026	Prob(F-statistic)		0.121252
Inverted AR Roots	.56			
Inverted MA Roots	.96			
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.330236	Probability		0.722797
Obs*R-squared	0.440695	Probability		0.802240
ARCH Test:				
F-statistic	1.118822	Probability		0.302189
Obs*R-squared	1.163394	Probability		0.280763

Source: Authors' calculations with Eviews software

Table 4.2.2.4. Forecast for dentists in the private sector with ARIMA(1,1,1)

Model	Forecast 2023	Forecast 2024	Forecast 2025
ARIMA (1,1,1)	17.552	18.285	18.980

Source: Authors' calculations with Eviews software

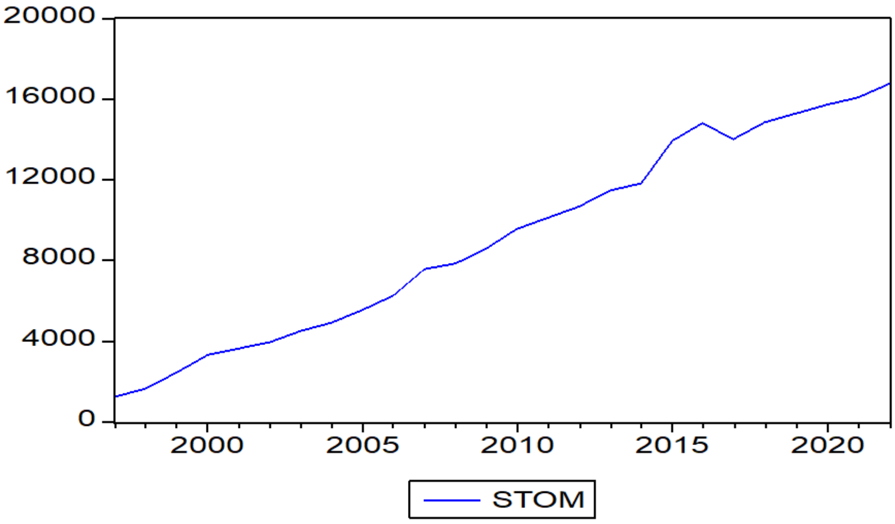

Figure 4.2.2.1. Dentists in the private sector

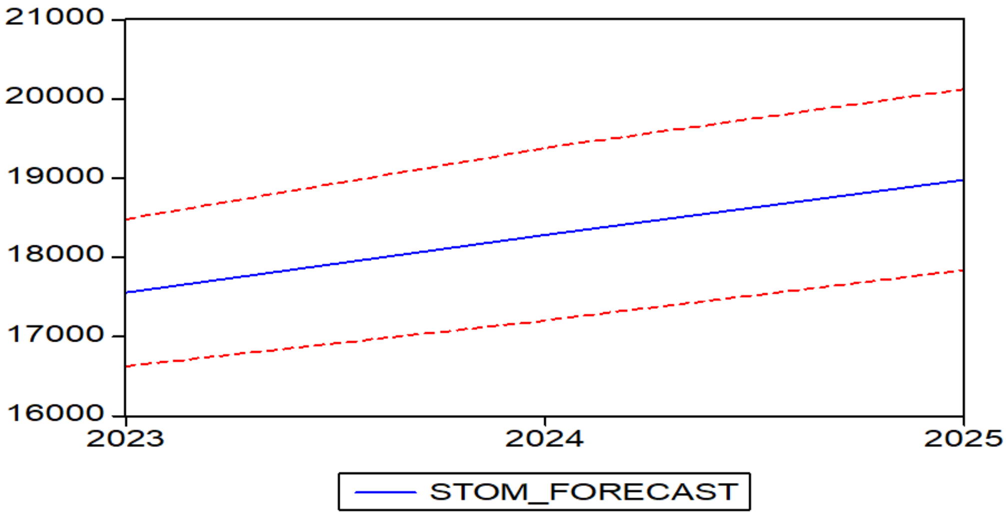

Figure 4.2.2.2. Forecasts for dentists in the private sector with ARIMA(1,1,1)

