sciendo

The Importance of FDI on Stimulating Entrepreneurship – A Regional Study in the Case of Romania

Horia TIGAU
Bucharest University of Economic Studies, Bucharest, Romania
tigauh@gmail.com

Abstract. *The world economy has been developing at a very fast pace for the past few decades, growth which is commonly linked to the development of technology. Innovative ideas become successful when certain individuals decide to face the multiple risks that appear when transforming these ideas in to reality. The vast literature on entrepreneurship has shown that startups are important players in driving the economy on an ascending path. It is no surprise that highly developed countries, such as USA, Israel or Singapore have governmental programs which stimulate startup creation. More recently, the Romanian government has also joined in on spending money to offer entrepreneurs the chance to create successful businesses. Using spatial panel data on the 41 counties of Romania and the capital, Bucharest, on the period 2011-2016, this study highlights some significant dependencies between the survival of startups (for a period of 3 years) and other factors – both internal and external. The analysis shows that the aforementioned survival is clearly and positively impacted by Foreign Direct Investment, the share of fresh businesses in the total business environment and the number of immigrants with a permanent residence in the respective counties. Moreover, there are significant spatial effects occurring between neighboring counties. These results suggest that foreign investors could benefit from bringing their capital in Romania, as startups greatly contribute to the specialization of markets, and moreover, spillover effects present suggest that a smaller number of investment centers can be highly effective in their regions.*

Keywords: entrepreneurship, FDI, spatial analysis, startup, autocorrelation.

Introduction

Developing economies have been more reliant on the consistent growth of entrepreneurial venturing. Not only that entrepreneurship stimulates creativity, helps a great deal in creating new jobs and increases the cash flow in the economy, but it also represents a very appreciated and sought-after occupation (Okrah et al., 2018). For example, based on the latest GEM Report with data available for Romania (GEM, Global Report, 2015-2016), 75.1 % of Romanians consider that entrepreneurs present a high societal status, while 72.4% think that entrepreneurship is a good career choice. It is interesting to note that although neighboring country Bulgaria presented a similar value in 2015-2016 for high-status perception (71.5%), only 57.5% of Bulgarians think entrepreneurship is a good career choice. The country's profile changes in the latest available report (GEM, 2018-2019) – the status indicator decreases to 69.3%, while the career choice indicator increases to 62.6%. This result might suggest that entrepreneurship in Bulgaria has shown explicit positive effects on the economy, pointing towards an increased affinity towards entrepreneurship as a profession. Even though GEM data for 2018-2019 Romania is unavailable, one could still predict a high societal value about entrepreneurship.

In order to keep up the favorable perceptions on entrepreneurship, and, implicitly, the aforementioned benefits of a start-up based economy, one has to ask oneself what exactly contributes to a start-up's success. In the article first mentioned (Okrah et al., 2018), the case is made for the two most important factors that define a new business's path – financing and innovation. These two factors stand together, as research with the goal of creating innovative value requires funding. The rapid advancement in technology (not only in terms of an end product, but from the marketing and servicing point of view, as well) obliges the entrepreneur to adapt his business to the forever changing requirements of the market.

An important result, although somehow counterintuitive, is that allowing startups to fail leads to increases in innovation due to entrepreneurs' will to further explore the creative process (Nanda & Rhodes-Kropf, 2017). This failure tolerance is synonymous to the term 'entrepreneurial experimentation', which, as one can tell from its name, requires variable investment sums. Small, emerging businesses present unpredictable outcomes. Therefore, the financial risks are usually undertaken by financial institutions, such as Venture Capital firms (Kerr et al, 2014). These firms, even though they are managed by highly-skilled investors, don't present a high success rate in their portfolios – in the last 30 years, more than a half of VC-backed firms were terminated at a loss and even at a very early stage. This is due to the fact that VC firms operate by investing more in companies that present signs of success while cutting costs as early as possible on the underperforming startups. As one can tell from this strategy, VC firms do not present a high failure tolerance. The authors (Nanda & Rhodes-Kropf, 2017) suggest a different approach for investors (either VC firms, governments or other): instead of defining the failure tolerance for each different project, based on the desire to experiment at a small cost, an investor should come up with a preceding strategy that only selects the projects which are subject to a high tolerance for failure.

