APPLICATION OF VECTOR AUTOREGRESSION MODEL FOR LITHUANIAN INFLATION

Ana Cuvak[1], Zilvinas Kalinauskas[2]
Vilnius Gediminas Technical University, Lithuania, [1]ana.cuvak@fm.vgtu.lt, [2]zkalinauskas@lb.lt

Abstract

Inflation is one of the crucial modern macroeconomic problems. Nowadays the issue of inflation is very relevant. Inflation is a constant and consistent increase in the general price level in the country, due to which the purchasing power of a national currency unit decreases. In practice, the measures of inflation are various price indices, such as a consumer price index (CPI), producer price index (PPI), or gross domestic product deflator. However, inflation is usually defined as a change in the HCPI over a year. Time series models, linear regression models and a vector autoregression model (VAR) can be used to model and forecast inflation processes. This paper examines Lithuanian consumer price inflation using a modern stationary time series and econometric theory. The vector autoregression model is proposed for inflation modelling. Theoretical aspects of model estimation are reviewed: time series stationarity, model identification, parameter estimation, model usage and forecasts. The stationarity of the HCPI index and exogenous variables are analyzed using the Augmented Dickey–Fuller (ADF) test. A vector autoregression model of Lithuanian inflation processes is investigated and proposed for inflation modelling. The obtained model is used for forecasting purposes and shows a fairly high degree of accuracy of the inflation forecast in the coming 12-month period.

Keywords: inflation, HCPI, vector autoregression model, stationary.

Introduction

Inflation is a constant and consistent increase in the general price level in the country, due to which the purchasing power of a national currency unit decreases. Inflation is one of the most burning and complicated issues of modern macroeconomics. Inflationary process has an impact on all macroeconomic indicators, especially, gross domestic product, external trade, the exchange and interest rates. Importance of inflation forecasts is substantial for decision-making in financial markets, especially in the turmoil periods. Every banker shall make a decision on the interest rate policy taking into account the inflation expectation and forecast. One of the most important relationships, which are discussed among economists, is relationship between inflation and money supply. As it is known from the economic theory, monetary indicators has a direct impact on inflation in a specific country, but there are discussions on the vice versa relation, i.e. development of monetary indicators depends on inflation in countries with fixed exchange rate or currency board.

Recently, the Lithuanian economy has been living through tough years: prices for essential food products, fuel, heating have been constantly growing. A constant growth in prices for goods and services provides a background not only to talking about inflation but also to expressing those processes as mathematical equations, i.e. modelling inflation processes, applying those models to the forecasting of inflation, as well as putting forward proposals concerning the reduction of inflation rates, more and more often.

In practice, the measures of inflation are various price indices, such as a consumer price index (CPI), producer price index (PPI), or gross domestic product deflator. Moreover, price trends are also shown by the indices of the unit value of exported (imported) goods, construction prices, and agricultural production purchase prices. However, inflation is usually defined as a change in the HCPI over a year.

The objective of this research is to calculate short-term inflation forecasts by applying a vector autoregression (VAR) model. Further in the article, the said model will be referred to as a **L**ithuanian **v**ector **a**utoregression (LVAR) model.

A question might arise as to why the VAR model is used, but not just separate regression equations or the so-called multi-equation econometric (structural) model? The question cannot be answered in any simple way, and yet the VAR model has several advantages. Usually, economics experts take a particular interest in short-term price changes (up to 12 months). In this case, time series models (VAR is part of these models) could be more advantageous than structural econometric models because the latter are more suitable for the analysis of propositions of econometric theory and are characterised by a smaller forecasting capacity. Secondly, most of the modern authors (e.g. Enders (1995), Fildes, Stekler (2000)) present time series models as an alternative to large structural models. In many cases, time series models do not confirm forecasts