4.2.3 Pharmacists

From Figure 4.2.3.1, an upward trend can be seen over the entire analyzed period 1997-2022. We initially applied the Dickey-Fuller test with constant and trend and it turned out that the initial series FARM was not stationary, having the probability attached to the test of 0.1803, accepting the null hypothesis of non-stationarity (Table 4.2.3.1). Applying the first difference to the series, a stationary series was obtained, denoted D(FARM), the probability attached to the Dickey-Fuller test being 0.0304 (Table 4.2.3.2). From checking the correlogram of the differentiated series and after analyzing several possible models, we chose the valid ARIMA(3,1,11) model (Table 4.2.3.3). The coefficients estimated by the model were representative at a threshold of 5%, the probabilities attached to the t-Statistic test being lower than 0.05 and the residuals of the model are not autocorrelated, a fact confirmed by the Durbin-Watson tests with a value of 1.87 and the Breusch-Godfrey tests with attached probability 0.92. Also, the ARCH test confirms the lack of heteroscedasticity, with the attached probability being 0.42. The ARIMA(3,1,11) model is stationary and invertible. The predictions are presented in Table 4.2.3.4 and are plotted in Figure 4.2.3.2 with the confidence interval.

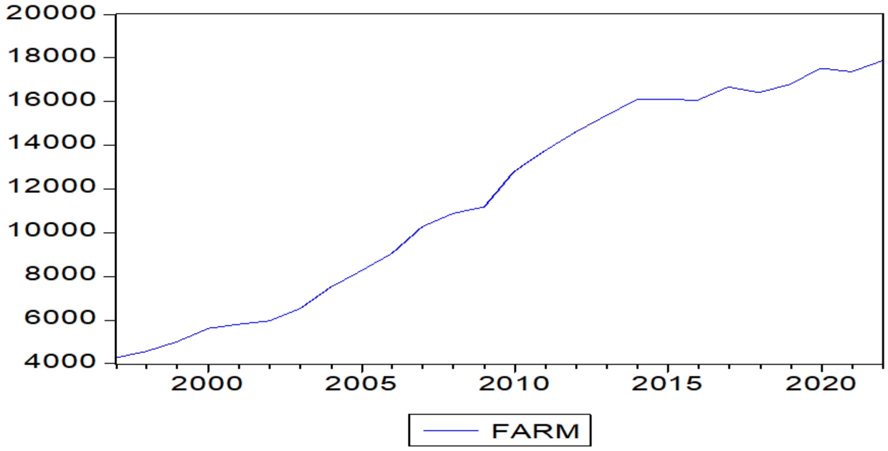

Figure 4.2.3.1. Pharmacists in the private sector

Table 4.2.3.1. Dickey-Fuller test at FARM in the private sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-2.921722	0.1803
Test critical values:	1% level	-4.616209	
	5% level	-3.710482	
	10% level	-3.297799	

Source: Authors' calculations with Eviews software

Table 4.2.3.2. Dickey-Fuller test at D(FARM) in the private sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-3.861562	0.0304
Test critical values:	1% level	-4.394309	
	5% level	-3.612199	
	10% level	-3.243079	

Source: Authors' calculations with Eviews software

Table 4.2.3.3. ARIMA (3,1,11) model to D(FARM) in the private sector

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	226.5387	191.4317	1.183391	0.2512
AR(3)	0.401629	0.168592	2.382260	0.0278
MA(11)	-0.930152	0.054200	-17.16136	0.0000
R-squared	0.737835	Mean dependent var		558.9091
Adjusted R-squared	0.710238	S.D. dependent var		459.5953

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Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
S.E. of regression	247.3980	Akaike info criterion		13.98600
Sum squared resid	1162909.	Schwarz criterion		14.13478
Log likelihood	-150.8460	F-statistic		26.73666
Durbin-Watson stat.	1.873242	Prob(F-statistic)		0.000003
Inverted AR Roots	.74	-.37+.64i	-.37 -.64i	
Inverted MA Roots	.99	.84+.54i	.84 -.54i	
	.41 -.90i			
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.081007	Probability		0.922541
Obs*R-squared	0.000000	Probability		1.000000
ARCH Test:				
F-statistic	0.669813	Probability		0.423263
Obs*R-squared	0.715109	Probability		0.397753

