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Socioeconomic Effects of COVID-19 Pandemic: Exploring Uncertainty in the Forecast of the Romanian Unemployment Rate for the Period 2020–2023

Adriana AnaMaria Davidescu [1,2,*], Simona-Andreea Apostu [2,3] and Liviu Adrian Stoica [4]

1 Department of Education, Training and Labour Market, National Scientific Research Institute for Labour and Social Protection, 010643 Bucharest, Romania
2 Department of Statistics and Econometrics, Bucharest University of Economic Studies, 010552 Bucharest, Romania; simona.apostu@csie.ase.ro
3 Institute of National Economy, 050711 Bucharest, Romania
4 Finance Postdoctoral School of Bucharest University of Economic Studies, 010352 Bucharest, Romania; liviu.stoica@csie.ase.ro
* Correspondence: adriana.alexandru@csie.ase.ro

Abstract: During the health crisis, it is vital to protect not only the critical sectors of the economy, the assets, technology, and infrastructure, but first and foremost, it is fundamental to protect jobs and workers. The current COVID-19 pandemic has had a strong impact on the labor market from three main perspectives: number of jobs (through unemployment and underemployment), quality of work (through wages, or access to social protection), and through the effects on specific groups, with a higher degree of vulnerability to unfavorable labor market outcomes. The measures aiming to reduce economic activity and social contacts lead to a reduction of labor demand and implicitly to the increase of the unemployment rate. In this context, it becomes even more relevant to be able to monitor the unemployment rate, providing relevant forecasts that include the effects of market shocks. Thus, our paper aims to forecast the unemployment rate for the period 2020–2023 using the Box-Jenkins methodology based on ARIMA models, exploring also the uncertainty based on fan charts. Although the baseline forecast offers valuable information, a good understanding of risks and uncertainties related to this forecast is equally important. The empirical results highlighted an ascending trend for unemployment rate during 2020, followed by a slow and continuous decrease until the end of 2023 with a high probability for the forecast to be above the central projection.

Keywords: socioeconomic effects; pandemics; unemployment rate; ARIMA models; Box-Jenkins procedure; forecast; uncertainty; Romania

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1. Introduction

"Sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs" [1]. In most conceptualizations of sustainable development, social sustainability is one of the three key pillars alongside environmental sustainability and economic sustainability.

Generating more decent jobs that provide a living wage, social protection, and worker rights is the best way to promote the three components of sustainable development: economic growth, social cohesion, and environmental sustainability.

However, in the last decades, the importance of the social sustainability concept highly increased, considered an independent sustainability rather than solely part of sustainable development. Various social issues and topics define social sustainability, including unemployment, education for sustainable development, separate waste collection, and sustainable retrofit [2].

Social sustainability includes achieving a correct level of social homogeneity, equitable income distribution, employment that allows the creation of decent livelihoods [3], and identifying the minimal social specifications for long-term development [4].

In this context, monitoring the unemployment rate and addressing specific policies in order to increase the employment can be an important channel for achieving social sustainability. For such, the unemployment rate represents an SDG (Sustainable Development Goals) core indicator, directly targeted in SDG8-promoting sustained, inclusive, and sustainable economic growth, full and productive employment, and decent work for all.

To further integrate social sustainability into European Union (EU) policy-making, the employment and social situation in Member States should be given the same weight as economic considerations.

While (un)employment rates may to some extent mirror a country's wider social development or well-being, they may also hide several social problems, such as in-work poverty, gender inequality, material deprivation, and lack of education.

This phenomenon is becoming even more important in the context of the coronavirus crisis, which caused sharp and profound changes, dramatically impacting the word's labor markets.

The rapid spread of infections with the new coronavirus left its mark on all of mankind in the first part of 2020, as it has practically placed economies and labor markets around the world in a state of emergency. One of the characteristics of the pandemic recession is that it mainly affects the labor market and, only complementary, the stock of fixed capital.

The COVID-19 crisis puts labor markets in many countries in a state of emergency, by disrupting supply chains, slowing world trade and export demand, reducing working hours, but especially by drastically shutting down domestic economic activities, especially those in the field of public services, which represents a new challenge [5].

The outbreak of the COVID-19 epidemic gave all states an external shock, both on the supply side and on the labor demand. The sudden deterioration of the health of the population, and especially of the active population, had destructive effects on human capital [6].

Poor health, as well as the risk of death, reduces both the number of hours that active people are willing to perform it, as well as labor productivity. The fact that the risks are higher for older workers with more professional experience, emphasizes the reduction of labor productivity. Reducing the intensity of economic activities has had and still has notable effects on the various components of the labor force supply. Thus, a segmentation of the employed population has been outlined, at the time of taking drastic measures of reduction of economic and social activity, in essential and non-essential workers [7].

The COVID-19 pandemic had significant effects on both the supply and demand of the labor force. Thus, especially in the acute phases of the epidemic crisis, we witnessed the segmentation of the supply of labor force, depending on the role played in combating the effects of the pandemic, on the degree of exposure to pathogens and on the access to information and communication technologies. On the side of the demand for labor force, the greatest recessionary effects have appeared in consumer support services, in administrative and business support services, as well as in the manufacturing industry. It was a consequence of the reduction of the income level, but also of the appearance of some major blockages in the international supply chains of raw materials [6].

Economic factors and non-economic crises, such as COVID-19, redefine the functioning and labor market efficiency and profoundly changes the demand for human capital, with direct effects on the education for the labor market.

In this context, the paper aims to offer reliable forecasts for the Romanian unemployment rate for the period 2020–2023, in order to provide valuable instruments for the future performance of labor market. In order to do that, we have applied the Box-Jenkins methodology based on ARIMA models, additionally exploring the uncertainty using fan charts.

The paper is organized as follows. The section of literature review was dedicated to the most relevant studies in the field, while the next section presents the characteristics of the Romanian labor market pre- and during pandemics. The section of methodology briefly introduces the main steps of Box-Jenkins procedure, together with the data description. The section of empirical results presents the main steps taken to determine both static and dynamic forecasts. Additionally, we present quantifying risks and uncertainties of the baseline forecast through the representation of fan charts. The paper ends with the discussions and conclusions stipulating the main measures that can support the post-pandemic labor market recovery.

2. Literature Review

The business dictionary defines unemployment rate as the percentage of the total workforce who are unemployed and are searching for a job [8]. A high value of unemployment rate means a weak economy, requiring a reduction in the interest rate. At the opposite side, a low rate reflects a growing economy, respectively higher inflation, requiring higher interest rates [9].

The unemployment rate represents one very important economic indicator for financial market participants. Unemployment rate is correlated with the country's business cycle, being significantly influenced by the monetary policy [10]. Accurate forecasting of the unemployment rate is vital to decision-making in the economy and the design of policy-making in order to recognize the problems early on [11].

The crises in the economy, such as the Great Recession of 2008–2009 and the euro debt crisis significantly influenced the evolution of unemployment, which in some countries increased and peaked shortly after, and which in other countries increased steadily and has remained very high [12]. The coronavirus crisis in 2020 has a similar impact, affecting the unemployment rate worldwide. The pandemic has severely disrupted the economic activity through various supply and demand channels, leading to large and protracted increases in unemployment and declines in inflation [13].

The pandemic upended the labor market, generating massive job losses and the highest spike in unemployment, which have been even greater than the increases caused by the Great Depression. The uncertainty regarding unemployment depends on the speed and success of coronavirus containment measures. Therefore, it is very important to provide regular forecasts in order to control and monitor this phenomenon with a significant effect on the labor market, mostly in this period of major exogenous shock. The analysis of such a phenomenon has its roots in the middle of the 1990s. Previous studies on unemployment pointed out the existence of an asymmetry in data for European countries [14], being inconsistent with a linear data generating process with symmetrically distributed innovations [15].

In the case of nonlinear time series models, within the class of regime switching models, threshold autoregressive models (TAR) are prominent, being used by Hansen [16], Koop and Potter [17], and Montgomery at al. [18]. During periods of rapidly increasing unemployment, but not globally, TAR and Markov-switching models outperform the linear ARIMA [19].

Skalin and Teräsvirta [20] used a logistic smooth transition autoregressive model (LSTAR) in order to differentiate the unemployment rate in the case of OECD. van Dijk et al. [21] highlighted that the LSTAR model is more appropriate than the linear AR counterpart in case of long-term forecast during downturns and in case of short-term during expansions.

In order to forecast the unemployment rate in the UK, Johnes [22] used the autoregressive model, GARCH, SETAR, and Neural network, highlighting that the SETAR model is the most appropriate model for non-linear data and short period forecasts. Peel and Speight [23] showed that out-of-sample SETAR forecasting registered a better performance comparative to AR models. Gil-Alana [24] used both the Bloomfield exponential spectral model and ARMA model to forecast unemployment, better results being provided by the Bloomfield model.

Chen [25] forecasted the unemployment rate in 10 countries using novel nonlinear grey Bernoulli model (NGBM). Kurita [26] forecasted the unemployment rate in Japan using fractionally-integrated autoregressive and moving average (ARFIMA), being a satisfactory representation of the data and of much use for forecasting purposes.

