Forecasting medical inflation in the European Union using the ARIMA model

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Article**
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Abstract

As healthcare costs continue to pose significant challenges for governments and policymakers, accurate forecasting of medical inflation has become crucial in the European Union. This study aims to provide insights into the trajectory of medical inflation within the EU using the Autoregressive Integrated Moving Average (ARIMA) model and to check whether this model is an effective tool for predictions of medical inflation. The findings of the study have significant implications across various sectors. With accurate forecasts of medical inflation, policymakers can proactively address challenges, insurers can determine appropriate premiums and develop innovative models, and healthcare entities can allocate resources strategically to ensure financial stability and quality care.

Keywords: medical inflation, HICP, ARIMA model, time series forecasting

1 INTRODUCTION

As healthcare expenses continue to escalate globally, there is an increasing need to comprehend and predict medical inflation accurately. This has become imperative for governments, policymakers, and healthcare providers. Additionally, forecasting medical inflation presents a significant challenge due to the differences in healthcare systems across EU member states. Many EU countries rely on public healthcare systems, meaning governments have to plan medical interventions according to the costs of medical products, equipment, outpatient services, and hospital services. Consequently, having an accurate forecast of medical inflation is crucial for national budget preparation. Advanced statistical models provide valuable insights into future trends.

This article examines the efficiency and accuracy of advanced models for the forecasting of medical inflation in order to provide insights into the potential trajectory of medical inflation in the EU. Accurate predictions of medical inflation have significant implications across various sectors. Policymakers can proactively address challenges, insurers can determine appropriate premiums and develop innovative models, and healthcare entities can allocate resources strategically for financial stability and quality care. This article aims to make an accurate forecast of medical inflation for members of the European Union. Hence, the research question is *whether the ARIMA model is effective for forecasting medical HICP for European Union members.*

In order to establish a conceptual framework for understanding the matter discussed, it is essential to outline some fundamental concepts. Medical inflation is the general level of price growth in healthcare procedures, including diagnostic tools, treatment methods, and pharmaceuticals. Typically, more developed healthcare systems experience higher levels of medical inflation. Given the rapid development of EU countries in recent years, we have witnessed a significant increase in medical inflation in the European Union. Key drivers of rising medical inflation include technological advances and structural changes in healthcare systems (Dular, 2010).

It is important to recognise that technological advances in healthcare do not reduce the required amount of labour, meaning that productivity does not increase. This differs from other sectors where productivity consistently improves. As a result, there is an increase in the relative price of healthcare services, which means that for one unit of healthcare services, an individual can purchase more units of products from other sectors. Labour productivity in healthcare thus lags behind labour productivity in other sectors. General inflationary pressures have a greater impact on prices in healthcare than in other sectors. This relative cost increase is referred to as the Baumol effect. The first reason for low labour productivity in healthcare is the inability to standardise processes due to the nature of working with diverse individuals. The second reason is that the quality of healthcare services is contingent upon the quantity of medical staff. Increasing the productivity of healthcare personnel can only be achieved by reducing patient treatment time or extending the working hours of medical staff. Unfortunately, both approaches result in declining service quality (Culyer and Newhouse, 2003).

Medical inflation can be considered a healthcare component within the Harmonized Index of Consumer Prices (HICP), which is calculated monthly by the Statistical Office of the European Communities (Eurostat). It is measured by the prices of consumer goods covering 700 products and services on average. HICP reflects the average household expenditure on a basket of goods in the euro area. As it is a harmonised index, all EU member states use the same methodology to calculate it, making values comparable. The calculation of the HICP is based on data collection of prices in physical and online stores in the euro area, aggregated into 295 categories. The next step involves determining and regularly adjusting the weights of individual groups of commodities or services. The weights are determined based on the results of surveys in which households report their expenditure patterns. They represent national averages that reflect the expenditures of all types of consumers. The final step in calculating the HICP is assigning the weights to individual countries, which are weighted according to their share of total consumption expenditures in the euro area. The HICP for individual countries is then calculated by national statistical offices, and the data is provided to Eurostat, which then calculates the HICP for the euro area as a whole (ECB, 2023).

The statistical approach of measuring medical inflation is somewhat more specific than the conventional measurement of inflation described above. Economic theory assumes the consumer is perfectly informed, rational, and financially responsible. Higher costs for medications would therefore imply better treatment outcomes for the consumer. However, a problem arises because medications cannot be equated with normal goods. It would be necessary to consider information asymmetry, decision-making imperfections regarding treatment, non-standard payment methods, and other factors (Morgan, 2002).

Moreover, another challenge in measuring medical inflation is due to the problematic determination of the healthcare component within the consumer price index.

