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A COMPARISON OF THE VAR MODEL AND THE PC FACTOR MODEL IN FORECASTING INFLATION IN MONTENEGRO

ABSTRACT: *Montenegro started using the euro in 2002 and regained independence in 2006. Its main economic partners are European countries, yet inflation movements in Montenegro do not coincide with consumer price fluctuations in the eurozone. Trying to develop a useful forecasting model for Montenegrin inflation, we compare the results of a three-variable vector autoregression (VAR) model, and a principle component (PC) factor model starting with twelve variables. The estimation period is January 2001 to December 2012, and the control months are the first six months of 2013. The results show that in forecasting inflation, despite a high level of Montenegrin economic dependence on international developments, more reliable forecasts are achieved with the use of additional information on a larger number of factors, which includes domestic economic activity.*

KEY WORDS: *Inflation forecasting, VAR model, factor model, principal component analysis*

JEL CLASSIFICATION: C53, C32, E31

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1. INTRODUCTION

When trying to establish price stability, economic authorities monitor price levels as one of the key indicators of overall economic performance. One way to do this is by forecasting inflation dynamics. Historically, inflation forecasting has had mixed results. Inflation forecasting initially relied on univariate models, later on transitioning to multivariate models, and now the attention is shifting towards testing alternative forecasting techniques.

In Montenegro, following a period of major socio-economic and political instability (due to the breakup of Yugoslavia, the subsequent transition, etc.) and very volatile price dynamics, the last decade has witnessed more price stability (with periodic oscillations due to structural reforms: introduction of the Deutsch Mark, euro, and VAT). Moreover, each year the statistical base improves and grows, enabling an increased interest in applying econometric methods to forecasting macroeconomic variables.

The ideas presented in this paper draw on the recent research carried out by the US economists Stock and Watson (1998, 1999, 2002). In a series of research papers these authors try to evaluate the utility (applicability) of factor analysis in forecasting key macroeconomic variables. They estimate several factors that summarize information from the entire US economy, based on a vast number of macroeconomic variables. In the next stage the factors obtained on the basis of principal components methodology are used to forecast output growth, inflation growth, etc. The factor forecasts obtained in this manner outperform the forecasts of the standardized time-series econometric models - univariate regression, auto-regression, and VAR models - which has spurred further testing of their applicability (Matheson, 2006; Camacho and Sancho, 2003; Camba-Mendez and Kapetanios, 2005).

In this paper, using monthly statistical data for the period 2001-2012, we will test the ability of a vector autoregression model and a factor model to forecast the price index in Montenegro and carry out a comparative analysis of these methods.

For the purpose of forecasting we use the monthly consumer price index published by Monstat[1] with 2003 as a base year, which represents statistically the most relevant series for constructing forecasting models, despite certain inconsistencies due to methodology change in the observed period.

1 MONSTAT - Montenegrin Statistical Office

Besides the price index in Montenegro, in constructing the VAR and factor models we have also used other available series that we found to be potential and important inflation determinants. The challenges in the construction of these forecasting models, besides an insufficiently developed statistical base, lie in the specificities of the Montenegrin economy affecting the choice of variables included in the model. Montenegro has the characteristics of a small and open economy, using the euro as its currency. The agricultural and processing industries make up less than 20% of GDP, making the Montenegrin economy highly import-dependent. Therefore inflation movement in Montenegro is specific, and the effect of the direct transmission of inflation in the euro, along with the growth of import prices, demands special analysis.

Following preliminary statistical analyses, the match and very close dynamics of price index and gross wages in Montenegro with the commodity price index were noted. These results are not surprising and they are in accordance with the economic theory and the knowledge of the economic situation in Montenegro. Prices in Montenegro grow mainly because of budget expenditure (with wages as the largest portion) and external factors, usually happening incidentally (oil and food price increases), whose movements can be monitored through the IMF Commodity Price Index. A vector autoregression model was constructed and its performance was tested on the basis of the correlation of these three variables.

In order to apply the method of principal components, twelve monthly time series were available: IMF Commodity Price Index (2005=100), consumer price index in Montenegro (2003=100), number of employees, euro/dollar exchange rate, IMF food and beverage index (2005=100), IMF fuel index (2005=100), gross wages, Eurostat's Harmonized Consumer Price Index in the EU, industrial production (2010=100), net wages, tourism arrivals, and tourism nights spent.

As these are monthly data we tested for the presence of seasonality and determined it to be pronounced in the following series: tourist arrivals and the number of tourist night spent. Using the program X12 – ARIMA[2], we filtered the data for the two series and use seasonally adjusted data for the further analysis[3].

2 An official program for seasonal adjustments used by the US statistical office (Census Bureau). Details on this method can be found on the web site: http://www.census.gov/srd/www/x12a.