From all methods of forecasting, the most commonly used methods to predict the unemployment rate are the ARIMA models. The Box-Jenkins methodology has been widely used in the literature.

Wong et al. [27] used it to develop Autoregressive Integrated Moving Average (ARIMA) models in order to analyze and forecast important indicators in the Hong Kong construction labor market: employment level, productivity, unemployment rate, underemployment rate, and real wage. Ashenfelter and Card [28] analyzed unemployment, nominal wages, consumer prices and the nominal interest rate, using the autoregressive moving average model. Kurita [26] forecasted the unemployment rate using autoregressively integrated fractional moving average, the model being much better than naive predictions.

Predictions of unemployment rate using the Box-Jenkins methodology have been done by Chih-Chou and Chao-Ton [29], Etuk et al. [30] and Nkwatoh [31] in Nigeria using the ARIMA and ARCH model, Kanlapat et al. [32] in Thailand, Nlandu et al. [33] in Barbados, using the seasonal integrated autoregressive moving average model (SARIMA), Dritsakis and Klazoglou [34] in the USA using SARIMA and GARCH models, and Didiharyono and Muhammad [35] in South Sulawesi using the ARIMA model.

At the level of UE, the unemployment rate has been forecasted using Box Jenkins and TRAMO/SEATS methods [36,37]. Empirical evidence has been provided for Germany using the ARIMA and VAR models [38], for the Czech Republic using the SARIMA model [39,40], for the German regions using a model spatial GVAR [41], for Greece, both as a dynamic process and as a static process using SARIMA models [38,42], and for Slovakia using ARIMA and GARCH models [43].

ARIMA model has been used in forecasting the Spanish and Swedish unemployment rate [44,45]. The classical ARIMA model was used for unemployment forecast across Europe [46,47] and Canada [48]. Instead, for forecasting the USA unemployment rate, used the classical nonlinear time series model [49,50] and threshold autoregressive (TAR) model were used [17].

Other nonlinear forecasting tools imply using artificial neural networks, deep learning, and support vector machines [51,52], being accurate instruments in unemployment forecasting over the asymmetric business cycle for case of USA, Canada, UK, France, and Japan [53,54]. The Box-Jenkins methodology has been used to predict the unemployment rate in Romania by Madaras [55], Bratu [56], Simionescu [57] using the VARMA and VAR models, Dobre and Alexandru [58], and at the level of two Romanian counties (Brasov and Harghita) were made using Box-Jenkins methodology and NAR model based on the artificial neural network, the empirical results revealing that the differences between the real and the predicted values became larger in the NAR models in comparison to ARMA forecasts, proving that the ARMA model offers more reliable estimates and forecasts. However, it is worth the lack of national studies regarding forecasts of unemployment rates at least for the last five to seven years.

3. An Analysis of Romanian Labor Market Pre- and during the Pandemic

Romania faced, even before the pandemic, a deep structural crisis in the labor market, especially in the health sector, IT and C (Information Technology and Communications), education, production, construction, and also in other parts of the industry. Although measures have been taken in order to mitigate the negative impacts, the coronavirus pandemic aggravated these aspects [59].

Romania was far behind the European average before the pandemic concerning the level of economic and social development, and the fundamental causes have been generated by recent demographic developments, but also the by the very large gaps that separate Romania from the situation of the developed EU states in terms of the distribution of labor on the three large sectors of the national economy.

The decrease in the active population in the last 10 years has been a direct consequence of the decreasing trend of the population at national level, but also of the changes in its age structure. The active population registered visible discrepancies in terms of gender and area of residence, the male and urban population exhibiting the highest values.

Another relevant indicator for monitoring the evolution of the labor market is the employment rate with a decreasing trend for the last decade, with significant discrepancies by gender [6].

The employment of young people is low in Romania, being in the last 10 years, in average, on a downward slope. In 2018, the level of employment rate of the population aged 20–64 was 69.9%, at a distance of 0.1 percentage points from the national target of 70%, set in the context Europe 2020 Strategy.

The unemployment rate is another important indicator for monitoring and analyzing the labor market, evolving differently in the period 2005–2018, being strongly influenced by the economic situation, in particular the effects of the economic crisis that manifested themselves in the period 2009–2011 and the policies of occupation for various shorter periods of time. Until 2015, it went through a period of stability, with relatively small variations from one year to another, while after 2015, the number of unemployed registered a continuous and significant decrease, reaching in 2018 almost 380,000 people, with approximately 70,000 less than in 2017 [6].

With the onset of the coronavirus pandemic, measures to restrict physical contact and block economic activity have led to an increase in the unemployment rate and at the same time, to a reduction in working hours. The coronavirus crisis represents a threat to the economy and to the living standards of citizens. Therefore, it is vital to protect both the critical sectors of the economy and the activities, technology, and infrastructure. The most important dimension needed to be protected is represented by the labor market, meaning jobs and workers.

The coexistence of the epidemic and recession curve caused by the epidemic raises the nature of the issue and duration of the intervention of public authorities to limit economic and social losses.

The establishment by public authorities of measures to drastically reduce economic activity and social contacts creates favorable conditions for the flattening of the epidemiological curve, but induces a state of severe recession, which can cause significant economic and social costs. The negative effects do not only translate into the reduction of labor demand and implicitly in the increase of the unemployment rate and of the social tensions, in the short and medium term, but also in the deterioration of the social capital [6].

A paradigm shift brought by the pandemic has been represented by teleworking, in Romania, 18.4% of employees started to work from home, and teleworking will continue to be the new normal for companies even after the end of the COVID-19 pandemic [60]. However, suspended employment contracts reached 1,000,000 in Romania, immediately after the crisis occurred and the recruitment market indicated a 94% drop in job supply [61].

The current COVID-19 pandemic has had a strong impact on the labor market from three main perspectives: number of jobs (through unemployment and underemployment), quality of work (through wages, or access to social protection) and through the effects on specific groups, with a higher degree of vulnerability to unfavorable labor market outcomes [8].

Labor supply was declining due to quarantine measures and the restriction of economic activities, accompanied by a reduction in incomes and working hours, which, in turn, lead to an adjustment in consumption patterns, a reduction in the consumption of goods and services, leading finally to an increase in the in-work poverty.

In Romania, the COVID-19 pandemic had, in March and April 2020, notable effects on employment. The types of imbalances between labor demand and supply have changed significantly both the economy as a whole and the different sectors. The sharp decline in economic activity has led to a severe diminish in labor force demand, in the total number of suspended employment contracts and completed employment contracts, which exceeded 1,000,000 since the first part of April [5].

It is noteworthy that in March, compared to February, the unemployment rate increased by 0.7% compared to the previous month (4.6% compared to 3.9%). The provisions of the military ordinances on stopping the spread of the new coronavirus have led many companies to partially or completely cease operations, which has led to the highest unemployment rate in the last two years [62].

The initial projection has been that the unemployment rate in 2020 will increase, the month of March being only the beginning of the health crisis in Romania. According to the Ministry of Labor and Social Protection [63], more than 276,000 people were in a position where their employment contract was completed on April 30, 2020. Wholesale and retail trade, manufacturing and construction have been the industries with the highest number of completed employment contracts.

Although the effects of the coronavirus crisis have been seen in the economy since the measures taken in March 2020, forecasts indicated that the highest level of unemployment reached 3.98% in the second quarter of 2020. Even the most pessimistic forecasts indicated that the unemployment rate in 2020 will not exceed 7%. The explanations for these low values compared to real figures were given by the fact that the persons returned to the country and the persons with terminated employment contracts are not included in the number of unemployed. At the end of March 111,340 terminated employment contracts and 250,000 people who have returned in Romania from abroad were registered. Another explanation is the fact that the labor market was not bigger at all during the crisis, therefore people were not searching for a job, an essential condition to be declared unemployed [64].

The crisis caused by the coronavirus affected activities in many sectors and the number of unemployed increased, but this has not been reflected by the unemployment rate, as the real unemployed were not included in the reporting base. Therefore, the underestimation of the unemployment phenomenon can be explained by the non-inclusion in the statistics, being included in the structural unemployment, the employment rate was reduced.

According to the estimates of the National Commission for Strategy and Forecast [65], the projection of the labor market indicators indicate an increase in unemployment from 5% in 2020 to almost 3.5% in 2023, and 3.2% in 2024.

Even in the presence of anti-crisis measures and government support to the economy, the sanitary crisis certainly had a significant impact on the Romanian labor market, leading to increases of unemployment at least in 2020, as a result of the restriction of activity in many branches [5].

Reduction of the number of active employees by over 900,000 people in April 2020, compared to the end of 2019, suspension of a significant number of individual employment contracts, which reached a maximum of approximately 1,000,000 and continuous increase of the number of terminated contracts at a maximum of over 340,000 in the first decade of May, are some of the key aspects of the impact of COVID-19 on the labor market, with implicit social effects.