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calculated based on structural econometric models. The latter models are designed according to economic theory, while to the estimates of their parameters various restrictions are applied. The main restriction is the so-called elimination restriction, which means that the variable, which does not explain the forecasted behaviour of the indicator from the economic point of view, must be removed from the model, even if it is statistically significant in the model. It was Sims (1980) who started criticising structural models. He stated that when forecasts of trends in an economic indicator are made, it is the striving for the accuracy of the forecast (i.e. obtaining the mean square errors of the forecast which would be as small as possible) that should be considered as the main objective, but not just the following of postulates of economic theory. The elimination restriction was the factor that made mathematicians and economist look for an alternative to structural econometric models in order to more precisely forecast changes in an economic indicator and avoid the impact of the elimination restriction on results. Enders (1995), Fritzer et al. (2002), Lutkepol (2001), Lutkepol (2003) and many other authors suggest that for the calculation of forecasts of economic indicators VAR models should be applied because all variables in these models are endogenous, and, therefore, not a single variable may be removed when explanations for the behaviour of other variables are offered. For the forecasting of economic indicators two types of VAR models may be applied: simple, or unrestricted, VAR models and models with certain restrictions on exogenous indicators present in them, or restricted VAR models.

Description of the model

For the modelling and forecasting of Lithuanian inflation, the HCPI is used. The Department of Statistics to the Government of the Republic of Lithuania publishes the said index broken down into 12, 38 and 93 groups of goods and services. In the present work, the indices of 12 groups of goods and services of the HCPI are modelled, which are denoted as follows: *V(1)* – the HCPI of food products and non-alcoholic beverages, *V(2)* – the HCPI of alcoholic beverages and tobacco products, *V(3)* – the HCPI of clothing and footwear, *V(4)* – the HCPI of housing, water, electricity, gas and other fuels, *V(5)* – the HCPI of furnishings, household equipment and routine maintenance, *V(6)* – the HCPI of health care, *V(7)* – the HCPI of transport, *V(8)* – the HCPI of communications, *V(9)* – the HCPI of recreation and culture, *V(10)* – the HCPI of education, *V(11)* – the HCPI of hotels, cafes and restaurants, *V(12)* – the HCPI of miscellaneous goods and services.

At first, a simple VAR model is designed (for further information, see Hamilton (1994), Enders (1995), Greene (2002)):

$$\boldsymbol{A}(L)\boldsymbol{V}_t = \boldsymbol{E}_t,\ t = 1, 2, \dots, T, \tag{1}$$

where: $\boldsymbol{V}_t$ – a 12 × 1 vector of endogenous indicators (HCPI groups of goods and services), $\boldsymbol{E}_t$ – a 12 × 1 vector of random errors, which may be mutually correlated, but may not be serially correlated, $\boldsymbol{A}(L)$ – polynomial matrix of the lag operator of *Lp* series:

$$\boldsymbol{A}(L) = I - A_1L - A_2L^2 - \dots - A_pL^p, \tag{2}$$

where A_s – 12 × 12 matrixes of parameters (s = 1, 2, …, p). In case of the Lithuanian HCPI, a VAR model LVAR(4) with four months lags (p = 1, 2, 3, 4) was analysed. Then the equation of the HCPI of the i-th group of goods and services would look as follows:

$$V_t(i) = \sum_{i=1}^{12}\sum_{j=1}^{4} a_{i,j}V_{t-j}(i) + c(i) + e_t(i),\ \ t = 1, 2, \dots, T, \tag{3}$$

(In this case, j may be left unchanged; however, it would be better to replace it with p because above in the article the number of lags was denoted in such a manner.) where: c – a constant term (a constant), $a_{i,j}$ – elements (parameters) of matrix $\boldsymbol{A}$. Indices i and j, respectively, denote groups of goods and services (from 1 to 12) and the number of lags (from 1 to 4). Lithuania is a small country with an open economy. Therefore, the price level within the country depends not only on internal factors but also on economic changes in the external environment. In this work, world oil price (in LTL per barrel), denoted *p_oil*, was selected as a factor reflecting the external environment (exogenous indicator). As model (1) is complemented by vector $\boldsymbol{X}$ of exogenous indicators, a new LVAR(4) model is obtained:

$$\boldsymbol{A}(L)\boldsymbol{V}_t = \boldsymbol{G}\boldsymbol{X}_t + \boldsymbol{E}_t,\qquad t = 1, 2, \dots, T, \tag{4}$$

where: $\boldsymbol{G}$ – a 12 × 12 matrix of unknown parameters.

