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:

$u_t = Z\beta_t$, $t = 1, 2, \dots , T$ (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:

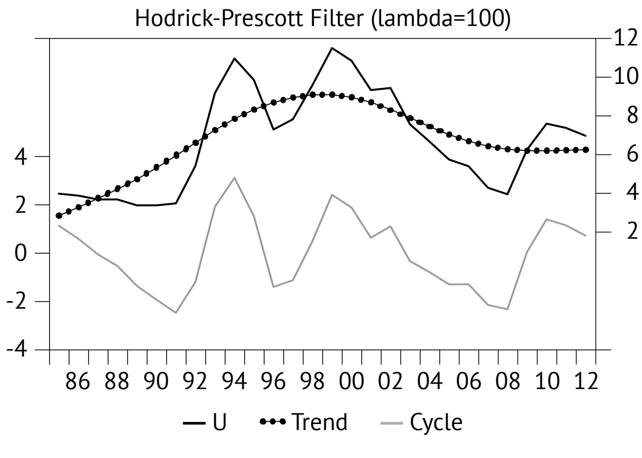
@signal u = sv1
*@state sv1 = c(2)*sv1(-1) + [var = exp(c(1))]*

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:

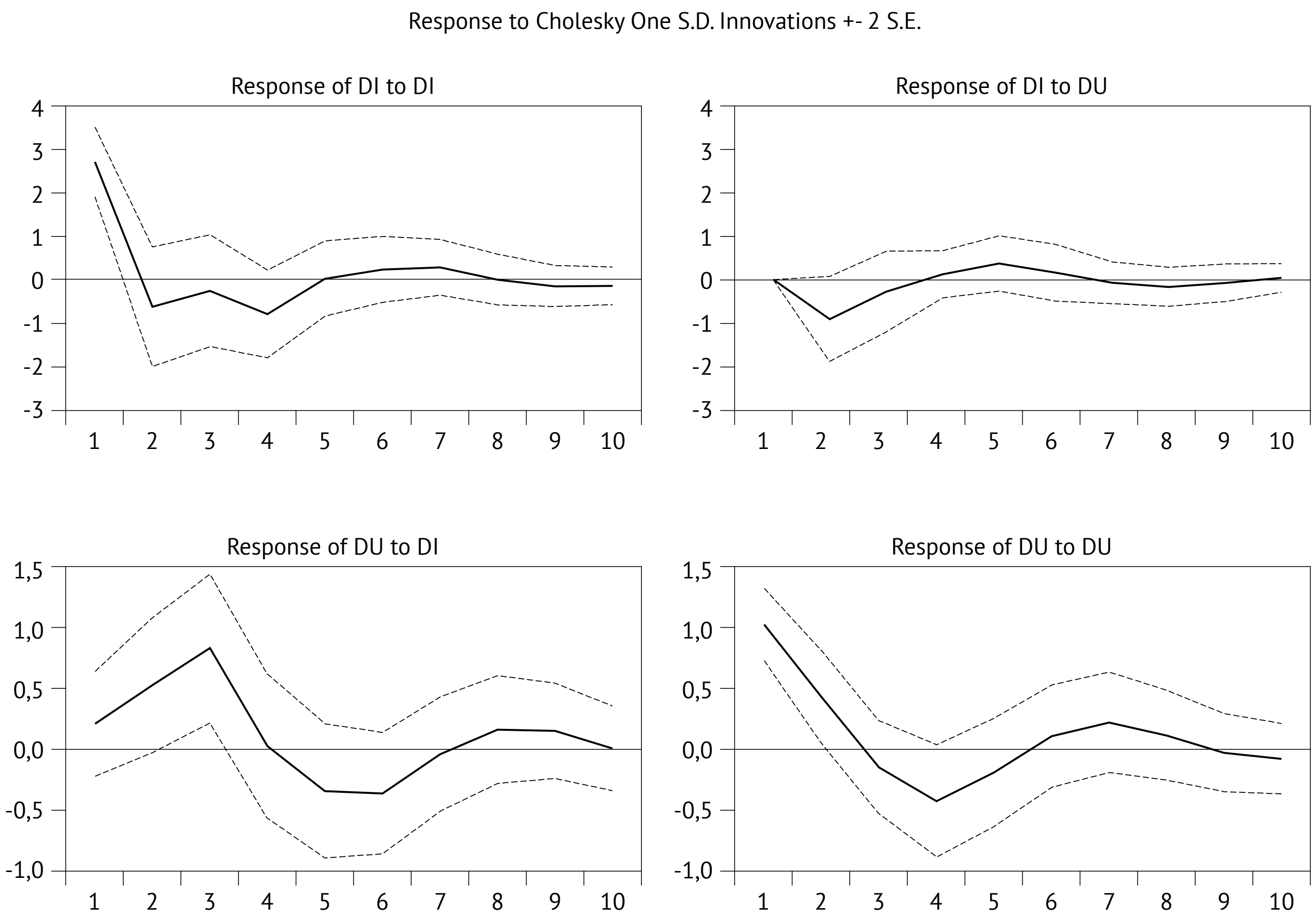
H0: The errors are not auto-correlated.