Therefore, our research hypothesis is the following:

Hypothesis 1: *The Romanian unemployment rate increases during the year 2020, the first year of the pandemic, and it follows a descending pattern from the beginning of 2021 until the end of 2023.*

4. Methodology

The Box-Jenkins methodology is a five-step iterative procedure, used widely for the forecasting of univariate time series comprising the identification stage, estimation, diagnostics, selection, and forecasting [50,59,66]. A detailed diagram of the main stages of the Box-Jenkins methodology is displayed in Figure 1.

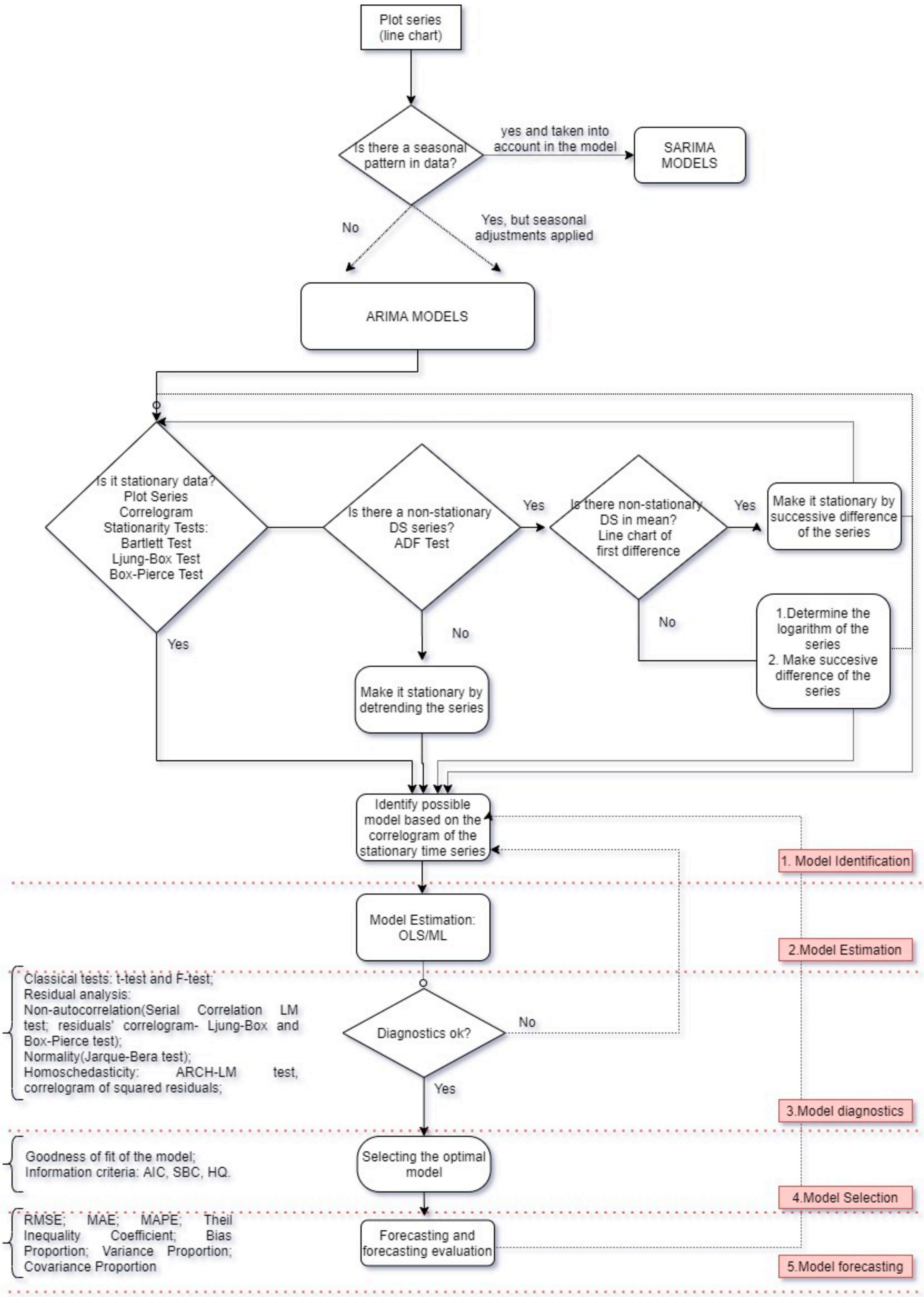


Figure 1. The main steps of the Box-Jenkins methodology. Source: The author's projection.

The first stage, the identification of the stochastic process model, involves specifying the ARIMA model, determining the proper values of p, d, and q. An ARIMA model has three components: the autoregressive term (p), the integration order term (d), and the moving average term (q).

Therefore, according to the Box-Jenkins methodology, any stationary series can forecast its future using data from the past. In order to identify if the time series is stationary, the graphical representation of the series together with the correlogram of the series in level, Bartlett test and Ljung-Box test can be applied. In order to test if the series has a unit root, the Augmented Dickey-Fuller and Philips-Perron tests can be applied. To obtain stationary time series, the corresponding value of d is estimated, in the case of a non-stationary series, meaning the series is differentiated, and in the case of a non-stationary series in variance the series is logarithmized.

In the Box–Jenkins (1976) methodology, the identification of an ARIMA model relies on the autocorrelation coefficients and partial autocorrelation coefficients for the stationary time series, because using the information offered by the correlogram, the optimal lag p of the AR process and the optimal lag q of MA process can be specified and furthermore the model can be identified [30].

The model estimation stage relies mainly on the usage of the following methods: the least squares method, the maximum probability method, or the Yule-Walker algorithm [66]. In case the series contain MA terms or a mix of both AR and MA terms (ARMA), the parameters can be estimated using nonlinear estimation methods, such as the maximum likelihood (ML) method [30].

The diagnostic checking stage is the next stage of the Box-Jenkins methodology investigating if the estimated model or models are firstly validated in accordance with the classical tests: *t*-test for the statistical significance of the parameters and F-test for the statistical validity of the model.

Secondly, the main hypotheses on the model residuals need to be tested, showing that they are white noise, homoscedastic, and do not exhibit autocorrelation. The normality of the residuals has been checked using the Jarque-Bera test, while for non-autocorrelation, Breusch-Godfrey test and residuals' correlogram-Ljung-Box and Bartlett tests have been applied. If the autocorrelations and partial autocorrelations are close to zero and Q-Statistics are insignificant with large probabilities regardless of lag, there is no correlation in model residuals [54].

For checking autoregressive conditional heteroskedasticity (ARCH) in the residuals, the squared residuals correlograms and the ARCH-LM test can be used.

In the model selection stage, we need to decide on the optimal model from several alternative estimated models. In order to be able to make a decision, we will rely on goodness of fit of the models (R^2, Adj.R^2, S.E. of regression) as well as on information criteria (Akaike, Schwarz, Hannan-Quinn), choosing as optimal model the model with the minimum values for those indicators.

The final stage is forecasting in order to design future time series values, using the most convenient model according to previous stages [54]. In the analysis, both dynamic and static forecasting procedures have been applied. The accuracy indicators used for evaluating the forecasts are: RMSE (root mean squared error) which measures the standard deviation of the forecast errors, Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE), Theil's inequality index and Bias, Variance, and Covariance Proportions.

Furthermore, allowing for error and coefficient uncertainty to be included in the model, the uncertainty in the forecast of the unemployment rate have been explored using a fan chart, which displays different confidence intervals. The widest band is the 90% confidence interval, highlighting the probability of 90% for the band to capture the true value of the unemployment rate forecast.

5. Data and Empirical Results

We have used in the empirical analysis the ILO unemployment rate for Romania covering the period 2000Quarter1(Q1)–2020Quarter4(Q4), summarizing up to a total of 84 quarterly observations. The data source is the Employment and Unemployment database of Eurostat. Therefore, we used for the model estimation and identification the training period covering 2000Q1–2018Q4.

The period 2019Q1–2020Q4 has been used as the test period, considered to be an ex-post forecast, while the out of sample forecast or ex-ante forecast covers the next three years. The evolution of unemployment rate revealed an oscillating trend, from peaks (10.3% in 2002Q1) at minimum levels (5.4% in 2008Q3, respectively 3.8% in 2019Q2). The winter quarters (Q4 and Q1) of the years 2000, 2001, and 2002 registered increases in the unemployment due to lack of jobs, the year 2002 recording the highest rate of the unemployment rate (10.3%) (Figure 2).

