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Modelling and Predicting the Fiscal Pressure Indicator in the European Union

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Abstract *The main goal of this research is to model and predict the fiscal pressure indicator and the real GDP rate in the European Union during 1996-2013 using the vectorial-autoregressive approach. According to Granger test for causality, only the real GDP rate is a cause of the weight tax in GDP, the relationship not being reciprocal. The fiscal pressure volatility is due mainly to the evolution of this indicator, but the influence decreases in time, not descending under 82%. More than 41% of the variation in real growth is explained by the fiscal pressure volatility starting with the 6th lag. The static and deterministic simulation generated the best predictions of the fiscal pressure indicator on the horizon 2011-2013.*

Key words Granger causality, VAR model, fiscal pressure, predictions

JEL Codes: C51, C53, E62, H30

1. Introduction

The main objective of this research is to construct a VAR (vectorial-autoregressive model) model for fiscal pressure indicator and real growth in order to make ex-post forecasts of these indicators. The VAR approach allows us to evaluate the variance decomposition of each indicator. In this way, we can determine if the variation in the variable's evolution is mainly due to the other variable or to its own evolution. The model is applied for the European Union on the period from 1996 to 2013, predictions being made for 2011-2013.

European Commission has launched the famous Internal Market Programme that has different objectives, one of them being the harmonization of national tax system. Therefore, it is necessary to diminish the contrary incentives for capital movements, production and goods generated by national purposes. In the context of fiscal convergence the study of the relationship between fiscal pressure indicators and different factors is important.

2. Literature review

With regard to approaching the concept of fiscal pressure there are several different opinions. In a first approach the tax burden is seen as "expression of relative tax burden paid by taxpayers". Tulai Constantin in his research asserts that pressure stands for how big is the tax for taxpayers. Another author considers that the tax burden is an indicator of measuring the production revenue, which conveys the budget through a process of compulsory public effect and, instead of being allowed to be freely available to private initiative. Nicolae Hoanta in his book entitled *"Tax Evasion" states* that: "The tax burden is generally given by the taxation rate, which is calculated as the ratio of tax revenue (central level and that of municipalities) including the contribution to the welfare budget in a given period, usually one year, and the value of the GDP, achieved in the same period, by a national economy." (Dobrotă and Chirculescu, 2010).

In a different approach, the tax burden reflects and tax expression competition between Member States. Overesch (2005), in a report of research on this subject, claims that in the international context, establishment of pressure actual tax is a measure of attractiveness of a location of one of the armies for multinational companies. It suggests a way of calculating the actual tax pressure and depending on the model proposed, make a ranking of States with the highest rate of taxation average actual perceived by the companies. This classification is led by Spain, Germany and France, with the actual average tax rate of more than 34% and concluded by Cyprus and Lithuania, with actual tax rates of nearly 3 times smaller, not exceeding 13%.

The fiscal pressure analysis is not at all a problem recently brought to the researchers' attention. Donnahoe (1947) suggested classification fiscal pressure in three categories represented graphically like straight with different slopes and an emphasis on interpretation of fiscal pressure as the ratio of ability of a state to generate taxes and fees and the level of their collection. Karageorgas (1973) talks about distribution fiscal pressure generated by taxes on income in the various social categories, using as an example Greece and taking into account transfers, too. By comparing Greece with other European countries, one could reach the conclusion that the system of Greek law enforcement does nothing but greater unfairness fiscal pressure distribution between the categories of tax payers. Browning (1978) demonstrates that indirect taxes display progressive features when they are analyzed in the context of a model of general equilibrium in which transfers are an important source of income for the population. In conclusion, it is emphasized that a system of charging down to mean a low fiscal impact for the categories of poor taxpayers (Vintilă and Ţibulcă, 2012).