3 Additive decomposition of the series is assumed. The use of seasonally adjusted data and the importance of elimination of the seasonal component are accentuated in many papers. Here, we are motivated by discussion in Camacho and Sancho, 2003, in the context of application of factor models on Spanish data.

This paper is organized as follows. Section II describes the methodology of the forecasting models: (a) vector autoregression model and (b) factor model based on principal component analysis. Section III presents the main empirical results with a comparison analysis at the end. Conclusions are offered in section IV. The appendix reports estimation details.

2. METHODOLOGY: ECONOMETRIC FRAMEWORK

The two alternative inflation-forecasting models utilized in this paper for the purpose of forecasting performance comparison, the vector autoregression (VAR) model and the factor model, are described in some detail in this section.

(A) VAR model specification and forecasting

Forecasting from a VAR model is similar to forecasting from a univariate AR model. The successful use of univariate models for forecasting has motivated researchers to extend the model class to the multivariate case. The VAR model has been used extensively to forecast inflation.

The attraction of the VAR approach as proposed by Sims[4] is mainly that there is no reliance on the restrictions of economic theory to indicate which variables occur in each equation. In VAR, every variable in the system is assumed to be endogenous. This contrasts with the standard theory-based method in which causal relationships between the variables are the starting point.

Let us consider a k-dimensional stochastic process X. We can define the reduced form of the general linear dynamic model of this process, a vector autoregression of order p, VAR(p), as follows:[5]

$$\mathbf{X_t} = \delta + A_1\mathbf{X_{t-1}} + A_2\mathbf{X_{t-2}} + \dots + A_p\mathbf{X_{t-p}} + U_t \tag{1}$$

The A_i, $i=1,2,\dots,p$, are k-dimensional quadratic matrices, and U represents the k-dimensional vector of residuals at time t. The vector of constant terms is denoted as δ. U_t is a vector stochastic white noise process, with the individual components being uncorrelated processes with constant mean and finite variance. Residuals

4 Sims, C. A., "Macroeconomics and Reality," *Econometrica*, 1980, 48, 1-48.

5 The representation of the VAR model is given according Kirchgassner & Wolters, 2007, p. 127-128

U_t are interdependent because they contain shocks from all endogenous variables in relation to each other.

The system is stable if, and only if, all included variables are weakly stationary, i.e., all roots of the characteristic equation of the lag polynomial are outside the unit circle. It holds that

$$\det(I_k - A_1 z - A_2 z^2 - \ldots - A_p z^p) \neq 0, \text{ za } |z| \leq 0 \qquad (2)$$

Generally, at any prediction horizon in period $t=n$, the optimal predictor of future value X_{t+h} is seen to be[6]:

$$X_n(h) = \mathbf{A}^h X_n = \mathbf{A} X_n(h-1). \qquad (3)$$

It is easily seen by induction with respect to h that:

$$X_n(h) = [x_n(h) \quad x_n(h-1) \quad \ldots \quad x_n(h-p+1)]' \qquad (4)$$

where $x_n(j) := x_{n+j}$ for $j \leq 0$. Defining the J matrix of dimension $K \times Kp$ with $J := [I_K : 0 : \ldots : 0]$, we get the optimal predictor X_{n+h} in time $t=n+h$ for h period ahead as:

$$\begin{aligned} x_n(h) &= JAX_n(h-1) = [A_1, \ldots, A_p] Y_n(h-1) \\ &= A_1 x_n(h-1) + \ldots + A_p x_n(h-p) \end{aligned} \qquad (5)$$

This formula may be used for recursive computing of the forecasts.

Using $X_{n+h} = A^h X_n + \sum_{i=0}^{h-1} A^i U_{n+h-i}$, if zero mean process, we can define forecast error as:

$$x_{n+h} - x_n(h) = J\left[Y_{n+h} - Y_n(h)\right] = J\left[\sum_{i=0}^{h-1} A^i U_{n+h-i}\right] = \sum_{i=0}^{h-1} JA^i J' U_{n+h-i} = \sum_{i=0}^{h-1} \Phi_i u_{n+h-i} \qquad (6)$$

where Φ_i are the MA coefficient matrices from MA representation.

6 The presented construction of the forecast for the VAR(p) model is based on Lutkepohl, H, 2005, p. 31-34

(B) Factor model estimation and forecasting

In the following lines we present the specification of the forecasting model proposed by Stock and Watson, aiming to forecast the value of variable y in period $T+h$ with available data up to time T. The specification of the so-called approximate dynamic forecasting factor model follows Stock and Watson (2002).

To be specific, let X_{it} be the value of i times series variable in time t, y_t the scalar times series variable to be forecast, and f_t m the dimensional vector of factors at time t.

