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NEW COMPANIES' FORMATION IN ROMANIA. A PVAR MODEL APPROACH

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Abstract: *This paper is an empirical analysis of determinants for new companies' formation and uses data from 42 Romanian counties (including Bucharest municipality) that belong to the 2010-2019 year interval. The exogenous here picked are found by the literature to be influential on new companies' formation. Results come out of a PVAR model applied (unrestricted vector autoregressive model applied on panel data). Granger causality results between regional GDP, unemployment rate, density of regional population, and entire entrepreneurial activity in Romania, on the one hand, and new companies' formation on the other, as endogenous. Stationarity and co-integration tests as well as lags criteria were done previously of estimating that PVAR model. All variables are found to be stationary of order one I(1), but test for co-integration was inconclusive. So, in absence of a certain co-integration, a VAR (and not a VECM) was chosen for estimations. Results confirm a relationship between almost all variables, tests for stability confirm that no root lies outside the unit circle and VAR satisfies the stability condition.*

Keywords: *new companies' formation, entrepreneurship, VAR model, panel data*
Jel Classification: *C3, C21, C23, M1, M13*

1. Introduction

This study aims to find some correlation and causal links between the formation of new companies in Romania at the regional level and some macroeconomic and regional variables here contributing to it. As similarly to some previous studies in the field, here the endogenous will be the formation of *new companies* at regional level and exogenous will be: unemployment rate, regional GDP, the size of existing entrepreneurship, specific population density and the number of immigrants (these are Romanian citizens, initially emigrating abroad, later returning to Romania, but this variable was then given up for reasons of non-stationarity.).

The determination links among these variables will be analysed in an auto-regressive vector model - VAR - on panel organized data for the 42 counties of Romania, here including Bucharest municipality, for the 2010-2019 years interval. Annual data come from INSSE (National Institute of Statistic) and ONRC(National Office of Company Registering) and , Eviews 10' program was used. Estimating a stable PVAR model - vector autoregressive on panel data - here helps to observe the impulse-response function and this is the one finding the reaction of the endogenous to shocks or changes met by the exogenous.

It is the VAR type autoregressive model here suggested since able to capture the connections between variables from at least two points of view : (i) the dynamic one, using several lags of each variable (e.g. past events influencing the present ones); (ii) the possibility of estimating an equation system in which each of variables becomes exogenous and endogenous in turn. The model will not reveal in this phase the specificities of counties, but restrict to drawing a general conclusion on the determinants of new companies at regional level in Romania through a number of observations used. Romania is divided into 41 counties, plus the municipality of Bucharest, distinctly managed as such (Bucharest is a municipality with similar county type rights, as by law, and the Ilfov county is just geographically surrounding it).

2. Literature review

As already mentioned above, this study bases on analyses of influences on the creation of new companies from factors like: unemployment rate, regional GDP, number of immigrants, size of entrepreneurship and population density. A series of studies on these determinative links had been conducted in Japan, Bulgaria, Czech Republic, Germany, Poland and USA before being in Romania, as well.

The endogenous will, of course, be the *newly established companies* at *regional level* in Romania. Two methods of measuring this variable are revealed in the literature. The ecological one approaches the new companies as a ratio to the whole mass of existing entrepreneurship. The other is the labour market method: the total of existing entrepreneurship relates to the number of people employed in the region. A study conducted in Bulgaria, on its 28 territorial districts, mentions these two approaches, then preferring the use of the ecological one (Alexandrova, 2015, mentioning also other authors). Another study conducted in the Czech Republic (Hajek and al., 2015), mentions this variable as the number of new companies to 1000 active individuals and this represents a measure for the entrepreneurial climate in the Czech micro-regions. A quality entrepreneurial climate can positively influence the individual's decision to become an entrepreneur, and other previous studies came to support such an idea (Armington & Acs, 2002; Delfmann, Koster, McCann and Van Dijk 2014). At the same, according to Fotopoulos (2014), new business formation would be influenced by entrepreneurial climate that is supposed to have been already settled in the past.