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:

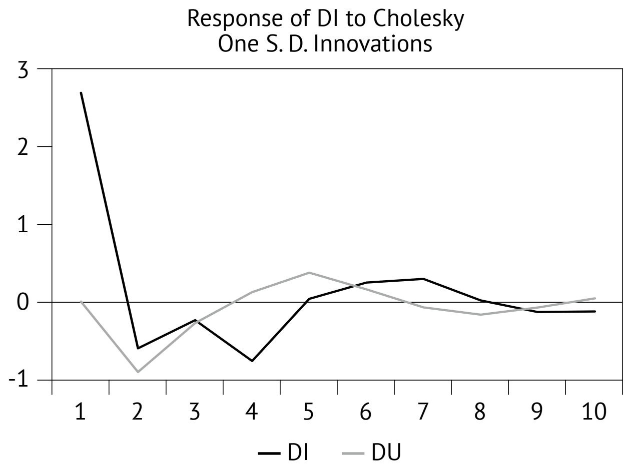
Period	DI	DU
1	0.217511	1.021384
2	0.534967	0.416467
3	0.837354	-0.167574
4	0.033907	-0.446814
5	-0.333998	-0.209706
6	-0.352703	0.091735
7	-0.031785	0.206300
8	0.169597	0.099136
9	0.159855	-0.046176
10	0.015591	-0.096744

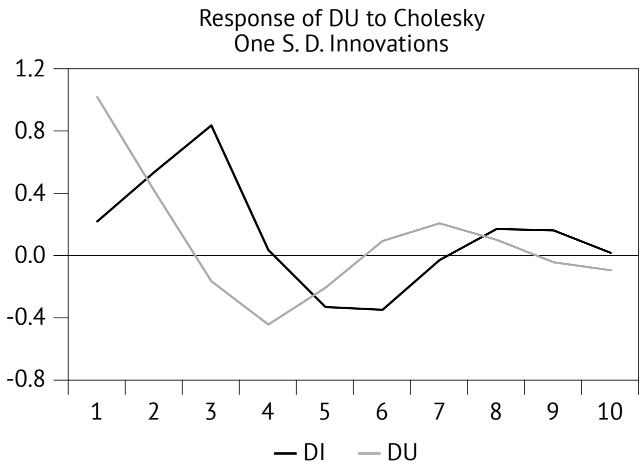
Variance Decomposition of DU:

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

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Examining the Export-led Growth Hypothesis: The case of Croatia

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Abstract

This paper examines the relationship between gross domestic product and exports of goods and services in Croatia between 1996 and 2012. The research results confirmed unidirectional Granger causality from the exports of goods and services to gross domestic product. Following the Engle-Granger approach to cointegration, long-term equilibrium as well as short-term correlation between the observed variables was identified. Exports of goods and services and gross domestic product (GDP) in Croatia move together. If the two observed variables move away from equilibrium, they will return to their long-term equilibrium state at a velocity of 24.46% in the subsequent period. In accordance with the results, we found evidence supporting the export-led growth hypothesis in Croatia. As the outcomes indicated, to recover the economy, Croatia should put more emphasis on the development of exporting sectors.

Keywords: gross domestic product, export, Croatia, Granger causality

1 Introduction

There are extensive discussions regarding relationships between exports and economic growth (Giles & Williams, 2000), and there are four possible outcomes of investigating that relationship (Chen, 2007). First is the export-led growth hypothesis, which means that export growth causes economic growth. Export growth is typically considered one of the main determinants of an economy's growth in production and employment. Empirically, it refers to unidirectional causality from exports to gross domestic product (GDP). The second possible outcome could refer to the growth-driven export hypothesis, which postulates that a rise in GDP generally leads to a corresponding increase in exports, thereby empirically indicating unidirectional causality from GDP to exports. The third possible outcome is a bidirectional relationship between exports and economic growth. Finally, the fourth possible outcome is a neutral relationship between exports and economic growth.