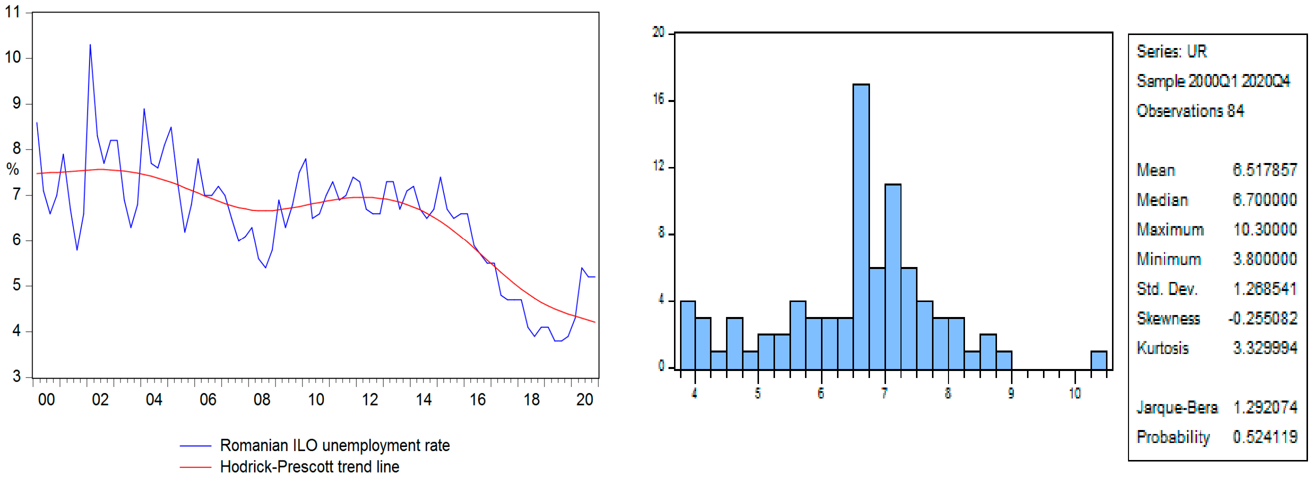


Figure 2. The Romanian ILO unemployment rate for the period 2000Q1–2020Q1.

A potential explanation could be the dismissals that took place as a result of the implementation of restructuring and privatization programs of different sectors of activity. The impasse in the general economic and social development of Romania, the low living standard, and the lack of future perspectives, from the period 1998–2000, reactivated the migration phenomenon, causing many Romanians to look for a job in more developed countries. After 1998, however, illegal migration predominated, which was mainly directed to Italy and Spain.

Young people represent the best professionally trained age group in Romania, but are also the most exposed to unemployment, highlighting the so-called phenomenon of brain-drain. The decrease in the unemployment rate in the period 2002–2006 is due both to legal and illegal departures of persons to work abroad. Thus, in 2006, according to the figures offered by Eurostat, it is estimated that over 2,000,000 Romanians work in countries in Western Europe or other developed countries. The economic crisis from 2008 created another peak in the evolution of the unemployment rate, registering in 2010Q1 the value of 7.8% and oscillating around this value until the 2015Q1 (7.4%) [67]. For the last years, the trend was continuously downward, with a minimum point in 2019Q3 (3.8%). For the last quarters, there can be observed a reversed trend due to high unemployment rate (18.5%) among young people (15–24 years) and seasonality in the construction and tourism sectors.

The Figure A1 (Appendix A) revealed that the Romanian unemployment rate exhibits seasonal fluctuations over the period 2000–2020, with peaks in the last and the first quarters of the year. Therefore, the series has been seasonally adjusted using Census X-13 method.

5.1. Testing for Non-Stationarity

In order to investigate the stationarity of the time series, which is the mandatory condition to apply the Box-Jenkins methodology, the analysis of the correlogram, the Bartlett and Ljung-Box tests as well as the Augmented Dickey-Fuller test have been applied. The graphical inspection of the autocorrelation and Partial Correlation Plot of Romania's quarterly unemployment rate revealed that the values of autocorrelation coefficients decrease slowly, pointing out the non-stationary pattern of our time series. Additionally, the time series plot of the first difference of the series highlighted that the unemployment rate is a non-stationary mean time series. The information is also confirmed by the empirical results of Bartlett and Ljung-Box tests.

In addition, the time series plot of the first difference of the series highlighted that the first difference of the unemployment rate seems a stationary mean time series. Therefore, the original quarterly series is a non-stationary time series.

The diagram in Figure A2b (Appendix A) indicates that possible stationarity exists in the first differences. Alternately, we investigated the presence of unit roots by applying the Augmented Dickey-Fuller, Phillips-Peron, and KPSS tests (Table 1) initially to the series in level and then to the series in first and second differences. The empirical results on unemployment rate are displayed in Table A1, indicating that all three tests confirmed that the series of unemployment rate is stationary in the first differences, being integrated of order 1. Therefore, for our model ARIMA (p,d,q) we will have the value d = 1.

Table 1. The empirical results of the ARMA models.

Variable	ARMA (4,4)
C	−0.038500 *
AR (4)	−0.874295 ***
MA (4)	0.536023 ***
R-squared	0.220905
Adjusted R-squared	0.199264
S.E. of regression	0.392084
Sum squared resid	11.06854
Log likelihood	−35.70792
F-statistic	10.20748
Prob(F-statistic)	0.000125
Akaike info criterion	1.032211
Schwarz criterion	1.124911
Hannan-Quinn criterion	1.069225

Note: ***, * means statistical significance at level 1% and 10%.

5.2. Identification of the Model

Achieving the stationarity, the ARMA (p,q) models can be defined based on the correlogram of the differenced series displayed in Figure 3. The optimal orders for p and q can be established based on the statistical significance of autocorrelation and partial autocorrelation coefficients using the Bartlett confidence intervals.

The correlogram of the stationary series lead to the identification of an ARMA specification based on the sharp decline of both auto-correlation and partial auto-correlation coefficients, after testing each component individually: a pure AR (4) autoregressive model, a MA (4) moving average model as well as the mix, an ARMA (4,4) model.

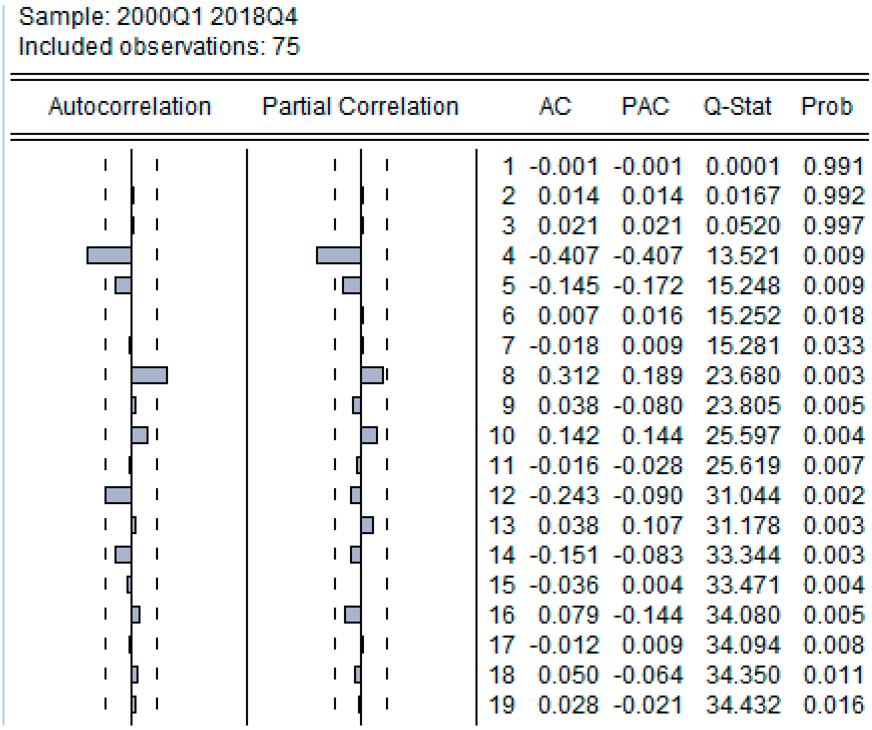
5.3. Model Estimation

Based on the models identified in the previous stage, we can proceed to the phase of model estimation using Maximum Likelihood method (ML), the empirical results of the optimal model being presented in Table 1. All three specifications have been estimated and compared. Based on the autocorrelation and partial-autocorrelation plot of the series and taking into account the value of R^2 (maximal value from all three models), S.E. of regression as well as the information criteria Akaike, Schwarz and Hannan-Quinn (minimum values from all three models), the optimal model was considered to be an ARMA (4,4) for the first difference of the seasonally adjusted series of unemployment rate.

Therefore, the series in level follows an ARIMA (4,1,4) model.

5.4. Diagnostic Checking of the Model

Apart from the classical tests, *t*-test for the statistical significance of the parameters and F-test for the validity of the model, the analysis on the residuals needs to be performed. Therefore, the normality of the residuals was tested using the Jarque-Bera test, the high computed value of the test together with the small probability attached to the test reveals the lack of normality in the residuals (Figure 4). The correlogram of the residuals and Breusch-Godfrey test can be used to check residuals' autocorrelation, while for checking autoregressive conditional heteroskedasticity (ARCH) in the residuals the squared residuals correlogram and the ARCH-LM test were used.


