Kalman Filter or VAR Models to Predict Unemployment Rate in Romania?

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Abstract

This paper brings to light an economic problem that frequently appears in practice: For the same variable, more alternative forecasts are proposed, yet the decision-making process requires the use of a single prediction. Therefore, a forecast assessment is necessary to select the best prediction. The aim of this research is to propose some strategies for improving the unemployment rate forecast in Romania by conducting a comparative accuracy analysis of unemployment rate forecasts based on two quantitative methods: Kalman filter and vector-auto-regressive (VAR) models. The first method considers the evolution of unemployment components, while the VAR model takes into account the interdependencies between the unemployment rate and the inflation rate. According to the Granger causality test, the inflation rate in the first difference is a cause of the unemployment rate in the first difference, these data sets being stationary. For the unemployment rate forecasts for 2010–2012 in Romania, the VAR models (in all variants of VAR simulations) determined more accurate predictions than Kalman filter based on two state space models for all accuracy measures. According to mean absolute scaled error, the dynamic-stochastic simulations used in predicting unemployment based on the VAR model are the most accurate. Another strategy for improving the initial forecasts based on the Kalman filter used the adjusted unemployment data transformed by the application of the Hodrick-Prescott filter. However, the use of VAR models rather than different variants of the Kalman filter methods remains the best strategy in improving the quality of the unemployment rate forecast in Romania. The explanation of these results is related to the fact that the interaction of unemployment with inflation provides useful information for predictions of the evolution of unemployment related to its components (i.e., natural unemployment and cyclical component).

Keywords: forecasts, accuracy, Kalman filter, Hodrick-Prescott filter, VAR models, unemployment rate

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1 Introduction

The macroeconomic forecasting process witnessed rapid development because economic policies should be based on anticipations regarding the evolution of the economic indicators of a country or region. This impressive development of forecasting methods brought about a practical problem: Different forecasts are provided for the same indicator, but various forecasting methods are used. In general, international organizations prefer to use quantitative methods to construct their predictions. The development of econometrics made it an essential tool in building predictions, even if many experts have contested the utility of econometric models, especially in the context of the recent economic crisis. However, these models should not be neglected. The correct solution is to continue the use of more alternative models while incorporating an accuracy assessment for the economic prognoses in order to select the best prediction. This demarche could be considered a good strategy for improving forecast accuracy, an important goal of contemporary economists mainly because the cause of the recent global crisis was the high uncertainty of macroeconomic forecasts.

The literature provides many quantitative tools for predicting macroeconomic indicators like the unemployment rate. For this indicator, the Kalman filter could also be used in making predictions. This method is usually applied in determining the natural unemployment rate, the value for which we have a reasonable level or a stability of inflation rate and wages. The Phillips curve used to describe the relationship between inflation and unemployment rate is not checked in Romania, but vector-autoregressive (VAR) models are an efficient method for providing evidence of the interdependences between the two variables.

The objective of this research is to conduct a comparative analysis of unemployment rate forecasts based on two econometric methods: Kalman filter and VAR models. The best method is actually a strategy of improving the predictions' accuracy by choosing the most suitable quantitative forecasting method. Moreover, we add another perspective to improve the predictions' accuracy. We also propose improving a certain method by making a suitable transformation of that method. In this case, the Kalman filter to make predictions is applied to the transformed data series based on another filter (i.e., the Hodrick-Prescott filter). Thus, a double adjustment is made to the data. The proposed state space model used in the literature for predicting the unemployment rate is applied to the Romania data. If this model is not valid, another one is chosen to fit the data.

The organization of this research is as follows: After a brief review of the literature presenting the quantitative methods used in predicting the unemployment rate, we explain the methodology used. Predictions are made for the unemployment rate in Romania from 2010 to 2012 using the Kalman filter and VAR models, and the steps for building these forecasts are presented in detail. The accuracy evaluation is based on common accuracy measures that lead us to determine the superiority of a certain method.

2 Literature

The accuracy of unemployment rate forecasts should be known by governmental decision makers, placement agency workforce, researchers interested in the labor market, and even employees and unemployed people. It is a subject of interest for the overall public opinion. Many studies have treated the problem of the accurate evaluation of macroeconomic forecasts, but only a few of them are related to unemployment predictions.

Camba-Mendez (2012) built conditional forecasts using VAR models and Kalman filter techniques. Kishor and Koenig (2012) made predictions for macroeconomic variables like unemployment rate using VAR models and taking into account that data are subject to revisions. Sermpinis**,** Stasinakis, and Karathanasopoulos (2013) made predictions for the unemployment rate in the United States using neural networks and compared the utility of support vector regression (SVR) and the Kalman filter in combining these forecasts. The accuracy was greater for the case of SVR approach. Smooth transition vector error-correction models were used by Milas and Rothman (2008) to predict the unemployment rate in numerous countries; for the United States, the pooled predictions based on the median value of point forecasts generated by the linear and STVECM forecasts outperformed the naïve predictions. Proietti (2003) compared the accuracy of several predictions based on linear unobserved components models for the monthly unemployment rate in the United States, concluding that the shocks are not persistent during the business cycle.

Van Dijk, Teräsvirta, and Franses (2000) used a logistic smooth transition autoregressive model to predict the Organization for Economic Cooperation and Development (OECD) countries, with their forecasts outperforming the naïve predictions. Franses, Paap, and Vroomen (2004) assessed the accuracy of unemployment rate forecasts of three G7 countries using an autoregressive time-series model with time-varying parameters; this variation depended on a linear indicator variable.

Kurita (2010) showed that ARFIMA model forecasts for Japan's unemployment rate outperformed the AR(1) model predictions. Allan (2013) improved the accuracy of OECD unemployment forecasts for G7 countries by applying the combination technique. The researcher used two types of methods to assess the accuracy: quantitative techniques and qualitative accuracy methods.

A detailed study regarding unemployment forecasts and predictions performance carried out by Barnichon and

Nekarda (2012) resulted in a model for the unemployment rate whose predictions outperformed the results offered by classical time-series or by the Survey and Professional Forecasters and Federal Reserve Board. Franses, McAleer, and Legerstee (2012) evaluated the performance of unemployment forecasts made by staff of the Federal Reserve Board and the Federal Open Market Committee (FOMC); the Diebold-Mariano test indicated insignificant differences in terms of forecast accuracy.