As for here, we preferred the approach through the labour market - the number of new companies, relative to the active population , resulting in 420 observations (42 counties * 10 years*) for each variable, after which the data will be transformed in logarithms.

3. The exogenous

Existent entrepreneurship is the number of existent entrepreneurs and it is taken as favourable for the new entrepreneurs /new entrepreneurship in the literature. It is the appropriate design of a stable business environment in a(n entire) country. Akihiro Otsuka (2008) here similarly sees the Japan's 43 districts through an ‚economic crowding' that defines a true entrepreneurship social mentality, partly inspired by Henderson at all (1995). Here the existing entrepreneurship is seen through the number of establishments related to the one of population in the same region. Basically, the higher the number of companies with their offices, the more the available capital boosting the rest of resources and factors, here including intelligence, talent and opportunities (Ciccone and Hall, 1996).

Then, it is argued in this study, together with Alexandrova (2015), for the mass of entrepreneurship with delayed effect on the newly attached business. Plus, this effect will limit to past influencing present and does not go to any influence in the future. A presumably positive relation of the future to the existing environment equals the opportunities opened and business encouraged; the negative one equals the same business opportunities rather embarrassed be it in general or in some of details. Hájek, Nekolová, & Novosák (2015) see the high entrepreneurship ratio to population as a *proxy* for the business climate.

GDP per capita at regional level

Most empirical studies in this field prefer rather the converse relation, i.e. focusing on new business formation effect on regional development. The empirical results of these studies (Fritsch, 2008) show that the effects of new business formation on economic development are not clear enough. Only few of them could provide persuasive evidence of such a positive relationship -- many others fail on this (Fritsch, 2008). On the contrary, the per capita growth as a predictor of new firm formation is found to have a positive effect by Armington & Acs (2002), not too much this way by Lee et al. (2004) and even contrary such effect (i.e., of per capita income growth on new firm formation) by Sutaria & Hicks (2004). Back here, in our study the per capita regional GDP is a measure of per capita growth.

Unemployment and unemployment rate

The literature finds unemployment as also influential for the new companies founded or business enlargement. It is here found as a natural labour resource on specific entrepreneurs' area – i.e., this part of labour is primarily searching for a profit specific to self employment, as primarily compared to unemployment benefits. But in other views the same unemployment rather is negative factor for new companies foundation and not only (Delfman, 2014; Sutaria and Hicks, 2004). Similarly, Fotopoulos (2014) and Bishop (2012) see unemployment as likely caused by deep structural economic and social causes, the ones equally affecting entrepreneurship and Otsuka (2008) and Hajeck (2015) find the business environment is with high unemployment.

The population density

The population density (i.e., inhabitants per square kilometer) adds to determinant factors for new companies born, in the literature's view. Alexandrova (2015) sees this through ‚savings crowding'. When and where labour and capital do concentrate, on the contrary, specific costs of resources' and consumers' distancing lower. Actually, high population in a region means more available labour skilled to which then young and educated from around will be also attracted. And there will be more potential entrepreneurs amongst.

4. Data methodology

So, this is once more about the same above variables in the working context. *New companies* made here account in the same ONRC's data along the 2010-2019 years interval and shared for those 42 territorial districts – there is just the number of new companies per year to talk about. Raw data as such will be related to the employed population for a better image of the new companies' territorial distribution – namely, this will be new companies to each thousand of employed people.

Existing *entrepreneurship* dimension will equally consist in a number of companies -- i.e. their total number in Romania and by counties each year of our study --, data collected from INSSE (National Institute of Statistics) - i.e., these might be all: legal entities, family business units and/or authorized persons.

GDP on region's data will come from the INSSE as expressed in million of RoN at current prices of each year during the 2010-2019 interval, then CPI will be applied as since 2010 and this will relate to district population – i.e., per capita GDP will be in RoN per inhabitant.

Unemployment will be taken as its rate noted in each of districts by INSSE statistics. Finally, *population density* always is the number of inhabitants per square kilometer and, of course, once more for each of territorial districts, for which surface is the same during the whole years' interval.

Just here adding that all our data will express in logarithms.

