Mixed Sampling Panel Data Model for Regional Job Vacancies Forecasting

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Abstract

We tested, for Romania, the relationship at regional level between the job vacancies rate (with quarterly frequency) as explained variable and, as explanatory variables (regressors) unemployment rate (available with monthly frequency), respectively gross domestic product growth rate (who is presented at annual frequency). To identify the regional (cross-sections) specific effects, we use a panel data model. Since the analysed variables have different frequencies, the panel data model was built based on the MIDAS methodology. To avoid the cross-section correlation between errors, we used the SUR methodology to estimate the model's parameters. We found that, for all eight Romanian regions, the job vacancies are negative associated with unemployment (this result is consistent with the theory of Beveridge curve), and positive correlated with economic growth (and this result is in line with Okun's theory). The data also show a significant inertial effect in regional dynamics of vacancies.

Keywords: job vacancy, unemployment rate, gross domestic product, panel data model, MIDAS, forecasting methods.

JEL Classification: C33, C53, J63, J64

1. Introduction

In the paper, we have developed a panel data model for forecasting vacancies at regional level. As the data on job vacancies, unemployment rates and GDP are not in the same frequency, we use the Mi(xed) Da(ta) S(ampling), or MIDAS techniques for solving the econometric model.

The negative relationship between the job vacancies and unemployment rate is referred in economic literature as *Beveridge curve*. A British lord, William Beveridge, in a 1944 report, discussed a same relationship in the context of reconstruction of the European western economies after the Second World War, for making welfare states (Beveridge, 1944).

The link between jobs and economic growth, or, in other version of this relationship which links the unemployment to economic growth is known in economic literature as Okun Law.

Nickell, et. al. (2002) analysed unemployment and wages in the OECD from the 1960s to the 1990s and they found that the Beveridge curves shifted to the right for almost all countries and these movements may be explained by changes in labour market institutions.

Hobijn & Sahin (2013) investigated relationship between the job vacancies and unemployment rate and found that Beveridge curve was remarkably stable from 2000 through 2007 in the U.S. and, since the Great Recession, Beveridge curve shifts rightward, the same as in Portugal, Spain and the U.K.

Bouvet (2012) examined national and regional data on job vacancies and unemployment for 5 European countries (Belgium, Germany, the Netherlands, Spain and the UK), over the period 1975 to 2004. He found that labour market rigidities and cyclical shocks are determined for outward shifts in a nonlinear European Beveridge curves. In Bouvet analysis, Germany exhibits the clearest example of a Beveridge curve, while for the other four countries Beveridge curves depict a downward-sloping relationship between vacancy rate and unemployment, but the shapes are not so close on theoretical curve, like in Germany.

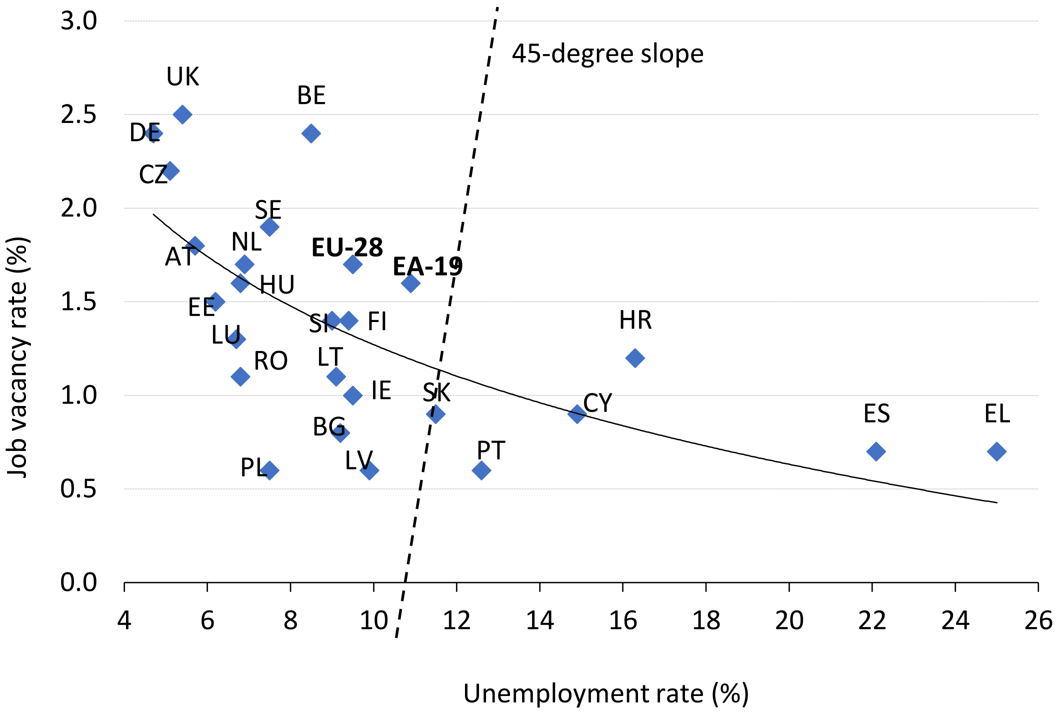
A recent paper, *Eurostat* (2017) gives an overview of the Beveridge curve (relationship between the job vacancy rate and the unemployment rate) in the European Union. The Beveridge curves, both for the EU-28 and for the Euro area, show that the unemployment rate is rising, while job vacancies are dropping, during the 2008-2009 worldwide recession and the ensuing sovereign debt crisis. The crisis period was followed by a significant outward shift in the Beveridge curves (2010-2013), which has deepened disparities across Member States and, after 2014, a movement to left, along the Beveridge curve, change that was caused by an increase of the job vacancy rates and a decrease in unemployment rates.

As depicted in figure 1 (the figure was taken from Eurostat article), Romania, with 6.8% unemployment rate and 1.1% job vacancy rate, has a better position than the European average, given that "the countries above the curve may have a comparatively poorer matching efficiency than countries situated below" (European Commission, Eurostat, Statistics Explained, 2017).

In Romania, Ferenț-Pipaș (2016) have studied the shifts in Beveridge Curve from Europe 2020 Perspectives. The author found different behaviour for EU-13 (new EU member states from the Central and Eastern European) and EU-28. For EU-13, Ferenț-Pipaș advocate that, during the 10-year period (2004-2013), the job vacancy decreasing rate "is higher as the minimum wage is higher as percentage of the median wage" (2016, p. 329).

As methodology, we mention that, in econometrics, standard regression models require that all the relate variables to have the same frequency. Mi(xed) Da(ta) S(ampling), or MIDAS, models handle series sampled at different frequencies.

Figure 1. Beveridge points for some EU-28 countries (2015q1-2015q4 average)



Note: The job vacancy rate and the unemployment rate is calculated as an average over four quarters (2015q1-2015q4). Among EU-28 countries there are not included Denmark, France, Italy and Malta.

Source: European Commission, Eurostat, Statistics Explained, *Job vacancy and unemployment rates - Beveridge curve*, Figure 2. Available at http://ec.europa.eu/eurostat/statistics-explained/index.php/Job_vacancy_and_unemployment_rates_-_Beveridge_curve.