Heilemann and Stekler (2013) offered several reasons for the lack of accuracy of G7 predictions in the last 50 years. They identified one continuous critique brought to macro-econometric models and forecasting techniques, but also concluded that the accuracy expectations are not realistic. Other aspects of the forecasts' failure related to forecasts' bias, data quality, the forecasting procedure, type of predicted indicators, and the relationship between forecast accuracy and forecast horizon.

The accuracy of forecasts based on VAR models can be measured using the trace of the mean-squared forecasts error matrix or generalized forecasts error second moment (Clements & Hendry, 2003). Robinson (1998) demonstrated better accuracy for predictions of some macroeconomic variables based on VAR models compared to other models, like transfer functions. Finally, Lack (2006) found that combined forecasts based on VAR models are a good strategy for improving predictions' accuracy.

3 Methodology

The Kalman filter is an econometric method for predicting the endogenous variables and for adjusting the estimated parameters in forecast equations. There are two systems of equations: a system of prediction equations and a system of update equations.

The stages for applying the Kalman filter are as follows:

1. Estimating endogenous variables values using available prior information.
2. Adjusting estimated parameters using adjustment equations and computing prediction errors.

A state space model includes two equations:

Measurement equation (relationship between observed and unobserved variables): $y_t = H_t\beta_t + Az_t + e_t$

Transition equation (dynamic of state (unobserved)): $\beta_t = \mu + F\beta_{t-1} + v_t$

y_t – data series
z_t – observed explanatory variables
H_t – variable coefficients of unobserved series
β_t, A, and F – constant coefficients
e_t and v_t – shocks

Assumptions

$e_t \sim iid.\ N(0, R)$
$v_t \sim iid.\ N(0, Q)$
$E(e_t, v_t) = 0$

The objectives are:

1. The estimation of state space model parameters

$y_t = H_t\beta_t + Az_t + e_t$
$\beta_t = \mu + F\beta_{t-1} + v_t$
$e_t \sim iid.\ N(0, R)$
$v_t \sim iid.\ N(0, Q)$

2. Restoration of the unobserved state

$y_t = H_t\beta_t + Az_t + e_t$
$\beta_t = \mu + F\beta_{t-1} + v_t$
$e_t \sim iid.\ N(0, R)$
$v_t \sim iid.\ N(0, Q)$

$\beta_{t/t-1}$ – the estimation of β_t latent state according to the information until $t-1$
$\beta_{t/t}$ – the estimation of β_t state according to the information until t
$P_{t/t-1}$ – the β_t covariance according to the information until t-1
$P_{t/t}C$ – the β_t covariance according to the information until t
$y_{t/t-1}P$ – the prediction of y using the information until t-1
$\eta_{t/t-1} = y_t - y_{t/t-1}$ – error prediction
$f_{t/t-1}$ – the variance of prediction error

The Kalman filter offers an optimal estimation for β_t, conditioned by the information related to the H_t state space parameters: A, μ, F, R, and Q. We suppose that μ, F, R, and Q are known.

The recursive Kalman filters involve three stages:

1. We start with the supposed values at the initial moment 0: $\beta_{0/0}$ and $P_{0/0}$.

2. The prediction: the optimal prediction $y_{1/0}$ at moment 1, using $\beta_{1/0}$.

3. The update: the calculation of the prediction error, using the observed value for y at moment 1

$$\eta_{1/0} = y_1 - y_{1/0}$$

The information included in the prediction error has data that can be recovered for redefining our assumption regarding the value that β could have

$$\beta_{1/1} = \beta_{1/0} + K_t\, \eta_{1/0}$$

K_t– the Kalman gain (the importance accorded to the new information).

The predicted values:

$$\beta_{t/t-1} = \mu + F\beta_{t-1/t-1}$$

$$P_{t/t-1} = FP_{t-1/t-1}F' + Q$$

The prognosis for y and the error prediction are:

$$\eta_{t/t-1} = y_t - y_{t/t-1} = y_t - x_t\beta_{t/t-1}$$

$$f_{t/t-1}= x_t P_{t/t-1} x'_t + R$$

The update:

$$\beta_{t/t} = \beta_{t/t-1} + K_t\eta_{t/t-1}$$

$$P_{t/t} = P_{t/t-1} - K_t x_t P_{t/t-1}$$

Kalman gain: $K_t = P_{t/t-1} x'_t\, (f_{t/t-1})^{-1}$.

The actual observed unemployment rate is the sum of two components: the natural unemployment rate quantifying the persistent shocks from the supply side (we assume it follows a random path) and the cyclical unemployment that refers to the shocks from the demand side, which are limited as persistence (this component exhibits serial correlation). Some authors consider the cyclical unemployment to influence the natural unemployment rate.

$$u_t = u_t^{nat} + \alpha_t$$

$$u_t^{nat} = u_{t-1}^{nat} + \varepsilon_t$$

$\alpha_t = \rho\alpha_{t-1} + \omega_t$
$\varepsilon_t \sim N(0;\sigma_\varepsilon^2)$
$\omega_t \sim N(0;\sigma_\omega^2)$
$E(\varepsilon_t, \omega_t) = 0$

A state space model for the natural unemployment can have the following form:

$u_t = Z\beta_t,\ t = 1, 2, \ldots, T$ (measurement equation)

$$Z=[1\ 1],\ \beta_t = \begin{bmatrix} u_t^{nat} \\ \alpha_t \end{bmatrix}$$

$\beta_t = T\beta_{t-1} + R\vartheta_t$ (transition equation)

$$\mathrm{T} = \begin{bmatrix} 1 & 0 \\ 0 & \rho \end{bmatrix},\ \vartheta_t = \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix}$$

$\varepsilon_t \sim N(0;\sigma_\varepsilon^2)$
$\omega_t \sim N(0;\sigma_\omega^2)$
$E(\varepsilon_t, \omega_t) = 0$

Under these conditions the Kalman filter generates optimal predictions and updates of the state variables. The Kalman filter determines the estimator of the minimum square error of the state variables vector. The literature has defined two approaches for the estimation of a variable using this filter. The first one assumes that the initial value of the non-stationary state variable can be fixed and unknown. On the other hand, the second approach considers that the initial value is random. The diffuse prior is specified. If we analyze the first observations, the approach is better even if it can generate numerical instability. If m is the number of state variables, we utilize the approach with Koopman, Shepard, and Doornik's (1999)diffuse prior and m predictions are provided. The unknown parameters that will be estimated are ε_t, ω_t and ρ. However, some authors give these parameters some reasonable values from the start. For ρ, we have to establish the value from the start, and the log-likelihood function is computed. The variance of the shocks coming from the demand side (σ_ω^2) is always greater than the variance of supply shocks (σ_ε^2).

