VARX Model Using Leading Cycles[1]

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Abstract

Composite leading indicators serve to the purpose of early identification of the stage of business cycle and its turning points. The indicators are constructed on the basis of statistical analysis for predicting the phase of business cycle via the VARX model approach. The model of Slovakia is composed of three variables: gross domestic product as reference series (endogenous variable), composite leading indicator for the domestic economy (endogenous variable) and composite leading indicator of external environment (exogenous variable). The quality of the model is verified using statistical tests of stationarity and causality of variables and tests of residuals. The VARX model exhibits some ability to adapt to changes of the business cycle, but the quantitative projections are rather unable to predict accurately the turning points.

Keywords: *business cycle, VARX model, leading indicators, small and open economy*

JEL Classification: C32, C52, C53, E32, E37

1. Introduction

Business cycles represent the co-movement of macroeconomic variables in basic phases of the cycle (recession, expansion), while in some areas it is reflected earlier than in others. The foundations of this thesis were laid by Burns and Mitchell (1946) preceded by the basics of business cycles empirical analysis by Mitchell (1913 and 1927). Later the approach (also called the “NBER[2] approach”) was criticized due to disconnection from scientific method approaches and the

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[2] National Bureau of Economic Research.

lack of economic theory (e.g. Koopmans, 1947). But it is still used today, e.g. in the methodology of leading indicators construction by the OECD or Conference Board, which use the so called indicator approach for business cycle analysis (construction of composite coincident and leading indicators). The methodology of NBER for leading indicators construction was applied for the Slovak economy by Bors et al. (1999) or Kľúčik (2010).

An alternative for the business cycle phases tracking is the modelling approach (Marcellino, 2006) which can be oriented either at unobserved variables of business cycle (Stock and Watson, 1999), regime switching models (Hamilton, 1989) or the classic VAR model. The VAR model can use for its estimation also leading indicators, as tested by Mendez, Kapetanios and Weale (1999), Cubadda and Hecq (2003), Fichtner, Rüffer and Schnatz (2009), and Savin and Winker (2011), allowing to observe also other properties of the model as for example the impulse response function.

The author's endeavour is oriented to find a suitable modelling approach for forecasting of small open economy (of which Slovak Republic represents a typical example) as follow up of previous research (e.g. Kľúčik, 2010), whereby the combination of VAR model and leading indicators can be most appropriate. VAR models were found to be useful for Slovakia's forecasts also in Banerjee, Marcellino and Masten (2005). The combination of VAR models and leading indicators' approach can be regarded as an original approach for forecasting small open economies.

The Slovak economy is facing major fluctuations of economic activities of its major trading partners and thus is exposed significantly to the global business cycle. For government agencies that make decisions about economic policy and for investors who make decisions about business activities in the future it is important to recognize the risk of market policies, especially with emphasis on the timeliness of information on the current direction of economic activities in the market. Given that traditional statistical indicators are available with considerable delay (gross domestic product – GDP, industry indicators), in practice, the leading indicators are often used as a tool for forecasting of economic activities.

This paper aims at identifying composite leading indicators for the Slovak economy through statistical and empirical analysis and to estimate VAR model making use of the domestic composite leading indicator (endogenous variable), composite leading indicator of the external environment (exogenous variable) and GDP as reference series (endogenous variable). The predictive ability of such model is tested in the last section of this paper.