The MIDAS model description in Ghysels, et al. (2006) and Clements & Galvão (2008) is the following: suppose that an explanatory variable $x_t^{(m)}$ is observed *m* times in the same period in which the explained variable y_t is available once. A simple MIDAS model that link the two variables, and h-step-ahead forecasting is:

$$y_t = \beta_0 + \beta_1 B(L^{1/m};\theta)\, x_{t-h}^{(m)} + \varepsilon_t, \quad \text{for } t = 1, \ldots, T$$

where $B(L^{1/m};\theta) = \sum_{k=1}^{K} b(k;\theta) L^{(k-1)/m}$ and $L^{s/m} x_{t-1}^{(m)} = x_{t-1-s/m}^{(m)}$. The lag coefficients in b(k; θ) of the corresponding lag operator $L^{(k-1)/m}$ are parameterized as a function of a small-dimensional vector of parameters θ.

MIDAS regression models were usually used for forecasting economic activity with higher frequency targeted predictors (Ghysels, et al., 2006), (Bulligan, et al., 2012). Clements & Galvão (2008) and (2009) used monthly macroeconomic indicators to forecast quarterly GDP's growth. To improve macroeconomic forecasting, Andreou, et al. (2010), by employing MIDAS regression models, assess whether daily financial data can be incorporated into forecasting of the quarterly GDP growth.

2. Data

Data concerning *regional job vacancies* (quarterly data), *regional unemployment rate* (monthly data) and *regional gross domestic product* (yearly data) are from the Romanian National Institute of Statistics, TEMPO-Online Time series tables (2017). For regional *Gross Fixed Capital Formation* and *GDP price index* (implicit deflator) the source is Eurostat.

According to *Eurostat* methodology:

> "A *job vacancy* is a post, either newly created, unoccupied or about to become vacant, which the employer: actively seeks to fill with a suitable candidate from outside the enterprise (including any further necessary steps); immediately or in the near future (…) A post that is open to internal candidates only, however, is not considered a job vacancy" (European Commission, Eurostat, Statistics Explained, 2017)

As expected, the Romanian National Institute of Statistics methodology, concerning job vacancies is a similar one:

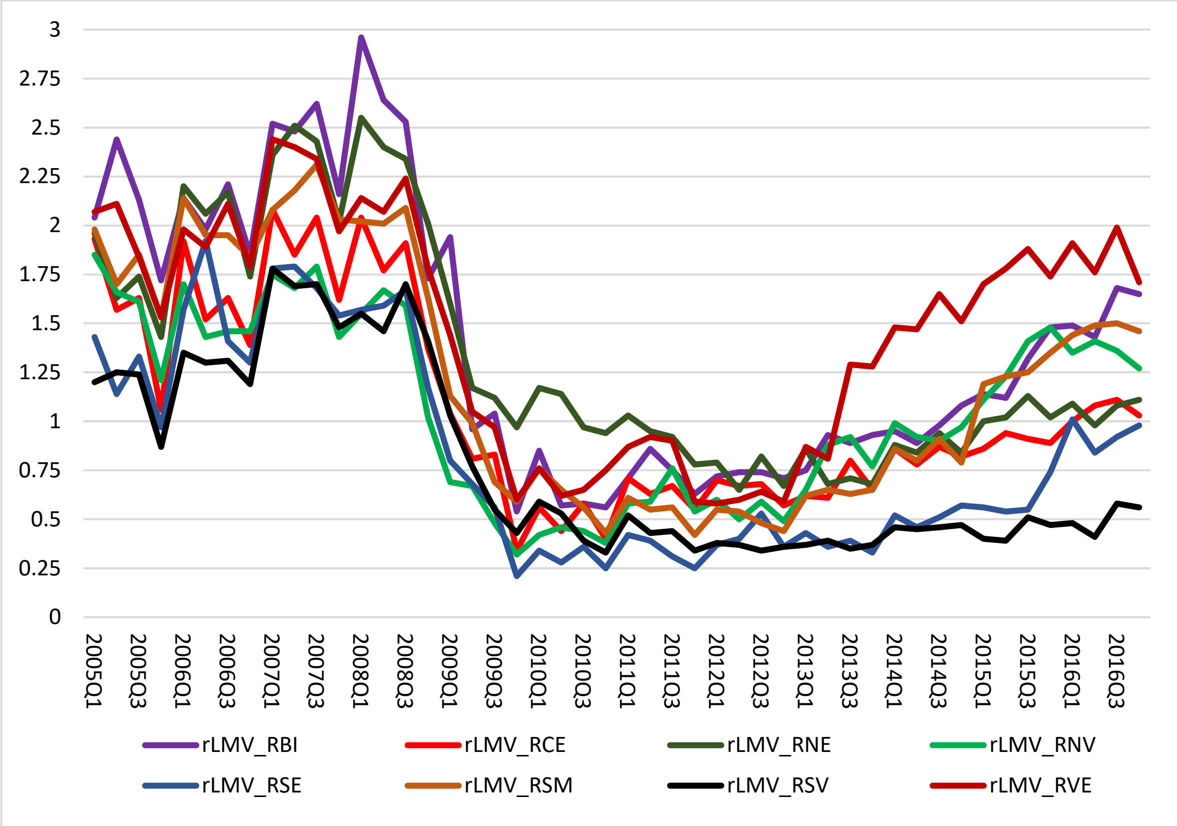
> "The number of *job vacancies* includes number of paid, newly created, unoccupied positions, or which are to become vacancies, for which (i) employer did concrete actions to find a candidate adequate to be employed in that position (examples of concrete actions done by the employer: announcing about the existence of vacancy through employment services, publicity in the newspapers, media, internet, direct contact of possible candidates etc.); (ii) employer wishes to have an immediate employment or in a specific time period" (maximum 3 months after the reference period, for 2005-208 period, established by the employer, 2009 onwards).
>
> (National Institute of Statistics, 2017), http://statistici.insse.ro/shop/index.jsp?page= tempo3&lang=en&ind=LMV101A.

The number of job vacancies are calculated by excluding the blocked jobs due to a normative document or those meant for promotion inside the enterprise or institution, namely, vacancies are considered only those positions for persons outside the enterprise.

Job vacancies rate represents the ratio (expressed as percentage) between the numbers of job vacancies and total number of jobs. Quarterly data on job vacancies and job vacancies rate have, as reference period, the middle month of the quarter.

The data are collected on Romania's 8 regions (NUTS-2 in Eurostat Nomenclature of territorial units for statistics classification), namely: Bucharest – Ilfov Region (symbol - RBI), Center Region (RCE), North-East Region (RNE), North-West Region (RNV), South-East Region (RSE), South-Muntenia Region (RSM), South-West Oltenia Region (RSV) and West Region (RVE).