Sample: 2000Q1 2018Q4
Included observations: 75

	AC	PAC	Q-Stat	Prob
1	-0.001	-0.001	0.0001	0.991
2	0.014	0.014	0.0167	0.992
3	0.021	0.021	0.0520	0.997
4	-0.407	-0.407	13.521	0.009
5	-0.145	-0.172	15.248	0.009
6	0.007	0.016	15.252	0.018
7	-0.018	0.009	15.281	0.033
8	0.312	0.189	23.680	0.003
9	0.038	-0.080	23.805	0.005
10	0.142	0.144	25.597	0.004
11	-0.016	-0.028	25.619	0.007
12	-0.243	-0.090	31.044	0.002
13	0.038	0.107	31.178	0.003
14	-0.151	-0.083	33.344	0.003
15	-0.036	0.004	33.471	0.004
16	0.079	-0.144	34.080	0.005
17	-0.012	0.009	34.094	0.008
18	0.050	-0.064	34.350	0.011
19	0.028	-0.021	34.432	0.016

Figure 3. Autocorrelation and partial correlation Plot of the first difference of the seasonally adjusted data.

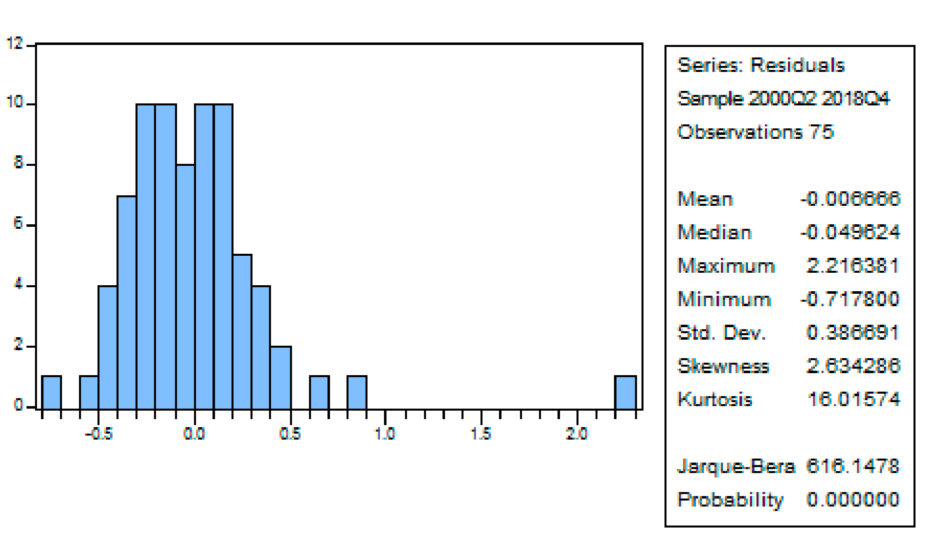


Figure 4. Empirical results of JB test for model 'residuals.

The correlogram of the residuals and Breusch-Godfrey test can be used to check the residuals' autocorrelation.

5.5. Forecasting the Unemployment Rate

Both static and dynamic procedures have been implemented in the forecasting process of the unemployment rate using the ARIMA (4,1,4) model. Figure 5 presents both types of forecasts-static and dynamic together with the original data for both ex-post and ex-ante forecast of the unemployment rate.

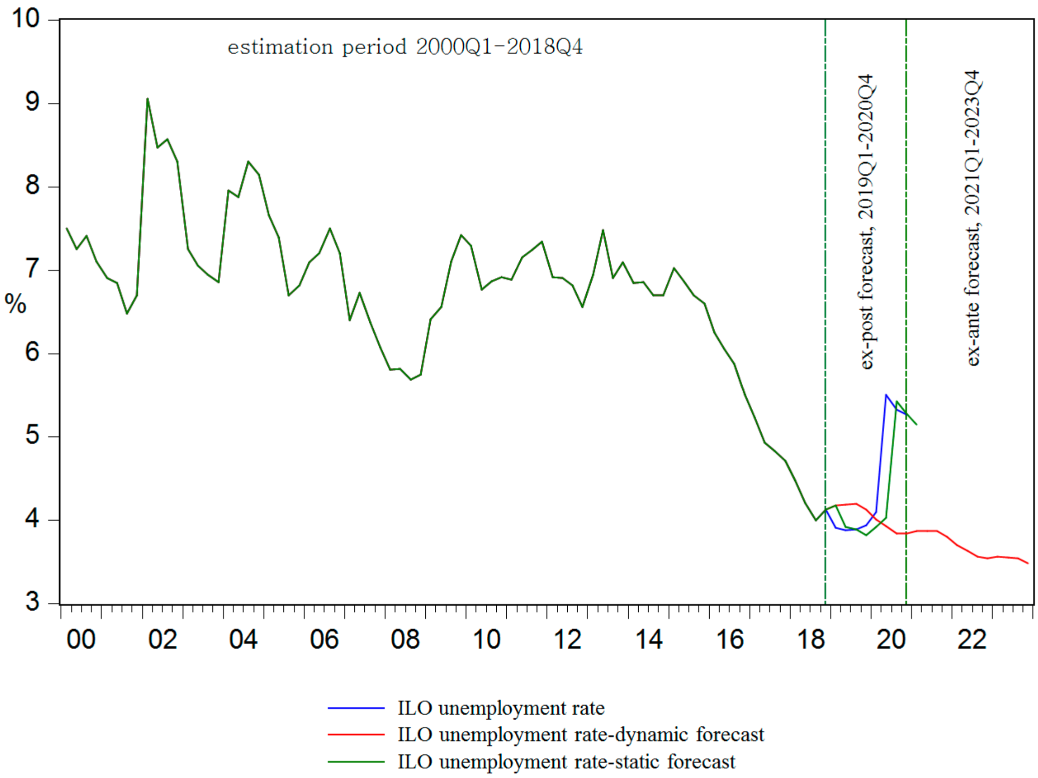


Figure 5. Static and dynamic forecast of the Romanian unemployment rate.

Figures 6 and 7 present the criteria for the evaluation of the forecasts in and out sample forecast for the unemployment rate, using dynamic and static forecast, respectively. Evaluating the quality for both static and dynamic forecasts, we can mention that the indices of RMSE, MAE, MAPE and Theil inequality coefficient have smaller values for the static forecast comparative with the results of the dynamic one. The same finding can be highlighted also by the bias and variance proportions, which registered very small values for the static forecasting procedure, while the covariance proportion on the contrary reach a value very close to 1, thus the sum of all three components is unitary.

The conclusion is unanimous: the static forecast provides better results than the dynamic one.

From Table A2 (Appendix A), we can conclude that the static forecast produces better and more reliable results, considering that the dynamic forecast follows a descending trend. The forecasted value of unemployment rate, based on the results of ARIMA (4,1,4) model for the ex-ante period, revealed the value of 5.15% in the 2021Q1 period in the case of a static forecast, and a value of 3.87% in the case of a dynamic forecast. It can highlight a continuous descending trend in the unemployment rate during the period 2021–2023 in the case of a dynamic forecast, reaching the value of almost 3.5% at the end of 2023.

Even if during the ex-post forecast, 2019–2020, the static forecast exhibited a very similar pattern to the real data, capturing the impact of the pandemic shock, for the first quarter of 2021, the expected tendency is a downward trend, with a small decrease in the value of unemployment rate (from 5.26% in the last real data, 2020Q4, to 5.15% in 2021Q1).

The dynamic forecast, however, does not manage to capture the size of the pandemic shock, marking a decreasing evolution for the period 2021–2023, with increases in the last quarters of each year.

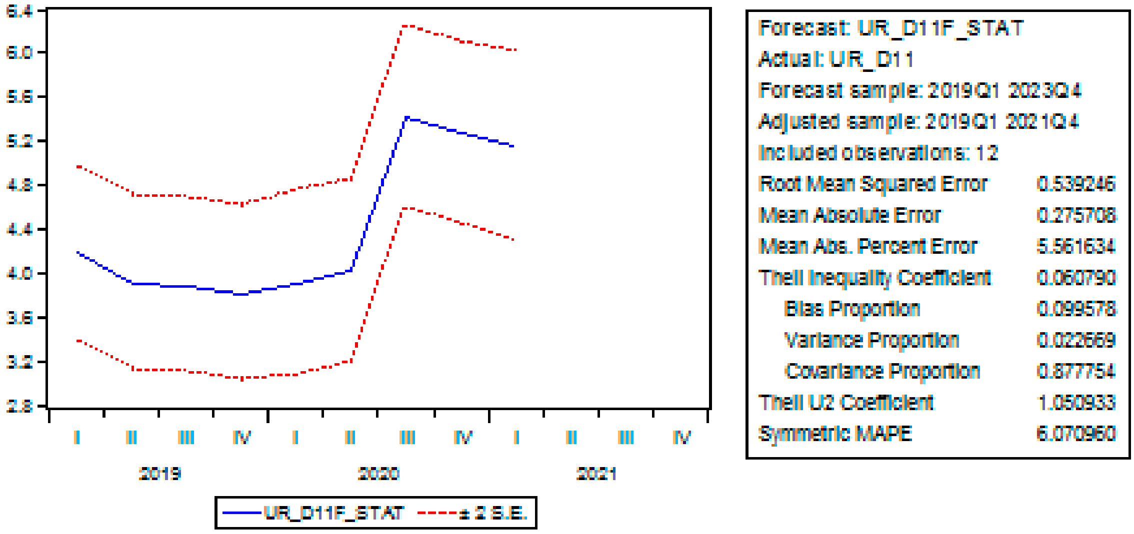


Figure 6. Static forecast of unemployment rate.