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LVAR(4) model estimation

The number of parameters estimated in the full model is 636. After stationarity tests had been carried out, it was figured out that from around January 2002 processes satisfy the conditions of stationarity. Therefore, the size of the sample of data used for parameter estimation made 143 observations (January 2002–December 2007). For the calculation of parameter estimates, a least squares method was used. The significance of parameter estimates is checked based on the Student's t-statistics. The value of a t-statistic is increasing by 0.3 in the interval [0.3; 2.1], i.e. the indicators the t-statistic of whose parameter estimates is lower than 2.1 are removed from equations. After each cycle, the values of insignificant coefficients are set equal to 0. Vector autoregression models are applied to the modelling of stationary time series. Therefore, the stationarity of all 12 HCPI groups was checked. For the checking of the stationarity of time series, an augmented Dickey–Fuller (ADF) test was used. Moreover, a deterministic factor (a constant) was included in the specification of the test equation because the actual process generating the observations is unknown. Time series of these groups may be considered to be stationary from January 2002 because t-statistics are lower than critical values (the critical value of a 1% significance level equals –3.5111, 5% – –2.8967, 10% – –2.5853). The test results are provided in the table below.

Table 1. ADF unit root test results for the time series of 12 HCPI groups (January 2002–December 2007)

Variable	Deterministic part	t-statistic of the parameter γ
V(1)	constant α	−5.2481
V(2)	–”–	−7.1823
V(3)	–”–	−5.5534
V(4)	–”–	−6.4036
V(5)	–”–	−9.2022
V(6)	–”–	−5.9940
V(7)	–”–	−8.6571
V(8)	–”–	−9.4433
V(9)	–”–	−5.9123
V(10)	–”–	−8.0569
V(11)	–”–	−6.0166
V(12)	–”–	−6.2848

Further in the article in the table 2, the equations of all 12 HCPI groups with numerical values of parameter estimates and their significance levels (in parenthesis), i.e. the probability that the value of a parameter estimator will be equal to 0, are provided. Relative coefficients of determination ($\overline{R}^2$), Durbin–Watson (DW) statistics, showing autocorrelation of errors, are also provided in the table.

Table 2. LVAR(4) model estimated equations of all 12 HCPI groups

HCPI group equation	$\overline{R}^2$	DW
$V(1) = \underset{(0.000)}{0.273\cdot V_{t-1}(1)} \underset{(0.000)}{-0.408\cdot V_{t-4}(1)} - \underset{(0.001)}{0.430\cdot V_{t-3}(2)} - \underset{(0.000)}{0.114\cdot V_{t-3}(3)} + \underset{(0.001)}{0.280\cdot V_{t-3}(4)} +$ $+ \underset{(0.000)}{0.807\cdot V_{t-4}(5)} + \underset{(0.001)}{0.302\cdot V_{t-1}(10)} + \underset{(0.000)}{0.295\cdot V_{t-2}(12)} - \underset{(0.001)}{0.021\cdot p\_oil_{t-2}}$	0.59	1.82
$V(2) = \underset{(0.000)}{0.855\cdot V_{t-3}(6)} + \underset{(0.000)}{0.069\cdot V_{t-2}(8)} + \underset{(0.000)}{0.109\cdot V_{t-3}(8)} + \underset{(0.000)}{0.601\cdot V_{t-3}(9)} - \underset{(0.002)}{0.030\cdot p\_oil_{-3}}$	0.81	1.54
$V(3) = \underset{(0.000)}{-0.774\cdot V_{t-2}(1)} - \underset{(0.032)}{0.687\cdot V_{t-2}(2)} + \underset{(0.000)}{1.107\cdot V_{t-4}(2)} + \underset{(0.000)}{0.300\cdot V_{t-1}(3)} - \underset{(0.000)}{0.539\cdot V_{t-2}(3)} -$ $- \underset{(0.001)}{0.450V_{t-4}(3)} + \underset{(0.000)}{0.453\cdot V_{t-3}(4)} - \underset{(0.001)}{0.629\cdot V_{t-4}(4)} + \underset{(0.002)}{0.919\cdot V_{t-4}(6)} - \underset{(0.020)}{0.241\cdot V_{t-3}(7)} +$ $+ \underset{(0.000)}{1.090\cdot V_{t-2}(9)} + \underset{(0.001)}{0.444\cdot V_{t-4}(12)}$	0.84	1.73
$V(4) = \underset{(0.000)}{0.272\cdot V_{t-1}(1)} + \underset{(0.000)}{0.090\cdot V_{t-4}(3)} + \underset{(0.000)}{0.577\cdot V_{t-3}(5)} - \underset{(0.000)}{0.213\cdot V_{t-1}(6)} - \underset{(0.005)}{0.3987\cdot V_{t-2}(6)} +$ $+ \underset{(0.012)}{0.382\cdot V_{t-3}(6)} + \underset{(0.001)}{0.703\cdot V_{t-3}(11)} - \underset{(0.000)}{0.409\cdot V_{t-3}(12)}$	0.57	2.12