Figure 2. Regional Job Vacancies Rate (%), quarterly data, 2005-2015



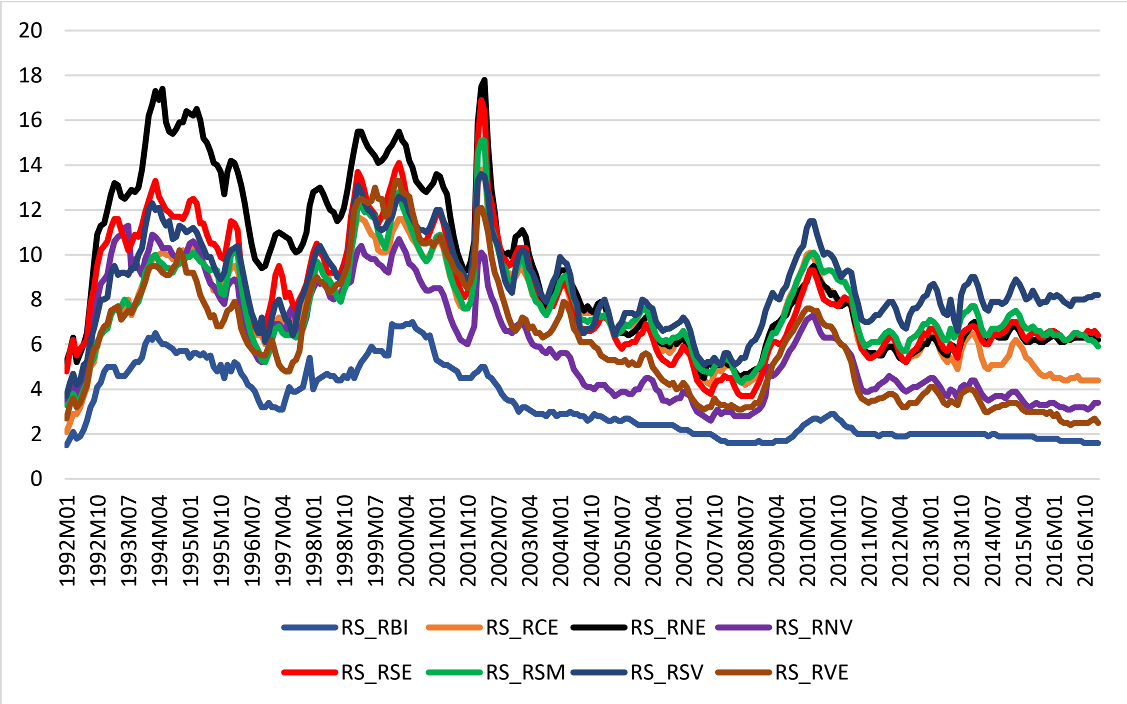
Source: National Institute of Statistics, Tempo-Online, table LMV101A: Vacancies rate by macroregions, development regions, activity of national economy at level of CANE Rev.1 section (for data up to Year 2008) and LMV101B: Vacancies rate by macroregions, development regions, activity of national economy at level of CANE Rev.2 section (2008 onwards).

The regional *unemployment rate* with monthly frequencies is obtained from Romanian National Institute of Statistics, TEMPO-Online Time series, table *SOM103B* (Unemployment rate by gender, macroregions, development regions and counties, at the end of the month).

The data concerning the *Regional Gross Domestic Product*, yearly data, are from the same source, tables CON103C (GDP by macroregions, development regions and countries, calculated according CANE Rev.1) and CON103I (GDP by macroregions, development regions and countries - ESA 2010, calculated according CANE Rev.2, for 2000-2014).

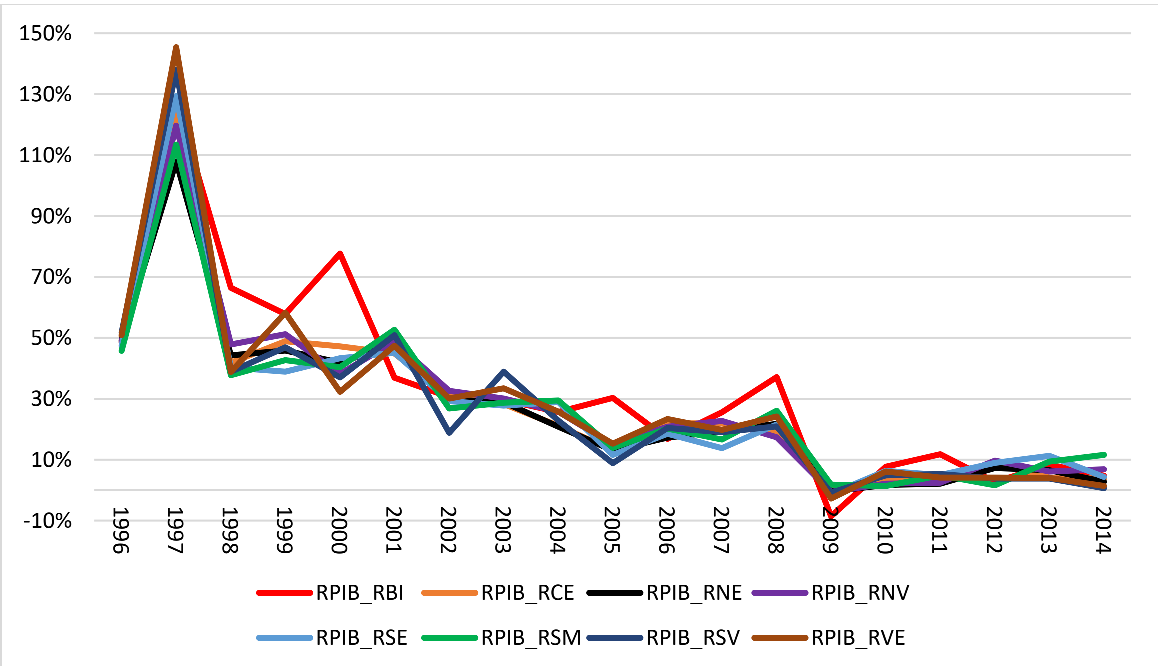
For *GDP price index* (implicit deflator), quarterly data, the source is Eurostat (GDP and main components - output, expenditure and income, namq_10_gdp table). The implicit deflator is calculated for gross domestic product at market prices in national currency, seasonally and calendar adjusted data.