2. Leading Indicators Identification

The analysis comprises quarterly data sample from 1997 till the 3rd quarter of 2011 (higher frequency data would require an approximation of GDP). The author's own database of time series is assembled using data from Statistical Office of Slovak Republic (SO SR), National Bank of Slovakia (NBS), Eurostat, OECD, ECB, IMF etc. This incorporates not only statistics concerning Slovakia but also foreign countries, specifically, Slovak main trading partners in trading of goods. The inclusion of foreign data reacts to the fact that Slovakia's economy openness, measured as the share of total exports and imports of goods on GDP in current prices, is exceptionally high – 148% (SO SR, year 2010). The main trading partners are according the data of SO SR for the year 2010 (trading of goods) the EU countries (75%), Asia countries with 13% share (of what China and South Korea comprise two thirds) and Russia with 7%. From the EU countries the main partners are Germany (17% from total goods trade), Czech Republic (12%), Poland (6%), Austria, Hungary, France (all 5%) and Italy (4% – comparable level to China). The target time series are from the areas of production, wages, prices and employment of main branches of economy (industry, retail trade, services), also money aggregates, exchange rates, share indexes, price indexes and finally, qualitative data (consumer and business tendency surveys). Together the database comprises over 10 thousand time series. This database represents the subject of leading indicator selection through identification of the relation with reference series (GDP).

2.1. Selection Criteria

According to the OECD methodology (OECD, 2008) the leading indicators should be in line with the following criteria: economic significance, breadth of coverage, frequency, revision, timeliness and length of time series. These criteria have to be taken into account in the selection process. This paper does not follow the criteria of frequency (higher frequency preferred) nor checks the time series for revision frequency. The main reason is that it is difficult to find an approximation of such indicator as GDP on monthly basis and that such amount of time series cannot be ranked according to revision frequency in reasonable time. The leading indicators can be according to the OECD methodology one of the following type: early stage indicators, rapidly responsive indicators, expectation-sensitive indicators or prime movers.

Identification of the leading indicators is carried out by cross correlation computation. This provides the measure of the association strength between the reference series and individual time series in the database and also finds the average lead/lag time for the whole sample of the time series. The basic cross correlation measure is performed in econometric software package EViews (2007).

All-time series need to be in comparable form for the cross correlation computation. Year over year (yoy) transformations of original time series are used (transformed primarily to base indexes of 2005 = 100 and normalized with zero mean and unit standard deviation). The yoy transformation removes the seasonality from the time series. The transformation is done for all-time series except consumer and business tendency surveys which are in the form of balances already understood as deviations from trend. The yoy measures are referred to in business cycles analysis as growth rate cycles.

Five thousand time series are identified automatically as leading indicators from the database. According to the correlation coefficient of more than 0.5 and a lead of minimally 1 quarter, 1409 leading indicators are selected for the next step of composite indicators construction. The sensitivity analysis shows that the number of leading indicators increases roughly linearly with the level of correlation coefficient, the choice of 0.5 is arbitrary.[3]

3. VAR Model Construction

An unrestricted VAR model is going to be estimated including the reference series and leading indicators. The unrestricted VAR model is used mostly for forecasting of variables contrary to a structural VAR which can be used for modelling of shocks. As was mentioned earlier the planned VAR model should consist of three variables – reference series (GDP), composite leading indicator of domestic economy (endogenous variable) and composite leading indicator for external environment (exogenous variable). This is because the Slovak economy is a small economy and it is improbable that it can have causal impact on the performance of economies such Germany, Russia and other countries, while the endogenous variables of a VAR model should show both ways causality. Therefore the composite indicator of exogenous variables should be used in the VAR model, usually referred to as VARX model of the following form:

$$Y_t = a_0 + A_1 Y_{t-1} + ... + A_p Y_{t-p} + B_1 X_{t-1} + B_q X_{t-q} + E_t \qquad (1)$$

The matrices of parameters of endogenous variables (of vector Y_p) are denoted A_p and of exogenous variables (of vector X_p) as B_q, where p, q are lags. E_t is a vector of random disturbances and a_0 the constant. The variables have to satisfy

[3] The calculations have been carried out using EViews and the documents are available by request from the author.

certain conditions to be included in the VAR model. Firstly, it is more appropriate to use stationary data, so the models are able to eliminate the autocorrelation with fewer lags than in case of non-stationary data. Secondly, the causality between the endogenous series (both ways causality) or exogenous time series (one way) and the reference series should be verified by statistical means.