Source: Authors' calculations with Eviews software

Table 4.2.3.4. Forecasts for pharmacists in the private sector with ARIMA(3,1,11)

Model	*Forecast 2023*	*Forecast 2024*	*Forecast 2025*
ARIMA (3,1,11)	18.189	18.296	18.565

Source: Authors' calculations with Eviews software

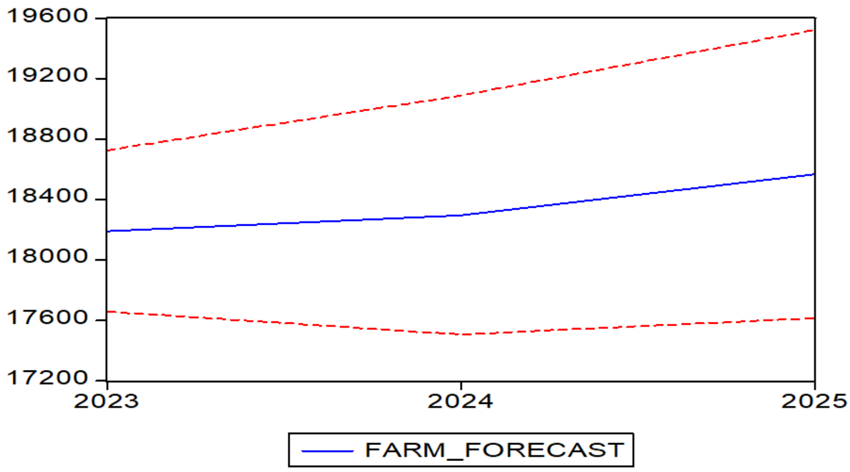

Figure 4.2.3.2. Forecasts for pharmacists in the private sector with ARIMA (3,1,11)

4.2.4. Medical assistants

An upward is observed in nurses from the health sector (Figure 4.2.4.1). For ARIMA forecasting we initially checked if the series was stationary. Since the probability attached to the Dickey-Fuller test with constant and trend was 0.4398 (Table 4.2.4.1) it follows that the ASIST series is non-stationary. We performed the first difference on the data series and obtained a stationary series D(ASIST), a fact confirmed by the Dickey-Fuller test with the attached probability 0.0250 (Table 4.2.4.2). From the analysis of the correlogram of the differentiated series and the verification of several possible models, we chose a valid ARIMA(1,1,1) model (Table 4.2.4.3). The estimated coefficients are significant at the 5% threshold, with the attached probabilities of the t-Statistic test less than 0.05 and the residuals of the model are not autocorrelated, according to the Durbin-Watson tests with the value of 1.99 and the Breusch-Godfrey tests with the attached probability of 0, 84. The ARCH test confirms the assumption of homoscedasticity, having the attached probability 0.72. The ARIMA(1,1,1) model is stationary and invertible. The predictions are in Table 4.2.4.4 and are plotted in Figure 4.2.4.2 along with the confidence interval of the prediction.

Table 4.2.4.1. Dickey-Fuller test at ASIST in the private sector

	Level	***t-Statistic***	***Prob.***
Augmented Dickey-Fuller test statistic		-2.257767	0.4398
Test critical values:	1% level	-4.374307	
	5% level	-3.603202	
	10% level	-3.238054	

Source: Authors' calculations with Eviews software

Table 4.2.4.2. Dickey-Fuller test at D(ASIST) in the private sector

	Level	***t-Statistic***	***Prob.***
Augmented Dickey-Fuller test statistic		-4.138477	0.0250
Test critical values:	1% level	-4.667883	
	5% level	-3.733200	
	10% level	-3.310349	