3. Methodology framework

Firstly, we consider that $thevectory_i$ has "m" variables. Each of these variables has "p" lags. The rest of the variables (the deterministic variables and the constant) are placed in a vector denoted by y_{*i} that has m* elements. The VAR model has the following form:

$$y_i = A(L)y_{i-1} + Cy_{*i} + e_i \,, \quad e_i \to \left(0, \sum_e \right) \qquad (1)$$

Number of regressors: k= mq+m*

Number of coefficients: c=mk

The VAR model is written in two equivalent forms (X- a Tk matrix, Y and E- Tm matrices, Im- identity matrix, α- mk vector, y and e- mTvectors):

Y=XA+E (1)

$$y = (Im^*X)\,\alpha + e, \quad e \to \left(0, \sum_e * I_T\right) \qquad (2)$$

For the selection of optimal lag a likelihood ratio is applied with the assumptions:

$$\begin{aligned} &H_0 : VAR(p_0) \\ &H_1 : VAR(p_1) \end{aligned} \qquad (3)$$

Different informational criteria are chosen for the optimal lag selection, the most known one being Akaike and Schwartz- Buniakovsky criterion. It is chosen the lag that minimizes the information criterion value for p=1, ... , p.

$$\begin{aligned} \mathrm{AIC} &= \ln|\boldsymbol{\Omega}| + \frac{2(\mathrm{n}^2\mathrm{p}+\mathrm{n})}{\mathrm{T}} \\ \mathrm{SBC} &= \ln|\boldsymbol{\Omega}| + \frac{(\mathrm{n}^2\mathrm{p}+\mathrm{n})\ln(\mathrm{T})}{\mathrm{T}} \end{aligned} \qquad (4)$$

Let us consider two random variables X and Y.

According to (Granger, 1969), X is cause for Y considering that the information given by X improves the prediction of Y.

Let us consider the lag length p.

$$X_t = c_1 + \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \ldots..\alpha_p X_{t-p} + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots.\beta_p Y_{t-p} + a_t \qquad (5)$$

OLS is used to test the assumptions:

$$H_0: \beta_1 = \beta_2 = \_\_\_ = \beta_p = 0 \qquad (6)$$
$$H_1: \quad \beta_i \neq 0$$

The restricted sum of squares is:

$$RSS_1 = \sum_t \hat{a}_t^{\,2} \qquad (7)$$

$$RSS_2 = \sum_t \hat{\hat{a}}_t^{\,2} \qquad (8)$$

The unrestricted sum of squares is:

$$F = \frac{(RSS_2 - RSS_1)}{RSS_1/(T - 2p - 1)} \qquad (9)$$

F statistic follows a chi-square distribution with p degrees of freedom. The variance decomposition shows the contribution of the orthogonalized innovation j to MSE-mean square error for the s-step-ahead prediction.

$$\begin{aligned}
&MSE(\hat{Y}_t(s)) = E(Y_{t+s} - \hat{Y}_t(s))(Y_{t+s} - \hat{Y}_t(s))' \\
&e_t(s) = Y_{t+s} - \hat{Y}_t(s) = a_{t+s} + \Psi_1 a_{t+s-1} + \ldots..\Psi_{s-1} a_{t+1} \\
&E[e_t(s)e_t(s)'] = \Omega_a + \Psi_1 \Omega_a \Psi_1' + \ldots. + \Psi_{s-1}\Omega_a \Psi_{s-1}' \\
&MSE(s) = Q^{-1}Q\Omega_a Q' Q^{-1'} + \Psi_1 Q^{-1} Q \Omega_a Q' Q^{-1'} \Psi_1' + \ldots. \\
&+\Psi_{s-1} Q^{-1} Q \Omega_a Q' Q^{-1'} \Psi_{s-1}' = \\
&= Q^{-1}Q^{-1'} + \Psi_1 Q^{-1} Q^{-1'} \Psi_1' + \ldots\ldots.\Psi_{s-1} Q^{-1} Q^{-1'} \Psi_{s-1}' = \\
&= M_0 M_0' + M_1 M_1' + \ldots\ldots..M_{s-1} M'_{s-1}
\end{aligned} \qquad (10)$$

The last relationship shows the contribution of the first innovation to MSE. The residuals decomposition for a standard VAR in a triangular way is called Choleski decomposition. Favero (2001) explained the differences between Choleski identification and Sims-Bernake one. 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. Lack (2006) found out that combined forecasts based on VAR models are a good strategy of improving the predictions accuracy.