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Most arguments in favor of an outward-oriented strategy emphasize trade openness by claiming that countries that increase their participation in international trade achieve long-term economic growth faster than countries that are less open to global trade (see, for example, World Bank, 1993). These arguments are often supported by the East Asian miracle, where the nexus between export and economic growth was evidenced during the last few decades of the 20th century.

A growing development gap can be identified between countries following the export-oriented path and those based on domestic market orientation, economic protectionism, and import-led (but sooner or later unsustainable) growth. However, for countries that would like to join the group of successful exporters with a certain time lag, the change from domestic demand-generated growth to export-oriented growth is by far not easy and even less self-evident (Inotai, 2013). Croatia belongs to the latter group of countries and relies on exports as one of its development pillars. Therefore, the main goal of this paper is to test the export-led growth hypothesis in Croatia by establishing the relationship between the exports of goods and services and GDP.

The paper consists of five parts. After the introductory part, the second part reviews the literature. The third part explains the methodology and data, and the fourth part provides the empirical analysis. The discussion and conclusion are included in the final part of the paper.

2 Literature Review

Many studies have tried to establish the causal link between export expansion and economic growth (Khalafalla & Webb, 2001). However, empirical research on the causality issue between export and economic growth has yielded contradictory results. Contradictions like these might be partly due to the different methods, variable selections, time frames, and frequencies (Kónya, 2006). The causal link between export promotion and economic development is neither straightforward nor universal (Sung-Shen, Biswas, & Tribedy, 1990).

Results of the study conducted by Doyle (1998) on the example of Ireland from 1963 to 1993 suggest that exports and GDP are cointegrated. She found evidence of short-run and long-run causality from exports to output. Meanwhile, Chen (2007) assessed the validity of the export-led growth and growth-driven export hypotheses in Taiwan by testing Granger causality using the vector error correction model and the bounds testing methodology. The results indicated that a long-run level equilibrium relationship exists among exports, output, terms of trade, and labor productivity of the model. In addition, a bidirectional causal relationship exists between exports and output in Taiwan. These results attest to the advantage of the export-led growth strategy for further growth in Taiwan (Chen, 2007).

Greenway, Morgan, and Wright (1999) showed that a strong positive relationship exists between real export growth and real output growth on a sample of 69 countries for the 1975–1993 period. They also showed that the composition of those exports is important in determining the strength of growth. Paul and Chowdhury (1995) found evidence of Granger causality running from exports to GDP growth in Australia for the 1949–1991 period, implying that the expansion of exports promotes economic growth in Australia.

McCarville and Nnadozie (1995) concluded that the Granger causality test confirmed the relationship between export growth and GDP growth in the Mexican case, as stated by development theory. In addition, Liu, Burridge, and Sinclair (2002) found bidirectional causality among economic growth, foreign direct investment (FDI), and exports in China based on monthly data between 1981 and 1997. According to the authors, these three variables appeared to be mutually reinforcing under the open-door policy.

Narayan, Narayan, Prasad, and Prasad (2007) examined the export-led growth hypothesis on a sample from Fiji (1960–2001) and Papua New Guinea (1961–1999). Their findings suggested that, for Fiji, there is evidence of export-led growth in the long run and, for Papua New Guinea, there is evidence of export-led growth in the short run.

Ekanayake (1999) used cointegration and error-correction models to analyze the causal relationship between export growth and economic growth in eight Asian developing countries for the 1960–1997 period. The results showed bidirectional causality between export growth and economic growth in seven of the eight countries in the sample. Ekanayake's (1999) evidence showed short-run Granger causality running from economic growth to export growth in all observed cases except one (i.e., Sri Lanka). In addition, despite the strong evidence for long-run Granger causality running from export growth to economic growth in all cases, evidence of short-run causality running from export growth to economic growth occurred in only two cases: Indonesia and Sri Lanka.

Biswal and Dhawan (1998) found that, in Taiwan between 1960 and 1990, the evidence indicates bidirectional causality, meaning exports and growth mutually reinforce each other. Their research further demonstrated that the causality testing results are very sensitive to model selection and to omitting variables. However, tests conducted by Afxentiou and Serletis (2000) on a sample covering 50 developing countries between 1970 and 1993 showed that export growth was not an engine of growth, not even in the cases of the Asian tigers. Their research did not support the hypothesis that export growth led to gross national product (GNP) growth in a Granger sense. Within the entire sample, only Indonesia and Oman appeared to exhibit reliable causality from export growth to GNP growth, and it is likely that their dependence on oil exports produced the obtained outcome. Causality tests from import growth to GNP growth also found that only Pakistan exhibited causality from import growth to GNP growth (Afxentiou & Serletis, 2000).