The Hodrick-Prescott (*HP*) filter is often used in macroeconomics to extract the trend of the data series and separate the cyclical component of the time series. The resulting smoothed data are more sensitive to long-term changes.

The initial data series is composed of trend and cyclical components:

$$inf_t = tr_t + c_t\ .$$

Hodrick and Prescott (1997) suggested the following solution to the minimization problem:

$$\min_{\{tr_t\}t=1,T} \sum_{t=1}^{T}(inf_t - tr_t)^2 + \gamma \sum_{t=2}^{T-1}(\nabla^2 tr_{t+1})^2$$

γ – penalty parameter

The solution to the above equation can be written as:

$$inf_t = (\gamma F + I_T) \cdot tr_T$$

inf_t – vector of the initial data series of the inflation rate

$$F=\begin{bmatrix} 1 & -2 & 1 & 0 & \dots & & & & & & & \\ -2 & 5 & -4 & 1 & 0 & \dots & \cdots & & & & & 0 \\ 1 & -4 & 6 & -4 & 1 & 0 & & & & & & \\ & & \vdots & & & \ddots & & \vdots & & & & \\ & & & & & & & & & & & \dots \\ & & & & & \cdots & 0 & 1 & -4 & 6 & -4 & 1 & 0 \\ & & & & & & 0 & 0 & 1 & -4 & 6 & -4 & 1 \\ 0 & & 0 & & & \dots & 0 & 0 & & 1 & -4 & 5 & -2 \end{bmatrix}$$

The trend is calculated as: $tr_T = [(\gamma \cdot F + I_T)]^{-1} \cdot inf_T$.

Razzak (1997) proved that the Hodrick-Prescott filter acts as true filter at the end of the sample and as a smoother over the entire sample. The output gap from the true filter generates better out-of-sample predictions of inflation.

4 Assessment of Forecasts based on Kalman Filter and VAR Models

The data series used in this study is represented by the average inflation rate (denoted by *i*) and the unemployment rate (denoted by *u*) registered in Romania between 1985 and 2012. The average inflation rate is computed as a geometric mean of the monthly indices of the chained base indexes of consumer prices minus the comparison base equal to 100. The unemployment rate is an indicator used to measure the unemployment intensity, which is computed as a ratio of the number of registered unemployed people and the active population. To model the unemployment rate, we used the data set for the 1985–2009 period, with the one-step-ahead predictions being made for 2010–2012. The data series were provided by a national data source—namely, the National Institute of Statistics. The *VAR* methodology is based on stationary data sets. The augmented Dickey-Fuller test application (see Appendix 2) provided evidence of the presence of one unit root in each data series. A differentiation of order for one of both data sets led us to stationary data. The new variables are denoted by *di* and *du*, respectively.

Initially we tried to estimate a state space model that explained the theoretical background with a diffuse prior value, but it was not valid (see Appendix 3). The estimations were made in EViews.

@signal u = sv1 + sv2
@state sv1 = sv1(-1) + [var = exp(c(2))]
@state sv2 = sv2(-1)+[var=exp(c(1))]

The two following models proved to be valid:

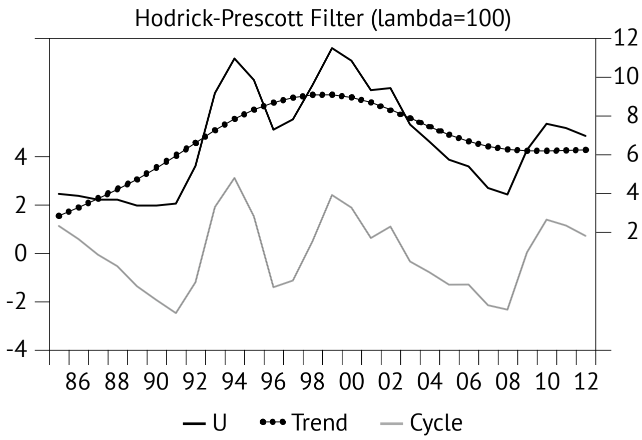
@signal u = sv1
*@state sv1 = c(2)*sv1(-1) + [var = exp(c(1))]*

and

@signal u = sv1
@state sv1 = sv1(-1) + [var = exp(c(1))]

Another strategy was based on the adjusted data using the Hodrick-Prescott filter. These new data were used to construct a new state space model using the Kalman technique in the estimation. New predictions were made for 2010–2012. Figure 1 depicts the two components of the data series: the trend and the cycle component.

Figure 1: Decomposition of unemployment rate data series using Hodrick-Prescott filter



The graph demonstrated an ascending trend until 1998, followed by a slow decrease until the end of the analyzed period, where the trend value was almost 6%.

The Granger causality test was applied for the stationary data series in order to establish if one variable causedanother one. In Granger acceptance, a variable *X* is a cause for *Y* if better predictions result when the information provided by *X* is taken into account.