The dynamic factor model is defined as follows:

$$y_{t+h} = \alpha_h + \beta(L)f_t + \gamma(L)y_t + \varepsilon_{t+h} \tag{7}$$

$$X_{it} = \lambda_i'(L)f_t + e_{it} \tag{8}$$

for $i=1,\ldots, N$, where $e_t = (e_{1t}, \ldots, e_{Nt})'$ is N × 1 vector idiosyncratic disturbances and $\beta(L)$ and $\gamma(L)$ are finite-order polynomials in variable L, and L is a standard lag operator. Therefore in (7) we assume that there is a linear dependence between scalar variable y at time $t+h$ and factors up to t. Also, we suppose that something can be said on the future of the variable of interest using information from its own history; therefore we include the term $\gamma(L)y_t$. It is important to note that the parameters from (7) cannot be estimated because not all predictors (factors f_t) are known. The true values of factors cannot be observed, but are estimated from (8). The main advantage of this static representation of the dynamic factor model is that factors can be estimated using the method of principal components. Accordingly, a time series of factors f_t (principal components) is estimated from a set of data given in X_{it}[7]. By the method of principal components we get the linear combinations of original variables which comprise the maximum variance and are mutually uncorrelated. In this way the original variables are transformed into new variables (linear combinations) called the principal components. The first principal component is constructed to include the maximum variance of the original set of data, and the following are computed so as to include the maximum of the variance that is not caught in the previously extracted components.

The coefficients of the regression in (7) are estimated by the least squares method on the data set up to time T, so we get estimated parameters $\hat{\beta}(L)$ and $\hat{\gamma}(L)$.

7 The proof that the principal components of X_t are a consistent estimator of the true latent factors is given in Stock and Watson, 2002a.

The forecast is constructed as:

$$\hat{y}_{t+h} = \hat{\alpha}_h + \hat{\beta}(L)\hat{f}_t + \hat{\gamma}(L)y_t \qquad (9)$$

In order for the forecast to be the best in the MSE[8] sense, we assume that $E(\varepsilon_{t+h} \mid I_t)=0$, where I_t is information available up to time *t*.

3. EMPIRICAL RESULTS

(A) VAR analysis

The preliminary analysis draws attention to the very strong match between the price index in Montenegro, gross wages, and the commodity price index in the period 2001-2012 (Graph 1). The value of the correlation coefficient signals the existence of a very strong direct relation between the mentioned variables (Table 1).

Table 1. Coefficient of correlation between price index, gross wages, and commodity price index, 2001-2012

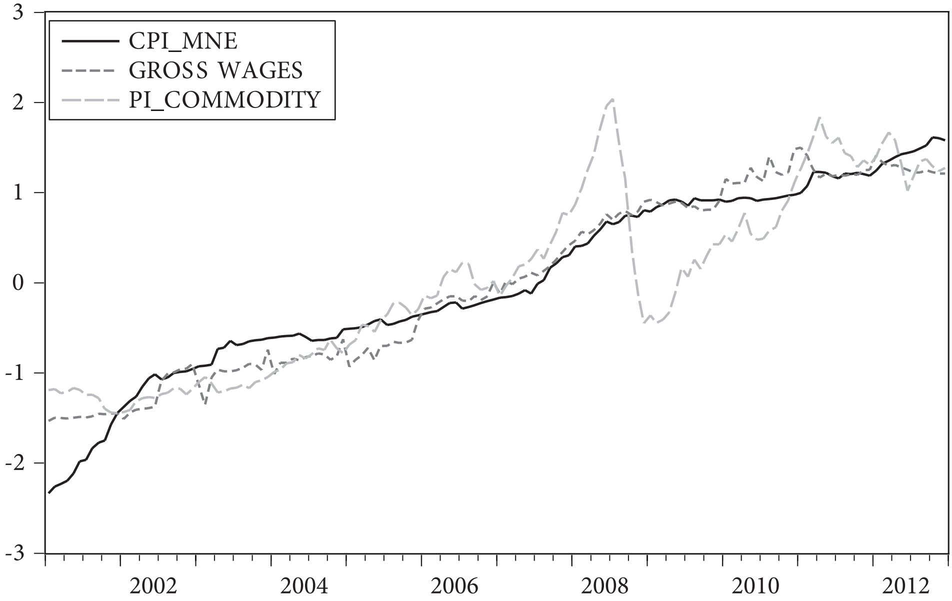
	CPI_MNE
GROSS WAGES	**0.968398**
PI_COMMODITY	**0.870608**

Source: Author's calculations[9]

8 MSE - Mean square error

9 All calculations in this paper are made in econometric software Eviews 7.

Graph 1. Price index movements, gross wages, and commodity price index, 2001-2012



Source: Author's calculations

The results of the unit root test for the price index in Montenegro and the commodity price index demonstrate that the mentioned series are trend-stationary, based on the standard ADF unit root test, with the results shown in Table 2. Due to a break in the series of wages that occurred at the beginning of 2011 (in March), the result of the standard ADF unit root test is unreliable. Consequently, Zivot-Andrews's unit root test (for when the series has one structural break in the series) is used, where the break point is identified (March, 2011) and it is established that the series does not have the unit root.