Source: Authors' calculations with Eviews software

Table 4.2.4.3. ARIMA (1,1,1) model to D(ASIST) in the private sector

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
C	2577.647	228.3081	11.29021	0.0000
AR(1)	0.732342	0.122724	5.967378	0.0000
MA(1)	-0.953590	0.047788	-19.95479	0.0000
R-squared	0.164182	Mean dependent var		2138.000
Adjusted R-squared	0.084581	S.D. dependent var		2014.322

Variable	Coefficient	Std. Error	t-Statistic	Prob.
S.E. of regression	1927.254	Akaike info criterion		18.08205
Sum squared resid	78000453	Schwarz criterion		18.22931
Log likelihood	-213.9846	F-statistic		2.062548
Durbin-Watson stat.	1.995305	Prob(F-statistic)		0.152115
Inverted AR Roots	.73			
Inverted MA Roots	.95			
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.164237	Probability		0.849733
Obs*R-squared	0.199779	Probability		0.904938
ARCH Test:				
F-statistic	0.129951	Probability		0.722083
Obs*R-squared	0.141452	Probability		0.706841

Source: Authors' calculations with Eviews software

Table 4.2.4.4. Forecasts for medical assistants in the private sector with ARIMA(1,1,1)

Model	Forecast 2023	Forecast 2024	Forecast 2025
ARIMA (1,1,1)	59.510	62.306	65.043