Figure 3. Regional rate of unemployment (%), monthly data, 1992-2016



Source: National Institute of Statistics, Tempo-Online, table SOM103B - Unemployment rate by gender, macroregions, development regions and counties, at the end of the month

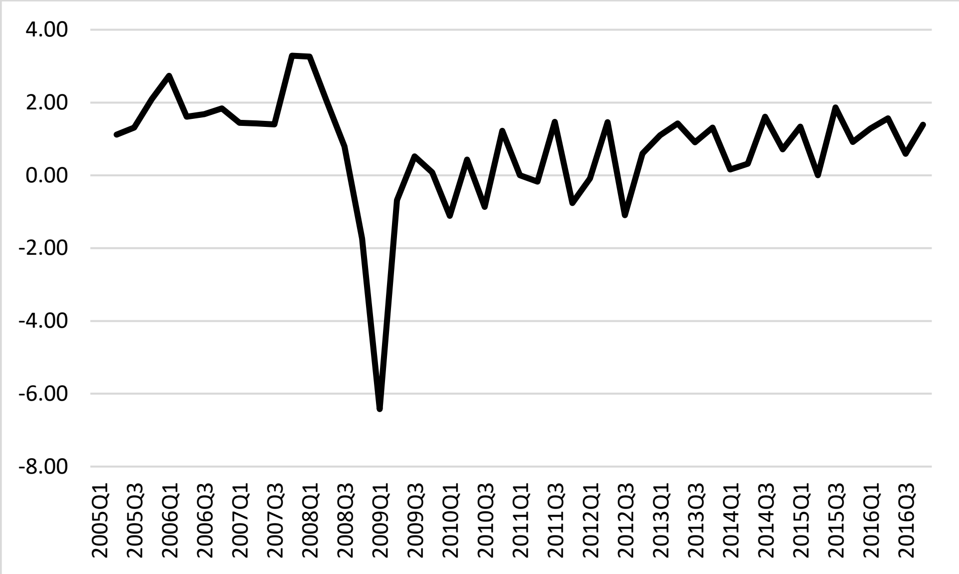
Figure 4. Nominal growth rates of Regional Gross Domestic Product



Source: National Institute of Statistics, Tempo-Online, tables CON103C and CON103I.

The same, the data regarding regional *Gross Fixed Capital Formation*, yearly data, is from Eurostat (Gross fixed capital formation by NUTS 2 regions, nama_10r_2gfcf table). The GDP price index is used for estimation of the real growth rates of GDP.

Figure 5. Growth rates of Regional Gross Domestic Product Volume



Source: Own estimation based on data from Eurostat (GDP and main components - output, expenditure and income, namq_10_gdp table).

3. Econometric model

We tested, for Romania, the relationship at regional level between the job vacancies rate, as explained variable and unemployment rate, respectively gross domestic product growth rate as explanatory variables (regressors). To identify the regional (cross-sections effects) specific effects we used a panel data model.

The data concerning regional job vacancy rate are at quarterly frequency, the regional unemployment rate is available in monthly frequency, while the regional GDP rate is presented at annual frequency. For this reason, we choose a MIDAS type approach.

Since unemployment refers to a stock variable, therefore is not suitable for aggregation under the MIDAS regression (Andreou, et al., 2010, p. 249). Furthermore, quarterly data on job vacancies and, consequently, job vacancies rate in the quarter *t* was registered as values at the middle month of the quarter. In these circumstances, we consider, for MIDAS regression, the unemployment rate, alike, at the middle month of the quarter. For the same reasons, we construct the quarterly data on regional GDP by distributing the annual growth rate for each trimester from that year and correcting those values with the quarterly deflator. The model is:

$$jvr_{i,t}^{(q)} = a_0 + a_1 un_{i,t}^{(m)} + a_2 gdp_{i,t}^{(a)} + \mu_i + e_{i,t}$$

where *jvr* is the job vacancies rate (quarterly data), *un* means the unemployment rate and *gdp* is gross domestic product, *t* is the index of time (in model, time is quarterly indexed). The superscripts (*q*), (*m)* and (*a)* stand for quarterly, monthly, and respectively, annual data, so that $un_t^{(m)}$ means the monthly regional unemployment rate converted to quarterly data and $gdp_t^{(a)}$ refers to annual growth rate of regional gross domestic product fitted as quarterly data. The index *i* is for the eight Romanian regions: Bucharest – Ilfov (RBI), Center (RCE), North-East (RNE), North-West (RNV), South-East (RSE), South-Muntenia (RSM), South-West Oltenia (RSV) and West (RVE). The μ_i coefficients are the cross-sections specific effects.

The model expectations are: $a_1 < 0$ (according to Beveridge curve) and $a_2 > 0$ (economic growth creates the jobs, according to Okun Law).

The errors in previous equation are serial correlated. Therefore, in the model specification we added autoregressive terms, as cross-section specific effects:

$$jvr_{i,t} = a_0 + a_1 un_{i,t}^{(m)} + a_2 gdp_{i,t}^{(a)} + b_i \cdot jvr_{i,t-1} + \mu_i + e_{i,t}$$

For the equation with autoregressive terms, the cross-section effects (μ_i) are not redundant. That is, the statistic value (3.872 for Cross-section *F* test) and the associated p-values (0.0005) reject the null hypothesis that the cross-section effects are redundant, at conventional significance levels (the redundant fixed effects tests are detailed in Annex 1, table 2).

Moreover, there are a cross-section dependences (correlations) between errors in the eight regional equations: all the four tests (Breusch-Pagan LM, Pesaran scaled LM, Bias-corrected scaled LM and Pesaran CD) strongly reject the null hypothesis of no cross-section correlation (Residual Cross-Section Dependence Tests are detailed in Annex 1, table 3). Consequently, we use the Seemingly Unrelated Regression (SUR) as the cross-section weighting method to estimate the panel data model. This is because cross-section SUR, estimating a feasible Generalized Least Squares (GLS) specification, is correcting heteroskedasticity and contemporaneous correlation (Beck & Katz, 1995).

Under these circumstances, for the panel data model, estimated by Pooled EGLS (Cross-section SUR) Method, the outcomes are the following:

Variable	Coefficient (std. error)
C	0.903117 (0.12113)
monthly\UN?	-0.045669 (0.01460)
annual\GDP? – monthly\DEFLATOR	0.465671 (0.08711)

Variable	Coefficient (std. error)
quarterly\JVR$_{RBI}$(-1)	0.649758 (0.05547)
quarterly\JVR$_{RCE}$(-1)	0.482798 (0.05437)
quarterly\JVR$_{RNE}$(-1)	0.621590 (0.04983)
quarterly\JVR$_{RNV}$(-1)	0.453251 (0.05766)
quarterly\JVR$_{RSE}$(-1)	0.568670 (0.05423)
quarterly\JVR$_{RSM}$(-1)	0.633772 (0.04271)
quarterly\JVR$_{RSV}$(-1)	0.542793 (0.05818)
quarterly\JVR$_{RVE}$(-1)	0.599779 (0.05032)
Adjusted R-squared	0.86966

Note: panel data model is estimated in EViews-9.

All the coefficients are significant at conventional significance levels and the errors are not correlated (neither serial, nor in cross-sections). The detailed outcomes are presented in Annex 1, table 1.

4. Reading the model outcomes. Conclusions

Since the variables included in the model have different frequencies, the panel data model was built on the MIDAS methodology. To avoid the cross-section dependence (correlation) between errors we used the SUR methods to estimate the model (Jula & Jula, 2017).

The estimators of model's coefficients have the expecting sign. For all the regions, the job vacancies are negative associate with unemployment, and positive correlated with economic growth. Also the autoregressive parameters (b_i) show a significant inertial effect in regional dynamics of vacancies. More specifically, we obtained that one percentage point growth in unemployment rate is associated with a diminishing of job vacancies rate by 0.046 percentage points. This result is consistent with the theory of Beveridge curve and the empirical results presented in the first part of this paper.

Furthermore, one percentage point real growth in regional gross domestic product is related with almost 0.47 percent growth in job vacancies rate. And this result is in line with Okun's theory.