Table 2. Unit root tests for variables in the VAR model

Augmented Dickey-Fuller test		**t-Statistic**	**Prob.***
	CPI_MNE	-3.489399	0.0443
	PI_COMMODITY	-3.707411	0.0250
Zivot-Andrews Unit Root Test		**t-Statistic**	**Prob.***
	GROS WAGES	-3.549406	0.0001

Source: Author's calculations

Following the additional examination and introduction of appropriate dummy variables[10], the final VAR model with 14 lags follows:

$$Y_{1t} = a_{10}+\Sigma_{i=1}^{14}a_{1i}Y_{1_{t-i}}+\Sigma_{i=1}^{14}b_{1i}Y_{2_{t-i}}+\Sigma_{i=1}^{14}c_{1i}Y_{3_{t-i}}+\Sigma_{j=1}^{4}d_{1j}D_{j_t}+t_{11}T+t_{12}TD+\varepsilon_{1t}$$

$$Y_{2t} = a_{20}+\Sigma_{i=1}^{14}a_{2i}Y_{1_{t-i}}+\Sigma_{i=1}^{14}b_{2i}Y_{2_{t-i}}+\Sigma_{i=1}^{14}c_{2i}Y_{3_{t-i}}+\Sigma_{j=1}^{4}d_{2j}D_{j_t}+t_{21}T+t_{22}TD+\varepsilon_{3t}$$

$$Y_{3t} = a_{30}+\Sigma_{i=1}^{14}a_{3i}Y_{1_{t-i}}+\Sigma_{i=1}^{14}b_{3i}Y_{2_{t-i}}+\Sigma_{i=1}^{14}c_{3i}Y_{3_{t-i}}+\Sigma_{j=1}^{4}d_{3j}D_{j_t}+t_{31}T+t_{32}TD+\varepsilon_{3t}$$

where t=1,2,...144, and the used variables are Y_1 = price index in Montenegro, 2003=100; Y_2 = gross wages in Montenegro, in euros; Y_3 = commodity price index, 2005=100 ; D_{1t} = 1 for period Jan 2008-June 2008, and 0 for the rest of the period; D_{2t} = 1 for period July 2008-Dec 2008, and 0 for the rest of the period; D_{3t} = 1 until March 2003, and 0 for the rest of the period; D_{4t} = 1 for period Jan 2003, Jan 2004 and Jan 2005, and 0 for the rest of the period; T = 1,2,3,...,144 (trend for period Jan 2001-Dec 2012); DT = 0 for period Jan 2001-Feb 2011, and 1,2,3,...,22 from March 2001 to the end of sample (partial trend from March 2011-Dec 2012).

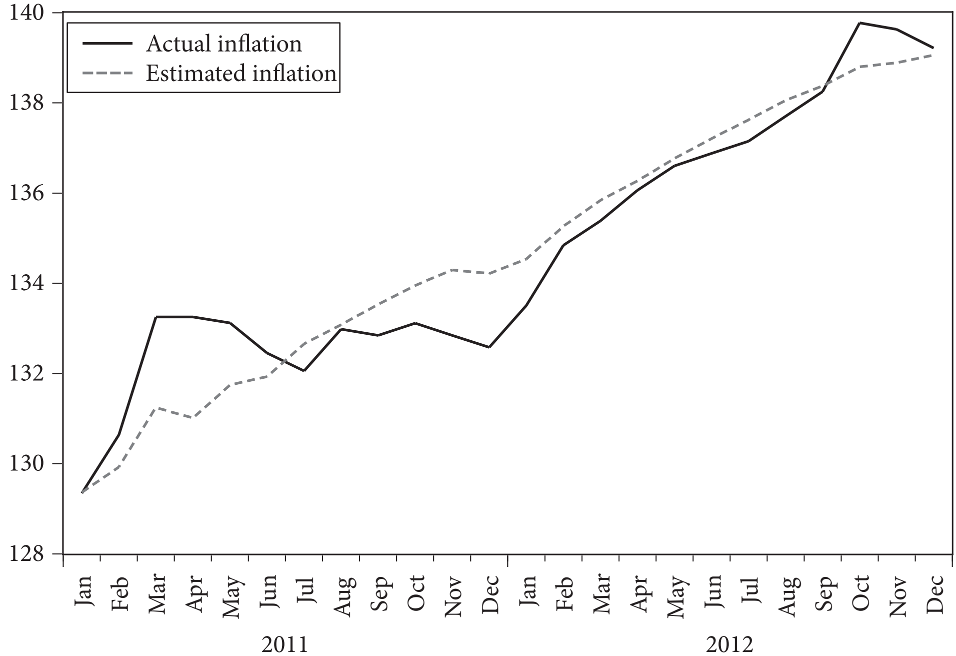
Based on the autocorrelation, heteroscedasticity tests, and residual normality, it is established that the model accomplishes all econometric criteria[11]. The model stability is a condition for implementing the remaining tests, so the stability of the VAR model must be established first. The test has confirmed that the model is stable and satisfactory.