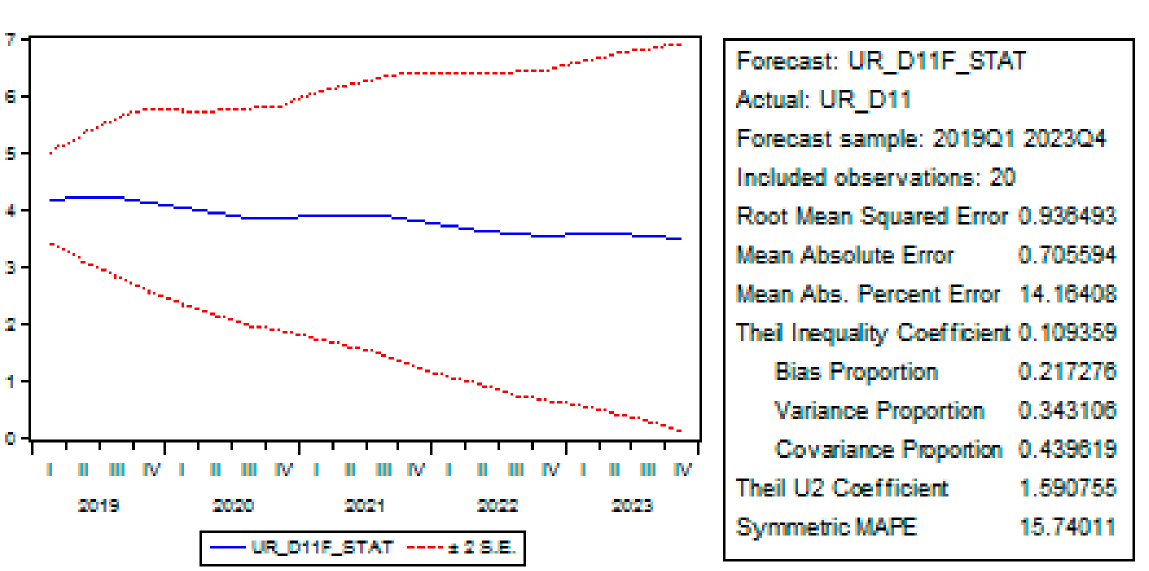


Figure 7. Dynamic forecast of unemployment rate.

The empirical results of Diebold-Mariano test (Table A3, Appendix A), implemented in order to test the accuracy of the forecast for the period 2019Q1–2023Q4 (comprising the test period together with the forecast horizon) revealed statistical differences between both types of forecasts, the static forecast providing better and more accurate results, at least of for the short-run.

If we consider the simple mean of both types of forecasts (Figure 8) as a composite forecast, which can be more appropriate, the unemployment rate is projected to follow a upward trend until the end of 2020 with a decrease in the first quarter of 2021, to 4.5%.

Figure 9 presents the fan chart of unemployment rate for Romania for the period 2019Q1–2023Q4, offering information regarding the degree of uncertainty surrounding the baseline forecast (central projection) at a specific point in time through the width of the fan chart.

The fan chart is usually plotted using different shades of color to represent the different confidence intervals. The widest band usually reflects the 90% confidence interval i.e., with 90% probability that the band captures the true value of the forecast variable.

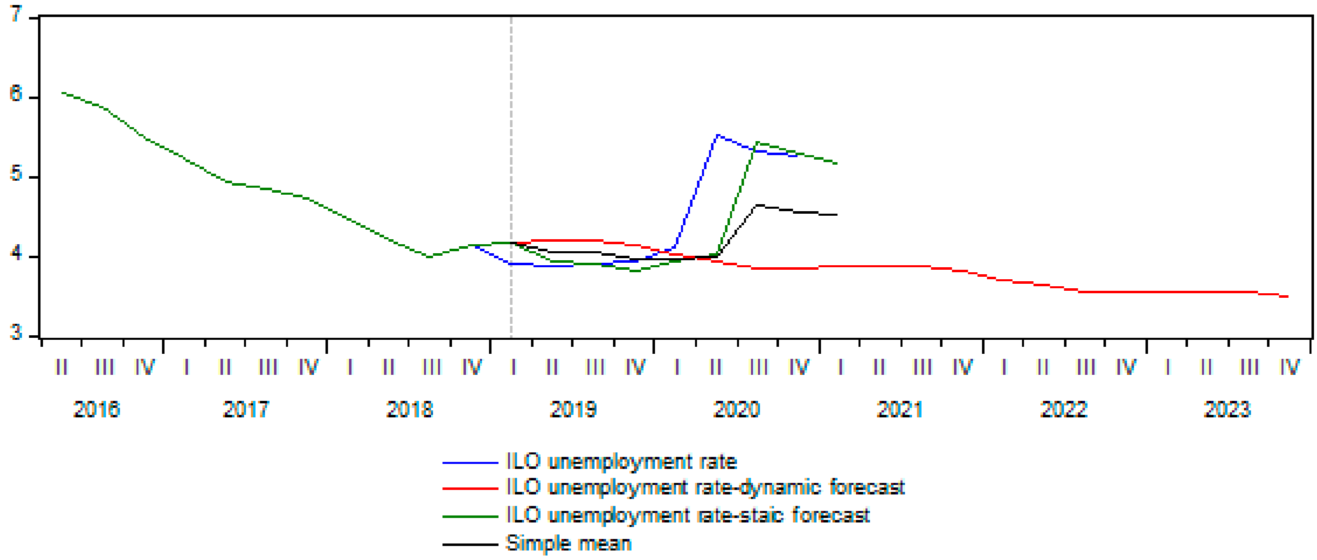


Figure 8. Forecast combination graph of unemployment rate.

The width of the fan chart provides valuable information about the uncertainty of the forecast, a higher level of uncertainty related to the baseline forecast being reflected by the wider bands of the fan chart. Therefore, as the forecast horizon increases, the width becomes larger as the baseline forecasts become more uncertain.

The skewness of the fan chart pointed out the potential risks in the central projection. If the distribution is positively asymmetric, the width of the above central projection area is larger than the one below the central projection, which means that the probability that the true value of the forecast to fall above the central projection is higher [68].

Thus, we can explore two types of information, according to Razi and Loke [68]: the first one concerns the probability of the forecast to fall above or below the baseline projection and this is reflected in the skewness of the distribution and the second one has to do with the probability of the forecast falling above or below a certain range.

For the year 2020, the year of the pandemic shock, the real unemployment rate for the second quarter, which was really the first quarter in which the coronavirus crisis effect can be captured, reached the value of 5.5% followed by a slow decrease, for 5.3% in autumn and 5.2% in the last quarter. The central projection registered smaller values for the year 2020, reaching almost 4% in the 2020Q2 and 3.7% in the last quarter. Based on this projection, a slowly descending trend can be highlighted in the forecasts of unemployment until 2023. The 90% confidence bounds range between 1% and 6.6%, with a central projection of 3.6% on a downward trend and a high probability for the forecast to be below the central projection.

Given that at the level of 2021Q1, the unemployment forecast range for Romania is around the values 1.5% and 6.3%, because the probability of unemployment rate falling below 3.9% is larger than the probability of unemployment rate being above 3.9%, there are larger downside risks for unemployment with respect to the forecast range.