The first difficulty lies in measuring effectiveness, which can be assessed in various ways. It could be measured in terms of reducing mortality rates or increasing quality of life. However, if we opt for the former measurement approach, the obtained statistics would not provide much information about the treatment of acute health issues that do not endanger life. The second challenge stems from the unequal relationship between the consumer and the intermediary, as patients are subordinate. Another aspect is the continuous advancement of medical technology, which prompts ongoing organisational changes in the healthcare sector. Therefore, most studies investigating medical inflation utilise a narrowed-down version of the harmonised consumer price index specifically focused on the healthcare sector, which is also the case in this study (Culyer and Newhouse, 2003).

2 LITERATURE REVIEW ON INFLATION FORECASTING METHODS

The first known analysis of inflation expectations in history was conducted by the American company Blue Chip Economic Indicators, established in 1976. In 1979, they conducted a survey in which respondents were asked to predict the average level of inflation for the next ten years. The survey included the top economists of that time in the United States. Before 1979, there had been no data regarding surveys on inflation expectations, so in the past, exponential smoothing of actual inflation values and the inflation gap were commonly used for the period before that year (Faust and Wright, 2012).

With the development of statistics, the first predictive methods also emerged. One of the first and simplest methods is direct forecasting. For each time step h, the prediction of the inflation value at time $t + h$ is obtained using classical regression. The inflation values at times $t + h$ are then used to forecast the inflation at time $T + h$. The index t represents the time point within the selected time interval, while T represents the upper limit of the selected time interval (Faust and Wright, 2012). A relatively simple method for predicting inflation is recursive autoregression (RAR). If the AR model is properly specified, the prediction asymptotically outperforms the selected benchmark. Marcellino, Stock, and Watson have demonstrated that, in general, forecasting with recursive autoregression is more accurate than direct forecasting. However, in the case of model misspecification, direct forecasting is more robust (Marcellino, Stock and Watson, 2006).

In addition to mathematical forecasting methods, there are more economically-oriented methods, one of which is forecasting based on the Phillips curve (PC). One of the early studies in which this method was employed is the study by Stock and Watson. They predicted inflation in the United States for 12 months. The inflation forecasts generated using the Phillips curve proved to be more accurate than forecasts made based on other macroeconomic variables such as interest rates, money supply, commodity prices, and others (Stock and Watson, 1999). Groen, Paap, and Ravazzolo (2013) also used the Phillips curve for inflation forecasting. They constructed a model based on various regression specifications selected from a group of potential predictors. These potential predictors include lagged inflation values, actual inflation values, characteristics of individual periods, and other statistically significant features for inflation prediction. The model also incorporates random shocks. This model specification type provides relatively accurate quarterly inflation predictions (Groen, Paap and Ravazzolo, 2013). Among the well-known models for inflation forecasting is the use of the classical random walk, which relies solely on past realisations of the random walk. We have the pure random walk model (RW) and the advanced random walk model (RW-AO) developed by Atkeson and Ohanian. The advanced random walk model often proves to be superior to models based on the Phillips curve. The Phillips curve is more successful in predicting inflation in industrialised economies than at the global level (Atkeson and Ohanian, 2001).

Univariate and multivariate factor-augmented models are also commonly used in inflation forecasting. However, these models are more suitable for analyses in which explanatory variables such as exchange rates, commodity prices, and similar factors can be incorporated. One of the early analyses or inflation forecasts in the European Union using these models was conducted by Bikker. The study argues that the best forecasts for the entire European region are constructed from different models for individual countries. The author focused on using nested models based on simple AR models (Bikker, 1998). Among other methods, the univariate stochastic volatility of unobserved components (UCSV) model is also used for inflation forecasting. Stock and Watson applied this model to inflation forecasting in the United States. They proposed a model with precisely determined parameters in which the deviation of inflation from long-term expected inflation is stable (Stock and Watson, 2010).

In recent years, predictive methods based on neural networks have been developing. Nakamura found that the accuracy of neural network predictions is higher than that of predictions obtained using univariate regression, but only for quarterly and semi-annual forecasts. Unfortunately, in the study published then, neural networks were not the most accurate for twelve-month forecasts (Nakamura, 2005). Eight years later, a study by Choudhary and Haider was published on the use of neural networks for inflation forecasting. They compared the use of neural networks with a first-order autoregressive model for predicting inflation in different countries. Neural networks provided more accurate inflation predictions for only 45% of the countries (Choudhary and Haider, 2012). In the last year, an article by Karadžić and Pejović was published, comparing the autoregressive integrated moving average model (ARIMA), the Holt-Winters model, and the neural network autoregression model (NNAR) for inflation forecasting in the Balkan countries and the European Union. The authors also found that the most accurate prediction of twelve-month inflation in EU countries can be achieved using the ARIMA model rather than the neural network. Most studies published in recent years that forecast inflation utilise the ARIMA model (Karadžić and Pejović, 2021).