Also, the inertial effect is important. Almost 60% of vacancies in a quarter are passed to the next quarter.

By combining the coefficient of homogeneity (a_0) with fixed cross-section specific effects (μ_i) and reducing the number of decimals, we obtained the following regional forecasting models:

$Q\backslash jvr_{rbi}$ = 0.744851 - 0.045669·$M\backslash un_{rbi}$ + 0.465671·($A\backslash gdp_{rbi}$ - M\deflator) + 0.649758·$Q\backslash jvr_{rbi}$(-1)

$Q\backslash jvr_{rce}$ = 1.013620 - 0.045669·$M\backslash un_{rce}$ + 0.465671·($A\backslash gdp_{rce}$ - M\deflator) + 0.482798·$Q\backslash jvr_{rce}$(-1)

$Q\backslash jvr_{rne}$ = 0.988274 - 0.045669·$M\backslash un_{rne}$ + 0.465671·($A\backslash gdp_{rne}$ - M\deflator) + 0.621590·$Q\backslash jvr_{rne}$(-1)

$Q\backslash jvr_{rnv}$ = 0.914360 - 0.045669·$M\backslash un_{rnv}$ + 0.465671·($A\backslash gdp_{rnv}$ - M\deflator) + 0.453251·$Q\backslash jvr_{rnv}$(-1)

$Q\backslash jvr_{rse}$ = 0.814667 - 0.045669·$M\backslash un_{rse}$ + 0.465671·($A\backslash gdp_{rse}$ - M\deflator) + 0.568670·$Q\backslash jvr_{rse}$(-1)

$Q\backslash jvr_{rsm}$ = 0.900208 - 0.045669·$M\backslash un_{rsm}$ + 0.465671·($A\backslash gdp_{rsm}$ - M\deflator) + 0.633772·$Q\backslash jvr_{rsm}$(-1)

$Q\backslash jvr_{rsv}$ = 0.915750 - 0.045669·$M\backslash un_{rsv}$ + 0.465671·($A\backslash gdp_{rsv}$ - M\deflator) + 0.542793·$Q\backslash jvr_{rsv}$(-1)

$Q\backslash jvr_{rve}$ = 0.933201 - 0.045669·$M\backslash un_{rve}$ + 0.465671·($A\backslash gdp_{rve}$ - M\deflator) + 0.599779·$Q\backslash jvr_{rve}$(-1)

In the above models, Q, M and A stand for quarterly, monthly and annual data, *jvr* means job vacancy rate, *un* signifies unemployment rate, *gdp* is nominal growth rate of gross domestic product, *deflator* denotes the *GDP price index* (implicit deflator), so that gdp-deflator evaluated the real growth rate of GDP. Also, the jvr_i(-1) represent the job vacancies rate, for each region, at *t-1* period, and the coefficients of these variables measure the intensity of the inertial effect. Wholly, the forecasting models are in Annex 1, table 4. The in-sampling forecasting performances are shown in Annex 2, figures 6-13.

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Annexes

Annex 1. Econometric model

Table 1. Panel data model

Dependent Variable: QJVR?
Method: Pooled EGLS (Cross-section SUR)
Sample (adjusted): 2005Q2 2014Q4

Included observations: 39 after adjustments
Cross-sections included: 8
Total pool (balanced) observations: 312
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.903117	0.121132	7.455655	0.0000
M\UN?	-0.045669	0.014602	-3.127650	0.0019
A\GDP? – M\DEFLATOR	0.465671	0.087107	5.345953	0.0000
quarterly\ JVR_{RBI}(-1)	0.649758	0.055465	11.71466	0.0000
quarterly\ JVR_{RCE}(-1)	0.482798	0.054371	8.879653	0.0000
quarterly \ JVR_{RNE}(-1)	0.621590	0.049828	12.47460	0.0000
quarterly\ JVR_{RNV}(-1)	0.453251	0.057656	7.861354	0.0000
quarterly\ JVR_{RSE}(-1)	0.568670	0.054226	10.48713	0.0000
quarterly\ JVR_{RSM}(-1)	0.633772	0.042711	14.83849	0.0000
quarterly\ JVR_{RSV}(-1)	0.542793	0.058179	9.329672	0.0000
quarterly\ JVR_{RVE}(-1)	0.599779	0.050320	11.91924	0.0000
Fixed Effects (Cross)				
μ_{RBI}	-0.158265			
μ_{RCE}	0.110504			
μ_{RNE}	0.085157			
μ_{RNV}	0.011244			
μ_{RSE}	-0.088449			
μ_{RSM}	-0.002908			
μ_{RSV}	0.012633			
μ_{RVE}	0.030085			
	Effects Specification			
Cross-section fixed (dummy variables)				
	Weighted Statistics			
R-squared	0.876784	Mean dependent var	2.350575	
Adjusted R-squared	0.869660	S.D. dependent var	2.620458	
S.E. of regression	1.010665	Sum squared resid	300.3044	
F-statistic	123.0624	Durbin-Watson stat	2.194630	
Prob(F-statistic)	0.000000			

Table 2. Redundant Fixed Effects Tests for Panel Data Model

Redundant Fixed Effects Tests
Pool: POOL_ QJVR
Test cross-section fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	3.872010	(7,294)	0.0005

Cross-section fixed effects test equation:
Dependent Variable: QJVR?
Method: Panel EGLS (Cross-section SUR)
Sample (adjusted): 2005Q2 2014Q4
Included observations: 39 after adjustments
Cross-sections included: 8
Total pool (balanced) observations: 312
Use pre-specified GLS weights

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.683262	0.094862	7.202703	0.0000
M\UN?	-0.030817	0.007896	-3.902890	0.0001
A\GDP?- M\DEFLATOR	0.436933	0.083523	5.231266	0.0000
quarterly\JVR$_{RBI}$(-1)	0.660909	0.044178	14.96007	0.0000
quarterly\JVR$_{RCE}$(-1)	0.649643	0.040558	16.01748	0.0000
quarterly\JVR$_{RNE}$(-1)	0.738912	0.032506	22.73143	0.0000
quarterly\JVR$_{RNV}$(-1)	0.583135	0.048242	12.08777	0.0000
quarterly\JVR$_{RSE}$(-1)	0.604976	0.048232	12.54292	0.0000
quarterly\JVR$_{RSM}$(-1)	0.707869	0.034802	20.34005	0.0000
quarterly\JVR$_{RSV}$(-1)	0.647531	0.045732	14.15940	0.0000
quarterly\JVR$_{RVE}$(-1)	0.702677	0.036452	19.27656	0.0000

Weighted Statistics			
R-squared	0.865425	Mean dependent var	2.350575
Adjusted R-squared	0.860954	S.D. dependent var	2.620458
S.E. of regression	1.043871	Sum squared resid	327.9897
F-statistic	193.5672	Durbin-Watson stat	2.276386
Prob(F-statistic)	0.000000		

Table 3. Residual Cross-Section Dependence Test

Null hypothesis: No cross-section dependence (correlation)
Pool: POOL_QJVR
Periods included: 39
Cross-sections included: 8
Total panel observations: 312
Cross-section effects were removed during estimation