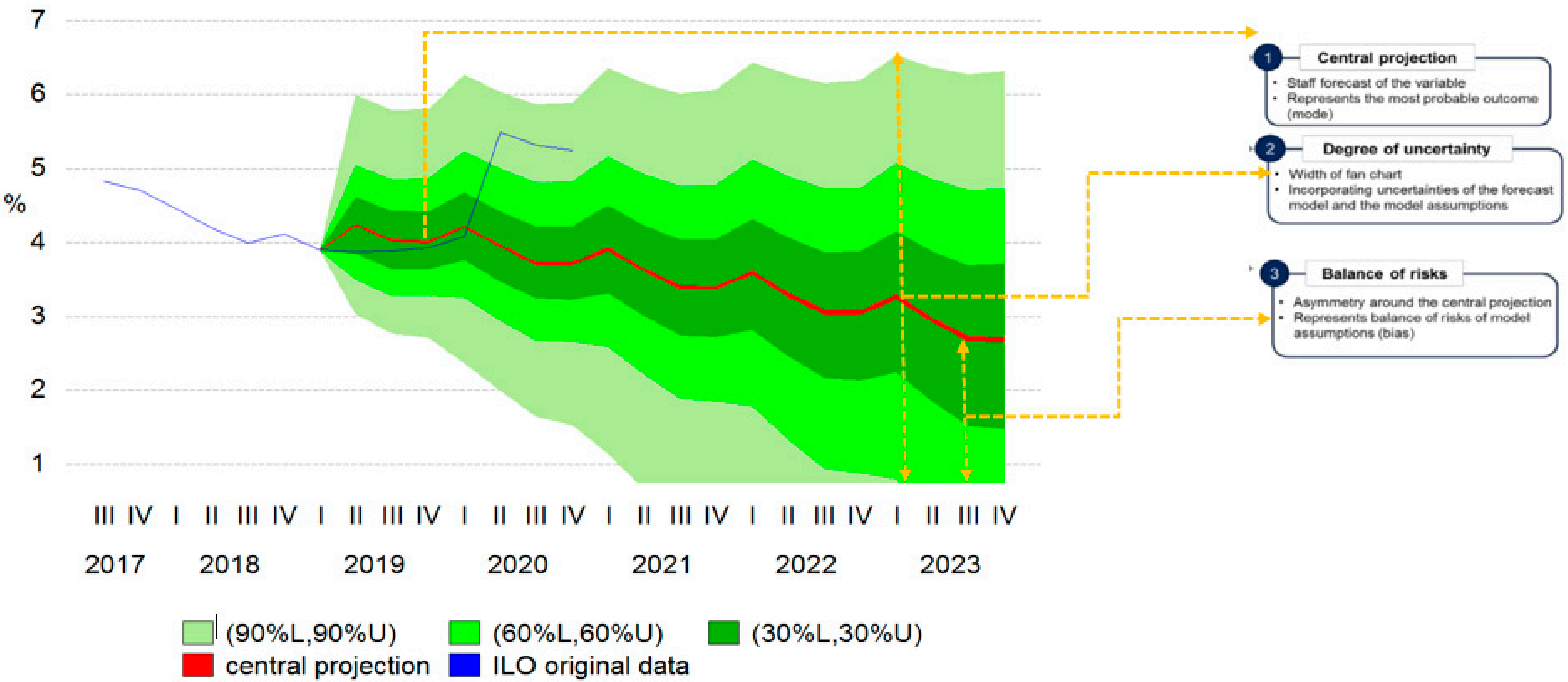


Figure 9. Fan chart of Romanian unemployment rate for 2019Q1–2023Q4.

6. Discussions

Given the actual situation facing an important exogenous shock—the global coronavirus pandemic and its effects at the level of a former transition country with an unstable economy even before the health crisis, it becomes even more important to provide forecasts of the unemployment rate for the next periods, one of the core indicators of the Romanian labor market with fundamental impact on the government future social policy strategies.

The pandemic created the highest number of unemployed in the last two years. In March 2020 the unemployment rate reached a value of 4.6% compared to 3.9% in the previous month. However, this last month of the first quarter of 2020 does not capture the effects of the pandemic shock, with companies resorting in the first phase to rest leave and other types of leave to be granted to employees. Projections showed that the unemployment rate in 2020 will increase, but will not exceed the 7% threshold, and will naturally decrease.

The forecast unemployment rate indicated an upward trend, reaching the value of almost 5.15% at the beginning of 2021, with a decreasing trend for the period 2021–2023. Therefore, unemployment will naturally slow down; a potential explanation for this is related to the fact that even if the crisis harmed the activities in some sectors, the number of unemployed increasing, which cannot be reflected by figures, because the unemployed will disappear from the reporting base. Methodologically, ILO unemployment involves unemployed and job-seeking people.

The labor market was not bidding during the crisis, discouraging searching for a job, and consequently, individuals looking for a job stay apart and wait for more opportunities and in such a way they are not anymore officially declared as unemployed.

Therefore, unemployment is reduced in this way, but this reduction is not a real one, as the unemployed disappear from the statistics, but in fact they move into the structural unemployment, the employment rate being reduced. Another reason for the low and unrealistic values of unemployment rate is the fact that people with terminated employment contracts and those who returned from abroad are not considered. At the end of March there were 111,340 terminated employment contracts and 250,000 people who had returned to Romania from abroad.

According to the Ministry of Labor and Social Protection information, over 276,000 people were in the process of terminating their employment contract at the end of April 2020, the most affected industries being wholesale and retail trade, production, and construction.

The effects of measures to reduce the spread of the pandemic are severe; the recovery will be long-term, the demand for consumption of goods and services being deeply restructured, which has major effects on employment and the labor market.

The effects are already manifesting and impacting short-term employment, summarized in the following:

- restricting the movement of people—potential consumers—increases the share of online purchases for consumer goods;
- contraction of the urban transport activity and the need to reconsider the work schedule;
- increase in the number of unemployed due to the temporary closures/restrictions of the companies' activity, having as consequence a reorganization of their activity and the elimination of additional or complementary employment; resort to state-subsidized technical unemployment;
- increasing the risk of poverty for informal workers, of the daily ones, of agricultural workers, insofar as the activities carried out by them are not organized according to the security requirements imposed by the legislation limiting the spread of COVID-19;

7. Conclusions

COVID-19 has been transformed from an effect on the human health plan of the Sars Cov2 pandemic, into the main cause or aggravating factor of the current economic crisis. Limiting the spread of the new coronavirus practically meant blocking human activities in proportions, which generated multiple crises—economic, social, cultural.

Basically, we will witness a major systemic reform of today's society, from the reconsideration of technologies to the reform of behavioral and living models. In this context, the labor market will be fundamentally restructured—we are witnessing a resettlement of labor fundamentals, a reconstruction of the system of industrial relations.

The labor resources and human capital concepts will reconfigure, in which the components of intellectual/professional potential, education and health are redefined as importance and management. Basically, only a few months after the pandemic, through the reaction of states and the resilience of economic systems, we are witnessing a redefinition of the role of the state in managing the labor market.

In this context, it becomes even more important to provide forecasts for the unemployment rate, a very important indicator of the Romanian labor market using the Box-Jenkins methodology.

The research approach used quarterly data for the horizon 2000Q1–2018Q4, with an ex-post forecast period of 2019Q1–2020Q4 and an ex-ante forecast period of 2021Q1–2023Q4.

Thus, following the five-step iterative procedure, the optimal model has been identified to be an ARIMA (4,1,4) model, being suitable for the future projections. The approach implies both types of forecasts—static and dynamic—and also allows for the inclusion of uncertainty surrounding the baseline forecast (central projection) by building a fan chart of unemployment rate for the period 2019Q1–2023Q4.

For the year 2020, the year of the pandemic shock, the real unemployment rate for the second quarter, which was really the first quarter in which the coronavirus crisis effect can be captured, reached the value of 5.5% followed by slow decreases, for 5.3% in autumn and 5.2% in the last quarter. The central projection registered smaller values for the year 2020, reaching almost 4% in the 2020Q2 and 3.7% in the last quarter. Based on this projection, a slowly descending trend can be highlighted in the forecasts of unemployment until 2023. The 90% confidence bounds range between 1% and 6.6%, with a central projection of 3.6% on a downward trend and a high probability for the forecast to be below the central projection.

As specific measures that can support the labor market, we can mention the following:

- supporting employment through strategic investments—transport infrastructure, IT system modernization in the central and local administration sector;
- ensuring decent, quality employment in strategic areas of development (essential, key jobs)—activities of extraction and processing of natural resources, energy, social services—health, education;
- Partial subsidization of jobs for small and medium-sized businesses, with the obligation to keep those persons employed for a period at least equal to the period of support from public funds and waiver of technical unemployment;
- Exemption from the payment of profit tax for investments made by companies for the digitization of activities—networks, equipment;
- The transition from informal employment and informal small business to formal employment in officially integrated companies in the business environment;
- Flexibility of employment contracts, from supporting part-time employment, to ensuring full-time contracts with modular working time, at the level of a calendar year, in compliance with the regulations for sharing work and rest time;
- Business-school partnership, by facilitating the local authority, respectively, the development at the level of the local authorities, in collaboration with the school units of the local strategy for employment;
- Development of partnership schemes for local employment and co-financing of training for the local labor market.