One could argue that a dynamic and innovative entrepreneurial environment can attract foreign investment – indeed, transnational companies strategically choose to extend their business in regions with distinguishing and active business habitats (Fahed, 2013). A free market in a stable, uncorrupted political state, with an economy open to new players represents a good target for Foreign Direct Investment. Moreover, FDI is a very important factor in the growth of developing countries, even more important than domestic investment, due to the transfer of technology (Borensztein et al., 1998). These results suggest that an attractive startup incubator redirects foreign funds, which also accelerates the transfer of technology, hence innovation, pointing towards more resilient new businesses and overall regional economic growth.

The present paper tries to extend the above directions to a spatial component: one can consider the selection process to be made with regards to geographic regions which, although present a high rate of failed new businesses, they also show increased economic performance – here, by the amount of Foreign Direct Investment. Moreover, the presence of spatial spillover effects could show that economic betterment can spread to neighboring regions, rendering a more efficient strategy for investing at a national level.

Literature review

A large part of literature considers entrepreneurship to be an important factor of growth and sustainability at a regional level of the economy (Valliere & Peterson, 2009 ; Fritsch, 2008 ; Koster et al., 2010). To be more precise, some of the benefits of the emergence of new businesses include stimulation of productivity (Baumol et al, 1988), increasing innovation by introducing new products and even new markets that seek to overturn the incumbent ones (Klepper & Sleeper, 2005 ; Kim & Mauborgne, 2004), or by increasing the availability of goods and services, and, therefore, the problem-solving aptitudes in the market.

Turning to regional effects of new businesses, it is important to note that benefits arise where resources aren't lacking, competition is not very fierce and the respective regions are productive (Fritsch, 2008). This is due to the fact that incumbent businesses from other, more productive regions can send new competitors towards failure. Moreover, the efficiency of one region can be shaped by the innovation system and educational level of its inhabitants (Fritsch & Mueller, 2007).

The dependent variable of most regional studies on the development of entrepreneurship focused on positive aspects which point out the success of startups: number of new annual VAT registrations (Ross, 2011), regional participation percentage in the creation of new companies (Espinoza et al., 2019), entry-level workforce occupation (Ghani et al., 2014) or a binary variable (used in a logistic regression) which considers the change of a startup ownership in four years from its inception – the authors believe that this indicates a high interest in the startup's activity from a larger company that acquires the startup (Silva et al., 2016). This last paper does not employ a spatial model, but uses individual firms' responses. It is interesting to note, however, that a spatial logistic regression model could be used to predict the probability of success for a well-defined startup in further research.

On the other side of the coin, startup failure is not as fully explored as startup success, even though 9 out of 10 startups fail (Kalyanasundaram, 2018). Looking at reasons for failure might be more revealing for striving entrepreneurs than looking at the success of others. Failure could be explained through three approaches that usually intersect: a determinist approach that observes environmental factors contributing to business failure, a voluntarist approach that considers a business' downfall to be the entrepreneur's full fault and an emotive approach which suggests that an entrepreneur's attitude is a good explanation to why they choose to give up on their business (Khelil, 2015). These approaches suggest the emergence of a tri-directional analysis of the dependent variables – environmental, decisional and emotional factors affect the failure of a startup.

Coming back to the analyses of success, the authors have used different dimensions to account as explanatory variables, as well as different types of models. The following paragraphs describe the models used in the aforementioned papers:

1st Paper (Ross, 2011)

The paper follows the panel data on 32 Scottish regions during a span of 10 years, using an OLS individual effects model. This model does not take into account the spatial dependencies between regions, as a spatial regression model would, but it does take the individual differences into account. The independent variables appear across three different dimensions, as follows:

Demand and Supply factors: annual wage growth change, annual population growth change, unemployment percentage in the working population and percentage of the population above a certain education level (N.B. : The level is NVQ4.)