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	508.3279	28	0.0000

Test	Statistic	d.f.	Prob.
Pesaran scaled LM	64.18652		0.0000
Bias-corrected scaled LM	64.08125		0.0000
Pesaran CD	22.28176		0.0000

Table 4. The regional forecasting models

quarterly\jvr$_{rbi}$ = -0.158265352657 + 0.90311662456 - 0.0456692040865·monthly\un$_{rbi}$ +
0.465671476125·(annual\gdp$_{rbi}$ - monthly\deflator) +
0.649757690903·quarterly\jvr$_{rbi}$(-1)

quarterly\jvr$_{rce}$ = 0.110503655888 + 0.90311662456 - 0.0456692040865·monthly\un$_{rce}$ +
0.465671476125·(annual\gdp$_{rce}$ - monthly\deflator) +
0.482797908358·quarterly\jvr$_{rce}$(-1)

quarterly\jvr$_{rne}$ = 0.0851573189453 + 0.90311662456 - 0.0456692040865·monthly\un$_{rne}$ +
0.465671476125·(annual\gdp$_{rne}$ - monthly\deflator) +
0.621589773461·quarterly\jvr$_{rne}$(-1)

quarterly\jvr$_{rnv}$ = 0.0112437491478 + 0.90311662456 - 0.0456692040865·monthly\un$_{rnv}$ +
0.465671476125·(annual\gdp$_{rnv}$ - monthly\deflator) +
0.453250519341·quarterly\jvr$_{rnv}$(-1)

quarterly\jvr$_{rse}$ = -0.0884491500533 + 0.90311662456 - 0.0456692040865·monthly\un$_{rse}$ +
0.465671476125·(annual\gdp$_{rse}$ - monthly\deflator) +
0.568670349049·quarterly\jvr$_{rse}$(-1)

quarterly\jvr$_{rsm}$ = -0.00290827864397 + 0.90311662456 - 0.0456692040865·monthly\un$_{rsm}$ +
0.465671476125·(annual\gdp$_{rsm}$ - monthly\deflator) +
0.633771707696·quarterly\jvr$_{rsm}$(-1)

quarterly\jvr$_{rsv}$ = 0.0126332122873 + 0.90311662456 - 0.0456692040865·monthly\un$_{rsv}$ +
0.465671476125·(annual\gdp$_{rsv}$ - monthly\deflator) +
0.542792745988·quarterly\jvr$_{rsv}$(-1)

quarterly\jvr$_{rve}$ = 0.0300848450867 + 0.90311662456 - 0.0456692040865·monthly\un$_{rve}$ +
0.465671476125·(annual\gdp$_{rve}$ - monthly\deflator) +
0.59977913351·quarterly\jvr$_{rve}$(-1)

Annex 2. The in-sampling forecasting performances of econometric model

Figure 6. The in-sampling forecasting of job vacancies rate – Bucharest–Ilfov Region (RBI)

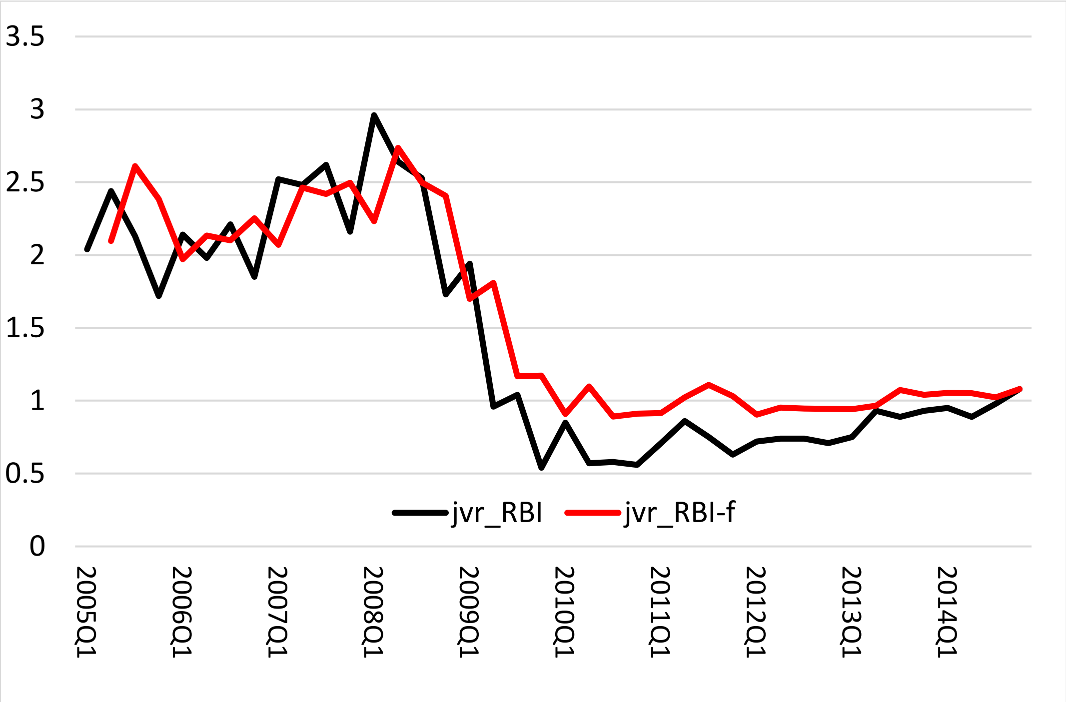

Figure 7. The in-sampling forecasting of job vacancies rate – Center Region (RCE)

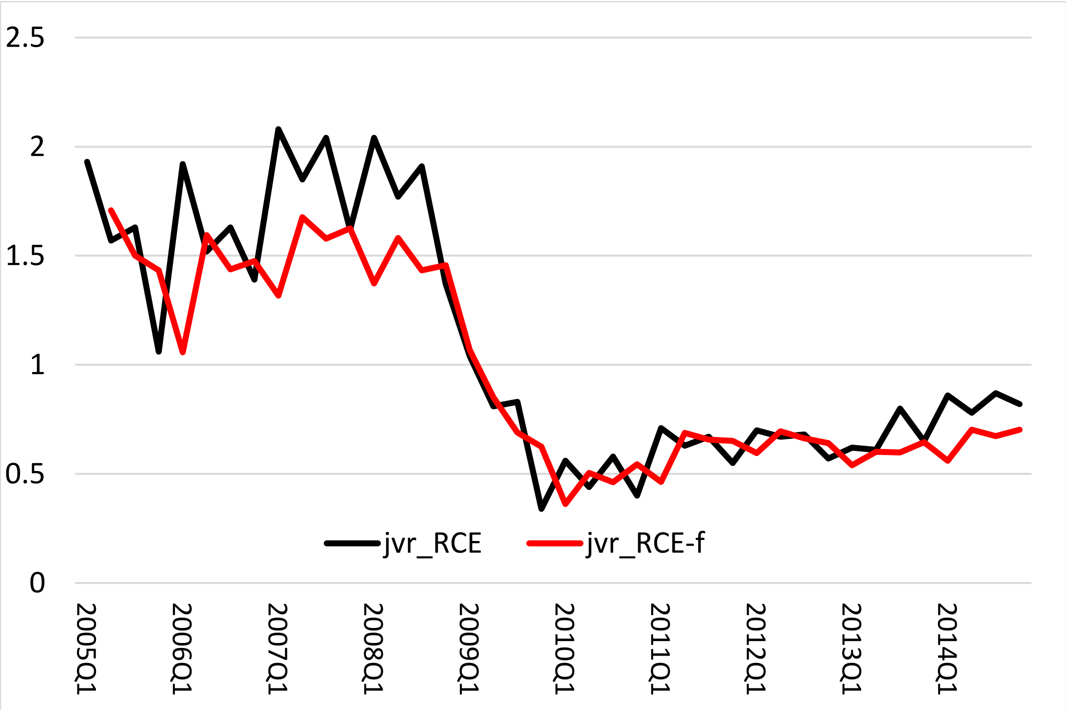

Figure 8. The in-sampling forecasting of job vacancies rate – North-East Region (RNE)

