Regional Effects of Fiscal Policy: Analysis with Spatial Vector Autoregressive Models

Changes in fiscal policy of a state can be aimed at both stimulating and slowing down the economy growthrate. Usually, government expenditures and taxes are considered to be two major tools of the fiscal policy. Renewed interest to the problems of fiscal policy in the literature was mostly due to 2008–2009 global financial crisis. During those events central banks of many developed countries were not able to affect the recovery of economies by using conventional monetary policy tools. As a result, governments all over the world provided strong financial support for fiscal stimulus programs, for example the US government allocated about 5% of GDP for such programs in 2009 (Boone et al., 2014).

The aim of this research project is to evaluate the effectiveness of fiscal policy measures. The most common metric used for this purpose in the literature is a fiscal policy multiplier. In case of Russia it is highly beneficial to perform analysis at the regional level because of at least two aspects. The first one is related to high variation of social and economic indicators across Russian regions which might lead to unpredictable responses of particular federation units to the common state policy. The second aspect is associated with some recent research results in the field. For instance, Dupor and Guerrero (2017) showed that estimation of local fiscal policy multipliers[1] requires presence of spatial or spillover effects in the model.

Currently, we do not know any studies concerning effectiveness of fiscal policy in Russian regions. We suggest to use a spatial vector autoregression model ($SpVAR$) in this research since it allows combine common, yet effective, $SVAR$ and VAR approaches used for multiplier estimation, as well as spatial econometric techniques. $SpVAR$ framework allows the computation of impulse response function (IRF) and also accounts for spillover effects through the spatial weights matrices. At present, $SpVAR$ models have not been used for evaluation of fiscal policy, but found applications in some other fields of economics, examples are the following papers (Beenstock and Felsenstein, 2007; Brandeis and Lambert, 2014; Kuethe and Pede, 2010).

In this research we used annual panel data from 80 units of the Russian Federation since 2005 till 2018. Similar to VAR terminology there are endogenous and exogenous variables in a $SpVAR$ model. Log transformed gross regional product (GRP) and 7 categories of government expenditures are included in the model as endogenous variables while factors reflecting state of investments, openness of the economy, human capital and infrastructure in regions are considered to be exogenous.

To sum up, we estimated 7 $SpVAR$ models. Each of them has a similar structure and appears to be a system of 2 equations:

$$grp_t = (I - \rho_1^1 W)(\mu^1 + \xi_t^1 + \beta_1^1 grp_{t-1} + \beta_2^1 exp_{t-1} + X_t\delta_1 + u_t^1) \quad (1)$$
$$exp_t = (I - \rho_2^2 W)(\mu^2 + \xi_t^2 + \beta_1^2 grp_{t-1} + \beta_2^2 exp_{t-1} + X_t\delta_2 + u_t^2)\ , \quad (2)$$

where $grp_t = (grp_{1t}, ..., grp_{Nt})'$, $exp_t = (exp_{1t}, ..., exp_{Nt})'$ are vectors of endogenous variables GRP and government expenditures, X_t is a matrix of exogenous variables, μ^1 и $\mu^2 = (\mu_1, ..., \mu_N)'$ are vectors of fixed effects, ξ_t^1 и $\xi_t^2 = (\xi_1, ..., \xi_T)'$ is a vector of time effects, δ_1 и δ_2 are vectors of estimated parameters, $\beta_1^1, \beta_2^1, \beta_1^2, \beta_2^2, \rho_1^1, \rho_2^2$ are estimated coefficients, u_t^1 и $u_t^2 = (u_{1t}, ..., u_{Nt})'$ are the error terms and ,finally, W is a spatial weights matrix. In this study we used a normally row-standardized first-order contiguity weights matrix which implies that spatial effects can channel only through common borders between regions (LeSage and Pace, 2009; Arbia, 2014).

[1] They are estimated with the use of data from all states of the USA.

One of possible approaches to analysis of *SpVAR* (1)–(2) is to estimate each equation separately as a dynamic panel regression with spatial effects (Kuethe and Pede, 2011; Civelli et al., 2018; Giannini et al., 2020). There is definitely a room for discussion on the estimation methodology, but a prevalent estimator for *SpVAR* equations in the literature (Wu and He, 2018; Civelli et at., 2018) is the Arellano-Bond (Arellano and Bond, 1991) method or some kind of its variation. Therefore, we used the same approach to our estimations.

SpVAR model also allows us to compute an impulse response function. Basically, *IRF* demonstrates the changes of endogenous variables occurred due to an exogenous shock in the system. It is possible to temporary omit fixed and time effects in the model (1)–(2)[2], and rewrite it in the following way:

$$Y_t \;=\; AY_{t-1} \;+\; BX_t \;+\; \psi_t \;, \tag{3}$$

where Y_t is a vector of endogenous variables, composed of grp_t и exp_t, X_t is a matrix of exogenous variables, ψ_t is a vector of errors, a product of $(I-\rho_1^1 W)^{-1}u_t^1$ and $(I-\rho_2^2 W)^{-1}u_t^2$. Thus, A and B are block matrices and for further calculations it is useful to write matrix A in detail:

$$A \;=\; \begin{bmatrix} (I-\rho_1^1 W)^{-1}\beta_1^1 & (I-\rho_1^1 W)^{-1}\beta_2^2 \\ (I-\rho_2^2 W)^{-1}\beta_1^2 & (I-\rho_2^2 W)^{-1}\beta_2^2 \end{bmatrix} \tag{4}$$

IRF values can be derived from the vector moving average process (*VMA*). It is possible to transform model (3) into *VMA* process if eigenvalues of the matrix A are less than 1. An equivalent condition is a significant difference between 1 and estimates of $\beta_1^1, \beta_2^1, \beta_1^2, \beta_2^2, \rho_1^1, \rho_2^2$ parameters. Therefore, in case such condition holds, transformation yields:

$$Y_t \;=\; A^t Y_0 \;+\; \left(\sum_{i=0}^{t-1} A^i X_{t-i}\right) B \;+\; \sum_{i=0}^{t-1} A^i \psi_{t-i} \tag{5}$$

Thus, A^i matrices correspond to *IRF* values. It is also worth mentioning that in this study we used Cholesky decomposition approach to shock identification.

In case of logarithmic specification *IRF* values demonstrate the average across all regions percentage change in GRP caused by shock of the government expenditures increase of 1% (not p. p.) in all regions. Responses of the *SpVAR* system to the disturbance in government expenditures dampen rather fast and often become insignificant after a 2 year time mark. So, we compared *IRF* values accumulated over 2 years for each category of expenditures in order to determine ones that provide the greatest impact on GRP (only 4 out 7 categories are displayed in the table):

Expenditures category	Cumulative *IRF* value, %
Total expenditures	3.80
Expenditures on national economy	7.08
Expenditures on education	1.795
Expenditures on healthcare	3.139

Our results suggest that expenditures on the national economy are very effective which is somewhat expected since they are aimed to support particular enterprises and industries of th economy. Another major finding is related to the healthcare expenditures. Its *IRF* value remain significant over a longer time period and a 6-year cumulative value is equal to 4.45% that is quite impressive.

[2]Since they do not affect further transformations.

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