4. The construction of a VAR model used in forecasting

According to ADF test, the data series are stationary. The Granger causality test is applied for data series in order to establish if a variable is cause for the other one. In Granger acceptance, a variable X is cause for Y if better predictions result when the information provided by X is taken into account.
The results of Granger causality test show that GDP real rate is the cause of fiscal pressure, but FP is not the cause of GDP rate.

Table 1. VAR Granger causality tests

Hypothesis	F Statistic	Prob.
FP does not Granger cause rGDP	0.62079	0.55533
rGDP does not Granger cause FP	3.13273	0.02826

Source: Authors' computations

Almost all the lag length criteria, excepting logL and HQ, at 5% level indicate that a VAR(1) model is the best model. All the tests necessary to be applied for checking the validity of the estimated VAR(1) model are displayed in the following table. The form of the VAR model is the following:

FP = 0.5495125477*FP(-1) + 0.1014812835*RGDP(-1) + 16.17781009

RGDP = 0.08045453988*FP(-1) + 0.2814769523*RGDP(-1) - 1.772799625

VAR Residual Portmanteau Tests are used to test the errors' autocorrelation for both identified model. The assumptions of the test are formulated as:

H_0: the errors are not auto-correlated

H_1: the errors are auto-correlated

For the lag 1 up to 12, the probabilities (Prob.) of the tests are greater than 0.05, fact that implies that there is not enough evidence to reject the null hypothesis (H0). So, we do not have enough reasons to say that the errors are auto-correlated. So, after the application of Residual Portmanteau Test, the conclusion is that there are not autocorrelations between errors for VAR(1) model.

Table 2. Residual Portmanteau test for errors auto-correlation

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	2.926939	NA*	3.109872	NA*	NA*
2	4.873869	0.3005	5.316393	0.2563	4
3	7.209174	0.5142	8.152121	0.4188	8
4	14.22427	0.2866	17.32571	0.1378	12
5	16.21726	0.4379	20.14911	0.2136	16
6	16.52599	0.6835	20.62624	0.4194	20
7	19.20719	0.7409	25.18427	0.3958	24
8	24.92415	0.6320	35.98299	0.1430	28
9	26.03744	0.7619	38.34872	0.2037	32
10	27.60347	0.8410	42.15194	0.2221	36
11	28.11060	0.9212	43.58881	0.3214	40
12	29.66245	0.9518	48.86511	0.2839	44

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

The homoscedasticity is checked using a VAR Residual LM test for the VAR(1) model. If the value of LM statistic is greater than the critical value, the errors series is heteroscedastic. LM test shows that there is a constant variance of the errors, because of the values greater than 0.05 for the probability. The Residual Heteroskedasticity test is applied in two variants: with cross terms and without cross terms. In this case we applied the variant without cross terms.

Table 3. VAR Residual Heteroskedasticity Tests: No Cross Terms

(only levels and squares)

Joint test:

Chi-sq	df	Prob.
18.96004	12	0.0895

Individual components:

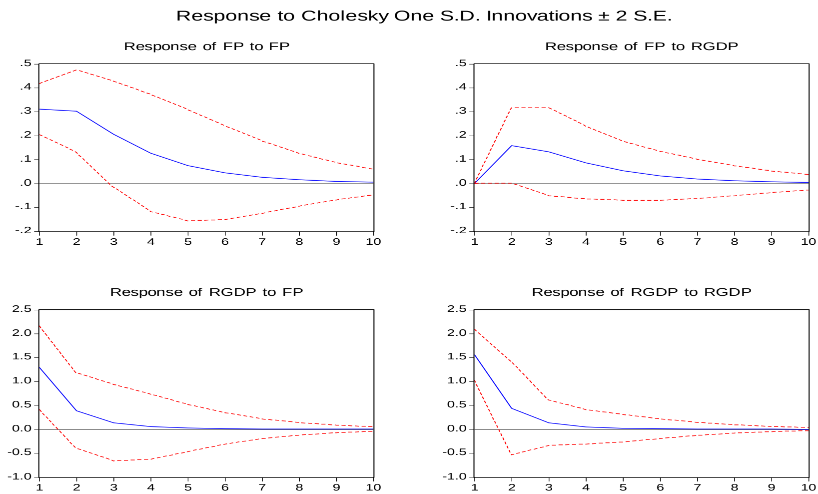
Dependent	R-squared	F(4,12)	Prob.	Chi-sq(4)
res1*res1	0.303631	1.308058	0.3218	5.161720
res2*res2	0.408829	2.074675	0.1474	6.950095
res2*res1	0.342513	1.562828	0.2468	5.822721

The normality tests are applied under the Cholesky (Lutkepohl) orthogonalization. If the Jarque-Bera statistic is lower than the critical value there is not enough evidence to reject the normal distribution of the errors.