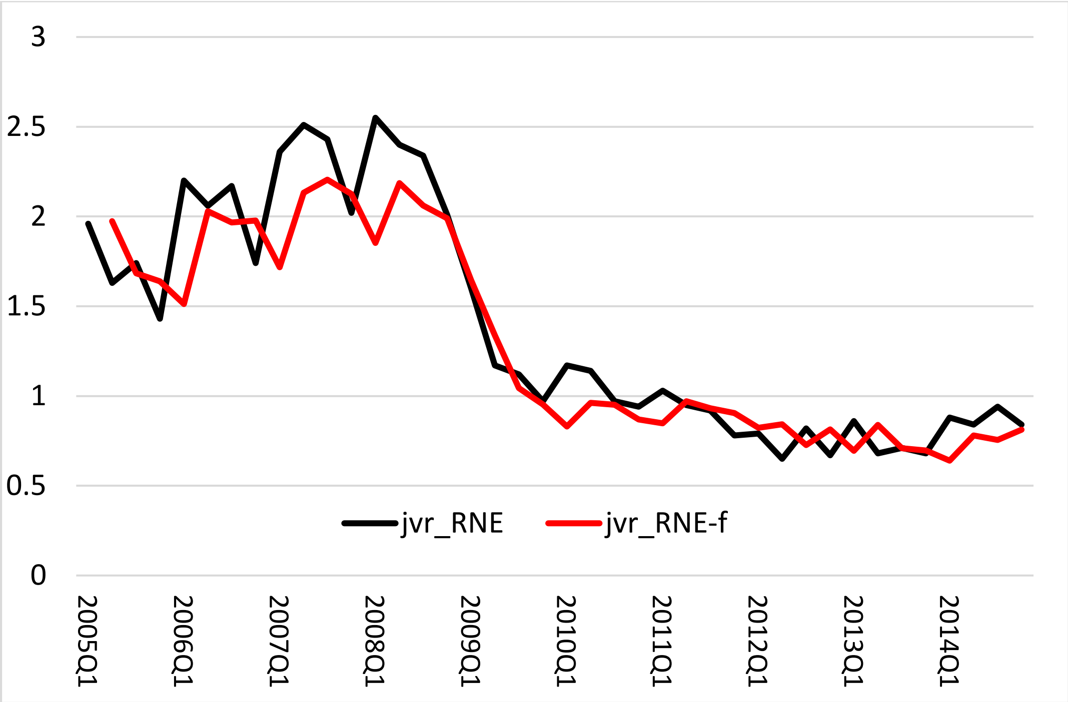

Figure 9. The in-sampling forecasting of job vacancies rate – North-West Region(RNV)

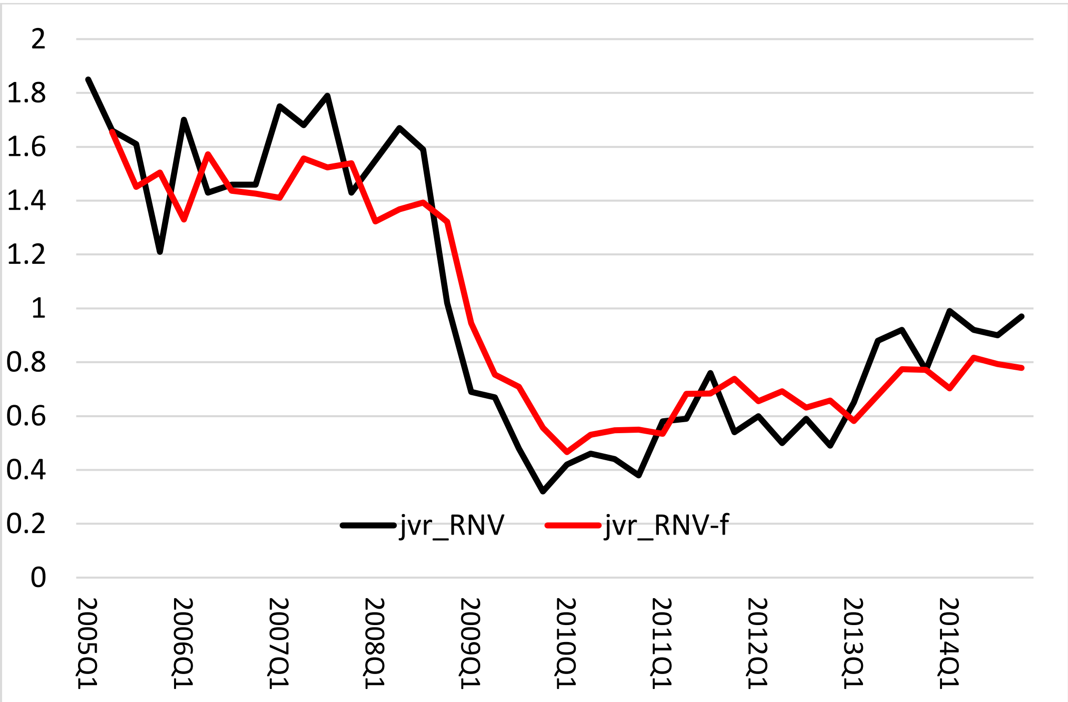

Figure 10. The in-sampling forecasting of job vacancies rate – South-East Region (RSE)