Asafu-Adjaye and Chakraborty's (1999) research on the sample of four less developed countries (i.e., India, Nigeria, Fiji, and Papua New Guinea) raised doubts about policy recommendations for the less developed countries based on the export-led growth hypothesis. Furthermore, Sharma and Dhakal (1994) investigated the *prima facie* causal relationship between the exports and output growth in 30 developing countries between 1960 and 1988. Of the 30 countries, a feedback *prima facie* causal relationship between export growth and output growth was found in only five countries, whereas export growth *prima facie* caused output growth in six other countries. Output growth *prima facie* caused export growth in another eight countries, and no causal relationship was observed between output growth and export growth in the remaining 11 countries. The authors also did not find any systematic pattern in the results of low-income, middle-income, and upper middle-income countries.

Kónya (2004a, 2004b) investigated the possibility of export-led growth and growth-driven export by testing Granger causality in 25 Organization for Economic Cooperation and Development (OECD) countries between 1960 and 1997. His results indicated that no causality exists between exports and growth in Luxembourg or the Netherlands; exports cause growth in Iceland; growth causes exports in Canada, Japan, and Korea; and bidirectional causality exists between exports and growth in Sweden and the United Kingdom. With less certainty, the results indicated that no causality exists between exports and growth in Denmark, France, Greece, Hungary, and Norway; exports cause growth in Australia, Austria, and Ireland; and growth causes exports in Finland, Portugal, and the United States. In Belgium, Italy, Mexico, New Zealand, Spain, and Switzerland, the results were too controversial to make a simple choice. Furthermore, some of the revealed causal relationships implied a negative delayed impact from exports to growth or vice versa.

Afxentiou and Serletis (1991) further found that no systematic relationship exists between exports and GNP in industrial countries for the 1950–1985 period. According to their research results, export growth is not the magic key to GNP growth, and many of the secrets continue to be hidden, refusing to reveal themselves in a straightforward quantifiable manner.

Ramos (2001) investigated the Granger causality among exports, imports, and economic growth in Portugal from 1865 to 1998. The empirical results did not confirm a unidirectional causality among the variables considered. In addition, Awokuse (2007) examined the impact of export and import expansion on growth in Bulgaria, the Czech Republic, and Poland. In the case of Bulgaria, the export-led growth hypothesis and growth-led exports hypothesis were confirmed. Empirical support existed for both the export-led growth hypothesis and import-led growth hypothesis in the Czech Republic. In Poland, only the import-led growth hypothesis was supported. These results indicate that simply focusing on the role of exports as the engine of growth might be misleading.

Tang (2006) found no long- or short-run causality between export expansion and economic growth in China between 1970 and 2001 in Granger's sense. However, he found that economic growth causes import expansion in the short run. Shan and Tian (1998) also tested the export-led growth hypothesis for Shanghai, using monthly time series data from 1990 to 1996. The research found unidirectional Granger causality running from GDP to exports, implying that exceptional economic performance in Shanghai during the 1990s was not propelled by export expansion, but by a set of domestic factors and foreign investment.

Hsiao (1987) investigated the existence and directions of causality between exports and GDP for Hong Kong, Taiwan, South Korea, and Singapore using Sims' unidirectional exogeneity test and Granger's causality test. Using the same set of data, applied tests were shown to have different causal implications, but the one common finding from the two tests was a lack of support for the hypothesis of unidirectional causality from exports to GDP. These results imply that the rapid economic growth of countries in the sample was not only achieved with the export promotion policy, but also derived from the domestic growth of industries and import substitution. The export-led growth hypothesis was rejected in the case of Australia as well (Shan & Sun, 1998).

Ahmad and Kwan (1991) found no causal link from exports to economic growth, or vice versa, on a sample of 47 African countries. Some subsets of countries provided weak support for causation running from economic growth to exports. The authors suggested the possibility of another independent factor that jointly influences both the growth of income and exports. However, the inclusion of omitted variables in the estimation of exports–income causality must remain arbitrary until a fully structural model that specifies the channels by which exports affect income and vice versa is developed (Ahmad & Kwan, 1991).

As for Croatia, empirical research regarding the relationship between exports and economic growth is very scarce. Dritsaki and Stiakakis (2014) studied the relationship among FDI, exports, and economic growth in Croatia using annual time series data for 1994 to 2012. Several econometric models were applied, including the bounds testing (ARDL) approach and the ECM–ARDL model. The results confirmed a bidirectional long-run and short-run causal relationship between exports and growth.