Graph 2 demonstrates the real and model estimated inflation in the period from January 2011 to December 2012. Based on model (10) the inflation forecasts were done for the first six months of 2013 and the quality of the forecasts was tested applying the standard accuracy forecasts measures (mean square error, root mean square error, mean absolute error, mean absolute percentage error). Their values are shown in Table 3.

10 Dummy variables are introduced in order to eliminate diversions from the studied dynamics. Here, exceptional variations are based on structural changes and external shocks (e.g., VAT introduction in April, 2013). The introduction of these variables contributes a more precise estimation of the controlled factors.

11 The test results are shown in Appendix.

Graph 2. Real and model estimated inflation in the period Jan 2011 to Dec 2012



Source: Author's calculations

Table 3. Forecast evaluation statistics of the chosen VAR model

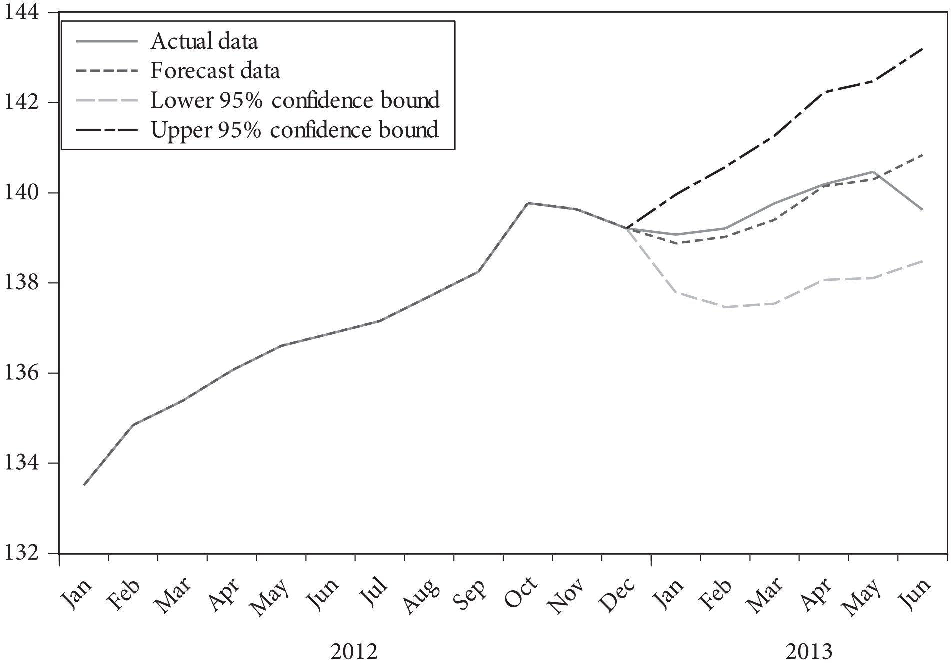
Statistics	Horizon					
	1	*2*	*3*	*4*	*5*	*6*
MSE	0.020	0.020	0.045	0.034	0.032	4.699
RMSE	0.141	0.141	0.213	0.185	0.178	2.168
MAE	0.141	0.141	0.198	0.151	0.151	1.972
MAPE	0.102	0.101	0.142	0.109	0.108	1.080

Source: Author's calculations

The very low values of the statistics in Table 3 indicate that there are excellent forecasting results for five periods ahead, but an overestimation in the sixth month.

Graph 3 gives a very clear impression of the quality of the inflation forecast when the VAR model is applied, where the forecast inflation largely coincides with the real inflation. However, the forecast results of this model will be re-estimated while comparing them with the factor model.

Graph 3. Real and model estimated inflation of the VAR model for the first six months of 2013.



Source: Author's calculations

(B) Principal components analysis and factor model

The first part of the construction of the forecasting model, the method of principal components, is implemented in the set of twelve available monthly time series for the period 2001-2012.

The main findings of the principal components analysis are presented in the following table.

Table 4. Eigenvalues and eigenvectors from the set of 12 variables

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	8.669329	7.150340	0.7224	8.669329	0.7224
2	1.518989	0.738791	0.1266	10.18832	0.8490
3	0.780198	0.253443	0.0650	10.96852	0.9140
4	0.526755	0.334367	0.0439	11.49527	0.9579
⋮	⋮	⋮	⋮	⋮	⋮
12	0.000497	---	0.0000	12.00000	1.0000

Eigenvectors (loadings):	Variable	EU	COMM	CPI	EMPL	F_B	FUEL	GROSW	HICP	INDPR	T_A	T_N	NETW
	PC 1	0.2785	0.3212	0.3255	0.3069	0.3276	0.3142	0.3303	0.0031	-0.1338	0.3098	0.2850	0.3300
	PC 2	0.118	0.2108	-0.072	-0.204	0.100	0.237	-0.0627	0.740	0.5190	-0.014	-0.002	-0.088

Source: Author's calculations

Based on the results presented in Table 4, we can see that 85% of the total variance in the data is explained by the first two principal components, and the first four components explain more than 95% of variation in the data set. The first of the components explains the maximum variance - in this case, even 72.24%. The first component is computed as a linear combination of all series in the observed group, covering the maximum of their variances; hence it could be considered as a constructed index from 12 time series. The second principal component is again a linear combination of all 12 series, orthogonal on the first (completely independent from the first), explaining about 12.66% of variation in the data.