Table 1 VAR Granger Causality Tests

Hypothesis	*Prob.*
di does not Granger-cause *du*	0.0042
du does not Granger-cause *di*	0.0731

Note: *di*- differential of inflation rate, *du*- differential of unemployment rate

The results of the Granger causality test show that *di* is the cause of *du*, but *du* is not the cause of *di*. Almost all the lag length criteria, except for *logL*, at the 5% level indicate that a *VAR(2)* model is the best model. All the tests required to check the validity of the estimated *VAR(2)* model are displayed in Appendix 1. The form of the *VAR* model is as follows:

$$di = -0.152048863149*di(-1) + 0.0573008404372*di(-2) - 0.888383240695*du(-1) - 0.0437580905699*du(-2) + 0.0754250947229$$

$$du = 0.166173513351*di(-1) + 0.282590212379*di(-2) + 0.407747364887*du(-1) - 0.182697623737*du(-2) + 0.136370162588$$

VAR residual portmanteau tests were used to test the errors' autocorrelation for both identified models. The assumptions of the test were formulated as:

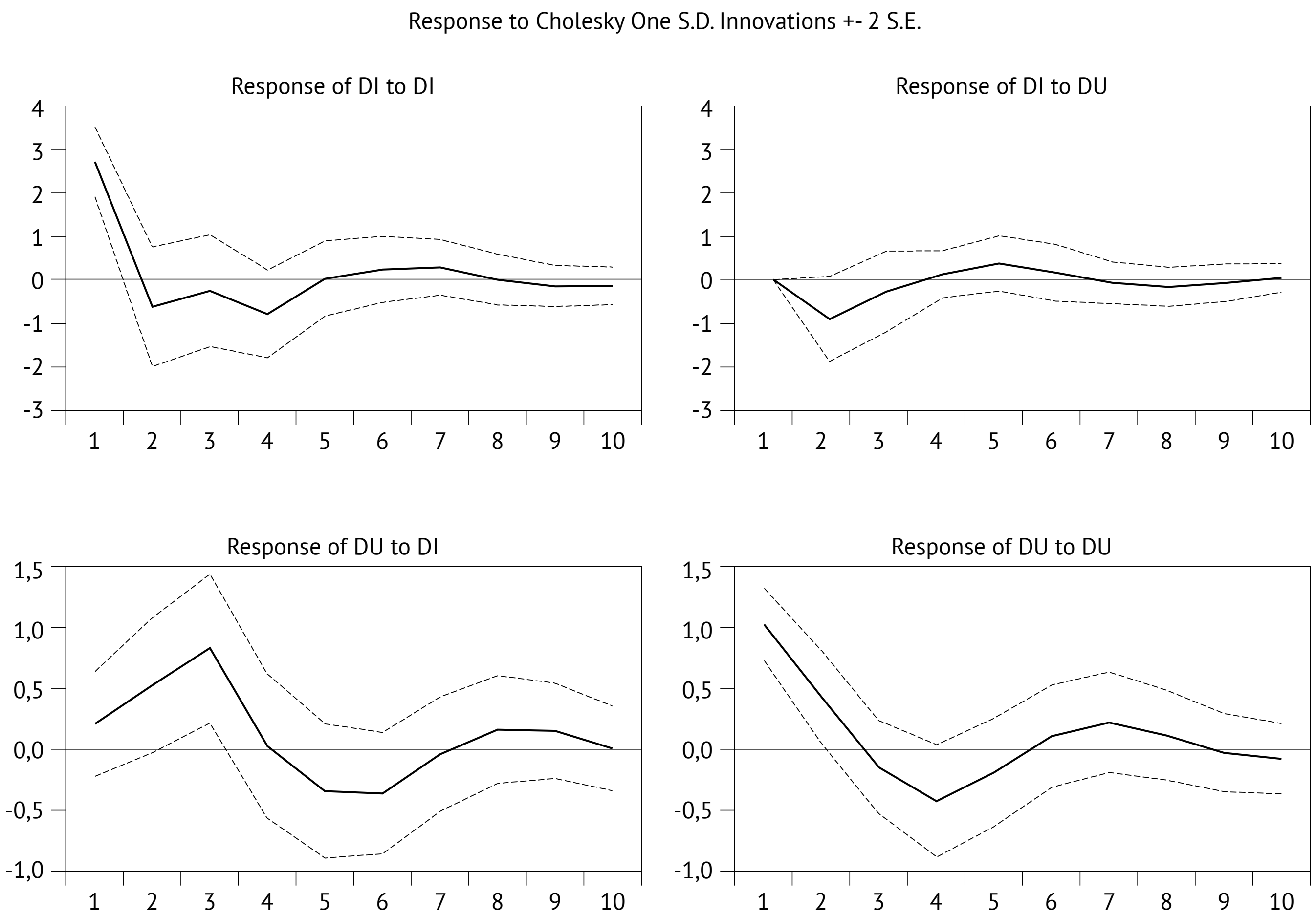
H0: The errors are not auto-correlated.

H1: The errors are auto-correlated.

For the lag 1 up to 12, the probabilities (*Prob.)* of the tests are greater than 0.05, which implies that there is not enough evidence to reject the null hypothesis (*H0*). Thus, we do not have sufficient reason to say that the errors are auto-correlated. After the application of the residual portmanteau test, we concluded that there were no autocorrelations between errors for the *VAR(2)* model.

The homoscedasticity is checked using a VAR residual LM test for the *VAR(2)* model. If the value of the *LM* statistic is greater than the critical value, the errors series is heteroskedastic. The *LM* test showed a constant variance in the errors because the values were greater than 0.05 for the probability. The residual heteroskedasticity test was applied in two variations: with cross-terms and without cross-terms.

Figure 2: Responses of each variable to their own shocks or other variable shocks



The normality tests were applied under the Cholesky (Lutkepohl) orthogonalization. If the Jarque-Bera statistic is lower than the critical value, there was not enough evidence to reject the normal distribution of the errors. The residual normality test provided probabilities greater than 0.05, implying that the errors series had a normal distribution when Cholesky (Lutkepohl) orthogonalization was applied. The impulse-response analysis and the decomposition of error variance were applied.

As Figure 2 demonstrates, there the unemployment rate had a stronger response to shocks in inflation than to its own shocks. According to Appendix 1, starting from the third lag the unemployment rate, variance of more than 40% is explained by the shocks in the inflation rate.

The Kalman filter and the *VAR* updated models were used to make unemployment rate forecasts for 2010–2012. The accuracy of the forecasts was checked to establish a better forecasting method. For the *VAR* predictions, four types of scenarios were considered:

- *S1*: Dynamic-Deterministic Simulation
- *S2*: Dynamic-Stochastic Simulation
- *S3*: Static-Deterministic Simulation
- *S4*: Static-Stochastic Simulation

We maintained a constant forecast for 2010–2012, when the Kalman filter was applied in the second version. For the other predictions based on the Kalman technique, a decrease in time occurred in the unemployment rate from one year to another. For the different variants of the *VAR* models' one-step-ahead predictions, the values registered in 2011 were greater than those in 2010 and 2012. The Kalman filter generated predictions less than 7%, while the VAR models forecasts showed a higher degree of variance, being located in the interval [6.6%; 8.65%].