Author Contributions: Conceptualization, A.A.D., S.-A.A. and L.A.S.; methodology, A.A.D., S.-A.A. and L.A.S.; software, A.A.D., S.-A.A. and L.A.S.; validation, A.A.D., S.-A.A. and L.A.S.; formal analysis, A.A.D., S.-A.A. and L.A.S.; investigation, A.A.D., S.-A.A. and L.A.S.; resources, A.A.D., S.-A.A. and L.A.S.; data curation, A.A.D., S.-A.A. and L.A.S.; writing—original draft preparation, A.A.D., S.-A.A. and L.A.S.; writing—review and editing, A.A.D., S.-A.A. and L.A.S.; visualization,

A.A.D., S.-A.A. and L.A.S.; supervision, A.A.D., S.-A.A. and L.A.S.; project administration, A.A.D., S.-A.A. and L.A.S.; funding acquisition, A.A.D., S.-A.A. and L.A.S. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

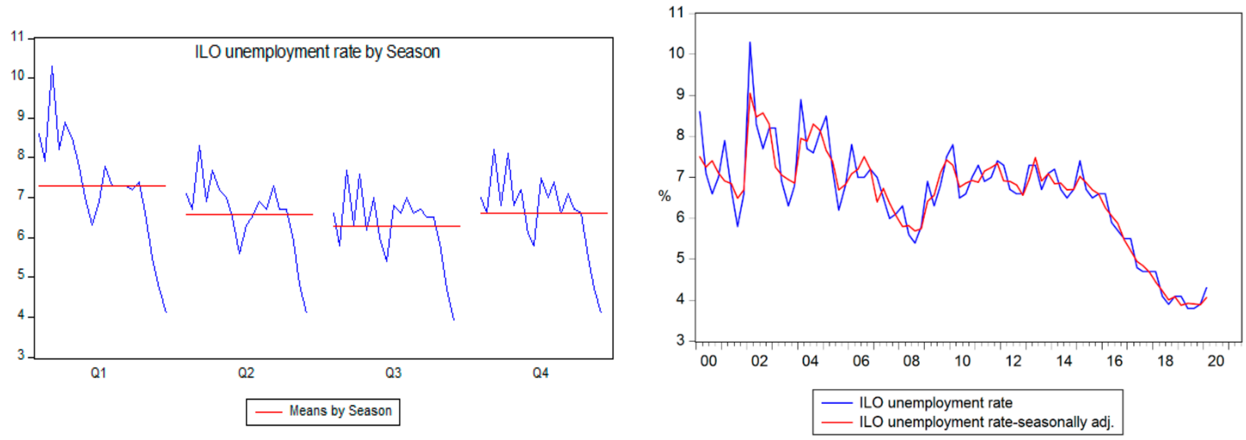
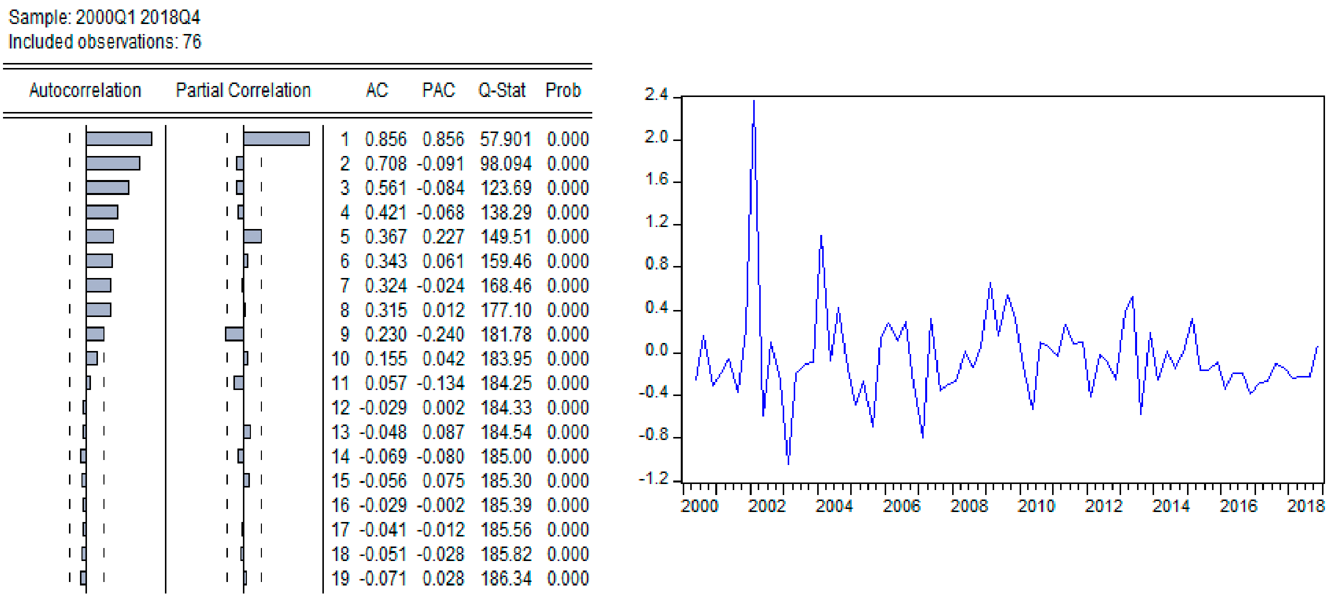


Figure A1. The seasonal pattern in the ILO unemployment rate.



Sample: 2000Q1 2018Q4
Included observations: 76

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.856	0.856	57.901	0.000
		2	0.708	-0.091	98.094	0.000
		3	0.561	-0.084	123.69	0.000
		4	0.421	-0.068	138.29	0.000
		5	0.367	0.227	149.51	0.000
		6	0.343	0.061	159.46	0.000
		7	0.324	-0.024	168.46	0.000
		8	0.315	0.012	177.10	0.000
		9	0.230	-0.240	181.78	0.000
		10	0.155	0.042	183.95	0.000
		11	0.057	-0.134	184.25	0.000
		12	-0.029	0.002	184.33	0.000
		13	-0.048	0.087	184.54	0.000
		14	-0.069	-0.080	185.00	0.000
		15	-0.056	0.075	185.30	0.000
		16	-0.029	-0.002	185.39	0.000
		17	-0.041	-0.012	185.56	0.000
		18	-0.051	-0.028	185.82	0.000
		19	-0.071	0.028	186.34	0.000

(**a**) (**b**)

Figure A2. Autocorrelation and partial correlation plot of Romania's quarterly unemployment rate (**a**) and the first difference of the seasonally adjusted data graph (**b**).

Table A1. Unit root analysis of the Romanian unemployment rate.

Variable	Unit Root (Trans.)		Level			First Difference			Second Difference		
			ADF	PP	KPSS	ADF	PP	KPSS	ADF	PP	KPSS
Unemployment rate	I(1) Δ(UR)	T&C	−1.49	−2.44	0.12	−8.54 [a]	−8.54 [a]	0.04 [a]	−10.26 [a]	−16.78 [a]	0.02 [a]
		C	−0.07	−1.21	0.678	−8.5 [a]	−8.5 [a]	0.1 [a]	−10.4 [a]	−16.92 [a]	0.02 [a]
		None	−1.05	−1.03		−8.48 [a]	−8.48 [a]		−10.37 [a]	−17.05 [a]	

[a] means stationary at 1%. T&C represents the most general model with a constant and trend. C is the model with a constant and no trend. None is the most restricted modelwithout a constant and trend. For the ADF test, the number of lags was determined using SCH crirerion for maximum 11 lags to remove serial correlation in the residuals. For PP test, the value of testwas computed using Newey-West Bandwith (as determined by Bartlett-Kernel). Both in ADF and PP tests, unit root tests were performed from the most general to the least specific model by eliminating trend and intercept across the models (see Enders, 1995; 254-255). KPSS test differs from the others in that the series is assumed to be (trend-) stationary, according to the null hypothesis. If the estimated values exceed the respective critical values, stationay must be rejected. The table shows the statistical tests of KPSS Tests for unit roots have been carried out in E-VIEWS 9.0.

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.590692	Prob. F(4,68)	0.6705
Obs*R-squared	2.518485	Prob. Chi-Square(4)	0.6413

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 06/10/21 Time: 16:02
Sample: 2000Q2 2018Q4
Included observations: 75
Coefficient covariance computed using outer product of gradients
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000523	0.014534	0.035974	0.9714
AR(4)	-0.058907	0.040347	-1.460016	0.1489
MA(4)	0.141949	0.119820	1.184692	0.2403
RESID(-1)	-0.040328	0.119768	-0.336721	0.7374
RESID(-2)	0.007833	0.119947	0.065302	0.9481
RESID(-3)	0.068235	0.124923	0.546218	0.5867
RESID(-4)	0.225801	0.264561	0.853490	0.3964

Heteroskedasticity Test: ARCH

F-statistic	0.000531	Prob. F(1,72)	0.9817
Obs*R-squared	0.000545	Prob. Chi-Square(1)	0.9814

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 06/10/21 Time: 16:04
Sample (adjusted): 2000Q3 2018Q4
Included observations: 74 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.148742	0.069650	2.135576	0.0361
RESID^2(-1)	0.002715	0.117846	0.023036	0.9817

Figure A3. The empirical results of Breusch-Godfrey and ARCH-LM test.

Table A2. Static and dynamic forecast of the Romanian unemployment rate.

		Ilo Rate Dynamic Forecast	Ilo Rate Static Forecast
Ex-Ante Forecast	2021Q1	3.87	5.15
	2021Q2	3.86	
	2021Q3	3.86	
	2021Q4	3.80	
	2022Q1	3.70	
	2022Q2	3.63	
	2022Q3	3.56	
	2022Q4	3.54	
	2023Q1	3.56	
	2023Q2	3.55	
	2023Q3	3.54	
	2023Q4	3.48	

Table A3. The empirical result of Diebold-Mariano test.Diebold-Marino test (HLN adjusted. Null hypothesis: Both forecasts have the same accuracy.

Accuracy	Statistic	< >prob	>prog	<prob
Abs. Error	1.992147	0.0866	0.9567	0.0433
Sq. Error	1.758877	0.1220	0.9390	0.0610

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