Živković, Živković, and Grdinić (2014) analyzed the relationship among GDP, the imports-coverage ratio, FDI, and gross fixed capital formation in selected Central Eastern European countries using an error-correction model. The empirical results confirmed a positive long-run influence of the imports-coverage ratio, FDI, and gross fixed capital formation on GDP growth for all of the countries except Croatia. In the case of Croatia, significant negative feedback occurred between FDI and GDP growth in the long run, but positive feedback occurred in the short run.

At the micro level, Valdec and Zrnc (2014) used propensity score matching to test for causal effects of starting to export on firm performance in Croatian manufacturing firm-level data. The results confirmed that exporters have characteristics superior to those of non-exporters. In the main sample specification, pervasive evidence existed of self-selection into export markets, meaning that firms were successful years before they became exporters.

3 Methodology, Data, and Hypothesis

Economic time series are often non-stationary time series. At the same time, one of the assumptions for regression model estimation is time series stationarity. For that reason, we employed the Phillips-Perron Unit Root Test to check the stationarity characteristics of the observed time series. If the variables are of the same order of integration, as is the case here, it can be assumed that they are cointegrated. For the purpose of testing the relationship among the variables, the error correction model or the Engle-Granger approach to cointegration (Engle & Granger, 1987) was assumed. According to this approach, a linear regression model was defined on a non-stationary time series, and then the stationarity of residuals of the defined regression model was tested. If two time series were cointegrated, then there must be Granger-causality in at least one direction. In order to empirically check causality between exports and GDP in Croatia, the Granger causality test must be applied. In this case, the test usage was a consequence of data properties, as is discussed later in the text. We found our variables of interest integrated of the same order and decided to model a non-stationary time series. Considering the research objective and available data span, we found these methods to be the most appropriate.

The Granger (1969) causality test is one of the earliest and most frequently used methods developed to quantify causal effects in a time series. It is based on a generally acknowledged fact that the cause precedes the effect, which it consequently creates. It can be said that X Granger-causes Y if the past values of X can contribute to anticipating the future values of Y, which is better than using the past values of Y alone. The Granger causality test can be carried out for stationary or cointegrated time series.

The Granger causality test assumes the evaluation of the following model:

$$Y_t = \mu_t + \sum_{i=1}^{p} \alpha_i \cdot Y_{t-i} + \sum_{j=1}^{q} \beta_i \cdot X_{t-i} + \varepsilon_t$$

where μ_t is the deterministic component and ε_t is white noise. The null hypothesis can be tested using an F-test. If the *p*-value is lower than the defined level of significance, the null hypothesis is not accepted and the conclusion is that the first observed time series Granger-causes the second time series.

In order to explore Granger-causality, two variables were observed: GDP level in Croatia from 1996 to 2012 at constant prices and exports of goods and services for the same period at constant prices as well. Furthermore, we tested the relationship among other GDP components for the same time period. The variable description and data sources are provided in Table 1.

Table 1 Variable Description and Data Sources from 1996 to 2012

Variable	Description	Unit	Source
GDP	GDP in Croatia	000 HRK	Croatian Bureau of Statistics
EGS	Croatia's exports of goods and services	000 HRK	Croatian Bureau of Statistics
C	Personal consumption in Croatia	000 HRK	Croatian Bureau of Statistics
G	Government consumption in Croatia	000 HRK	Croatian Bureau of Statistics
I	Investment in Croatia	000 HRK	Croatian Bureau of Statistics

4 Empirical Analysis

Figure 1 shows the movement of GDP, exports of goods, exports of services, and exports of both goods and services for 1996 to 2012 in Croatia.

As shown in Table 2, we found GDP to be integrated at an order of two, while the exports of goods and services was integrated at the 1% empirical level of significance; thus, we assumed a long-term relationship between the observed variables.

Table 2 also indicates that the investment variable is integrated at an order of one and the other variables are integrated at an order of two. In order to determine causality between the variables of the same integration order, we employed Granger causality tests. The results are presented in Table 3.