Agglomeration factors: percentage of manufacturing companies in the general business population, similar percentage for the business sector and the population density.

Policy and Cultural factors: percentage of the workforce employed in the public sector and percentage of small businesses in the total population.

The model's summary suggests some interesting results: unemployment is significantly inverse to entrepreneurship development, meaning that people do not start a business to create jobs for others, but rather that they start their own business due to limited employment opportunities; a high level of education is linked to creation of businesses, probably due to the ability to spot opportunities; population density indicates a high level of urbanization, meaning more opportunities for the startup in terms of exposure to clients and potential partners; the factor which stood out the most was the percentage of small businesses in the region – it shows that there is a startup culture in the region, attitude that promotes entrepreneurial venturing. The author then suggests, after using only external factors, looking at entrepreneurial motivation for further analysis, suggestion that follows Khelil's (Khelil, 2015) division of approaches.

2nd Paper (Espinoza et al., 2019)

In their article, Espinoza et al focus their attention on the 15 regions of Chile in a two-year period – 2013-2014. The explanatory variables were divided into five different categories:

Demographic factors that were taken into account were percentages of women and immigrants, respectively, as well as the average age of the population.

Average years of education, percentage of people with a graduate degree and existence of certain types of universities in the region were all considered to be educational factors.

Geographic factors included urban or rural membership, while *technological ones* studied the populations' internet access and the number of patents per capita.

Lastly, *economic factors* were considered, such as per capita income, unemployment rate, Gini index, and percentage of employers or self-employed in each population.

The results have revealed that there is indeed a spatial effect of entrepreneurship present in regions across Chile. Studying the coefficients of the statistically significant independent variables, the authors draw some conclusions – immigrant population has a positive impact on entrepreneurial growth, as the infusion of new culture and propensity towards risk of newly-arrived immigrants tends to regenerate the business environment, as it was suggested in previous work (Kalantaridis & Bika, 2006); the training offered by universities helps sustaining the entrepreneurial spirit through innovative action – this action is also positively correlated to the number of patents in the population, as one would expect; lastly, income per capita and accessibility to the World Wide Web show a positive contribution to the creation of new businesses.

3rd Paper (Ghani et al., 2014)

This paper introduces a few more explanatory variables, along with some of the ones seen before – quality of physical infrastructure, the requirements of individual banking, the travel time to important economic centers and the harshness of labor laws, of which the last two have shown a positive significant impact.

Foreign Direct Investment

Turning our attention to the FDI, opportunity-driven entrepreneurs benefit from both inwards and outwards investment (Albulescu & Tamasila, 2014). The authors of the study make use of GEM data on entrepreneurship for 16 European countries to set their dependent variables – the total entrepreneurial activity rate shows the percentage in the working population of people who have started or are just starting their own business; the necessity and opportunity-driven entrepreneurship rate represent the percentage of entrepreneurs that have started the business for one of the two motives. In general, necessity-driven entrepreneurs are pushed into starting a business due to the lack of job options for them, while the other category believes there are some opportunities which can bring them a higher income, as well as financial freedom. The explanatory variables represent data collected from the GEM and UNCTAD (United Nations Conference on Trade and Development) reports – inwards FDI represents the stock volume of investment to the respective country, while the outwards FDI represent the volume leaving from the respective country; GDP per capita, Fear of failure and Entrepreneurial intentions finish the list of independent variables in the authors' analysis. Apart from the major result described at the beginning of this paragraph, the paper also links the outward flow of investment to lower job creation, which in turn pushes some people (necessity-driven) into starting their own business. Other significant results include a positive correlation between entrepreneurial rates and GDP per capita and entrepreneurial intentions, while fear of failure has a negative effect on these rates.