There are also other models for inflation forecasting, but they are relatively unexplored. They include autoregressive forecasting in output gap form (AR-GAP), fixed λ-based forecasting, Phillips curve-based forecasting in output gap form (PC-GAP), Phillips curve-based forecasting in output gap form with time-varying NAIRU (PCTVN-GAP), time-conditioned forecasting based on VAR (Term Structure VAR), time-varying parameter VAR forecasting (TVP-VAR), exponentially weighted averages forecasting (EWA), Bayesian model averaging forecasting (BMA), factor-augmented vector autoregressive forecasting (FAV), dynamic stochastic general equilibrium forecasting (DSGE), dynamic stochastic general equilibrium with time-varying mean forecasting, and others (Faust and Wright, 2012).

As presented, methods for predicting inflation are well-researched. However, the situation is different in the field of predicting medical inflation. The first comprehensive study on this topic was published by DePamphilis in 1976. He presented a model for predicting quarterly healthcare costs using selected macroeconomic variables using multivariate regression (DePamphilis, 1976). In the following years, more studies predicting healthcare costs were published, and even the prediction of medical net discount rates emerged. Ewing, Piette, and Payne demonstrated that it is possible to improve predictions of medical net discount rates using an ARMA model by modelling time-varying characteristics of net discount rate volatility (Ewing, Piette and Payne, 2003).

American economists have also predicted long-term growth in healthcare expenditures using a dynamic general equilibrium model. They assumed that the introduction of new medical treatments is endogenous, and the demand for healthcare services depends on the state of technology. These projections covered 75 years (Borger, Rutherford and Won, 2008). Additionally, economists have often used linear autoregressive moving average models (ARMA) to predict medical inflation in recent studies. Cao, Ewing and Thompson conducted a comparative study where they compared this method with nonlinear neural networks. The research findings are similar to the previous conclusions of Karadžić, Pejović, and Nakamura. Neural network predictions are also slightly more accurate in this case, but primarily for shorter periods (Cao, Ewing and Thompson, 2012).

3 METHODOLOGY

In this article, I decided to use the time series theory, precisely the ARIMA model, to analyse and predict medical inflation in the European Union. The first part of this chapter provides a brief overview of fundamental definitions and characteristics of time series, which are essential for understanding the analysis and forecasting of medical inflation. While the second part presents the methodology used for the analysis and forecasting.

It is known that a stochastic process is a family of random variables defined on the same probability space. A stochastic process X_t, $t \in T$, where $T \subseteq \mathbb{R}$, is then called a time series. A time series is stationary if its properties do not depend on the time at which the time series is observed. A weakly stationary time series X_t is an ARMA(p,q) process, an autoregressive moving average process of order (p,q), for

$p,q \in \mathbb{N} \cup \{0\}$, if there exists a sequence $Z_t \sim WN(0, \sigma^2)$ and real parameters $\rho_1, \rho_2, \ldots \rho_p$ and $\theta_1, \theta_2, \ldots \theta_q$ such that for all $t \in \mathbb{Z}$, the following holds (Basrak, 2022)

$$X_t - \rho_1 X_{t-1} - \cdots - \rho_p X_{t-p} = Z_t - \theta Z_{t-1} - \cdots - \theta_q Z_{t-q} \tag{1}$$

Process X_t is an ARIMA(p,d,q) process, an autoregressive integrated moving average process of order (p,d,q), where $d \in \mathbb{N} \cup \{0\}$, if $(1-B)^d X_t$ is a causal ARMA(p,q) process, where B is a linear filter. In this case, X_t satisfies the equations

$$\rho(B)(1-B)^d X_t = \theta\left(b\right) Z_t, t \in \mathbb{Z} \tag{2}$$

Moreover, $Z_t \sim WN(0, \sigma^2)$ and ρ and θ are polynomials such that $\rho(z) \neq 0$ for $|z| \leq 1$. A time series X_t can be decomposed into three components. A decomposition is (Basrak, 2022)

$$X_t = m_t + s_t + Y_t, t \in \mathbb{Z} \tag{3}$$

The first component m_t is called the trend, which represents the long-term movement or direction of the average of the time series. The second component s_t is called the seasonal component; it includes the influences of seasons and calendars and has a specific period. The third component Y_t is called the irregular component, consisting of fluctuations that do not belong to either of the first two components and can be weakly or strongly stationary. In practice, determining these three components of a time series is often difficult. Therefore, when choosing a model, it is important to strive for simplicity and adhere to the principle of Occam's razor (Basrak, 2022).