The prediction error was computed as the difference between the effective value and the forecasted one of variable *X*, denoted by e_x. For the number of forecasts on the horizon, it used the notation *n*. The most frequently used statistical measures for assessing forecasts' accuracy, according to Bratu (2012), are root mean squared error (*RMSE*), $RMSE=\sqrt{\frac{1}{n}\sum_{j=1}^{n} e_X^2}$, mean error (*ME*), ME= $\frac{1}{n}\sum_{j=1}^{n} e_X$ and mean absolute error (*MAE*), MAE= $\frac{1}{n}\sum_{j=1}^{n} | e_X |$.

RMSE is influenced by outliers. These absolute measures depend on the unit of measurement, although this disadvantage is eliminated unless the indicators are expressed as a percentage.

Theil's U statistic, used in making comparisons between predictions, can be used in two variants, which were also presented by the Australian Treasury. The following notations are used:

a – actual/registered value of the analysed variable
p – value for the predicted variable
t – time
e – error (difference between actual value and the forecasted one)
n– number of periods

U_1 takes a value between 0 and 1. A value closer to zero indicates better accuracy for that prediction. If there are alternative forecasts for the same variable, the one with the lowest value of U_1 is the most accurate.

$$U_1=\frac{\sqrt{\sum_{t=1}^{n}[a_t-p_t]^2}}{\sqrt{\sum_{t=1}^{n} a_t^2}+\sqrt{\sum_{t=1}^{n} p_t^2}}$$

Instead of U_1, the mean absolute scaled error can be computed (*MASE* = *mean* | es_t|), the result being the same:

$$es_t=\frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n}|X_i-X_{i-1}|}$$

Table 2 Predictions of Unemployment Rate (%) based on VAR(2) Models and KalmanFilter

	Forecasting method							
Year	Kalman filter 1	Kalman filter 2	Kalman filter based on adjusted data using Hodrick-Prescott filter 1	Kalman filter based on adjusted data using Hodrick-Prescott filter 2	*VAR(2)* models (*S1*)	*VAR(2)* models (*S2*)	*VAR(2)* models (*S3*)	*VAR(2)* models (*S4*)
2010	6.1243061140	6.275	6.293586886	6.2306	7.39341	7.382116478	7.39341	7.338550845
2011	5.9772311361	6.275	6.357197078	6.2306	7.4468778	7.447944295	7.8966003	8.625306581
2012	5.8336881581	6.275	6.421450187	6.2306	6.5904475	6.648923963	7.2046512	8.474405877

Source: Author's computations.

Table 3 Accuracy Measures of the Proposed Forecasts

Accuracy measure	Forecasting method							
	Kalman filter 1	Kalman filter 2	Kalman filter based on adjusted data using Hodrick-Prescott filter 1	Kalman filter based on adjusted data using Hodrick-Prescott filter 2	*VAR(2)* models (*S1*)	*VAR(2)* models (*S2*)	*VAR(2)* models (*S3*)	*VAR(2)* models (*S4*)
ME	1.3633	1.0667	0.9843	1.1111	0.1981	0.1820	**-0.1566**	-0.8044
MAE	1.363258197	1.066666667	0.984255283	0.9843	0.2293401	**0.213967951**	0.310947167	1.111066667
RMSE	1.3707	1.0975	1.0320	1.1407	**0.2730**	0.2480	0.3377	1.1191
MASE	0.1029	0.0806	***0.0753***	0.0840	0.0188	**0.0171**	0.0227	0.0721
U_2	0.6546	0.8031	0.8468	0.7734	0.3497	0.6357	0.8041	0.8607

Source: Author's calculations.

To make comparisons with the naive forecasts, Theil's U_2 coefficient is used.

$$U_2 = \sqrt{\frac{\sum_{i=1}^{n-1}\left[\frac{p_{t+1}-a_{t+1}}{a_t}\right]^2}{\sum_{i=1}^{n-1}\left[\frac{a_{t+1}-a_t}{a_t}\right]^2}}$$

If U_2=1, there are no differences in terms of accuracy between the two forecasts compared. If U_2<1, the forecast compared has a higher degree of accuracy than the naive one. If U_2>1, the forecast compared has a lower degree of accuracy than the naive one.

According to all accuracy indicators, the forecasts based on *VAR(2)* models are more accurate than the Kalman filter predictions. The positive values for mean errors of the Kalam technique forecasts suggest the tendency to underestimate the forecasts for all these methods. In the case of *VAR* predictions, only the dynamic simulations generated underestimated expectations. It is interesting that a considerable improvement was obtained for the Kalman filter prediction of the first space state model by adjusting the initial data using the Hodrick-Prescott filter. The second scenario of *VAR* predictions (dynamic-stochastic simulations) was the best according to the *MASE* indicator used in making comparisons.

5 Conclusions

Many quantitative methods are used to make predictions. In this study, we selected two econometric techniques that are rather commonly used in the literature: the Kalman filter method and *VAR* models. These methods were used to make short-term unemployment rate forecasts for Romania for 2010–2012. According to all accuracy measures, the Kalman technique predictions were underestimated and less accurate than the different scenarios of the VAR model forecasts. It seems that the causality between the first difference data series of inflation and unemployment rate helped improve the forecasting process more. The Kalman filter predictions based only on natural unemployment and cyclical component were not strong enough to generate more accurate forecasts. The superiority of *VAR* models in forecasting was valid only for this particular case of the Romanian economy, where we demonstrated that inflation is a cause of the unemployment rate's evolution.

Another interesting strategy this article proposed to improve Kalman filter predictions is the application of the technique on adjusted data series based on another filter: the Hodrick-Prescott filter. Applying two filters to the same data set improved the predictions' accuracy in the case of the first proposed state space model.

Another important conclusion is that the classical state space model used in the literature to determine the natural unemployment rate did not provide the expected results for the Romanian economy. Therefore, other, more simplistic state space models were proposed for Romania's unemployment rate.

All in all, this research provides pertinent results regarding the prediction of unemployment rate in Romania, but the study could be improved by comparing other predictive quantitative techniques, like *Bayesian VAR* or *VARMA* models.