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$V5 = -\underset{(0.029)}{0.048}\cdot V_{t-3}(3) + \underset{(0.000)}{0.022}\cdot V_{t-4}(3) + \underset{(0.000)}{0.251}\cdot V_{t-3}(5) + \underset{(0.000)}{0.661}\cdot V_{t-4}(5) - \underset{(0.000)}{0.054}\cdot V_{t-1}(7) + \underset{(0.026)}{0.157}\cdot V_{t-1}(11) + \underset{(0.029)}{0.010}\cdot p\_oil_{-1}$	0.65	2.23
$V(6) = \underset{(0.001)}{0.153}\cdot V_{t-2}(1) + \underset{(0.000)}{0.575}\cdot V_{t-1}(5) + \underset{(0.000)}{0.507}\cdot V_{t-2}(5) - \underset{(0.007)}{0.503}\cdot V_{t-3}(5) + \underset{(0.002)}{0.293}\cdot V_{t-2}(6) - \underset{(0.017)}{0.076}\cdot V_{t-3}(10) + \underset{(0.009)}{0.185}\cdot V_{t-1}(11) - \underset{(0.008)}{0.133}\cdot V_{t-3}(12) + \underset{(0.000)}{1.005}$	0.49	1.62
$V(7) = \underset{(0.001)}{0.440}\cdot V_{t-1}(1) + \underset{(0.000)}{0.866}\cdot V_{t-2}(9) - \underset{(0.000)}{0.371}\cdot V_{t-1}(10) + \underset{(0.001)}{0.068}\cdot p\_oil_{-1}$	0.38	2.09
$V(8) = \underset{(0.001)}{0.370}\cdot V_{t-2}(4) + \underset{(0.000)}{0.326}\cdot V_{t-7}(3) + \underset{(0.000)}{0.300}\cdot V_{t-2}(8)$	0.43	1.98
$V(9) = -\underset{(0.001)}{0.413}\cdot V_{t-2}(2) - \underset{(0.000)}{0.290}\cdot V_{t-3}(2) + \underset{(0.000)}{0.043}\cdot V_{t-4}(3) - \underset{(0.007)}{0.272}\cdot V_{t-2}(9) - .128\cdot V_{t-3}(10) + \underset{(0.017)}{0.524}\cdot V_{t-1}(11) - \underset{(0.036)}{0.141}\cdot V_{-4}(12) + \underset{(0.000)}{1.187}$	0.45	1.94
$V(10) = \underset{(0.000)}{0.350}\cdot V_{-3}(4) - \underset{(0.001)}{0.267}\cdot V_{-2}(8) + \underset{(0.001)}{0.917}\cdot V_{-2}(9)$	0.36	2.02
$V(11) = \underset{(0.001)}{0.186}\cdot V_{t-2}(1) + \underset{(0.001)}{0.212}\cdot V_{t-2}(2) + \underset{(0.000)}{0.130}\cdot V_{t-4}(4) + \underset{(0.004)}{0.362}\cdot V_{t-1}(5) + 0.237\cdot V_{t-3}(11) - \underset{(0.000)}{0.127}\cdot V_{t-4}(12)$	0.59	2.29
$V(12) = \underset{(0.001)}{0.265}\cdot V_{t-1}(1) + \underset{(0.001)}{0.736}\cdot V_{t-2}(2) - \underset{(0.015)}{0.454}\cdot V_{t-3}(2) + \underset{(0.000)}{0.691}\cdot V_{t-3}(5) - \underset{(0.000)}{0.237}\cdot V_{t-1}(10)$	0.33	1.87

In Figure 1 below, actual and model-based (baseline) curves of each monthly HCPI group are pictured (the y – axis presents the *HCPI change,* and the x – axis is a *Year*).