These two conditions are tested primarily (before the selection of appropriate indicators according to the OECD methodology) as there are too many potential leading indicators after the last step of analysis (1 409 indicators). The stationary time series are filtered from the database of 1 409 indicators in the first step, after that the causality between the individual time series and GDP is tested.

The stationarity is tested via the ADF test. The stationarity test is performed mechanically for all-time series by including the constant in the equation (i.e. assumption of average constant growth).

Causality between the evolvement of various variables can be verified by the Granger causality test. Granger causality test is used to verify that the series can be explained (predicted) by the development of the other time series or vice versa, i.e. the domestic and foreign time series can be used to predict the Slovak GDP as the reference cycle and vice versa. Four lags are chosen for the test, which is an arbitrary choice, believing a maximum one year shift between the variables is realistic. In case the variables are showing both-side causality it is included into the group of potential endogenous variables for the VAR model. In case of causality flowing from the side of the variable to the GDP, they are classified as exogenous variables, showing the possibility of predicting GDP of Slovakia using the exogenous variable (but not the other way around).

The result is 279 potential indicators of endogenous variables and 957 indicators for exogenous variables for the VARX model. In the next stage we have to choose the final indicators. According to Reijer (2010) a VAR model for small systems can be implemented only in composition of two to six variables. Given the limited dimensionality it is therefore necessary to aggregate a number of selected indicators into one composite indicator. The VARX model thus contains three variables – two endogenous variables (GDP, a composite indicator of endogenous variables) and one exogenous variable (a composite indicator for exogenous variables).

Selection of leading indicators follows the criteria of the OECD mentioned in Section 2.1. Most of the endogenous variables, i.e. with bilateral causality between a given variable and GDP do not satisfy the economic interpretability, i.e. they are not directly related to the development of GDP, their development is only close from the statistical point of view. Some indicators do not meet the criterion of timeliness (balance of payments) and sufficient coverage (detailed indicators of industry and foreign trade).

From the list of suitable endogenous leading indicators the consumer and business survey indicators are according to OECD methodology a type of indicator sensitive to expectations, it is a weighted index of the individual questions in the survey. Drivers are indicators of imports and exports. Indicators of early stages are new orders in industry. Indicators of rapid response are not found in the list of leading indicators for the endogenous variables of the VARX.

For composite indicator for endogenous variables four indicators are chosen:

Imports of goods, as a driver indicator, the import of goods into Slovakia is indicating an increase in economic activity (GDP), this may indicate an increase in domestic consumption or investment (expansion of production). *Sales in the industry,* it is an indicator driving the development of GDP and includes information about the production capacity of industry. *Competitive position of industrial enterprises in the EU market,* is a sensitive indicator of expectations, directly indicates the perceived position of industrial companies on the market and expected activities, it is part of the business tendency survey. *Industrial sales for exports,* reflects the development of export capacities of Slovak industry, it is a driving indicator for a small and open economy.

Much more variables have met the OECD criteria for exogenous variable: Index Dow Jones Euro Stoxx Eurozone – basic materials (source ECB), Commodity prices – non-fuel index, Commodity prices – food and beverage index (both IMF), Industrial new orders EU-27, Assessment of order books in Construction EU-27, Industrial confidence indicator EU-27, Employment expectations in Industry EU-27, Assessment of order-book levels in Industry EU-27, Production expectations in Industry EU-27, Production trend in Industry EU-27, Retail trade confidence indicator EU-27, Expected business situation in Retail trade EU-27, Orders placed with suppliers in Retail trade EU-27 and Present business situation in Retail trade EU-27 (all Eurostat).

As there are many combinations possible for constructing a composite indicator, a set of VARX models is chosen out of the combinations of different composite exogenous indicator and with identical composite endogenous indicator and GDP. This way the set of VARX models will compete with each other on behalf of the VARX model estimation criteria and the best one will be presented and used for forecasting of the GDP.