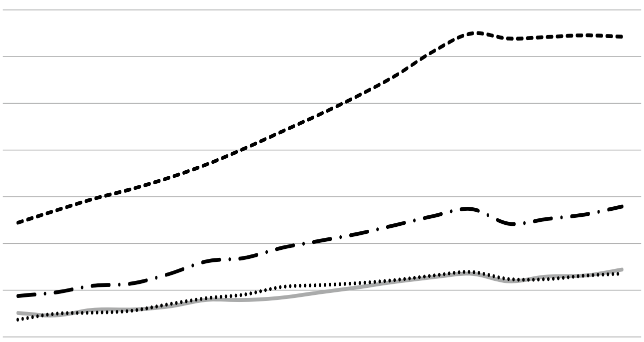
The results in Table 3 indicate causality from exports of goods and services to the GDP level in Croatia. Furthermore, the exports of goods and services Granger-cause

Table 2 Phillips-Perron Unit Root Test

Variable		*p*-value
GDP	in levels around zero	0.99
	in levels around constant	0.61
	in levels with trend around constant	0.96
	first difference around zero	0.25
	first difference around constant	0.61
	first difference with trend around constant	0.80
	second difference around zero	0.00
EGS	in levels around zero	0.99
	in levels around constant	0.70
	in levels with trend around constant	0.84
	first difference around zero	0.03
	first difference around constant	0.02
	first difference with trend around constant	0.05
	second difference around zero	0.00
C	in levels around zero	0.99
	in levels around constant	0.46
	in levels with trend around constant	0.98
	first difference around zero	0.08
	first difference around constant	0.19
	first difference with trend around constant	0.39
	second difference around zero	0.00
I	in levels around zero	0.73
	in levels around constant	0.48
	in levels with trend around constant	0.96
	first difference around zero	0.01
G	in levels around zero	0.99
	in levels around constant	0.80
	in levels with trend around constant	0.75
	first difference around zero	0.17
	first difference around constant	0.18
	first difference with trend around constant	0.45
	second difference around zero	0.00

Source: Authors' calculations.

Figure 1. GDP level, exports of goods, exports of services, and exports of goods and services in Croatia, 1996–2012 (millions of HRK)



Source: Croatian Bureau of Statistics. Retrieved from www.dzs.hr (August, 30, 2014).

Table 3 Pairwise Granger Causality Tests

Pairwise Granger Causality Tests
Sample: 1996 - 2012
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
G does not Granger-cause C	16	1.21339	0.2906
C does not Granger-cause G		14.2909	0.0023
GDP does not Granger-cause C	16	0.00752	0.9322
C does not Granger-cause GDP		1.45383	0.2494
EGS does not Granger-cause C	16	7.16449	0.0190
C does not Granger-cause EGS		0.02769	0.8704
GDP does not Granger-cause G	16	20.6470	0.0006
G does not Granger-cause GDP		8.59429	0.0117
EGS does not Granger-cause G	16	12.4689	0.0037
G does not Granger-cause EGS		0.01042	0.9202
EGS does not Granger-cause GDP	16	10.6073	0.0062
GDP does not Granger-cause EGS		0.03242	0.8599

Source: Authors' calculations.

Table 4 Long-term Relationship between GDP and Exports of Goods and Services in Croatia

Dependent Variable: GDP
Method: Least Squares
Sample: 1996–2012
Included observations: 17
GDP = C(1) + C(2)*EGS

	Coefficient	Std. Error	*t*-Statistic	Prob.
C(1)	22449.58	9698.265	2.314804	0.0352
C(2)	2.216773	0.094976	23.34046	0.0000
R-squared	0.973204	Mean dependent var		237169.0
Adjusted R-squared	0.971417	S.D. dependent var		74876.43
S.E. of regression	12658.95	Akaike info criterion		21.84025
Sum squared resid	2.40E+09	Schwarz criterion		21.93827
Log likelihood	-183.6421	Hannan-Quinn criter.		21.84999
F-statistic	544.7770	Durbin-Watson stat		0.853790
Prob(F-statistic)	0.000000			

Source: Authors' calculations.

Table 5 Phillips-Perron Unit Root Test of the Residuals (US) in the Long-term Equilibrium Model

Null Hypothesis: US has a unit root
Exogenous: None
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. *t*-Stat	Prob.
Phillips-Perron test statistic		-2.025241	0.0442
Test critical values:	1% level	-2.717511	
	5% level	-1.964418	
	10% level	-1.605603	

Source: Authors' calculations.

Table 6 Short-term Relationship between GDP and Exports of Goods and Services in Croatia

Dependent Variable: D2GDP
Method: Least Squares
Sample (adjusted): 1998–2012
Included observations: 15 after adjustments

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
D2EGS	0.745318	0.136327	5.467143	0.0001
US(-1)	-0.244612	0.101890	-2.400742	0.0320
R-squared	0.692751	Mean dependent var		-967.4870
Adjusted R-squared	0.669116	S.D. dependent var		7273.988
S.E. of regression	4184.179	Akaike info criterion		19.63957
Sum squared resid	2.28E+08	Schwarz criterion		19.73398
Log likelihood	-145.2968	Hannan-Quinn criter.		19.63857
Durbin-Watson stat	2.157031			

Source: Authors' calculations.

personal consumption (C) as well as government consumption (G) while government consumption Granger-causes GDP. At the same time, GDP Granger-causes government consumption, and personal consumption Granger-causes government consumption (G).