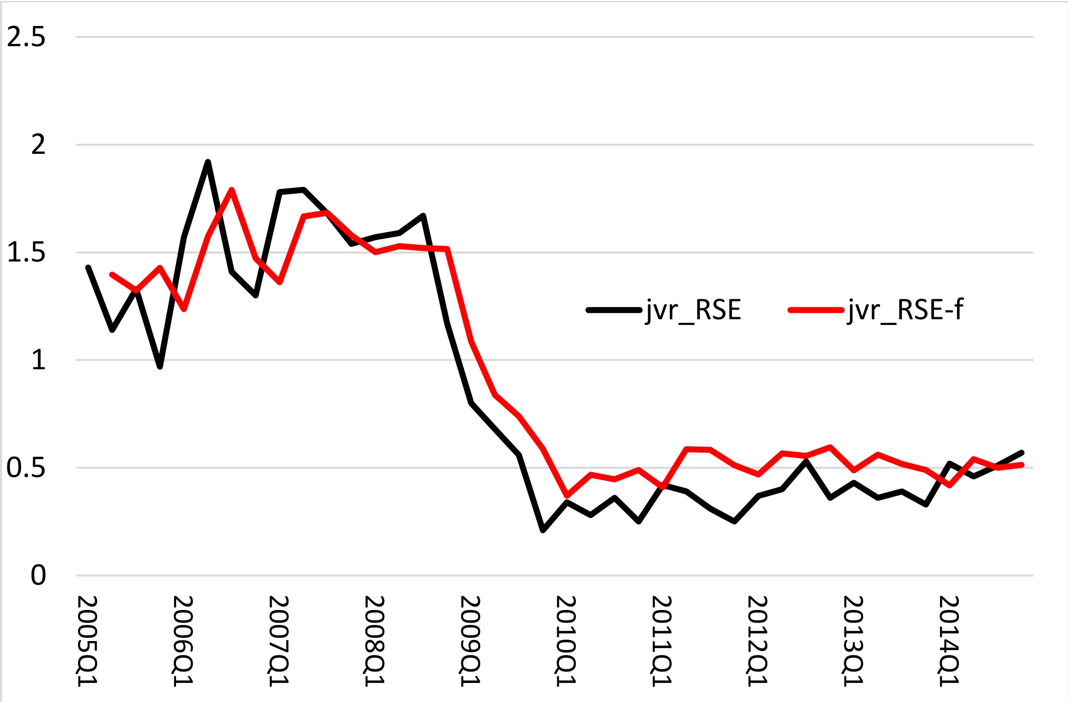

Figure 11. The in-sampling forecasting of job vacancies rate – South-Muntenia Region (RSM)

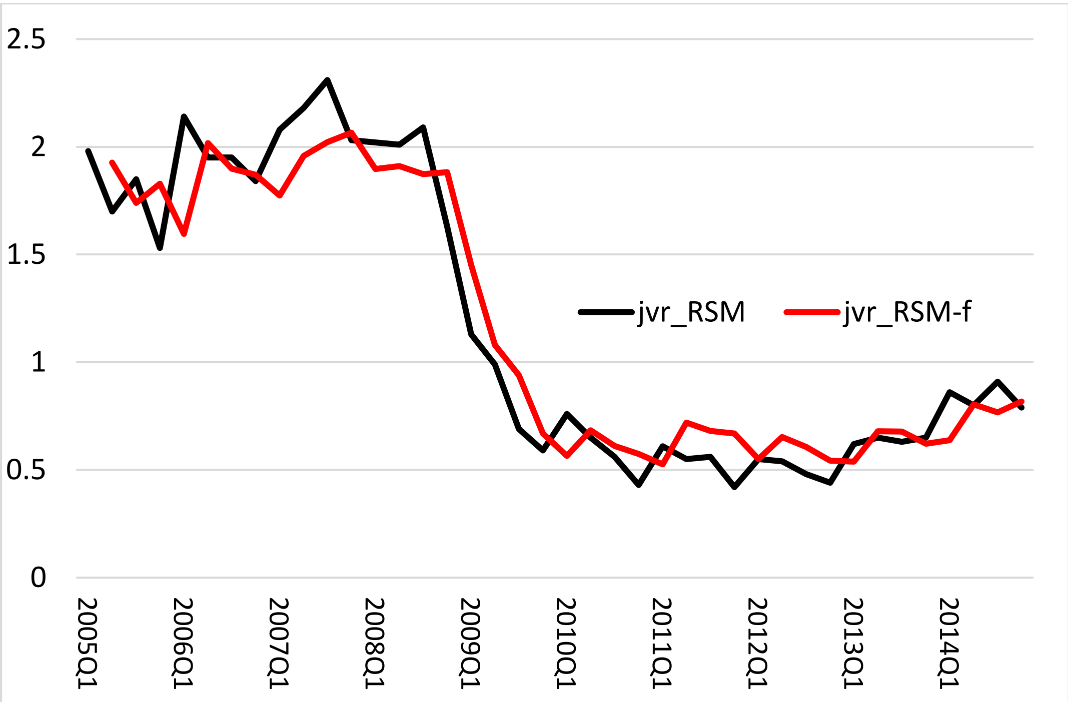

Figure 12. The in-sampling forecasting of job vacancies rate – South-West Oltenia Region (RSV)

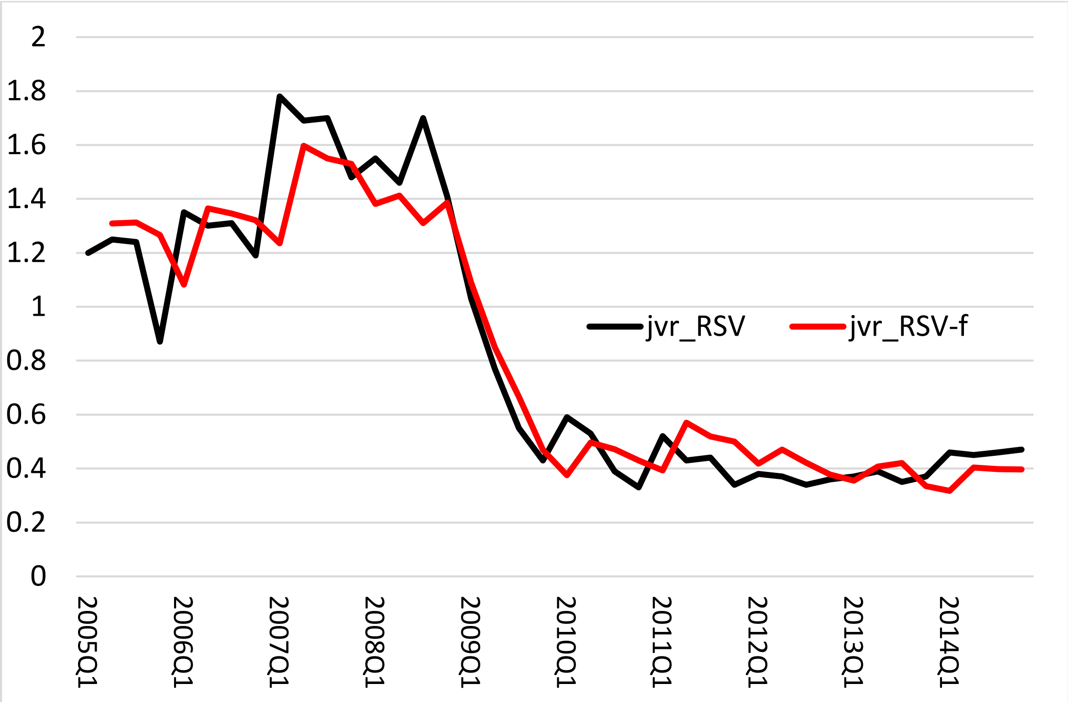

Figure 13. The in-sampling forecasting of job vacancies rate – West Region (RVE)