Usually, exploratory analysis of a time series is based on the following steps:

- plotting the observed values and identifying deviations from stationarity,
- removing trend and seasonality,
- selecting an appropriate model for modelling the residuals.

Deviations from stationarity can be tested using statistical tests, with the modified Dickey-Fuller test (ADF test) and the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS test) being the more well-known. In practice, time series are often non-stationary, so it is necessary to remove trend and seasonality. Moreover, the removal of trend using estimation can be done using various methods, such as linear filer, exponential smoothing and polynomial approximation. Furthermore, the removal of seasonality is usually done by differencing (Hamilton, 1994).

When examining a time series, it is typical to complement the exploratory analysis with a spectral analysis, which entails decomposing the time series into periodic components of sinusoidal functions. The purpose of spectral analysis is to identify prominent or significant frequencies in the given time series. The visual representation of the spectral analysis is a periodogram, which quantifies the contributions of individual frequencies to the regression of the time series. The periodogram values can be interpreted in terms of data variance with respect to frequency or period.

Furthermore, usually, the Fourier linear spectrum is used. This is a graph of the periodogram against the corresponding frequencies. In practice, the Fast Fourier Transformation (FFT) is commonly used for calculating the periodogram efficiently, which is also used in R for generating periodograms and spectral analysis (Wearing, 2010).

4 ANALYSIS OF MEDICAL INFLATION IN EU COUNTRIES

The data on medical inflation or the Harmonized Index of Consumer Prices (HICP) in the healthcare sector in EU countries was obtained from Eurostat, where monthly data on inflation growth rate changes are available. The data was collected for all EU member states, including Austria, Belgium, Bulgaria, Czech Republic, Cyprus, Denmark, Estonia, Finland, France, Greece, Croatia, Ireland, Italy, Latvia, Lithuania, Luxembourg, Hungary, Malta, Germany, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden. The categories within the healthcare sector of HICP include medical products, appliances and equipment, outpatient services, and hospital services (Eurostat, 2023). The time frame covers the period from 2000 to 2022. The R programming language was used for the practical part of the task. The data was imported and cleaned using the *readxl* and *tidyverse* packages. Subsequently, a time series object was constructed for each country. For the analysis and forecasting presented below, the *tseries*, *forecast*, and *TSA* packages were used.

The first step in the analysis is to identify any deviations from stationarity, which was done by graphical analysis of the time series for all countries. On the one hand, medical inflation of some member states appeared stationary, since graphical analysis suggests a constant variance, with no evident seasonal components or trend. On the other hand, the majority of them appear non-stationary, as there is a noticeable downward or upward trend. For a more comprehensive analysis, the time series for each country was decomposed, meaning that their trend, seasonal component, and irregular component were plotted. Based on the graphical decomposition, it is challenging to determine the trend as there is no clear upward or downward trend in any of the counties. Nevertheless, the seasonal component is visible in the graphical decomposition of all countries, and a recurring pattern is noticed. Despite the indications of a seasonal component in the decompositions, it is difficult to observe it clearly in the curve plots by years. To facilitate the identification of any exceptional months, polar coordinates were used, yet the plots did not suggest any exceptional months.

For a more precise stationarity analysis, two statistical tests were conducted: the Dickey-Fuller test and the Kwiatkowski-Phillips-Schmidt-Shin test (Vijay Kumar, 2023). If both tests confirmed stationarity, one can conclude that the time series is stationary at a significance level of 0.05. The results of the tests, shown in table 1, indicate that 12 out of 27-time series are stationary. Based on the comprehensive analysis the time series were deseasonalised and differenced, which effectively removes the seasonality and trend. The transformed time series are now stationary and suitable for further analysis.

Table 1
Results of ADF and KPSS tests

Member state	ADF test	KPSS test	Stationarity
Austria	0.02*	0.10	Stationary
Belgium	0.49	0.10	Non-stationary
Bulgaria	0.41	0.07	Non-stationary
Croatia	0.01*	0.10	Stationary
Cyprus	0.08	0.10	Non-stationary
Czechia	0.01*	0.10	Stationary
Denmark	0.01*	0.10	Stationary
Estonia	0.23	0.10	Non-stationary
Finland	0.08	0.10	Non-stationary
France	0.05	0.10	Stationary
Germany	0.01*	0.10	Stationary
Greece	0.28	0.80	Non-stationary
Hungary	0.01*	0.10	Stationary
Ireland	0.13	0.03*	Non-stationary
Italia	0.01*	0.10	Stationary
Latvia	0.28	0.10	Non-stationary
Lithuania	0.21	0.08	Non-stationary
Luxembourg	0.01*	0.10	Stationary
Malta	0.28	0.10	Non-stationary
Netherlands	0.08	0.10	Non-stationary
Poland	0.65	0.04*	Non-stationary
Portugal	0.01*	0.10	Stationary
Romania	0.01*	0.02*	Non-stationary
Slovakia	0.04*	0.10	Stationary
Slovenia	0.51	0.03*	Non-stationary
Spain	0.01*	0.10	Stationary
Sweden	0.07	0.10	Non-stationary

Note: $^{*}p < 0.05$, $^{**}p < 0.01$ *and* $^{***}p < 0.001$.