Romanian Start-Up Nation

The case for a regional analysis in Romania is timely since the beginning of the governmental Start-Up Nation program in 2017 (OUG-3, 2017). The program has brought credits of up to 200,000 RON (almost 40,000 Euros) to 8,600 new firms. The budget for the second year of implementation, 2018, had shrank to 700 million RON, able to sustain 3,500 new businesses, although the government's program suggested an annual budget of 2 billion RON for the period 2018-2020 (Zamfir, 2017). This mismatch could be caused by the lack of regional studies on the performance of Romanian startups. For this reason, the present paper aims to fill the gap in the available literature on Romanian new businesses.

Based on the literature review, the next chapter looks at the models and variables to be employed in this paper.

Methodology

The present study tries to answer two main research questions:

Question 1: Do FDIs affect the survival of startups?
Question 2: Is there a spatial dependence in the data between regions?

In order to answer these questions, a spatial panel regression model was used with data from all Romanian counties in the period 2011-2016. The variables used in the model which were selected based on the previous literature review are described in Table 1 below.

Table 1. Variables considered in the model

No.	Name	Description	Source
1	*Survival_3*	Total number of enterprises* newly born in t-3 which survived to t.	*Eurostat (Regional Business Demography at NUTS 3 level)*
2	*Share_3*	Percentage of 3 year old enterprises' share in the total business population.	

No.	Name	Description	Source
3	*Employment_3*	The employment growth rate of 3 year old enterprises: calculated by dividing the number of employees at t by the number of employees at t-3 for enterprises born at t-3, expressed as a percentage change.	
4	*Pop_Density*	Population density expressed in inhabitants per square kilometer.	*Eurostat (Population Density by NUTS 3 level)*
5	*Age_15_64*	The percentage of people between 15 and 64 years old out of total population.	*Eurostat (Population on 1 January by broad age group, sex and NUTS 3 level)*
6	*GDP_per_Cap*	GDP per inhabitant in Euro.	*Eurostat (GDP at current market prices by NUTS 3 regions)*
7	*Unemployment*	Unemployment rate as a percentage.	*Romanian National Statistics Institute (Workforce)*
8	*R&D_per_Cap*	Number of employees working in R&D for every 10,000 employees.	*Romanian National Statistics Institute (R&D and Innovation)*
9	*Immigrant_Pop*	Total population of immigrants with a permanent residence.	*Romanian National Statistics Institute (Migration)*
10	*BAC_Prom*	Promotion rate at the Romanian Baccalaureate Exam – calculated by dividing the number of Baccalaureate promoted students by the number of high school graduates.	*Romanian National Statistics Institute (Education)*
11	*FDI_per_Cap*	The capital value of foreign participation companies per capita, measured in thousands of Euro.	*National Trade Register Office*

*N.B. : *Enterprises from Eurostat data refer to ones which belong to "Industry, construction and services except insurance activities of holding companies".*

The first variable acts as the dependent variable in this analysis, while the rest of them are explanatory. When looking for multicollinearity, one usually sets the correlation cutoff point between IVs at 0.8 (Berry & Feldman, 1985). In this analysis we find correlations above the cutoff between *FDI_per_Cap*, *Pop_Density* and *GDP_per_Cap*. For this reason, four different sets of independent variables could be used for the models – each of them created by deleting either 0, 1 or 2 of the highly correlated variables.

As a spatial analysis is pursued, a spatial weight matrix must be defined to describe the geographical dependencies between regions. Several methods can be employed, such as the kth nearest neighbor matrices, inverse distance matrices or binary contiguity matrices to name a few (Elhorst, 2014). The method used here is based on binary contiguity, i.e. let $\boldsymbol{W} = (w_{ij}) \in \mathbb{R}^{n\times n}$, where n is the number of regions considered, be the weight matrix, such that $w_{ij} = 0$ if the region i does not share a border with region j , and $w_{ij} = 1$ otherwise. The consensus also attributes the value of 0 to the elements of the first diagonal, meaning that a region is not a neighbor to itself. Once the matrix is constructed, it is then row standardized to form the weights used in the regression. Following the collection of data and creation of the weight matrix, spatial panel regression models are used to explain the spatial dependencies between regions. All subsequent operations are done in the statistical software R.