The composite leading indicators – endogenous and exogenous variables of the VARX model – are constructed on basis of simple average indices. Using equal weights in the composite indicator may not be optimal, but as pointed out by Marcellino (2006), in practice, the forecasts are sufficiently powerful.

The exogenous composite indicator (COMPEXOG) is used in the VARX models in time-shifted form (on the basis of lead of each variable), enabling also the feasibility of using the model for forecasting. The endogenous indicators in the composite endogenous indicator (COMPENDOG) are combined in the original non-shifted form because it is present in the VARX model only in lagged form.

By combining exogenous variables, using 4, 5, 6 and 7 variables (in order to limit the possible combinations due to computational demandingness), there exists 9 438 possible VARX models. After the ADF stationarity test of composite indicators 9 375 competing models remain in the set.

3.1. Model Estimation Criteria

When estimating a VARX model it is necessary to determine the number of lags. To determine the optimal number of lags usually information criteria are used like Akaike information criterion or Schwarz information criterion or others.

Determination of the optimal number of lags for the VAR model is just the preliminary step. The important criteria deciding about the usability and quality of the model are *stationarity of the VAR model, exogeneity test of endogenous variables, test of lag exclusions and residuals tests.*

The AIC criterion is used for the optimal lag determination. In testing it is counted with four maximum lags (an arbitrary choice as explained earlier) and the model of lag order with lowest value of AIC criterion is chosen.[4]

For each number of lags the models are tested by Wald statistics for significance of the variables for given number of lags (5% significance level). Non-significant lags are automatically excluded from the VARX model.

The primary condition of a VARX model is its stationarity, i.e. roots of autoregressive polynomials must have a value less than one, therefore, must lie inside the unit circle. Roots greater than one indicate instability of the model. The test indicates that all of the VARX models in the set of VARX models are stationary.

Using two-way Granger causality test it is checked whether the endogenous variables can be considered exogenous. Two variables are checked, i.e. endogenous and exogenous composite indicators and their relation to the GDP. The significance of variables on 5% level is checked on the basis of Wald statistics. The filter condition for the competing VARX models is that the Granger causality flows both ways in case of the endogenous composite indicator and one way in case of exogenous composite indicator (from exogenous environment to Slovak GDP). None of the VARX model from the set fulfils the mentioned condition. Therefore the condition is softened to 10% level, which produces 48 VARX models.

[4] The EViews software package offers another five information criterions; the results are predominantly identical.

Using the residual test the presence of autocorrelation in residuals is verified (Breusch-Godfrey LM test), normality of residuals (Cholesky orthogonalization) and presence of heteroskedasticity in the residuals (White test). Eight VARX models do not violate any of these test conditions at a 5% level significance. The best model is chosen according to the strongest hypothesis validation of absence of autocorrelation (14% significance); this model clearly passed the test of absence of heteroskedasticity in residuals and presence of normality of residuals. The model is estimated with three lags, while the second lag is excluded due to the results of lag exclusion tests. The best competing model fulfils the criteria of stability (stationarity of the model) and exogeneity tests of variables in the model on the 10% level. The composite exogenous indicator contains the time series of non-fuel index, order books in construction of EU, order-book levels in industry of EU, expected business situation in retail trade of EU and present business situation in retail trade of EU. This model will be used for forecasting and evaluation of forecasts. The above tests are presented in Annex 1 at the end of the article.

3.2. Forecasts

The estimated model is used for testing of its forecasting ability. Given the short time series of macroeconomic variables (quarterly data) of the Slovak economy, the robustness of the model in an adjusted sample is questionable, nevertheless the predictive ability of the GDP equation (subset VARX model) is tested on the sample before the impact of global crisis on the Slovak economy (i.e. from 1997 until the 3rd quarter of 2008 – the end of expansion phase of basic macroeconomic variables) till the end of the sample (3rd quarter of 2011). The forecast proceeds one step ahead, i.e. the model is estimated anew after each quarter. The forecast horizon is one and two quarters ahead. The insignificant parameters have been excluded stepwise (over-fitting) from the estimated GDP equation from the model as in Alles et al. (2006) or Di Fonzo and Marini (2005).