After that, a spectral analysis was conducted in order to identify periodicities. For each country a smoothed periodogram was plotted according to which it was possible to identify the values of the medical HICP with the highest frequencies and calculate the corresponding periods of occurrence. For most countries, the period was 3 months or one quarter of a year. After exploratory and spectral analysis, the ARIMA model was determined. The traditional way to determine the model and the values of its parameters is by plotting the autocorrelation function (ACF) and partial autocorrelation function (PACF). The optimal parameters can be selected according to the graphs and with the use of the Akaike information criterion (AIC). However, in R, there is a function called *auto.arima* that uses the Hyndman-Khandakar algorithm. This algorithm minimises both the AIC value and the maximum likelihood value to better fit the model to the data. Thus, because of the algorithm's ability to fit models effectively, the *auto.arima* function was used.

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5 RESULTS

Firstly, for each country test forecasts were created using only the data from 2000 to 2022. A 12-month forecast for the medical HICP was generated and then compared with the actual measurements. For example, figures 1 and 2 are the test forecasts for Italy and Ireland with 95% CI. Measured values are determined by a black line, while a red line determines forecasted and actual values.

Figure 1
Test forecast – Italy

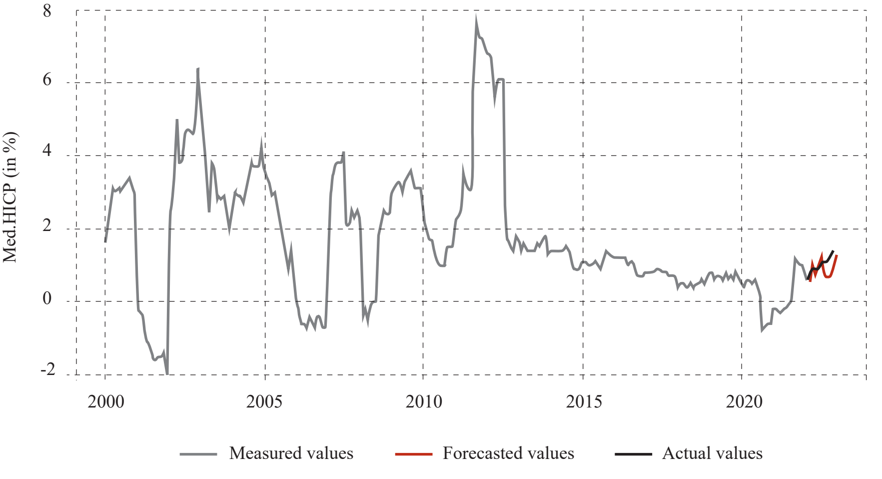
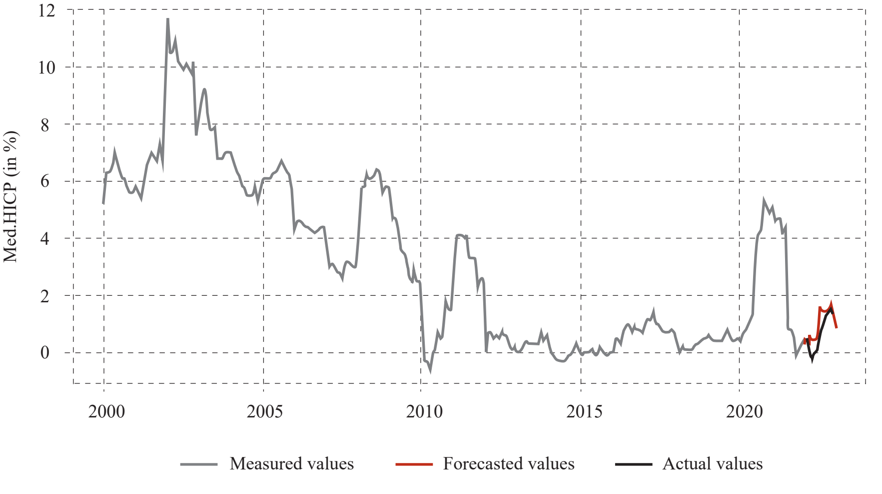


Figure 2
Test forecast – Ireland



Secondly, actual forecasts for the next 12 months were generated. For example, figures 3 and 4 are the forecasts for the medical HICP for the Netherlands and Cyprus with 95% CI. Measured values are determined by a black line, while a red line determines forecasted values.