According to Kaiser criteria, for this analysis we can consider only the first two components as relevant, with eigenvalues higher than one.

If we insist on the interpretability of the components, the inspection of the correlation between the original variables and the principal components could signal that the first principal component is primarily characterized by prices (of imported goods), and the second by economic activity.

Using Akaike information criteria, we estimated the optimal lag length that should be included in the model and got the following specification:

Table 5. The factor model

Dependent Variable: CPI		Sample (adjusted): 2001M07 2012M12		
Method: Least Squares		Included observations: 138 after adjustments		
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
CPI(-1)	0.958127	0.013396	71.52371	0.0000
F1(-1)	0.190274	0.071839	2.648606	0.0091
F2(-6)	0.077748	0.041817	1.859242	0.0653
MAR11	2.330736	0.611019	3.814509	0.0002
APRIL3	2.509697	0.610775	4.109040	0.0001
NOV01	2.155754	0.621910	3.466342	0.0007
JUL06	-1.762659	0.609153	-2.893621	0.0045
C	5.130533	1.514417	3.387793	0.0009
Adjusted R-squared (0.998538), S.E. of regression (47.62550), Durbin-Watson stat (1.899)				

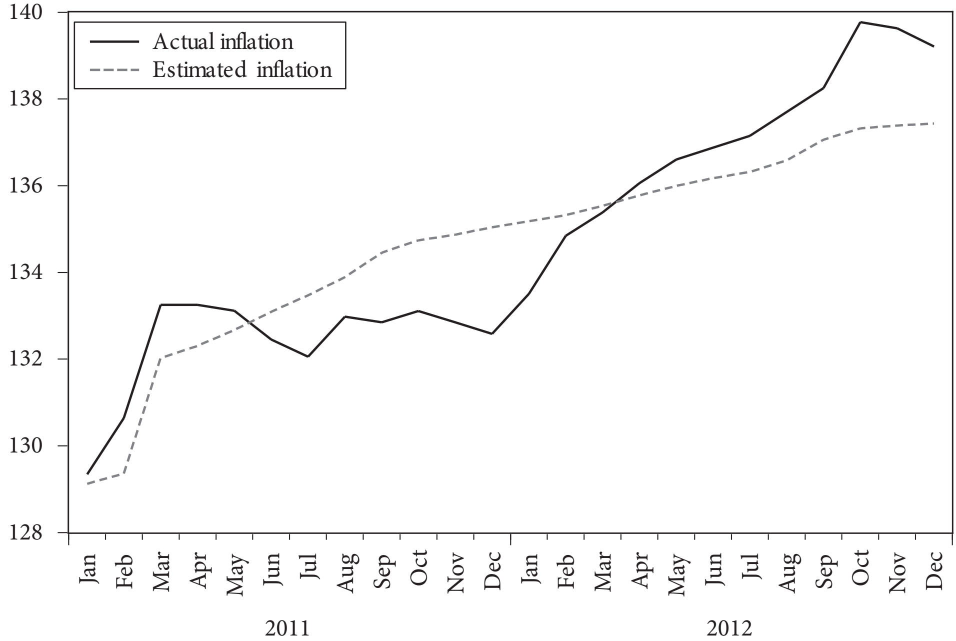
Source: Author's calculations

Due to the results of the relevant statistical and econometric tests[12] (residual normality test, autocorrelation test, heteroscedasticity test), it can be concluded that the estimated model of principal components is satisfactory. The presence of the lag-dependent variable as a regressor, as well as the dynamic structure of the model (impact of original variables from different periods) contributes to this conclusion.

The inflation simulation is made for the period Jan 2011 to Dec 2012. The next graph presents the series of the original and model estimated data.

12 Results of the tests are reported in Appendix.

Graph 4. Actual and estimated inflation from the factor model in the period Jan 2011-Dec 2012



Source: Author's calculations

For the purpose of prognosis, it is necessary to explain the procedure of getting the values of factors for a period of prognosis. Bearing in mind that the aim of this paper is to compare the forecasting performance of different models, for out-of-sample factor estimation we used already known (statistically published) data for the first six months of 2013. In practice, however, prognoses are made on the basis of predicted movements of the relevant factors (or their combinations). That is why the so-called factor model is sometimes less reliable, with more chance of making a mistake, so that in practice autoregression models (univariate or multivariate) are more often used. However, predictions made by factor models are not only conditional but could also be alternatively given for different values of future determinants of inflation, in order to undertake corrective action if and where possible.