Table 4. VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)

Component	Skewness	Chi-sq	df	Prob.
1	-0.303953	0.261764	1	0.6089
2	-0.518856	0.762765	1	0.3825
Joint		1.024529	2	0.5991

The Residual normality test provided probabilities greater than 0.05, fact that implies that the errors series has a normal distribution when Cholesky (Lutkepohl) Orthogonalization is applied. The impulse-response analysis and the decomposition of error variance are made.



Source: Authors' graph

Figure 1. The responses of each variable to own shocks or the other variable shocks

The fiscal pressure volatility is due mainly to the evolution of this indicator, but the influence decreases in time, not descending under 82%. More than 41% of the variation in real growth is explained by the fiscal pressure volatility starting with the 6th lag.

Table 5. Variance decomposition of the variables

Variance Decomposition of FP:

Period	S.E.	FP	RGDP
1	0.311076	100.0000	0.000000
2	0.461533	88.23685	11.76315
3	0.522005	84.45441	15.54559
4	0.543953	83.17716	16.82284
5	0.551577	82.74030	17.25970
6	0.554170	82.59179	17.40821
7	0.555042	82.54171	17.45829
8	0.555333	82.52492	17.47508
9	0.555431	82.51931	17.48069
10	0.555463	82.51744	17.48256

Variance Decomposition of RGDP:

Period	S.E.	FP	RGDP
1	2.024915	40.66050	59.33950
2	2.108071	40.91178	59.08822
3	2.116697	40.97763	59.02237
4	2.117955	40.99431	59.00569
5	2.118209	40.99888	59.00112
6	2.118273	41.00024	58.99976
7	2.118292	41.00067	58.99933
8	2.118298	41.00081	58.99919
9	2.118300	41.00086	58.99914
10	2.118301	41.00088	58.99912

The VAR model is used to make fiscal pressure- tax weight in GDP and real GDP forecasts on the horizon 2011-2013. For the VAR predictions four types of scenarios are considered:

- S1 scenario (Dynamic-Deterministic Simulation);
- S2 scenario (Dynamic-Stochastic Simulation);
- S3 scenario (Static-Deterministic Simulation);
- S4 scenario (Static-Stochastic Simulation).

Table 6. Predictions of fiscal pressure indicator- tax weight in GDP (%) based on VAR(1) models

Year	VAR(1) model (S1)	VAR(1) model (S2)	VAR(1) model (S3)	VAR(1) model (S4)
2011	35.90299	35.90299	35.89638	31.07369
2012	36.07423	35.97905	36.075679	32.463074
2013	36.16137	35.85038	36.1674208	30.874290

Source: Own computations

The fourth scenario generated lower values for the fiscal pressure indicator compared to the other three scenarios. If we make the comparison with real data, the third scenario generated the most accurate predictions and it could be used to make forecasts for 2014 and 2015.

Table 7. Predictions of real GDP growth (%) based on VAR(1) models

Year	VAR(1) model (S1)	VAR(1) model (S2)	VAR(1) model (S3)	VAR(1) model (S4)
2011	1.6484	1.6484	1.6916	2.0538
2012	1.5797	1.5795	1.6275	2.1203
2013	1.5741	1.0008	1.5603	1.9272

Source: Own computations

The fourth scenario generated higher values for the real growth compared to the other three scenarios. If we make the comparison with real data, the second scenario generated the most accurate predictions and it could be used to make forecasts for the next years.

6. Conclusions

According to this analysis based on VAR model, we can conclude that for the European Union during 1996-2013, only the real GDP rate is Granger cause of the fiscal pressure, the relationship not being reciprocal. Up to 10 lags, the variation in each variable is determined more by the own volatility than the other variable variations. The static and deterministic simulations generated more accurate predictions of the weight tax in GDP on the horizon 2011-2013.

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