Figure 3
Forecast – Netherlands

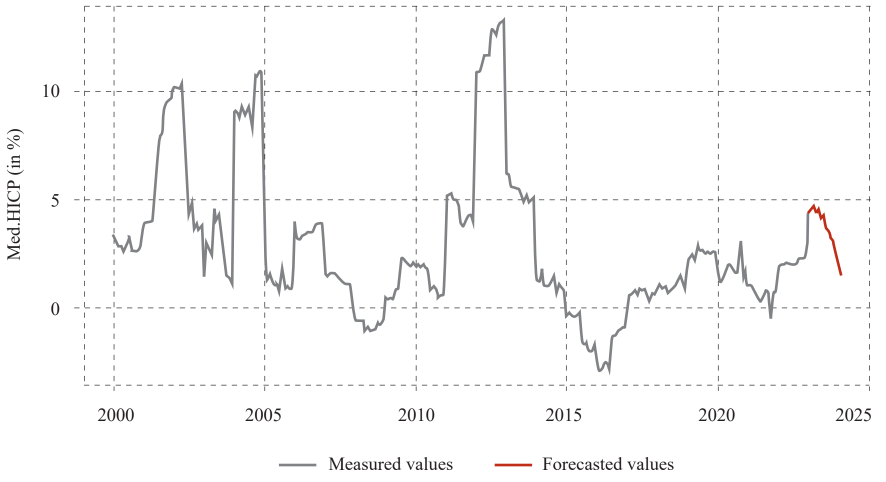


Figure 4
Forecast – Cyprus

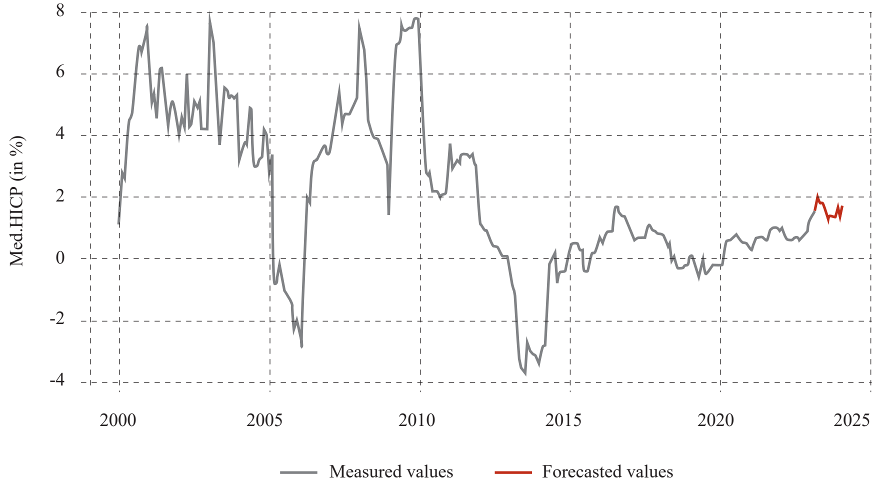


Table 2
Absolute differences between forecasted and actual values of medical HICP in pp