Therefore, for this comparison analysis, the known values of independent variables (out-of-sample) are used. Based on the model given in Table 5, we got the price indexes as a measure of inflation for the first six months of 2013. The appropriate calculated statistics (indicators) in the process of evaluation of the forecast, signal that inflation could be forecasted very well with this model for the two- to three-step forecasting horizon, after which the forecasting error suddenly rises, to diminish again at the end of the prognostic periods.

Table 6. Evaluating factor model prognosis

Statistics	Horizon					
	1	*2*	*3*	*4*	*5*	*6*
MSE	0.017	0.009	0.085	0.284	0.542	0.471
RMSE	0.132	0.095	0.291	0.533	0.737	0.686
MAE	0.132	0.079	0.215	0.396	0.568	0.529
MAPE	0.095	0.057	0.154	0.283	0.405	0.378

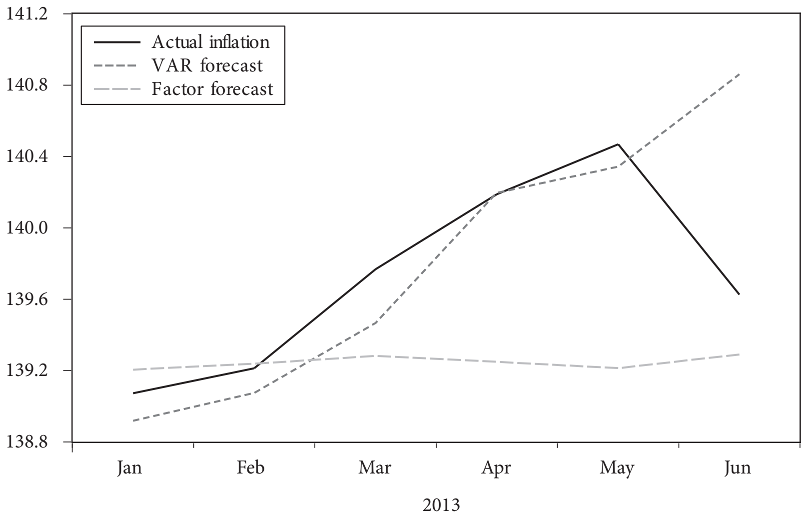
Source: Author's calculations

(C) Comparison analysis: VAR versus Factor model

After estimating the two models that best fit the data and testing their individual forecast qualities, here we make a comparison of the obtained forecasts and conclude which one gives better forecasting results in the period of the first six months of 2013.

Graphic presentation of the forecasted values of both models, together with the original data, is given in Graph 5.

Graph 5. Actual inflation and model forecasts



Source: Author's calculations

In Table 7 we give MSE statistics (the most often used measure for comparing the forecasting performance of two or more concurrent models) for a one to six month horizon. The best prognosis is the one with the smallest value of MSE statistics. It is clear from Graph 5, and especially from Table 7, that the factor forecasts in the horizon of the two periods is very close to the actual data, and that VAR model forecasts show smaller deviations from the real data for periods 3-5, while the sudden change in the inflation dynamics in June 2013 is better forecast by the factor model.

Table 7. MSE statistics in absolute values

Model	Horizon					
	1	*2*	*3*	*4*	*5*	*6*
VAR	0.020	0.020	0.045	0.034	0.040	4.699
Factor	0.017	0.009	0.085	0.284	0.542	0.472

Source: Author's calculations

4. CONCLUSIONS

Despite the fact that forecasting is difficult under the conditions of a short series of relatively bad quality in a period of massive structural economic change (introduction of VAT and the euro, and the global financial crisis), it can be concluded that the results of the presented forecasting models are not negligible and could have an important use value for further work in this field.

The results of this analysis show that for inflation forecasting in Montenegro, information from a larger group of variables representing domestic economic activity are relevant. The inclusion of a larger number of variables determining inflation in Montenegro leads to better prognoses, possibly especially in the longer term.

However, the presented analysis is not rigorous as it is carried out on the basis of concrete selected models, and with possible improvements it may be realistically expected that the results would be different. It should also be kept in mind that the use of additional information, however much it contributes to the improvement of the prognosis of the value of the dependent variable, demands independent prognoses of the factors used in the forecasting period, and therefore independent errors are possible, on top of potential errors in the very construction and choice of the forecasting model.

However, this analysis establishes guidelines for further work and some open questions for the improvement of the existing forecasting models, which will be possible to apply when the quality and quantity of the statistical base significantly improves. For example, it would be particularly interesting to examine the possibility of inclusion of other variables relevant to the movement of prices within the vector autoregression model, when the relevant data become available. Further, the estimation of the lag length of variables in the VAR model is a very interesting econometric question which is always challenging for a researcher, so the quality of the model is largely dependent both on the included variables and their lags and on possible external factors (trends, incidental shocks, etc.).