Using the SLM1 marginal test described in Baltagi's paper (Baltagi et al., 2003), results show that all four considered models present individual random effects. Moreover, the Hausman test for spatial models (Pace & LeSage, 2008) reinforces the presence of random effects. We proceed by describing the model (Millo & Piras, 2012), which presents spatial lag autocorrelation, as well as spatial error autocorrelation:

$$\boldsymbol{y} = \lambda(I_T \otimes W)\boldsymbol{y} + X\boldsymbol{\beta} + \boldsymbol{u} \qquad (\mathbf{1})$$

$$\boldsymbol{u} = \rho(I_T \otimes W)\boldsymbol{u} + \boldsymbol{\varepsilon} \qquad (\mathbf{2})$$

$$\boldsymbol{\varepsilon} = (\boldsymbol{\iota_T} \otimes I_N)\mu + \boldsymbol{\nu} \qquad (\mathbf{3})$$

, where **y** is the NT×1 vector of observations for our dependent variable, I_T is the T×T identity matrix, W is the spatial weight matrix described above, λ is the spatial dependence parameter, X is the NT×k matrix of observations from the independent variables, **u** is the disturbance term, composed of an autoregressive error part whose effects are described by ρ, and an error part $\boldsymbol{\varepsilon}$, which is also split in a specific effects part $\boldsymbol{\mu}$ with $\mu_i \sim IID(0, \sigma_\mu^2)$ related to each region and a novelty part $\boldsymbol{\nu}$ with $\nu_{it} \sim IID(0, \sigma_\nu^2)$ that accounts for both changes in time and regions; $\boldsymbol{\iota_T}$ is a vector of T ones. In the present paper, N=42, as for the number of counties in Romania, T=6 for the period 2011-2016 and k is 10, 9 or 8, depending on the selected model.

Based on the following formulas (LeSage & Pace, 2009), the direct and indirect impacts are estimated for each variable. These impacts are calculated as means of the impacts in each region i. The direct and indirect impacts for variable x_k in the region i and region j, respectively are given by the following formulas:

$$S_k(W)_{ii} = \frac{\partial y_i}{\partial x_{ki}} \qquad (\mathbf{4})$$

$$S_k(W)_{ij} = \frac{\partial y_i}{\partial x_{kj}} \qquad (\mathbf{5})$$

Lastly, with the use of GeoDa spatial statistical software we verify the significance of local autocorrelation between neighboring regions (Anselin, 2003). The next section presents the results obtained by applying the previously described methodology to the collected data.

Results and discussions

Computing the Moran's I parameter (LeSage & Pace, 2009) for the Survival_3 and FDI_per_Cap variables offers a significant result, which points towards rejecting the null hypothesis that the spatial dependencies are due to random processes. The following figure presents this result, by forming spatial clusters based on similarities on the two variables:

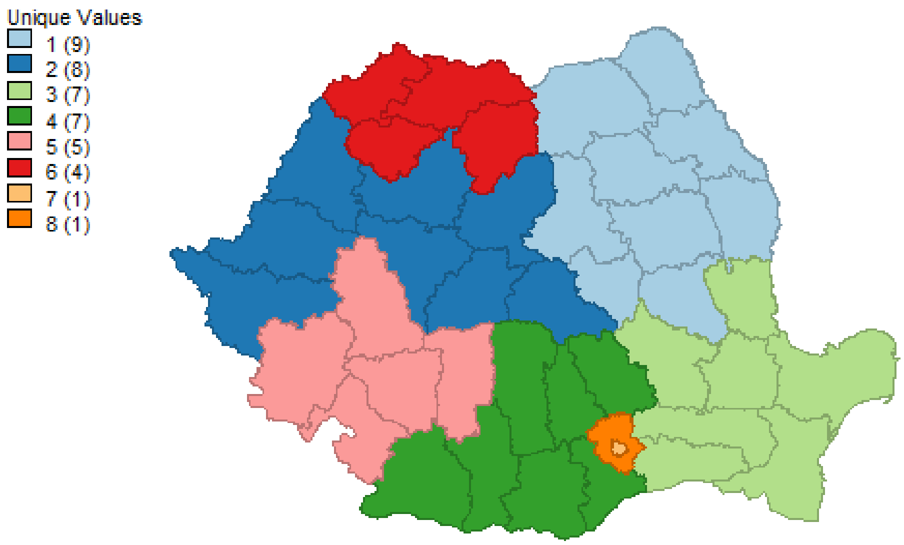

Figure 1. K Means Cluster Map with 8 Clusters for Survival_3 and FDI_per_Cap mean values 2011-2016
Source: Own work in GeoDa.

We can distinguish in Figure 1 seven different cluster regions and the highly developed area Bucharest and Ilfov county. By performing a bivariate Local Moran's I analysis, four counties show significant results. The four regions– Iasi, Bacau, Galati and Bucharest – present spatial dependence described as follows: FDIs in the highlighted regions have a significant impact on the survival of startups in the neighboring counties.

The following table (Table 2) compares the estimated parameters and their significance for each of the four models described in the methodology section.

Table 2. Description of the models

Name	Model 1 (Full Model)	Model 2 (without GDP_per_Cap)	Model 3 (without Pop_Density)	Model 4 (without Pop_Density and GDP_per_Cap)
Intercept	-3741.4016 (0.0033) **	-1638.7308 (0.1801)	-3407.3030 (0.0059) **	-1468.5016 (0.1934)
FDI_per_Cap	0.1027 (0.0796) .	0.3364 (7.9e-09) ***	0.3257 (2.3e-10) ***	0.4420 (<2.2e-16) ***
Share_3	142.3852 (<2.2e-16) ***	131.1884 (2.2e-16) ***	125.0222 (2.2e-16) ***	122.4494 (<2.2e-16) ***
Employment_3	0.355172 (0.7033)	0.1543 (0.8575)	0.3682 (0.6558)	0.1964 (0.8062)
Pop_Density	0.3969 (9.3e-09) ***	0.2535 (0.0073) **		
Age_15_64	3837.6363 (0.0267) **	1623.0236 (0.3185)	3809.6902 (0.0192) *	1515.3950 (0.3076)
GDP_per_Cap	0.1537 (2e-07) ***		0.1150 (0.0004) ***	
Unemployment	0.0137 (0.9938)	-2.0332 (0.2402)	-0.2123 (0.9034)	-1.8439 (0.2696)
R&D_per_Cap	0.3950 (0.4478)	0.2304 (0.6541)	-0.0291 (0.9536)	-0.0023 (0.9962)

Name	Model 1 (Full Model)	Model 2 (without GDP_per_Cap)	Model 3 (without Pop_Density)	Model 4 (without Pop_Density and GDP_per_Cap)
Immigrant_Pop	0.1092 (8.7e-06) ***	0.0981 (5.4e-05) ***	0.1026 (1.2e-05) ***	0.0940 (4.6e-05) ***
BAC_Prom	66.6080 (0.8530)	258.276 (0.4564)	-323.1600 (0.3808)	9.2631 (0.9781)
λ	0.0463 (0.7064)	0.2404 (0.0298) *	0.20795 (0.0497) *	0.2987 (0.0024)**
ρ	-0.0815 (0.6165)	-0.3636 (0.0286) *	-0.4133 (0.0024) **	-0.5135 (8.4e-05) ***
ϕ	1.1094 (0.0044) **	2.5617 (0.0057) **	3.0635 (0.0003) ***	3.9278 (0.0002) ***

N.B. : *p-values are in parentheses. The ϕ parameter is equal to $\sigma_{\mu}^2/\sigma_{\varepsilon}^2$. If ϕ=0 at a significant level, then we can reject the hypothesis that random effects describe the data better than fixed effects. In all models, ϕ was significantly different from 0, confirming once again the presence of random effects.*