5. Panel data unit root tests for stationary

We organised the data by grouping individual time series to form a panel with a longitudinal structure for an N (42 counties), T (11 years) period and K (4 independent variable panel). The next step is to test the basic statistical assumptions for the panel model. The first condition is stationarity. According to Lukáčik and Pekár (2009), non-stationarity causes a false regression and misinterpretation of the results (Lukáčik & Pekár, 2009). We applied panel unit root test that uses c*ommon root*: Levin, Lin, and Chu (2002), Breitung and Candelon (2005), Im, Pesaran, and Shin (2003) and *individual root* tests Augmented Dickey and Fuller-Fisher (ADF-Fisher) and Phillips and Perron-Fisher (PP-Fisher) using automatic lag length selection *Schwartz Info criterion* where the null and alternative hypotheses are expected for unit root or stationarity. So:

(a) H0: the unit root of this panel data is for all: new companies, entrepreneurship, density of population, immigrants, per capita GDP, unemployment.

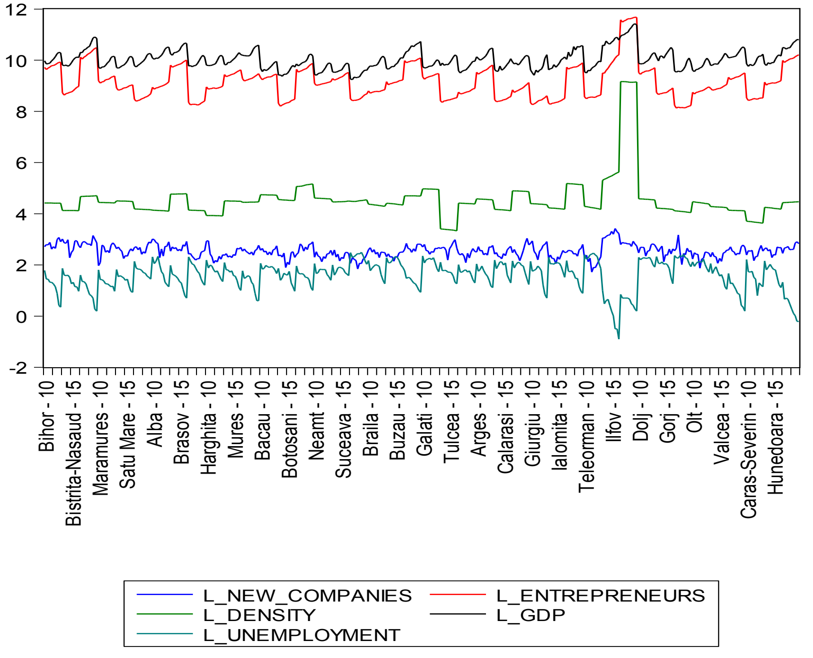
(b) H1: the panel data are stationary – see the admitted significance threshold of 0.05 or 5%. Data aren't stationary at level, but get *stationarity* with their first difference.

(c) All variables are found as integrated of order one I (1).

While Im, Pesaran, and Shin (IPS), Augmented Dickey and Fuller-Fisher (ADF-Fisher) and Phillips and Perron-Fisher (PP-Fisher) unit root tests assume single unit root and the autocorrelation coefficients change for cross sections but Levin-Lin-Chu (LLC) and Breitung unit root tests (Levin, Lin, and Chu, 2002; Breitung and Candelon, 2005) allow common unit root along cross sections.