Source: Authors' calculations with Eviews software

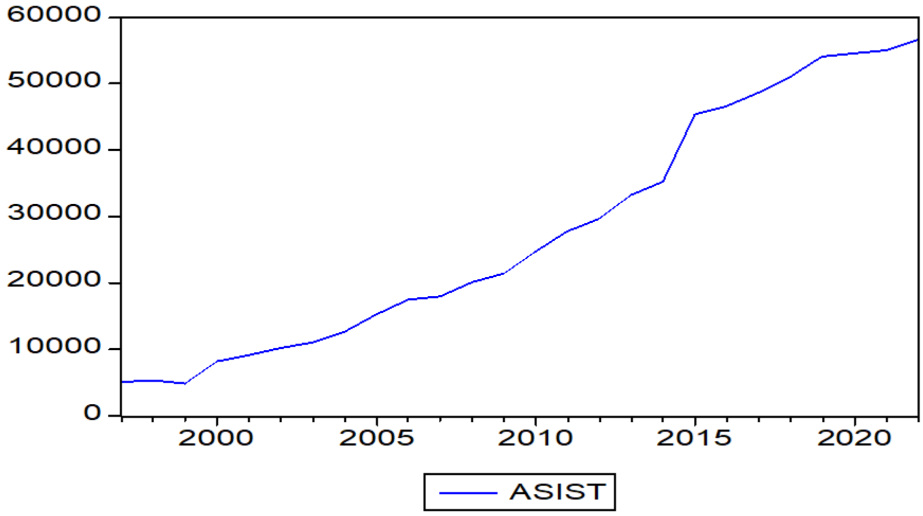

Figure 4.2.4.1. Medical assistants in the private sector

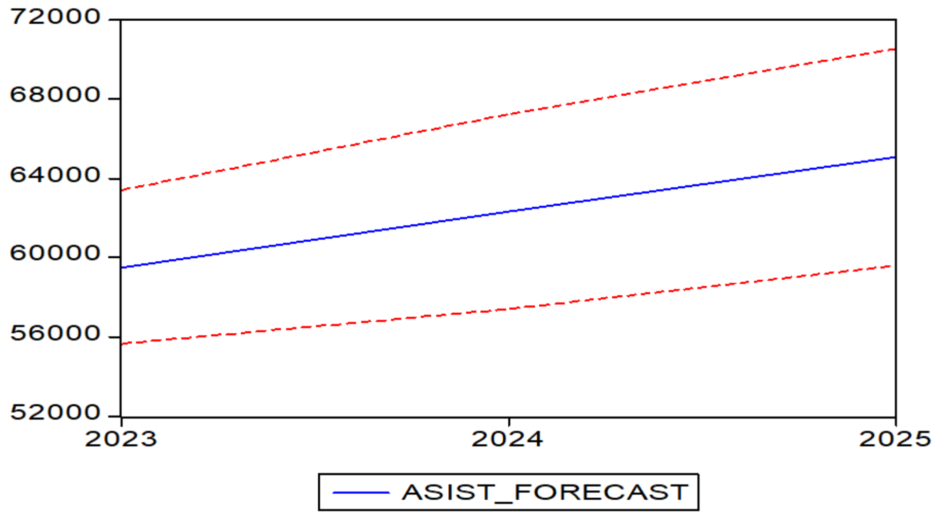

Figure 4.2.4.2. Forecasts for medical assistants in the private sector with ARIMA (1,1,1)

4.2.5. Auxiliary health personnel

From the analysis of the graph in Figure 4.2.5.1, an upward trend can be observed starting from 2002. It can be seen that the initial data series (AUX) is not stationary (Table 4.2.5.1) and remains non-stationary even after applying the first difference (Table 4.2.5.2) and the second difference (Table 4.2.5.3), according to the Dickey-Fuller test, which has a probability greater than 0.05 for all three cases. We transform the original series by logarithmization and obtain a new series LOG(AUX), to which we apply the Dickey-Fuller test. Since the probability attached to the test is 0.526 (Table 4.2.5.4), it follows that the null hypothesis is accepted and the log series is also not stationary. We apply the first difference and obtain the series D(LOG(AUX)), which is stationary according to the Dickey-Fuller test with attached probability 0.0378 (Table 4.2.5.5). From the analysis of the correlogram of the logarithmic and differentiated series and after checking several possible models, we chose a valid ARIMA(1,1,5) model (Table 4.2.5.6). Estimated coefficients are significant at the 5% threshold, with probabilities attached to the t-Statistic test less than 0.05. The model residuals are not autocorrelated, according to Durbin-Watson tests with a value of 2.09 and Breusch-Godfrey with a probability attached of 0.83. Also, the ARCH test confirms the assumption of homoscedasticity, having the attached probability 0.68. The ARIMA(1,1,5) model is stationary and invertible. The predictions are in Table 4.2.5.7 and are plotted in Figure 4.2.5.2 along with the confidence interval of the prediction.

Table 4.2.5.1. Dickey-Fuller test at AUX in the private sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-2.458708	0.3436
Test critical values:	1% level	-4.374307	
	5% level	-3.603202	
	10% level	-3.238054	

Source: Authors' calculations with Eviews software

Table 4.2.5.2. Dickey-Fuller test at D(AUX) in the private sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-1.271580	0.8596
Test critical values:	1% level	-4.616209	
	5% level	-3.710482	
	10% level	-3.297799	

Source: Authors' calculations with Eviews software

Table 4.2.5.3. Dickey-Fuller test at (AUX,2) in the private sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-1.562853	0.7617
Test critical values:	1% level	-4.667883	
	5% level	-3.733200	
	10% level	-3.310349	

Source: Authors' calculations with Eviews software

Table 4.2.5.4. Dickey-Fuller test at LOG(AUX) in the private sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-2.079701	0.5267
Test critical values:	1% level	-4.467895	
	5% level	-3.644963	
	10% level	-3.261452	

Source: Authors' calculations with Eviews software

Table 4.2.5.5. Dickey-Fuller test at D(LOG(AUX)) in the private sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-3.870844	0.0378
Test critical values:	1% level	-4.616209	
	5% level	-3.710482	
	10% level	-3.297799	

Source: Authors' calculations with Eviews software

Table 4.2.5.6. ARIMA(1,1,5) model to D(LOG(AUX)) in the private sector

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	0.126107	0.024224	5.205900	0.0000
AR(1)	0.116112	0.028638	4.054506	0.0006
MA(5)	0.987456	0.006666	148.1346	0.0000
R-squared	0.988430	Mean dependent var		0.139126
Adjusted R-squared	0.987328	S.D. dependent var		0.508520
S.E. of regression	0.057244	Akaike info criterion		-2.766512
Sum squared resid	0.068815	Schwarz criterion		-2.619255
Log likelihood	36.19814	F-statistic		897.0091
Durbin-Watson stat.	2.096656	Prob(F-statistic)		0.000000
Inverted AR Roots	.12			
Inverted MA Roots	.81 -.59i -1.00	.81+.59i	-.31+.95i	-.31 -.95i
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.183324	Probability		0.833954
Obs*R-squared	0.330991	Probability		0.847474
ARCH Test:				
F-statistic	0.173411	Probability		0.681323
Obs*R-squared	0.188371	Probability		0.664276