We found no cointegration between the GDP level and government expenditure level (p-value = 0.12). Therefore, we defined the GDP level as the dependent variable and exports of goods and services as the independent variable in the assumed linear regression model. The estimated results are shown in Table 4.

As shown in Table 4, we found a strong relationship between GDP level and the level of exports of goods and services in Croatia. Changes in the GDP level in 97.32% of the cases move together with changes in the level of exports of goods and services in Croatia.

After we estimated the long-term equilibrium between the observed variables, we tested stationarity characteristics of residuals from the estimated long-term relationship model (US). As Table 5 demonstrates, at the 5% level of significance, we found stationary residuals in the long-term equilibrium model.

In order to model the short-term relationship between the observed variables, we applied a stationary time series. As variables are integrated at an order of two, we used the variables in the second difference and residuals in the long-term equilibrium model levels. The results are shown in Table 6.

The estimated results in Table 6 indicate that the GDP level and exports of goods and services move together. The coefficient with the variable US(-1) is significant and in accordance with theoretical assumptions (negative). If the two observed variables move away from equilibrium, they will return to equilibrium at a velocity of 24.46%. In other words, if the two observed variables move away from the state of their long-term equilibrium over time, in the next period they will speedily return to the state of their long-term equilibrium. In addition, there is a strong relationship between GDP development and exports of goods and services in the long term. Moreover, as the Granger causality test results indicate, the influence from exports to GDP might occur through personal consumption or government consumption. In order to check the assumptions of the illustrated model, White's test for homoscedasticity of variance, the Jarque-Bera test for normality of residuals, and the test for the autocorrelation of the residuals were run (see Appendix). Following these, it was established that the assumptions of the model were met at the 95% confidence level.

5 Discussion and Conclusion

Regarding the relationship between exports and economic growth, as has been noted, some analysts believe that the causality direction is from export to economic growth, which is expressed as the export-led growth hypothesis (Balassa, 1978; Bhagwati, 1978; Edwards, 1998). In addition, various studies support growth-led export in a way that the causality direction is from economic growth to export growth. Regarding the growth-led exports hypothesis, an increase in exports is supported through the benefits of efficiency caused by the increase in the national workforce's skill levels and technology advancement (Bhagwati, 1978; Krugman, 1984). These two approaches do not overlap. Studies dealing with developed countries usually show that trade openness can have a positive impact on economic growth, especially in the long run, through the import of high-tech products, spillover effects resulting from FDI (Grossman & Helpman, 1990), and various reforms and programs that aim to create better conditions for participation in international markets (Ram, 1987). There is also the possibility that no relationship exists or just a simple contemporaneous relationship exists between these two variables.

The research results presented in this paper suggest unidirectional causality from exports of goods and services to GDP level in Croatia. Furthermore, we found several influence channels from exports of goods and services to GDP. Exports of goods and services Granger-cause personal consumption (C), personal consumption (C) Granger-causes government consumption (G), and government consumption (G) Granger-causes GDP. Exports of goods and services Granger-cause government consumption (G), which Granger-causes GDP, and GDP Granger-causes government consumption (G). The empirical evaluation herein leads to the conclusion that, in Croatia, the growth of exports of goods and services Granger-causes GDP growth. Moreover, exports of goods and services and GDP in Croatia move together. If the two observed variables move away from equilibrium, they will return to equilibrium at a velocity of 24.46 % in the next period.

The results of this research suggest that an export-led growth model can be acceptable for achieving economic growth and development in Croatia. In accordance with the results, we found that Croatia should put more emphasis on exports development and improvement of its trade relations. However, this research does have limitations, as reflected in its coverage and scope. It would be interesting to examine in detail which measures or policies Croatia should apply. Furthermore, a study that would establish separate relationships between exports of goods and GDP as well as between exports of services and GDP would perhaps give different results.