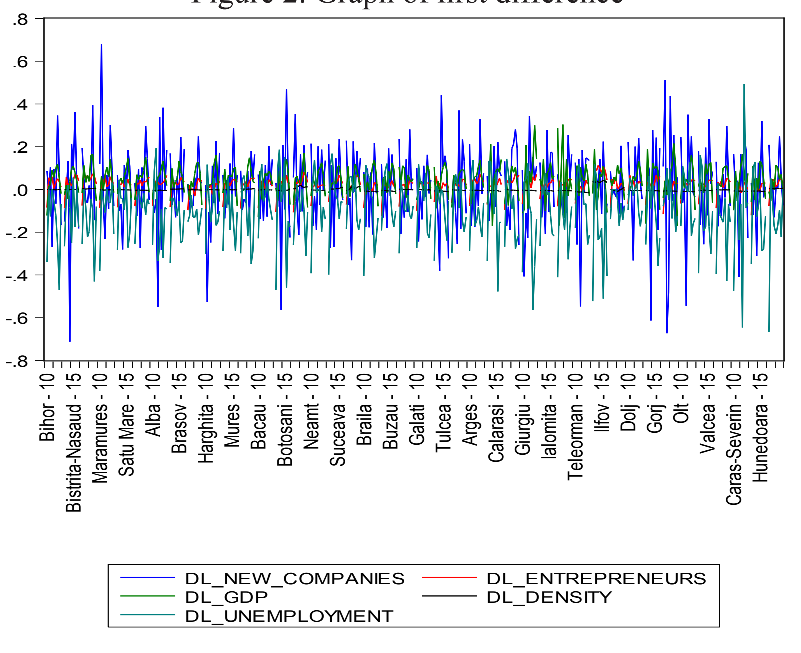
For each unit root test, the models are implemented with a deterministic trend and intercept (Kirikkaleli, et al., 2018).

Figure 1. Graph of level data



Source: Author calculation under Eviews technique

Figure 2. Graph of first difference



Source: Author calculation under Eviews technique

6. Co-integration; Pedroni Residual Co-integration Test

According to Granger and Newbold (1974), to have an order of integration of one, I (1), variables are pre-conditioned before performing the panel cointegration tests. Then, *Pedroni (Engel-Granger based) Residual Co-integration Test* and *Kao Cointegration test* using automatic lag as length selection the S*chwartz Info criterion w*as applied under the null hypothesis Ho:no cointegration versus alternative hypothesis of common AR coefficients. The purpose of Pedroni and Kao panel cointegration tests is to investigate the long-run relationships between the variables. Cointegration tests applied on level data is summarized below:

Table 1. (a) Pedroni Residual test for co-integration - Null Hypothesis: No co-integration versus alternative hypothesis: common AR coefficients. within-dimension)

	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	-3.377473	0.99960	-4.64957	1.0000
Panel rho-Statistic	4.809048	1.00000	4.718942	1.0000
Panel PP-Statistic	-10.57421	0.00000	-14.22772	0.0000
Panel ADF-Statistic	-1.293413	0.09790	-2.643786	0.0041

Source: Author calculation under Eviews technique

Table 1. (b) Pedroni Residual Co-integration test for co-integration - Null Hypothesis: No co-integration versus alternative hypothesis: individual AR coefficients. (between-dimension)

	Statistic	**Prob.**
Group rho-Statistic	7.021131	1.0000
Group PP-Statistic	-25.34726	0.0000
Group ADF-Statistic	0.159492	

Source: Author calculation under Eviews technique

As stated by Pedroni (1999), the Pedroni cointegration test is "based on pooling among both within dimensions and between dimensions. Pedroni (2001) has developed statistics that are based on pooling among dimensions, which will allow for heterogeneity in the autoregressive term" (Kirikkaleli, 2016, p. 213). Most of p-values to all statistics are higher than 0.05 as significance level our variables appear as no co-integrated, or test could be considered inconclusive. The null hypothesis is so accepted for which VAR, (unrestricted) model will be appropriate – i.e., the opposite co-integrated variables hypothesis would be the one of restricted autoregressive vector (VECM) alternative model.

7. Model specification – PVAR (3) model; Lag length criteria

We chose the optimal number of lags to estimate the model. Most of the lag selection criteria for estimating PVAR suggested choosing lag 3: LR-sequential modified LR statistical test (each test at 5% level), FPE- Final prediction error and AIC- Akaike information criterion