The delay of the endogenous variables in the model is maximum three quarters and of exogenous variable one quarter. Due to the earlier publication of indicators of exogenous variable (after the end of the quarter) before the official publication of GDP, also the forecast of the second quarter is possible. The estimate of one quarter ahead can be considered as nowcast of GDP due to the mentioned delayed publication of GDP (45 days after the end of the quarter – flash estimate, 60 days – official GDP estimate).

For comparison of forecasts of the VARX model a simple autoregressive (AR) model is used as a proxy model with three lags (maximal number of lags same with VARX model).

For the evaluation of forecasts the Theil's U method is used (Savin and Winker, 2011): Theil's U (TU) represents the share of RMSFE (root mean squared forecast error) of the VARX model on the forecast error of the reference model (AR model) – u_t. RMSFE – the mean square error of forecast:

$$RMSFE = \sqrt{\frac{1}{T_2 - T_1 + 1}\sum_{t=T_1}^{T_2} e_t^2} \tag{2}$$

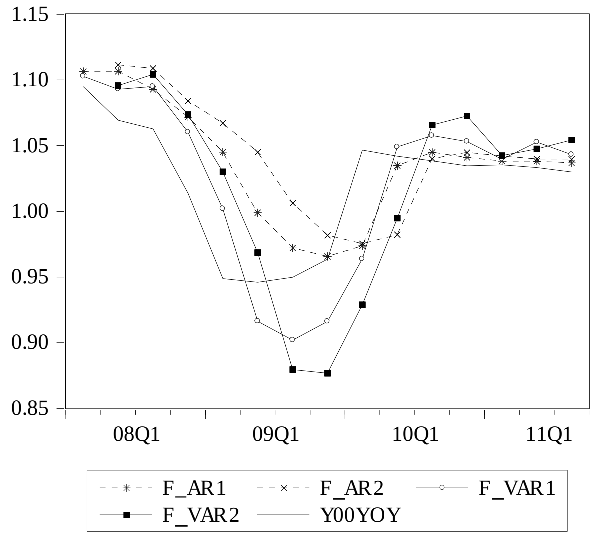
The T_1 and T_2 is the first and the last forecast period, e_t is the difference between the real and forecasted GDP rate. The forecast with the lowest RMSFE is the best.

$$TU = \sqrt{\sum_{t=T_1}^{T_2} e_t^2} \;/\; \sqrt{\sum_{t=T_1}^{T_2} u_t^2} \tag{3}$$

In the following figure (Fig. 1) the graphical comparison of forecasting models VARX and AR is shown. The forecast for one quarter ahead, always with new estimated model, is marked on the chart as number 1, forecast for the 2nd quarter by number 2. The VARX model clearly responds better to the breaks of the GDP line, while with the arrival of the crisis in the second half of 2008 the VARX models absorb the change better than the AR models, which show higher inertia.

F i g u r e 1

Comparison of AR and VAR Forecasts with Reality (Growth Rates)



Source: Authors' own calculations, EViews.

T a b l e 1

Evaluation and Comparison of Forecasts

Observation	Forecast on 1st Quarter	Forecast on 2nd Quarter
	Theil's U	Theil's U
2008q1	0.822526	X
2008q2	0.796057	0.791294
2008q3	1.037337	0.950493
2008q4	0.896284	0.923651
2009q1	0.742998	0.828912
2009q2	0.748963	0.477105
2009q3	1.464040	1.116521
2009q4	4.771517	2.181684
2010q1	1.066511	1.285070
2010q2	0.987518	0.888185
2010q3	1.723855	4.136089
2010q4	1.714690	1.935842
2011q1	1.229763	1.031455
2011q2	2.024901	1.490256
2011q3	1.391601	1.583613
Success rate of VAR against AR	**6/15**	**6/14**

Source: Authors' own calculations, EViews.