Source: Authors' calculations with Eviews software

Table 4.2.5.7. Forecasts for auxiliary health personnel in the private sector with ARIMA(1,1,5)

Model	*Forecast 2023*	*Forecast 2024*	*Forecast 2025*
ARIMA (1,1,1)	59.510	62.306	65.043

Source: Authors' calculations with Eviews software

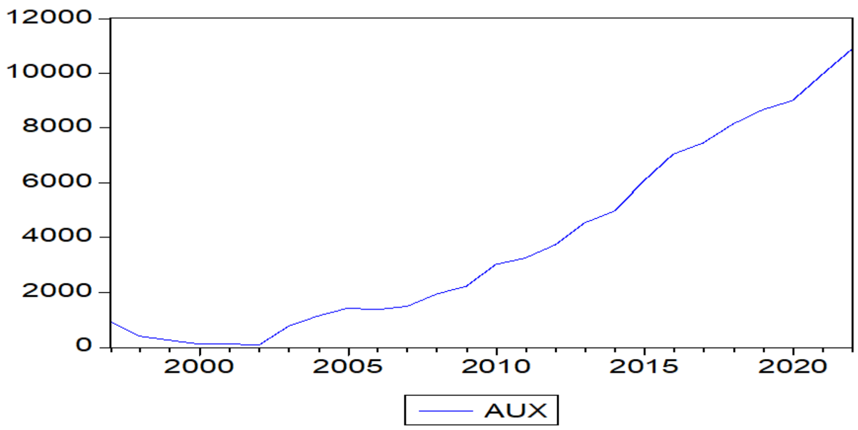

Figure 4.2.5.1. Auxiliary health personnel in the private sector

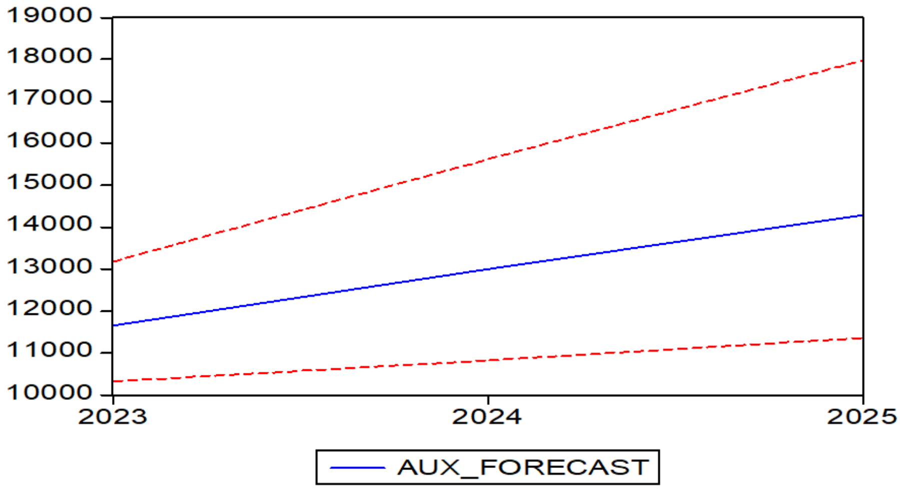

Figure 4.2.5.2. Forecasts for auxiliary health personnel in the private sector with ARIMA(1,1,5)