Table 2. VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-149.0537	NA	2.70E-05	3.667944	3.812636	3.726109
1	818.7822	1797.409	4.81E-15	-18.78053	-17.91238	-18.43154
2	977.975	276.6921	1.98E-16	-21.97559	**-20.38399***	**-21.33578***
3	1014.261	**58.74836***	**1.54e-16***	**-22.24430***	-19.92924	-21.31367
4	1034.96	31.04831	1.76E-16	-22.14189	-19.10337	-20.92043
5	1058.94	33.11587	1.90E-16	-22.11762	-18.35564	-20.60534
6	1088.472	37.26604	1.84E-16	-22.22551	-17.74008	-20.42241
7	1107.664	21.93463	2.36E-16	-22.08725	-16.87836	-19.99332
8	1133.954	26.91553	2.69E-16	-22.11795	-16.1856	-19.7332

Source: Author calculation under Eviews technique

According to definition, a VAR model (Geamănu M., 2014) represents a linear system of regressions in which a set of variables are estimated on the basis of past values of each variable, together with the other variables in the set. Model is used for its power to foresee joint dynamics of multiple time series based on linear functions of past observations. Under VAR model analyses can be made on impulse-response function (IRF) and error variance decomposition (FEVD) can be forecast for assessing the impact of shocks from one variable on the others. VAR model will develop with data arranged in panel and this will be called a PVAR - balanced panel (number of time observations is the same for each variable in ten years, 2010-2019). The same will be for a short panel since the number of cross-sectionals (see, the 42 counties in Romania) is higher than the number of time periods (for the same ten years).

In its basic form, a VAR consists of a set of K variables

$$Y_t = Y_{1t},\ldots,Y_{kt},\ldots,Y_{Kt}, \quad \text{for } k = 1,\ldots, K \tag{1}$$

After including ‘p’ lags of the endogenous, the $VAR_{(p)}$ model may be defined as:

$$Y_t = A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + \varepsilon_t \tag{2}$$

in which A_i are (K×K) coefficient matrices for i=1,…,p and ε is a K-dimensional *white noise process*.

8. Results and interpretation

New companies’ formation appears to be influenced by its values corresponding to the previous years. An increase of 1% of new companies' formation in the previous three years could lead, on the contrary, to a decrease in formation of new companies in the current year with 0,27%.

Then, there is direct-positive relationship between entrepreneurial population and new companies' formation, as proved by the same results with a p-value lower than 0,05 significance level. An increase of 1% in number of entrepreneurial activity in last three years leads to an increase of about 2.0% per year in the number of new companies’ formation. This means that an already done and stable business environment clears the way for new entrepreneurs.

Another positive and direct influence on new companies – i.e. as current new business – comes from the previous year GDP of the region. A 1% increase of previous GDP makes a plus of 0.36% in the business formation.

But really the most influential and positive factor on new companies’ formation seems to be the density of population. An 1% increase of population density in the past three years leads to an increase as high as 11% for the new companies in current year, in given areas.

Instead, unemployment is found as insignificant exogenous in given context, due to p-value for all lagged variables found as higher than the significance level of 0.05. Increase or decrease in unemployment actually misses all direct influences on new companies’ formation. It might be not quite directly available the entrepreneurship option for unemployed people, as usually.

The R^2 determination coefficient is 0.65 and so expresses that 65% of the evolution of new companies' formation could be explained by here above considered exogenous: entrepreneurship, GDP, unemployment and population density. The remaining 35% is the percentage of total variation of endogenous being explained by factors other than those above considered. The intercept value of 0.02 represents the intersection between the OY axis and the regression line or the average value of variable Y (new companies) when the other factors are zero.

Granger Causality/Block Exogeneity Wald Tests

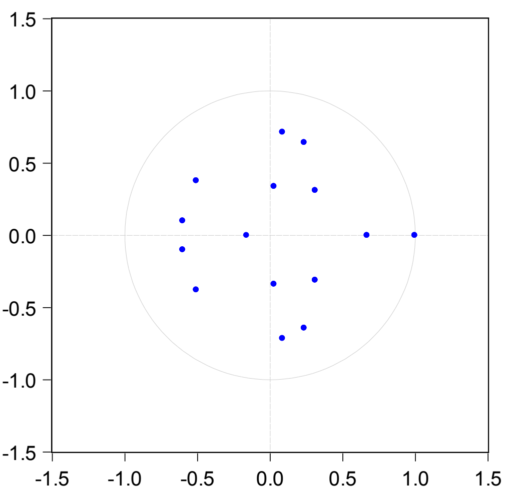
Once the VAR system estimation is done, then VAR Granger Causality test – i.e. Block Exogeneity Wald Tests -- is applied to find whether and/or how much all exogenous in turn might claim some cumulative causality influence upon the endogenous. This test's H0 null hypothesis means there is no Granger causality from all variables (jointly) to each of them. The H1 alternative hypothesis is, of course, that there is such Granger causality between all variables and each of them.