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Appendix 1

Tests for Checking the Assumptions Related to the VAR Model

Lag-length criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-97.51033	NA	19.63724	8.653072	8.751811	8.677905
1	-89.69603	13.59009	14.13464	8.321394	8.617609	8.395891
2	-82.84189	10.72821*	11.15128*	8.073208*	8.566901*	8.197370*

Residual Portmanteau test for checking errors' autocorrelation

Lags	*Q*-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.175105	NA*	0.183064	NA*	NA*
2	1.326585	NA*	1.444209	NA*	NA*
3	2.837075	0.5855	3.181272	0.5280	4
4	3.579113	0.8930	4.079529	0.8499	8
5	5.432702	0.9419	6.448004	0.8918	12
6	8.810793	0.9210	11.01836	0.8084	16
7	9.136089	0.9813	11.48598	0.9326	20
8	11.53810	0.9846	15.16906	0.9157	24
9	16.88601	0.9508	23.95490	0.6839	28
10	18.92214	0.9675	27.55730	0.6911	32
11	19.42491	0.9890	28.52093	0.8081	36
12	21.16431	0.9937	32.15787	0.8067	40

* The test is valid only for lags larger than the VAR lag order.
df is degrees of freedom for (approximate) chi-square distribution

Residual LM test for checking errors' homoscedasticity
VAR Residual Serial Correlation LM Tests
Null Hypothesis: no serial correlation at lag order *h*

Lags	LM-Stat	Prob
1	0.460020	0.9773
2	2.681114	0.6125
3	2.075462	0.7219
4	0.950521	0.9172
5	1.816200	0.7695
6	3.531397	0.4731
7	0.341387	0.9870
8	3.978712	0.4089
9	6.746046	0.1499
10	2.243840	0.6910
11	0.547576	0.9687
12	3.694621	0.4489

Probs from chi-square with 4 df.

VAR Residual Heteroskedasticity Tests
VAR Residual Heteroskedasticity Tests: No cross-terms (only levels and squares)
Joint test:

Chi-sq	df	Prob.
25.24139	24	0.3927

Individual components:

Dependent	R-squared	F(8,14)	Prob.	Chi-sq(8)
res1*res1	0.322277	0.832175	0.5894	7.412368
res2*res2	0.233480	0.533044	0.8131	5.370029
res2*res1	0.625253	2.919816	0.0383	14.38082

VAR Residual Heteroskedasticity Tests: Includes cross-terms

Joint test:

Chi-sq	df	Prob.
52.21834	42	0.1342

Individual components:

Dependent	R-squared	F(14,8)	Prob.	Chi-sq(14)	Prob.
res1*res1	0.916236	6.250420	0.0068	21.07342	0.0998
res2*res2	0.523429	0.627613	0.7870	12.03886	0.6032
res2*res1	0.929029	7.480110	0.0038	21.36766	0.0926

Jarque-Bera Test for Checking Normal Distribution

Component	Skewness	Chi-sq	df	Prob.
1	0.400022	0.613399	1	0.4335
2	0.184908	0.131066	1	0.7173
Joint		0.744465	2	0.6892

Component	Kurtosis	Chi-sq	df	Prob.
1	3.034727	0.001156	1	0.9729
2	3.009473	8.60E-05	1	0.9926
Joint		0.001242	2	0.9994

Component	Jarque-Bera	df	Prob.
1	0.614555	2	0.7354
2	0.131152	2	0.9365
Joint	0.745707	4	0.9456

Impulse–Response Analysis

Response of DI:

Period	DI	DU
1	2.685611	0.000000
2	-0.601577	-0.907380
3	-0.239417	-0.276710
4	-0.765368	0.120726
5	0.035891	0.370063
6	0.245921	0.156501
7	0.292615	-0.074911
8	0.013271	-0.166930
9	-0.134527	-0.076009
10	-0.128219	0.038676

Response of DU:

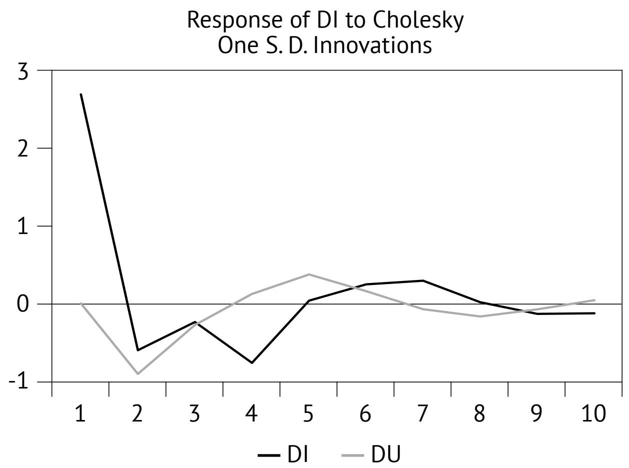
Period	DI	DU
1	0.217511	1.021384
2	0.534967	0.416467
3	0.837354	-0.167574
4	0.033907	-0.446814
5	-0.333998	-0.209706
6	-0.352703	0.091735
7	-0.031785	0.206300
8	0.169597	0.099136
9	0.159855	-0.046176
10	0.015591	-0.096744

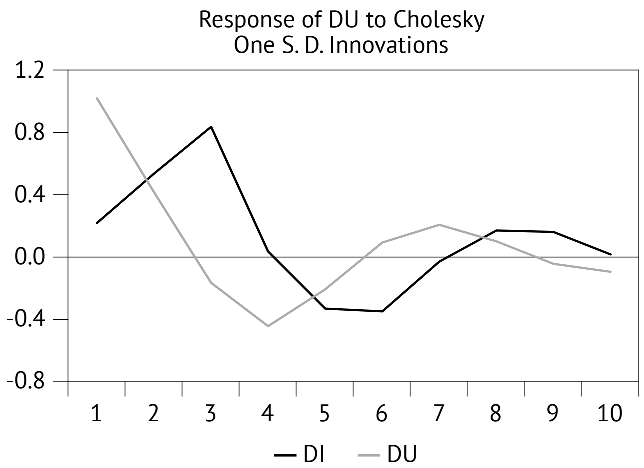
Variance Decomposition of DU:

Period	S.E.	DI	DU
1	1.044287	4.338332	95.66167
		(8.29004)	(8.29004)
2	1.245058	21.51381	78.48619
		(15.6848)	(15.6848)
3	1.509772	**45.39161**	54.60839
		(17.4357)	(17.4357)
4	1.574867	**41.76315**	58.23685
		(16.8917)	(16.8917)
5	1.623495	**43.53115**	56.46885
		(17.3532)	(17.3532)
6	1.663896	45.93614	54.06386
		(17.3496)	(17.3496)
7	1.676938	45.26035	54.73965
		(17.4312)	(17.4312)
8	1.688405	45.65663	54.34337
		(17.6840)	(17.6840)
9	1.696584	46.10526	53.89474
		(17.6590)	(17.6590)
10	1.699412	45.96038	54.03962
		(17.7893)	(17.7893)

Variance Decomposition of DI:

Period	S.E.	DI	DU
1	2.685611	100.0000	0.000000
		(0.00000)	(0.00000)
2	2.897885	90.19570	9.804295
		(10.1231)	(10.1231)
3	2.920895	89.45210	10.54790
		(9.83838)	(9.83838)
4	3.021919	89.98595	10.01405
		(9.22464)	(9.22464)
5	3.044705	88.65800	11.34200
		(10.4016)	(10.4016)
6	3.058626	88.49921	11.50079
		(10.8627)	(10.8627)
7	3.073505	88.55088	11.44912
		(10.8456)	(10.8456)
8	3.078063	88.29066	11.70934
		(11.3968)	(11.3968)
9	3.081939	88.25927	11.74073
		(11.6589)	(11.6589)
10	3.084847	88.26568	11.73432
		(11.8730)	(11.8730)





Appendix 2

ADF Test for Inflation and Unemployment Rate

Null Hypothesis: D(I) has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic—based on SIC, maxlag=6)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.372594	0.0002
Test critical values:	1% level	-3.711457	
	5% level	-2.981038	
	10% level	-2.629906	

*MacKinnon (1996) one-sided *p*-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(I,2)

Method: Least Squares

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
D(I(-1))	-1.091922	0.203239	-5.372594	0.0000
C	-0.024845	0.519951	-0.047783	0.9623
R-squared	0.546011	Mean dependent var		-0.003846
Adjusted R-squared	0.527095	S.D. dependent var		3.855228
S.E. of regression	2.651166	Akaike info criterion		4.861680
Sum squared resid	168.6883	Schwarz criterion		4.958456
Log likelihood	-61.20183	Hannan-Quinn criter.		4.889548
F-statistic	28.86477	Durbin-Watson stat		2.014213
Prob(F-statistic)	0.000016			

Null Hypothesis: D(I) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic—based on SIC, maxlag=6)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.346732	0.0010
Test critical values:	1% level	-4.356068	
	5% level	-3.595026	
	10% level	-3.233456	

*MacKinnon (1996) one-sided *p*-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(I,2)

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
D(I(-1))	-1.109342	0.207480	-5.346732	0.0000
C	0.640661	1.152837	0.555725	0.5838
@TREND(1985)	-0.045920	0.070771	-0.648849	0.5229
R-squared	0.554172	Mean dependent var		-0.003846
Adjusted R-squared	0.515405	S.D. dependent var		3.855228
S.E. of regression	2.683736	Akaike info criterion		4.920464
Sum squared resid	165.6561	Schwarz criterion		5.065629
Log likelihood	-60.96603	Hannan-Quinn criter.		4.962266
F-statistic	14.29471	Durbin-Watson stat		2.019481
Prob(F-statistic)	0.000092			

Null Hypothesis: D(I) has a unit root

Exogenous: None

Lag Length: 0 (Automatic—based on SIC, maxlag=6)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.482909	0.0000
Test critical values:	1% level	-2.656915	
	5% level	-1.954414	
	10% level	-1.609329	

*MacKinnon (1996) one-sided *p*-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(I,2)

Method: Least Squares

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
D(I(-1))	-1.091849	0.199137	-5.482909	0.0000
R-squared	0.545968	Mean dependent var		-0.003846
Adjusted R-squared	0.545968	S.D. dependent var		3.855228
S.E. of regression	2.597725	Akaike info criterion		4.784852
Sum squared resid	168.7044	Schwarz criterion		4.833240
Log likelihood	-61.20307	Hannan-Quinn criter.		4.798786
Durbin-Watson stat	2.014156			

Null Hypothesis: D(U) has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic—based on SIC, maxlag=6)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.350208	0.0023
Test critical values:	1% level	-3.724070	
	5% level	-2.986225	
	10% level	-2.632604	

*MacKinnon (1996) one-sided *p*-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(U,2)

Method: Least Squares

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
D(U(-1))	-0.853569	0.196213	-4.350208	0.0003
D(U(-1),2)	0.506854	0.184224	2.751288	0.0117
C	0.114034	0.241543	0.472105	0.6415
R-squared	0.465821	Mean dependent var		-0.008000
Adjusted R-squared	0.417259	S.D. dependent var		1.571431
S.E. of regression	1.199591	Akaike info criterion		3.314005
Sum squared resid	31.65840	Schwarz criterion		3.460270
Log likelihood	-38.42506	Hannan-Quinn criter.		3.354573
F-statistic	9.592329	Durbin-Watson stat		2.031800
Prob(F-statistic)	0.001011			

Null Hypothesis: D(U) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 1 (Automatic—based on SIC, maxlag=6)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.375020	0.0100
Test critical values:	1% level	-4.374307	
	5% level	-3.603202	
	10% level	-3.238054	

*MacKinnon (1996) one-sided *p*-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(U,2)

Method: Least Squares

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
D(U(-1))	-0.873002	0.199542	-4.375020	0.0003
D(U(-1),2)	0.513185	0.186062	2.758141	0.0118
C	0.512914	0.566368	0.905621	0.3754
@TREND(1985)	-0.026409	0.033848	-0.780212	0.4440
R-squared	0.480869	Mean dependent var		-0.008000

Null Hypothesis: D(U) has a unit root

Exogenous: None

Lag Length: 1 (Automatic—based on SIC, maxlag=6)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.399596	0.0001
Test critical values:	1% level	-2.660720	
	5% level	-1.955020	
	10% level	-1.609070	