Additional questions relate to the factor models. The number of factors included in the forecasting model is relevant for the construction and quality of the factor model. Does a model with one, two, or more factors give better forecasting results? What criterion should be used for its determination? Also, in the construction of the principal components, a data availability issue emerges regarding relevant economic series, especially their values in the forecasting period. These and many other questions are a challenge for further research in this field, and so far remain unexplored in Montenegro.

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APPENDIX[13]

(1) Normality test for estimated VAR model

VAR Residual Normality Tests				
Orthogonalization: Cholesky (Lutkepohl)				
Null Hypothesis: residuals are multivariate normal				
Sample: 2001M01 2012M12				
Included observations: 130				
Component	Skewness	Chi-sq	df	Prob.
1	-0.103363	0.231484	1	0.6304
2	-0.296902	1.909938	1	0.1670
3	0.329654	2.354555	1	0.1249
Joint		4.495977	3	**0.2126**
Component	Kurtosis	Chi-sq	df	Prob.
1	3.222630	0.268471	1	0.6044
2	3.524588	1.490628	1	0.2221
3	3.779324	3.289793	1	0.0697
Joint		5.048892	3	**0.1683**
Component	Jarque-Bera	df	Prob.	
1	0.499955	2	0.7788	
2	3.400566	2	0.1826	
3	5.644348	2	0.0595	
Joint	9.544869	6	**0.1452**	

13 The presented results are extracted from econometric software Eviews 7.

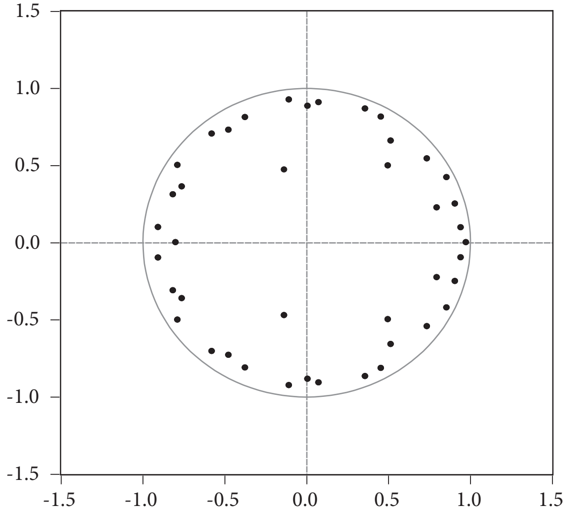
(2) Serial correlation LM test for estimated VAR model

VAR Residual Serial Correlation LM Tests		
Null Hypothesis: no serial correlation at lag order h		
Sample: 2001M01 2012M12		
Included observations: 130		
Lags	LM-Stat	Prob
1	2.943520	0.9665
2	15.44756	0.0794
3	9.912380	0.3576
4	13.11433	0.1575
5	13.77400	0.1306
6	9.623583	0.3818
7	6.401134	0.6992
8	5.423798	0.7959
9	3.190739	0.9562
10	6.302696	0.7093
11	10.14796	0.3386
12	4.884999	0.8442
13	6.729645	0.6652
14	7.656421	0.5691

(3) Heteroskedasticity test for estimated VAR model

VAR Residual Heteroskedasticity Tests: No Cross Terms (only levels and squares)					
Sample: 2001M01 2012M12					
Included observations: 130					
Joint test:					
Chi-sq	df	Prob.			
591.4642	552	**0.1189**			
Individual components:					
Dependent	R-squared	F(92,37)	Prob.	Chi-sq(92)	Prob.
res1*res1	0.792102	1.532304	0.0729	102.9733	0.2040
res2*res2	0.784843	1.467040	0.0956	102.0296	0.2228
res3*res3	0.775817	1.391777	0.1299	100.8562	0.2477
res2*res1	0.667405	0.807025	0.7956	86.76261	0.6347
res3*res1	0.781127	1.435301	0.1089	101.5465	0.2328
res3*res2	0.706285	0.967093	0.5638	91.81709	0.4858

(4) Inverse Roots of AR Characteristic Polynomial (stable VAR model)



(5) Heteroskedasticity test for estimated factor model

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	1.221578	Prob. F(7,130)	**0.2955**
Obs*R-squared	8.517038	Prob. Chi-Square(7)	**0.2892**
Scaled explained SS	9.951713	Prob. Chi-Square(7)	**0.1913**

(6) Residual autocorrelation test for estimated factor model

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.299171	Prob. F(2,128)	**0.7419**
Obs*R-squared	0.642086	Prob. Chi-Square(2)	**0.7254**

(7) Normality test for estimated factor model

Jarque-Bera	4.812748
Probability	**0.097142**

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