Our results show that new companies' formation in Romania is significantly influenced by all mentioned variables since jointly p-value for Granger causality block test is lower than 0.05 level of significance. It is an opposite result for density of population as endogenous – i.e., no any block impact of variables on density of population, the same as joint p-value of Granger causality block test is higher than 0.05 level of significance.

Testing the VAR stability

According to Lutkepohl (2005) and Hamilton (1994), the VAR model is stable if *all moduli of the companion matrix are strictly less than the unit.* The stability of a system assumes that the shocks are transient and then disappear after a certain period of time. In our case, the estimated PVAR model satisfies the stability condition. (Figure 3).

Figure 3. Inverse Roots of AR Characteristic Polynomial



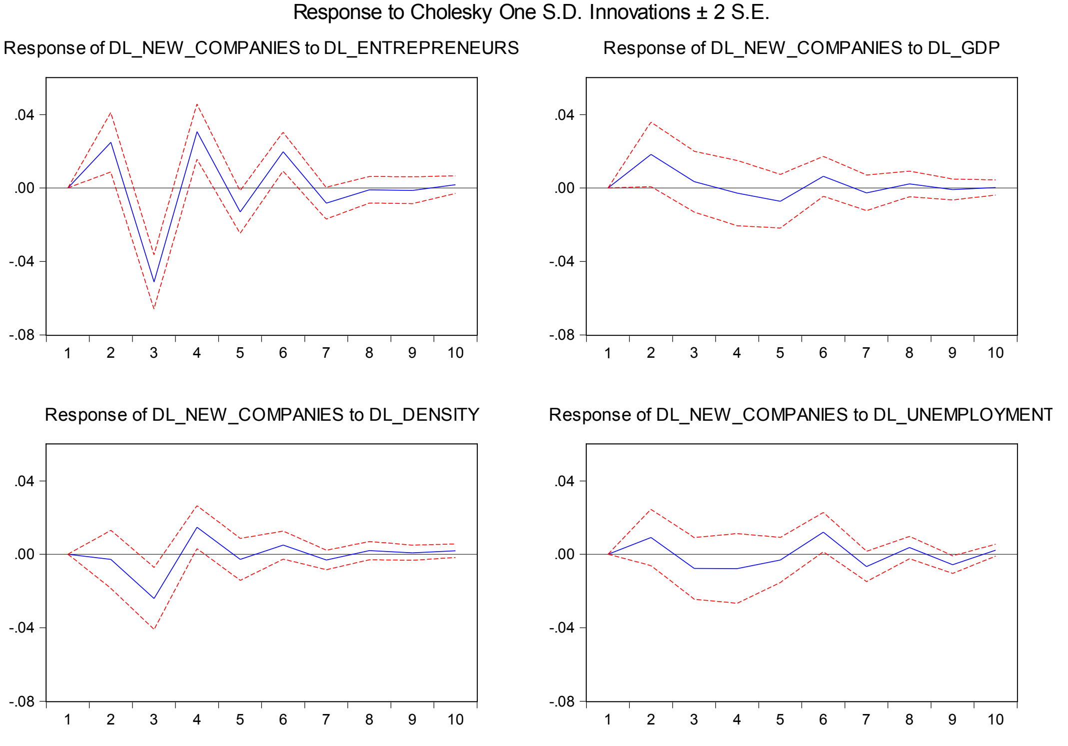
Source: Author calculation under Eviews technique

The impulse-response function

This function can be performed only for/when a stable PVAR and it captures the time profile of the effect of shocks at a given point in time on the expected future values of variables in a dynamic system (Simo-Kengne, 2012). *An impulse-response is the reaction of any dynamic system in response to some external change.* In economics, and especially in contemporary macroeconomic modeling, impulse-response functions are used to describe how the economy reacts over time to exogenous impulses usually called ‚shocks' and often modelled in contexts of vector auto-regression.