4.2.6. Family physicians

An upward trend is observed until 2015, followed by a downward trend (Figure 4.2.6.1). To be able to apply the ARIMA model for forecasting, we initially checked whether the series was stationary, using the Dickey-Fuller test (Table 4.2.6.1). It turned out that the original series (FAM) is non-stationary, the attached probability finding 0.5820. Applying the first difference to the data series and obtaining a stationary series D(FAM), a fact confirmed by applying the Dickey-Fuller test with the attached probability 0.0103 (Table 4.2.6.2). Following the analysis of the correlogram of the differentiated series and after testing several possible models, the ARIMA(3,1,3) model was chosen (Table 4.2.6.3) where the Akaike and Schwarz criteria had the lowest values. The estimated coefficients are representative at a threshold of 5%, having the probabilities attached to the t-Statistic test lower than 0.05 and the residuals of the model are not autocorrelated, according to the Durbin-Watson tests with the value of 2.01 and the Breusch-Godfrey tests with the attached probability of 0,96. The model is homoscedastic according to the ARCH test with probability attached 0.68. The ARIMA(3,1,3) model is stationary and invertible. Projections for family doctors in the private sector can be found in Table 4.2.6.4 and are graphically represented in Figure 4.2.6.2 together with the confidence interval.

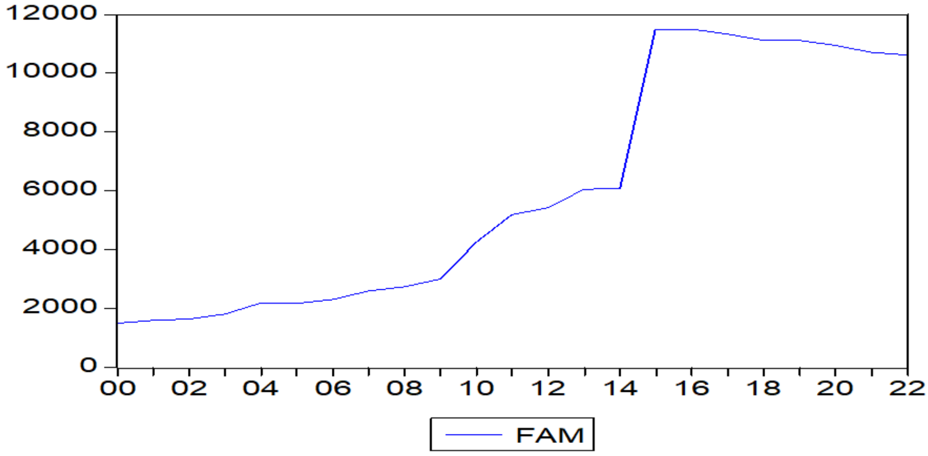

Figure 4.2.6.1. Family physicians in the private sector

Table 4.2.6.1. Dickey-Fuller test at FAM in the private sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-1.975299	0.5820
Test critical values:	1% level	-4.440739	
	5% level	-3.632896	
	10% level	-3.254671	

Source: Authors' calculations with Eviews software

Table 4.2.6.2. Dickey-Fuller test at D(FAM) in the private sector

	Level	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-4.452318	0.0103
Test critical values:	1% level	-4.467895	
	5% level	-3.644963	
	10% level	-3.261452	

Source: Authors' calculations with Eviews software

Table 4.2.6.3. ARIMA (3,1,3) model to D(FAM) in the private sector

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	198.6828	309.0500	0.642882	0.5294
AR(3)	0.631979	0.214845	2.941562	0.0096
MA(3)	-0.992503	3.22E-05	-30783.42	0.0000
R-squared	0.185108	Mean dependent var		464.2632

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Adjusted R-squared	0.083246	S.D. dependent var		1260.701
S.E. of regression	1207.087	Akaike info criterion		17.17375
Sum squared resid	23312949	Schwarz criterion		17.32287
Log likelihood	-160.1506	F-statistic		1.817247
Durbin-Watson stat.	2.012531	Prob(F-statistic)		0.194447
Inverted AR Roots	.86	-.43+.74i	-.43 -.74i	
Inverted MA Roots	1.00	-.50+.86i	-.50 -.86i	
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.031969	Probability		0.968607
Obs*R-squared	0.000000	Probability		1.000000
ARCH Test:				
F-statistic	0.165669	Probability		0.689383
Obs*R-squared	0.184468	Probability		0.667561