T a b l e 2

The Comparison of GDP Growth Rate Forecasts

Observation	F_AR1	F_AR2	F_VAR1	F_VAR2	Y00YOY
2008Q1	1.106431	X	1.102701	X	1.094901
2008Q2	1.106539	1.111530	1.092895	1.095738	1.069290
2008Q3	1.092773	1.108740	1.095059	1.104296	1.062720
2008Q4	1.071762	1.083939	1.060329	1.073613	1.013633
2009Q1	1.045102	1.067058	1.001981	1.030067	0.948840
2009Q2	0.998836	1.045063	0.916340	0.968539	0.945986
2009Q3	0.972139	1.006176	0.901948	0.879542	0.949809
2009Q4	0.965661	0.981834	0.916191	0.876693	0.963579
2010Q1	0.973720	0.975312	0.963704	0.928877	1.046597
2010Q2	1.034832	0.982252	1.049056	0.994873	1.042033
2010Q3	1.044943	1.040073	1.057674	1.065640	1.038486
2010Q4	1.040969	1.044811	1.053151	1.072619	1.034690
2011Q1	1.038181	1.041962	1.039655	1.042387	1.035305
2011Q2	1.037994	1.039726	1.052630	1.047604	1.033273
2011Q3	1.036817	1.039659	1.043201	1.054224	1.030000

Source: Authors' own calculations, EViews.

The quantitative comparison of TU results (Table 1) shows that the VARX model did not outperform the AR model in more than half cases. The VARX model forecasts are clearly better during the cycle change phase (Theil's U smaller than 1), the results are similar for the 1st and the 2nd quarter forecast. The forecast for the 2nd quarter of endogenous variables was taken from the 1st step of the forecast. The aim of the leading indicators is to sufficiently identify in advance the changes of phases of business cycle. The transition of Slovak economy into a recession (negative GDP growth)[5] pointed out by a decrease in GDP growth in 1st quarter of 2009 is not forecasted by the VARX model one quarter before the official publication of GDP (F_VAR1 in Table 2), but is showing almost zero growth (0.2%) and is the most successful model forecast. The forecast for two quarters ahead, i.e. the forecast from 4th quarter of 2008 (F_VAR2 – 2009q1) has pointed to a GDP increase (3.0%).

Also the onset of expansion phase in the 1st quarter of 2010 (GDP growth 4.7% yoy) has not been anticipated by the forecasts of AR and VARX models.

Conclusions

This work presents an attempt to design a VAR model with leading indicators, thus a modelling approach as opposed to the non-model approach currently used in the construction of leading indicators for Slovak economy by the OECD. The process of selection of leading indicators has been adapted to the requirements for causality and stationarity of variables of a VAR model. The resulting VAR models fulfil the necessary conditions for model estimation and its application for forecasting.

The VAR model forecasts based on leading indicators proved its potential to adapt to changes of the business cycle, but the forecast ability can be considered to be rather low, but in the transition between particular phases of the business cycle it is superior to the AR model.

One way leading to a more robust model is towards increasing the R-squared in the VAR equation for GDP growth. This can be achieved by decomposition of composite indicators components into the model or with a more effective combination of variables. An alternative could be a transformation of the variables (logarithms, normalization methods etc.). One of the main obstacles to deal with is the shortness of time series (about 50 observations), which could be regarded as insufficient for a more robust VAR model. The answer may be to focus the analysis of macroeconomic variables on monthly frequency data but with the difficulty to approximate the business cycle of the whole economy facing the absence of aggregate GDP (Kľúčik, 2010).