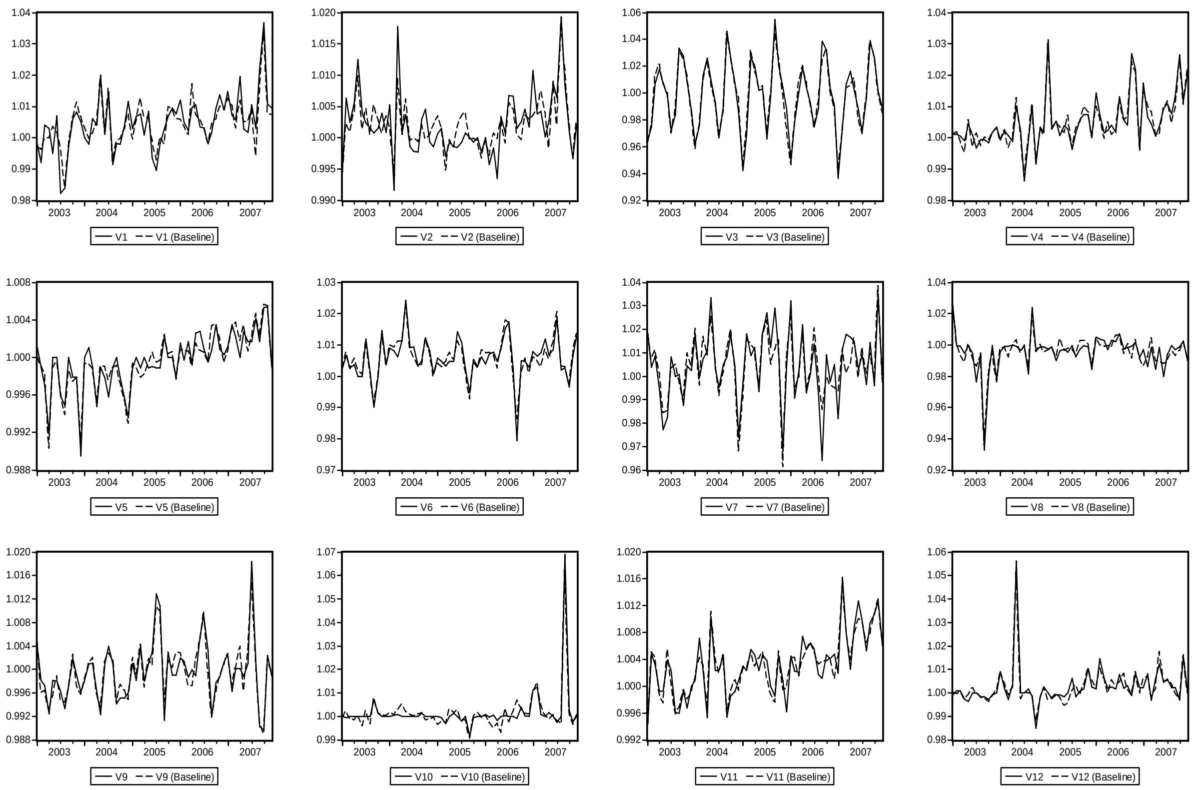

Figure 1. Actual and LVAR(4)model-based curves of 12 HCPI groups

As it is seen from the charts, the above-applied model quite accurately describes the development of all 12 groups of the HCPI. In all cases the accuracy does not exceed 10 per cent, while for some groups does

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not exceed 1 per cent. Hence, LVAR(4) model can be used to forecast the short-term development of Lithuania's inflation.

LVAR(4) model-based HCPI forecasts

By applying the estimated LVAR(4) model comprising 12 equations, inflation forecasts up to the end of the year 2008 were calculated. When forecasts of an exogenous indicator included in the model were being prepared, a premise that for the forecast of world oil prices the oil process of futures contracts up to December 2008 had been used was followed. The forecasts calculated for each group were used for the calculation of the forecast of the overall HCPI.