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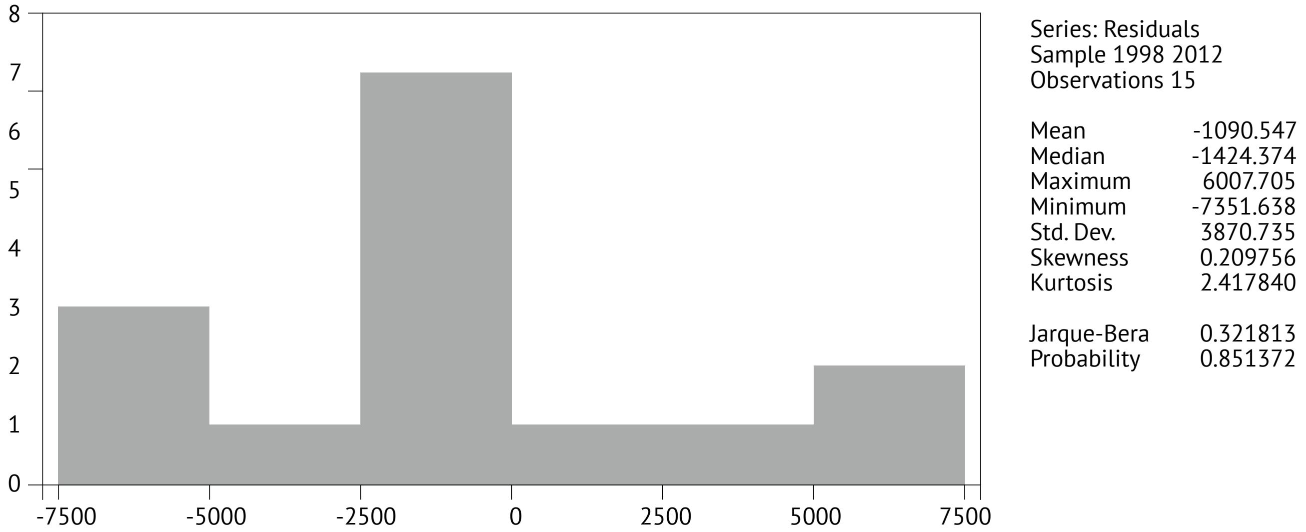
Appendix

Table 7 White Heteroskedasticity Test

F-statistic	2.873553	Prob. F(3,11)	0.0847
Obs*R-squared	6.590496	Prob. Chi-Square(3)	0.0862
Scaled explained SS	3.181509	Prob. Chi-Square(3)	0.3645

Source: Authors' calculations.

Figure 2. Jarque-Bera normality test



Source: Authors' calculations.

Table 8 Correlogram

Sample: 1998–2012
Included observations: 15

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.*| . |	.*| . |	1	-0.187	-0.187	0.6340	0.426
.**| . |	.**| . |	2	-0.270	-0.316	2.0627	0.357
. |* . |	. | . |	3	0.088	-0.043	2.2271	0.527
. | . |	.*| . |	4	-0.015	-0.102	2.2323	0.693
. |* . |	. |* . |	5	0.178	0.195	3.0366	0.694
. | . |	. | . |	6	-0.039	0.027	3.0795	0.799
.**| . |	.*| . |	7	-0.214	-0.120	4.5350	0.717
.*| . |	.**| . |	8	-0.101	-0.250	4.9095	0.767
. |* . |	. | . |	9	0.202	0.040	6.6479	0.674
.*| . |	.**| . |	10	-0.181	-0.296	8.3190	0.598
. | . |	. | . |	11	-0.032	-0.046	8.3855	0.678
. |* . |		12	0.119	0.020	9.5946	0.651

Source: Authors' calculations.

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Testiranje hipoteze o izvozno podprti rasti: primer Hrvaške

Izvleček

V članku preverjamo povezanost bruto domačega proizvoda in izvoza blaga in storitev na Hrvaškem v obdobju med letoma 1996 in 2012. Izsledki raziskave potrjujejo enosmerno Grangerjevo vzročnost od izvoza blaga in storitev do bruto domačega proizvoda. Skladno z Engle-Grangerjevim pristopom h kointegraciji smo ugotovili dolgoročno ravnovesje in kratkoročno korelacijo med opazovanimi spremenljivkami. Izvoz blaga in storitev in bruto domači proizvod se na Hrvaškem gibljejo skupaj. Če se gibanje opazovanih spremenljivk odmakne od ravnovesja, se v naslednjem obdobju vrnejo v dolgoročno stanje ravnovesja s hitrostjo 24,46 %. Skladno z izsledki smo potrdili hipotezo o izvozno podprti rasti na Hrvaškem. Rezultati nakazujejo, da bi morala Hrvaška za okrevanje gospodarstva večji poudarek dati razvoju izvoznih sektorjev.

Ključne besede: bruto domači proizvod, izvoz, Hrvaška, Grangerjeva vzročnost