*MacKinnon (1996) one-sided *p*-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(U,2)

Method: Least Squares

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
D(U(-1))	-0.842845	0.191573	-4.399596	0.0002
D(U(-1),2)	0.501249	0.180709	2.773790	0.0108
R-squared	0.460409	Mean dependent var		-0.008000
Adjusted R-squared	0.436948	S.D. dependent var		1.571431
S.E. of regression	1.179151	Akaike info criterion		3.244085
Sum squared resid	31.97914	Schwarz criterion		3.341595
Log likelihood	-38.55106	Hannan-Quinn criter.		3.271130
Durbin-Watson stat	2.021484			

Appendix 3

Estimation of State Space Models

Sspace: SS01

Method: Maximum likelihood (Marquardt)

	Coefficient	Std. Error	*z*-Statistic	Prob.
C(1)	-0.000273	3.200618	-8.52E-05	0.9999
C(2)	-0.056874	3.425824	-0.016602	0.9868
	Final State	Root MSE	*z*-Statistic	Prob.
SV1	3.457560	707.1167	0.004890	0.9961
SV2	3.542440	707.1168	0.005010	0.9960
Log likelihood	-55.56132	Akaike info criterion		4.111523
Parameters	2	Schwarz criterion		4.206680
Diffuse priors	2	Hannan-Quinn criter.		4.140614

Sspace: SS01

Method: Maximum likelihood (Marquardt)

Sample: 1985–2012

Included observations: 28

Convergence achieved after 25 iterations

	Coefficient	Std. Error	*z*-Statistic	Prob.
C(1)	0.656488	0.259550	2.529331	0.0114
C(2)	0.975983	0.036640	26.63683	0.0000
	Final State	Root MSE	*z*-Statistic	Prob.
SV1	6.831881	1.388528	4.920234	0.0000
Log likelihood	-50.44527	Akaike info criterion		3.746090
Parameters	2	Schwarz criterion		3.841248
Diffuse priors	0	Hannan-Quinn criter.		3.775181

Sspace: SS01

Method: Maximum likelihood (Marquardt)

	Coefficient	Std. Error	*z*-Statistic	Prob.
C(1)	0.634768	0.241763	2.625574	0.0087
	Final State	Root MSE	*z*-Statistic	Prob.
SV1	7.000000	1.373530	5.096359	0.0000
Log likelihood	**-55.54141**	Akaike info criterion		4.038672
Parameters	1	Schwarz criterion		4.086251
Diffuse priors	1	Hannan-Quinn criter.		4.053217

@signal u1 = sv1

@state sv1 = c(1)*sv1(-1) + [var = exp(c(2))]

Sspace: SS02

Method: Maximum likelihood (Marquardt)

Sample: 1985–2012

Included observations: 28

Convergence achieved after 13 iterations

	Coefficient	Std. Error	*z*-Statistic	Prob.
C(1)	1.010108	0.011748	85.97780	0.0000
C(2)	-1.869310	0.521787	-3.582511	0.0003
	Final State	Root MSE	*z*-Statistic	Prob.
SV1	6.335985	0.392721	16.13354	0.0000
Log likelihood	-20.90208	Akaike info criterion		1.635863
Parameters	2	Schwarz criterion		1.731020
Diffuse priors	1	Hannan-Quinn criter.		1.664953

@signal u1 = sv1

@state sv1 = sv1(-1) + [var = exp(c(2))]

Sspace: SS02

Method: Maximum likelihood (Marquardt)

Sample: 1985–2012

Included observations: 28

Convergence achieved after 9 iterations

	Coefficient	Std. Error	*z*-Statistic	Prob.
C(2)	-1.837286	0.441786	-4.158767	0.0000
	Final State	Root MSE	*z*-Statistic	Prob.
SV1	6.272583	0.399060	15.71839	0.0000
Log likelihood	*-21.33485*	Akaike info criterion		1.595346
Parameters	1	Schwarz criterion		1.642925
Diffuse priors	1	Hannan-Quinn criter.		1.609892

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Kalmanov filter ali VAR-modeli za napovedovanje stopnje brezposelnosti v Romuniji?

Izvleček

V prispevku predstavljamo v praksi pogost ekonomski problem. Ko imamo za isto spremenljivko več napovedi, pri odločanju pa potrebujemo samo eno, je za izbiro najboljše treba te napovedi oceniti. Namen prispevka je predlagati nekaj strategij za izboljšanje napovedi stopnje brezposelnosti v Romuniji s primerjalno analizo točnosti na podlagi dveh kvantitativnih metod, Kalmanovega filtra in vektorskih avtoregresijskih modelov (VAR-modelov). Pri prvi metodi je upoštevan razvoj komponent brezposelnosti, pri VAR-modelih pa medsebojne odvisnosti med stopnjo brezposelnosti in inflacijsko stopnjo. Po Grangerjevem testu vzročnosti je inflacijska stopnja v prvi diferenci vzrok za stopnjo brezposelnosti v prvi diferenci pri stacionarnih podatkih. Za napovedi stopnje brezposelnosti v obdobju 2010–2012 v Romuniji dobimo z VAR-modeli (v vseh različicah VAR-simulacij) bolj točne napovedi kot s Kalmanovim filtrom na osnovi dveh modelov prostora stanj za vse mere točnosti. Upoštevajoč povprečno absolutno tehtano napako, so dinamične stohastične simulacije, uporabljene za napovedovanje brezposelnosti, ki temeljijo na VAR-modelu, najbolj točne. Pri drugi strategiji za izboljšanje začetnih napovedi, ki temelji na Kalmanovem filtru, so uporabljeni popravljeni podatki o brezposelnosti, transformirani s Hodrick-Prescottovim filtrom. Uporaba VAR modelov namesto različic Kalmanovega filtra je najboljša strategija za izboljšanje kakovosti napovedi stopnje brezposelnosti v Romuniji. Medsebojna povezanost med brezposelnostjo in inflacijo namreč ponuja uporabne informacije za napovedi, ki so zanesljivejše kot napovedi na osnovi razvoj brezposelnosti glede na gibanje njenih komponente (naravna brezposelnost in ciklična komponenta).

Ključne besede: napovedi, točnost, Kalmanov filter, Hodrick-Prescottov filter, VAR-modeli, stopnja brezposelnosti