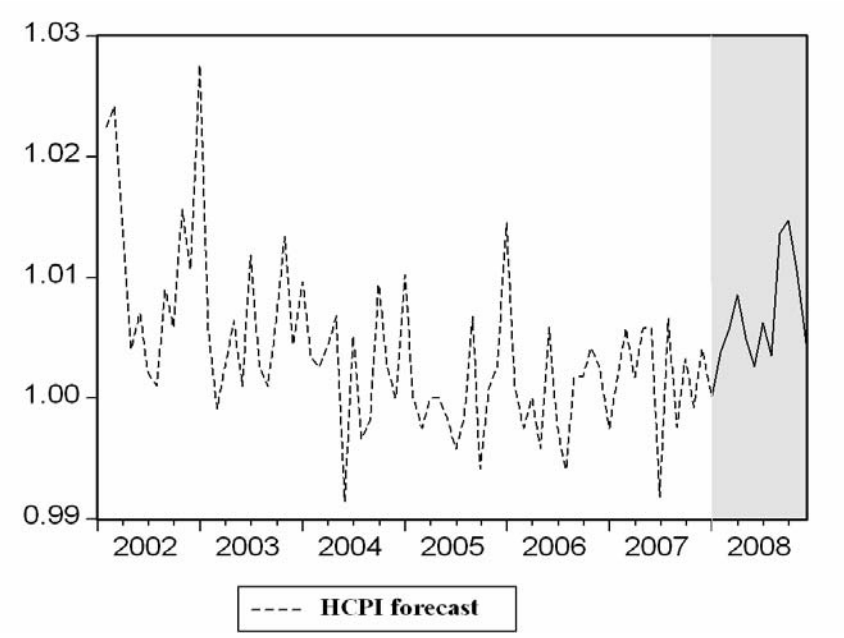

Figure 2. LVAR(4) model-based forecasts for HCPI

In Figure 2 the forecast of the overall HCPI up to the curve of the end of 2008 (the coloured time interval) is pictured (the y – axis presents the *HCPI change,* and the x – axis is a *Year*). The model forecast is very accurate and according to real inflation changes in year 2008 LVAR(4) model estimated forecast does not exceed 1% percent estimation error. It means the LVAR(4) model is suitable to forecast inflationary process in Lithuania.

Conclusions

The designed LVAR(4) model comprising 12 equations is not a perfect one, which is because of a high number of parameters estimated, while the definability of some equations is relatively low (a low relative coefficient of determination). However, they may be applied to the forecasting of inflation because the mean square errors of the forecast conform to the selected minimum criteria (1 or 5% should be mentioned). When inflation forecasts were being prepared, only the forecasts of endogenous indicators and the exogenous indicator (world oil price) included in the model were taken into account; however, the impact of the national fiscal policy and state administered price trends should also be taken cognisance of. One of the main drawbacks of the LVAR(4) model, where the VAR methodology is used, is the fact that each time additional observations appear and the model is estimated anew the equation of each HCPI group may be complemented (or reduced) by different variables. However, given stable parameters, the accuracy of results is not damaged. Nevertheless, the designing of a structural VAR or multi-equation econometric model for the forecasting of the HCPI should probably be considered in future.

According to the accuracy of the forecast calculated by the LVAR(4) model, this model could be suggested as a tool applied by the economists-analysts in the decision making procedure.

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References

1. Enders, W. (1995). Applied Econometric Time Series. New York: John Wiley&Sons.
2. Fildes, R., Stekler, H. (2000). The State of Macroeconomic Forecasting. Lancaster University, Discussion Paper, No 99–04.
3. Fritzer, F., Moser, G., Scharler, J. (2002). Forecasting Austrian HCPI and its Components using VAR and ARIMA Models. Oesterreichische National bank, Working Paper, No 73.
4. Greene, W. H. (1997). Econometric Analysis. Prentice Hall.
5. Hamilton, J. (1994). Time Series Analysis. Princeton: Princeton University Press.
6. Lutkepol, H. (2001). Vector Autoregressive and Vector Error Correction Models. Institute of Statistics and Econometrics.
7. Lutkepol, H. (2003). Vector Autoregression Models. Companion to Theoretical Econometrics.
8. Sims, C. (1980). Macroeconomics and Reality. Econometrics, No 48: 1–48.