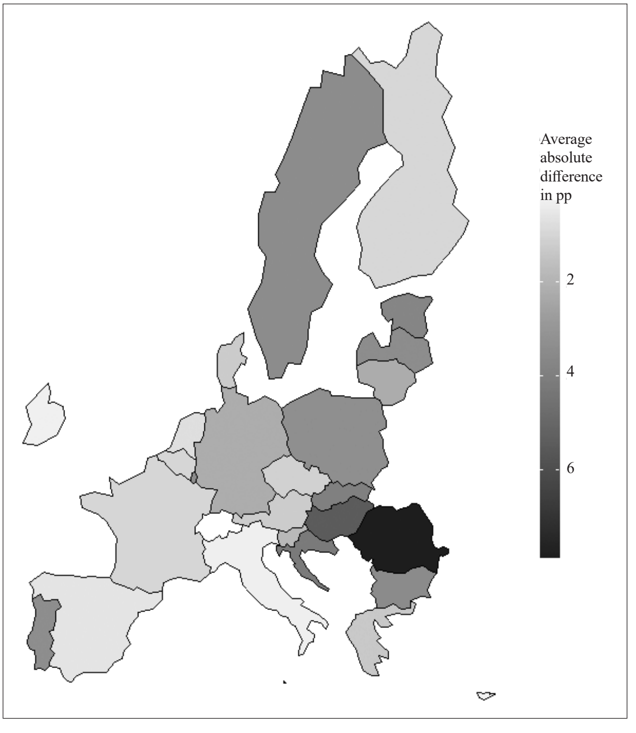
Member state	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Average
Austria	0.68	1.02	0.12	0.91	0.69	0.77	0.43	0.89	2.00	1.86	2.12	3.34	1.23
Belgium	0.06	0.25	0.25	0.30	0.33	0.63	0.82	1.07	1.16	1.30	1.48	4.07	0.98
Bulgaria	0.17	0.45	0.92	1.37	1.86	2.02	1.64	1.89	4.22	6.70	9.59	11.02	3.49
Croatia	0.28	1.38	2.14	2.27	2.48	3.66	5.06	5.67	6.12	6.28	6.59	8.17	4.18
Cyprus	0.09	0.14	0.66	0.41	0.46	0.33	0.02	0.11	0.06	0.08	0.47	0.12	0.25
Czechia	0.69	0.87	0.11	0.38	0.64	0.98	0.83	1.49	0.51	1.56	2.19	2.86	1.09
Denmark	0.72	0.69	0.43	0.12	1.35	1.03	1.02	0.69	1.71	1.92	2.67	2.71	1.25
Estonia	0.67	1.31	1.15	2.03	2.57	3.05	3.21	4.93	6.18	5.65	6.83	7.22	3.73
Finland	1.30	1.22	1.52	2.00	0.40	0.68	0.60	0.92	0.76	0.77	0.84	0.29	0.94
France	0.42	0.82	1.19	0.95	1.14	0.66	0.17	1.06	1.58	1.01	1.15	1.58	0.98
Germany	0.01	0.18	0.06	0.03	0.45	0.45	1.99	2.41	2.60	2.64	2.71	2.73	1.35
Greece	0.38	0.59	0.15	0.87	1.59	2.00	2.17	3.01	3.51	3.33	4.07	4.88	2.21
Hungary	0.20	0.00	0.51	1.26	2.17	3.48	5.25	6.95	9.34	11.16	12.75	12.64	5.48
Ireland	0.11	0.59	0.64	0.38	0.38	0.73	0.34	0.01	0.06	0.14	0.13	0.01	0.29
Italia	0.04	0.16	0.08	0.15	0.03	0.18	0.26	0.43	0.52	0.63	0.37	0.81	0.30
Latvia	0.08	1.29	1.72	2.55	2.88	3.23	3.19	3.94	4.76	4.66	5.91	6.29	3.38
Lithuania	0.11	0.04	0.72	1.40	1.76	2.23	2.75	2.59	3.70	3.39	4.58	3.62	2.24
Luxembourg	0.83	0.64	2.47	3.04	3.27	3.27	3.57	4.58	4.22	4.59	5.21	5.65	3.45
Malta	0.46	0.07	0.32	0.70	0.25	0.45	0.93	1.49	1.93	1.93	2.39	2.11	1.09
Netherlands	0.40	0.04	0.37	0.32	0.14	0.18	0.61	0.40	0.91	0.47	1.10	3.66	0.72
Poland	0.51	1.34	1.97	2.72	2.89	3.06	3.09	3.40	4.21	5.01	5.06	6.67	3.33
Portugal	0.37	0.12	0.04	0.17	5.05	5.45	5.34	5.18	5.46	4.47	4.39	4.23	3.36
Romania	0.51	1.45	2.97	4.30	6.11	7.25	8.33	9.55	11.11	12.84	14.37	15.64	7.87

Member state	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Average
Slovakia	0.48	0.92	1.56	2.89	2.60	3.25	4.20	5.20	5.03	6.22	7.28	7.68	3.94
Slovenia	0.95	0.67	0.28	0.52	0.48	0.09	1.97	2.00	1.44	3.95	5.50	3.75	1.80
Spain	0.32	0.20	0.11	0.07	0.50	0.41	0.57	0.80	0.81	1.18	1.05	1.05	0.59
Sweden	0.45	1.54	2.23	2.92	3.16	2.52	4.01	4.36	3.95	4.24	5.33	6.08	3.40
Average	0.42	0.66	0.91	1.30	1.70	1.93	2.31	2.78	3.25	3.63	4.30	4.77	2.33

For each EU member state, the absolute difference between the test forecasted values and actual values for each month from March 2022 to February 2023 was calculated. The results are shown in table 2. As the forecast horizon increases, the absolute differences between the forecasted and actual values also increase. The most accurate forecasts are observed within a 3-month horizon, where the differences are less than 1 pp. On average, the forecasted and actual values differ by 2.33 pp. Notably, the countries with an average absolute difference of less than 1 pp are Belgium, Cyprus, Finland, France, Ireland, Italy, the Netherlands, and Spain. On the other hand, the countries with the highest average absolute differences, exceeding 4 pp, are Croatia, Hungary, and Romania.