A shock to one variable not only directly affects this variable, but is also transmitted to all of the other endogenous through the dynamic (lag) structure of the VAR. An impulse-response function reveals the effect of a one-time shock to one of the innovations on current and future values of the endogenous. More generally, an impulse response refers to the reaction of any dynamic system in response to some external change (Cao Lu & Zhou Xin, 2010). The method used was: *Analytic (asymptotic) - SEs based on the response asymptotic distribution (Lütkepohl, 1990); SEs condence bands; confidence interval computed as +/– 2 SE confidence bands.*

Figure 4. Impulse Responses function of PVAR



Author calculation under Eviews10 technique

The blue line represents the impulse response function and the red lines represent 95 percent confidence interval. The impulse response function must lie within 95 percent confidence interval. Now, just keeping interested in the presumptive effect of these five variables' system on the companies' formation, as endogenous. The impulse-response function among the rest of variables will extend its report from the above graphs to the multiple graphs.

When the impulse is one standard deviation of existing entrepreneurship, new companies' formation responds with an obvious fluctuation that is the highest positive in the first two years, then decreases in the next two years and finally the impulse-response function gets smooth and positive till the end of 10-year considered interval. When the impulse is one standard deviation of GDP per capita, all response of new companies' formation is positive at most time responsive period and the fluctuation is very smooth. A smooth fluctuation is also found in new companies' formation as a result of one standard deviation shock on unemployment rate. A negative impact on new companies' formation could have one standard deviation in density of population, as starting in the second year, after first year with no fluctuation; starting with 6th year, fluctuation of new companies' formation as a response of a shock in population density, become smooth.

Variance decomposition of the new companies' variable (Lütkepohl, 2007)

Variance decomposition, also called forecast error variance decomposition (FEVD), is used to help the interpretation of a vector auto-regression (VAR) model once done.

Table 3. Variance decomposition of new companies, as a variable

Period	S.E.	DL_NEW_ COMPANIES	DL_ ENTREPRENEURS	DL_GDP	DL_ DENSITY	DL_ UNEMPLOYMENT
1	0.121105	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.127288	93.53471	3.829245	2.073944	0.046390	0.515715
3	0.139851	77.94972	16.52939	1.779524	3.010228	0.731137
4	0.145536	73.83930	19.71631	1.679935	3.807675	0.956786
5	0.146413	73.04103	20.26650	1.904833	3.797959	0.989676
6	0.149020	71.25313	21.32892	2.020028	3.779888	1.618031
7	0.149474	70.84829	21.50457	2.039384	3.799860	1.807898
8	0.149601	70.79316	21.47210	2.058164	3.811239	1.865332
9	0.149752	70.69545	21.43572	2.057234	3.806659	2.004940
10	0.149794	70.65677	21.43885	2.056348	3.821341	2.026694

Cholesky Ordering: DL_NEW_COMPANIES DL_ENTREPRENEURS DL_GDP DL_DENSITY DL_UNEMPLOYMENT

Author calculation under Eviews10 technique

Variance decomposition function is here employed in ‘Ewiews10’ program to forecast on 10 years ahead and to understand shorter and longer run associations between variables. The variance decomposition indicates the amount of information through which each variable contributes to the other variables. It finds how much of the forecasting error variance of each of the variables can be explained by exogenous shocks to the other variables. For the first year forecast, 100 % of forecasting error variance of new companies' formation is explained by the variable itself; all the other variables in the model miss all influence on new companies' formation in first year -- i.e. new companies’ formation variable is as *strongly endogenous* as implying strong influence from its own, as a variable.