Source: Authors' calculations with Eviews software

Table 4.2.6.4. **Forecasts for family physicians in the private sector with ARIMA(3,1,3)**

Model	Forecast 2023	Forecast 2024	Forecast 2025
ARIMA (3,1,3)	10.633	10.533	10.571

Source: Authors' calculations with Eviews software

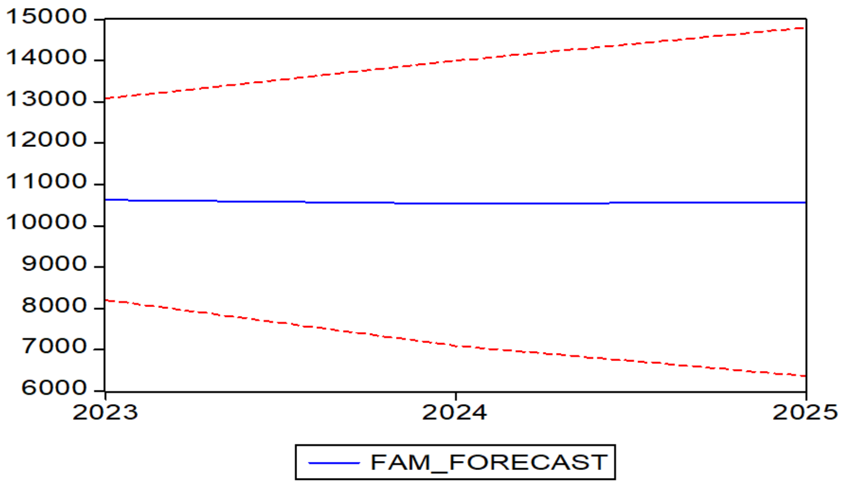

Figure 4.2.6.2. **Forecasts for family physicians in the private sector with ARIMA (3,1,3)**

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5. Conclusions

In this paper, using the ARIMA method, the forecasts were presented together with the associated confidence intervals, on the evolution of the human resource in the health field, represented by physicians, dentists, pharmacists, family physicians, medical assistants, auxiliary personnel, both in the public sector, as well as in the private one, for the period 2023-2025. After the completion of the work, the INS published the data for the year 2023, so we can make a comparison between the forecasts and the actual values. Comparing the forecasts from the public health system, with the real data from the year 2023 obtained later, (Table 5.1) it can be seen that for physicians (excluding dentists), pharmacists, medical assistants, auxiliary health personnel and family physicians, the forecasts made with the ARIMA method are close to the data real, the latter falling within the confidence intervals of the predictions made with a probability of 95%. In contrast, for dentists, the forecast is higher than the actual number in 2023, and the confidence interval of the forecast does not include the actual value. As for the forecasts for the year 2023, in the private sector, they are found to be close to the actual values, the latter being within the confidence intervals for all staff categories (Table 5.2).

Table 5.1. Forecasts for health personnel in the public sector

	Value 2023	Forecast 2023	Forecast 2024	Forecast 2025
Physicians (excluding dentists)	48.332	49.384	47.445	48.284
Dentists	3.771	4.626	4.446	3.289
Pharmacists	4.237	4.917	3.743	3.507
Medical assistants	99.300	98.873	97.224	95.286
Auxiliary personnel	64.697	64.896	64.281	63.827
Family physicians	2.020	1.999	2.144	2.152

Source: Authors' calculations

Table 5.2. Forecasts for health personnel in the private sector

	Value 2023	Forecast 2023	Forecast 2024	Forecast 2025
Physicians (excluding dentists)	24.408	24.737	25.138	25.900
Dentists	17.429	17.552	18.285	18.980
Pharmacists	17.499	18.189	18.296	18.565
Medical assistants	56.968	59.510	62.306	65.043
Auxiliary personnel	11.588	11.663	12.991	14.283
Family physicians	10.451	10.633	10.533	10.571

Source: Authors' calculations

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