Figure 5

Average absolute difference between forecasted and actual values of medical HICP



One of the key reasons for the large differences between forecasted and actual values in the latter group of countries is the fluctuation of domestic currencies since these countries are not part of the euro area but have their own currencies. On the other hand, the remaining countries are part of the euro area and follow the common European monetary policy, which ensures price stability. Price stability is achieved with the use of various instruments such as open market operations, open offers, and maintenance of required reserves (Rakić, 2023). The mentioned differences between the two groups of countries are visible in figure 5.

6 DISCUSSION

The analysis findings reveal the ARIMA model's effectiveness for the euro area countries in capturing the temporal patterns and dynamics of medical inflation. The model demonstrates its ability to consider both short-term fluctuations and long-term trends. However, considering multiple time series, the opportunity arises to extend the analysis by checking possible dependencies among them; specifically, one could explore the application of methods specialised for panel data analysis. Furthermore, extending the forecasting horizon and adjusting the length of the primary time series of medical inflation would be a significant enhancement as well. Furthermore, future researches on this topic could explore the inclusion of exogenous variables such as demographic trends, technological advances and policy changes. Moreover, other forecasting techniques such as machine learning algorithms can be used to predict medical inflation. All these improvements would enable the model to capture complex time series patterns, consequently resulting in more accurate forecasts and valuable insights into the dynamics of medical inflation.

Given that the ARIMA model has not been previously used for forecasting medical inflation, it is challenging to validate the congruence of the obtained results with existing conclusions. Nevertheless, the findings do partially align with the latest findings in the field of inflation forecasting using various methods, as presented in section 2, particulary in studies conducted by Ewing, Piette, Payne, Karadžić and Pejović. Additionaly, the obtained results align with articles exploring the ARMA model's capability to forecast medical inflation, considering that the ARIMA model is essentially an enhancement of the ARMA model. However, there are some limitations and disadvantages of using the ARIMA model for forecasting medical inflation in the EU. Firstly, since ARIMA models are inherently linear, they may not fully capture the complex non-linear relationships that could exist in healthcare economics, and factors such as sudden policy changes or technological breakthroughs may not be appropriately modelled using ARIMA model alone. Secondly, ARIMA models provide accurate predictions only for short or medium term forecasting, while for long-term projections alternative approaches should be used.

The predictions provide an insight into the anticipated trajectory of medical inflation, allowing policymakers of euro area countries to proactively address potential challenges and make appropriate policy responses, especially regarding the issues of an ageing European population and the rapid progress in medical technology and practices. Moreover, reliable predictions of medical HICP provide guidance specifically for policymakers in the ministries of health for enhancing the efficiency of public spending in the healthcare sector. The situation is even more delicate for EU countries, as many rely on a public healthcare system. These systems usually operate on a national level, with the government covering the majority of medical expenses. At the same time, residents are only required to pay small fees in the form of compulsory health insurance.

Furthermore, by anticipating future healthcare costs, health insurance companies can benefit in several ways. By analysing and predicting healthcare costs, insurers can gain insight into the expected expenditure in different areas of healthcare services, which would enable them to determine appropriate premiums to charge and develop innovative health insurance models. Besides, accurate projections allow insurers to engage in informed discussions with hospitals and other healthcare entities and thus negotiate payment agreements which align with the projected costs. This would ensure a fair and sustainable partnership between insurers and healthcare providers.

Besides, projections of medical inflation play a vital role in the administrative aspects of hospitals and other healthcare entities. Considering such forecasts, they can gain valuable insights into the expected cost increases. Such predictions would enable them to make informed decisions and allocate their resources to areas that are likely to experience the highest inflationary pressures. This proactive approach would help to ensure the financial stability of healthcare organisations, enabling them to continue providing quality care to their patients without compromising their financial integrity.

7 CONCLUSION

Since the European Union continues to grapple with the complexities of healthcare financing and accessibility, forecasting medical inflation is becoming essential. Accurate forecasts of medical HICP enable policymakers to address challenges proactively, insurers to set appropriate premiums and develop innovative models, and healthcare entities to strategically allocate resources to ensure financial stability and quality care. Thus, forecasting medical inflation using the ARIMA model holds substantial significance for public sector economics in the European Union.

In this article, I have explored the application of the ARIMA model to forecast medical inflation within the European Union. Through rigorous analysis of historical data and advanced time series techniques, the study provides valuable insight into the future trajectory of medical inflation, especially for euro-area countries. The findings of the analysis show the effectiveness of the ARIMA model, which has the potential to capture complex temporal patterns and dynamics of medical inflation.

Disclosure statement

The author has no conflict of interest to declare.

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