Let us have an example of the 3rd year forecast. 77.9% of forecasting error variance of new companies’ formation explains by the variable itself. Then, a shock to entrepreneurial activity can cause 16.5 % fluctuation in new companies’ formation; a shock to GDP can cause 1.77% fluctuation of new companies’ formation; a shock to density of population can cause 3.01% fluctuation of new companies’ formation and finally, a shock to unemployment rate can cause 0.73% of new companies’ formation – i.e., sum of all these percentages makes 100%. For a *longer term*, let us have another example of 10th year ahead, 70.65% of forecasting error variance of new companies explain by variable itself. Shock to entrepreneurial activity can cause 21.43 % fluctuation in the variance of new companies’ formation; a shock to GDP can cause 2.05% fluctuation of new companies' formation; a shock to density of population can cause 3.82 % fluctuation of new companies' formation; finally, a shock to unemployment rate can cause 2.02 % fluctuation on new companies' formation.

These are to conclude that even own shock contribution is supposed to go down in the long run. New companies’ formation shows a strong influence since the first period towards the future. The influence of entrepreneurial climate increases in the long run, but remains stable at around 21% (*least exogenous variable*). The influence of GDP, density and unemployment rate remain all week in longer run, at 2%-3% in explaining forecasts of variance in number of new companies. Variables are *strongly exogenous* since implying a weak influence on the dependent variable. After estimation of the panel P-VAR model, it becomes equally important performing panel data series correlation tests to confirm the validity of this panel – i.e., together with the above-mentioned model stability.

Then, *VAR Residual Portmanteau Tests for Autocorrelations* was performed with its Null Hypothesis H0: of no residual autocorrelations up to lag h, and alternative hypothesis H1: residuals are correlated. The probability of p-values for all lags are more than 0.05 significance level, therefore the null hypothesis (we accepted the null hypothesis) cannot be rejected and this means that all the equations are free from serial correlation.

9. Summary and conclusions

Let us first reiterate that the above study was for newly created business and presumable determinants like: business environment in place, unemployment rate, GDP of the region and density of population in the same region during the analysed period. Data of Romania's 42 counties – i.e. as territorial districts – have been used and the reference period was the 2010-2019 years interval. These data came from Romania's National Institute of Statistics (INSEE) and National Registering Office for companies (ONRC). All data series were found as non stationary at level, then *stationary* was obtained at first difference – i.e. Schwartz Info criterion and Test for *stationary*. *Pedroni Residual Co-integration* test for co-integration between variables was then employed in order to search for presumable long run association of the same variables. Results looked inconclusive. Next step consisted in an autoregressive VAR model applied – i.e. an equation system for these variables. This system was going to be one of three lags according to tests already mentioned as applied – i.e. *sequential modified LR statistic test,* with each test at 5% level, *Final Prediction Error (FPE)* and *Akaike Information criterion (AIC)*. Then, *stacked Pair-wise Granger causality test* came to establish bi-, versus uni-directional causality between variables.

Results of the VAR estimation model revealed significant effects on new companies' formation from: already existent business environment, regional GDP – e.g. estimating income per inhabitant in that region – and population density. These variables' influences proven significant – i.e. lower than 0.5 significance p-value.

Then, the unemployment rate was found to be *insignificant* for a p value higher than 0.05 significance level – i.e., there is rather no direct relation between unemployment and companies' formation.

The *determination coefficient* R^2 *squared* was found at 0.65, and says that 65% from the evolution of new companies' formation could be explained by the exogenous: entrepreneurship, GDP, unemployment and population density. The *"F statistic"* **used in combination with the p-value** proves that overall results are significant since comparing the joint effect of all the variables together – i.e. our model F statistics p-value is 0.0.

The *Durbin Watson (DW)* statistic test for residuals' auto-correlation always has a value between 0 and 4. A value of around 2.0 means that there is no auto-correlation detected in the sample -- i.e. our model show a *Durbin Warson statistic* value = 2.10. Also, our PVAR model with three lags was found stable according to *Roots of Characteristic Polynomial* graph and table, with no roots outside the unit circle.

Finally, we performed *VAR Residual Portmanteau Tests for Autocorrelation, impulse-response* function and forecast *variance decomposition* which determines the reaction of each endogenous variable to shocks or changes manifested by the rest of variables.

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