According to Hamilton (2011) there are three factors why it is difficult to forecast business cycle turning points: the unpredictability of certain events, a variety of different data signals and changing economic relationships over time. The role of research is to create such indicators and models, whose predictive power can identify indications of coming changes of economic activity in

[5] The identification of business cycle phases analyzing "growth rate" cycles may be the same as in "classical cycles" in levels, i.e. the phase of recession (negative growth rate versus decline of GDP in level) and a phase of expansion. In contrast the "growth cycles", not focused on in this paper, tell about acceleration or slowing down of an economy, unlike recession or expansion phases in the case of classical and growth rate cycles.

official statistics data. VAR modelling tools can absorb only phenomena through official published indicators, however, the linear model is unable to cope with changes in economic fundamentals in time, the business cycles are asymmetric in their development and the lead of indicators may vary in different phases of the cycle (Paap, Segers and Dijk, 2009). This may be the cause of rather poor outcome of VAR model forecasts. The role of research in the future is to test also nonlinear models, utilize heuristic methods (leading indicators and their lead selection) or theoretical models.

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ANNEX 1 – ADF Tests, Granger Causality Tests and VARX Model Outputs

VAR Stability Test
Roots of Characteristic Polynomial
Endogenous variables: Y00YOY COMPENDOG
Exogenous variables: C COMP
Lag specification: 1 1 3 3

Root	Modulus
0.709169 – 0.503327i	0.869631
0.709169 + 0.503327i	0.869631
0.755488	0.755488
–0.224979 – 0.536051i	0.581349
–0.224979 + 0.536051i	0.581349
–0.535406	0.535406

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: residuals are multivariate normal
Sample: 1993Q1 2011Q3
Included observations: 52

Component	Jarque-Bera	df	Prob.
1	4.668942	2	0.0969
2	1.971751	2	0.3731
Joint	6.640692	4	0.1561

VAR Residual Serial Correlation LM Tests
Null Hypothesis: no serial correlation at lag order h
Sample: 1993Q1 2011Q3
Included observations: 52

Lags	LM-Stat	Prob
1	3.514927	0.4756
2	3.230269	0.5201
3	7.004374	0.1357

VAR Residual Heteroskedasticity Tests:
– no Cross Terms (only levels and squares)
Sample: 1993Q1 2011Q3
Included observations: 52
Joint test:

Chi-sq	df	Prob.
31.61480	30	0.3857

Vector Autoregression Estimates
Sample (adjusted): 1998Q4 2011Q3
Included observations: 52 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	Y00YOY
Y00YOY(–1)	0.294126 (0.13738) [2.14094]
Y00YOY(-3)	0.176415 (0.12624) [1.39749]
COMPENDOG(-1)	0.109333 (0.06944) [1.57454]
COMPENDOG(-3)	–0.117161 (0.06517) [–1.79783]
C	0.396623 (0.13093) [3.02916]
COMPEX	0.161812 (0.07068) [2.28943]
R-squared	0.608637
Adj. R-squared	0.566098
Sum sq. resids	0.036364
S.E. equation	0.028116
F-statistic	14.30759
Log likelihood	115.1164
Akaike AIC	–4.196783
Schwarz SC	–3.971639
Mean dependent	1.042483
S.D. dependent	0.042683

Pairwise Granger Causality Tests
Sample: 1993Q1 2012Q4
Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
Y00YOY does not Granger Cause COMPEX	51	0.2850	0.886
COMPEX does not Granger Cause Y00YOY		3.0213	0.028

VAR Granger Causality/Block Exogeneity Wald Tests
Sample: 1993Q1 2011Q3
Included observations: 52

Excluded	Chi-sq	df	Prob.
Dependent variable: Y00YOY			
COMPENDOG	4.766987	2	0.0922
All	4.766987	2	0.0922
Dependent variable: COMPENDOG			
Y00YOY	4.610981	2	0.0997
All	4.610981	2	0.0997