The models described above present us with different results, although there are some constants in them. For example, FDI per Capita presents a significant positive influence on the survival of new businesses, along with the immigrant population and the share of new businesses in the total business population. Connecting these results suggests that startups have a higher chance of surviving if there is a deep entrepreneurial culture in the region, freshly infused with new ideas and perspectives from newcomers that are accompanied by foreign capital. On the other side of the coin, insignificant results across the table show that unemployment does not play a part in the survival of Romanian startups, along with R&D employment or Baccalaureate promotion rate. This result could mean that Romanians tend to start their own business more as a desire, rather than a necessity. And while R&D trends show that Romanian startup innovation doesn't necessarily rely on research, entrepreneurs are prepared to face risks in order to push their business forward.

Comparing the four models, it is revealed that Model 3 contains the most significant variables. The model is consistent with the previously performed tests and answers the second hypothesis by offering a significant value for λ that is different from 0. On the other hand, model 4, while only presenting three explanatory variables, is obtained by eliminating the multicollinearity in the data and it presents the strongest autocorrelation.

We can therefore say that the two hypotheses are confirmed: FDIs positively affect startup survival, as the data also presents significant spatial dependencies. We can further analyze which of the variables present stronger spatial links by looking at the impacts of the models – table 2 presents the mean direct and indirect impacts for each variable in model 4.

Table 3. Direct, indirect and total impacts of the explanatory variables in model 4

Name	Direct impact	Indirect impact	Total impact
FDI_per_Cap	0.4514 (<2.2e-16) ***	0.1789 (0.022) *	0.6304 (1.5e-10) ***
Share_3	125.0516 (<2.2e-16) ***	49.5736 (0.022) *	174.6252 (3.2e-11) ***
Employment_3	0.2006 (0.74)	0.0795 (0.764)	0.2801 (0.7463)
Age_15_64	1547.5993 (0.34)	613.5081 (0.399)	2161.1074 (0.3417)

Name	Direct impact	Indirect impact	Total impact
Unemployment	-1.8831 (0.24)	-0.7465 (0.335)	-2.6296 (0.2529)
R&D_per_Cap	-0.0023 (0.93)	-0.0009 (0.937)	-0.0033 (0.9298)
Immigrant_Pop	0.0960 (1.7e-05) ***	0.0380 (0.05) *	0.1341 (2.2e-04) ***
BAC_Prom	9.4599 (0.98)	3.7501 (0.982)	13.2101 (0.98146)

N.B. : *p-values are in parentheses.*

One can observe in the above table that both direct and indirect impacts of the main three explanatory variables – FDI per capita, share of new businesses in total business population and population of immigrants – take significant values. This means that county values for the three influence the county's startup survival, while it also means that changes in the neighbors' explanatory variables produce change in the county's survival rate. In other words, geographical proximity plays a big role in producing spillovers in foreign investment and immigration, while spillovers of entrepreneurial culture might actually suggest competitiveness between neighboring (or rival) counties. It is trivial to see that direct impacts are larger in magnitude than indirect ones, due to distance decay. Also, there is no inverse relation between impacts, suggesting that neighboring regions don't externalize costs to one another.

Conclusion

The research performed in this article was based on a spatial model at the level of Romanian counties. The data selected was for the 42 regions at NUTS 3 level for the period 2011-2016. The period resulted from the availability of several variables. It is worth mentioning that larger time periods might have brought more significant results.

Performing a spatial analysis implies both advantages and disadvantages. A spatial analysis is more specialized, taking into account the geographic properties of the observations. However, this type of analysis is very dependent to the spatial place it studies. Therefore, although similar studies on different countries could result in similar results, the regional distribution of counties gives the study a statute of particularity. Hence, we could mention here the difficulty to replicate the study for other countries to be its first limitation.

The results discovered in the previous section confirm what the research questions were intuiting: Foreign Direct Investment (or FDI) has a significant positive effect on the survival of startups; moreover, the factors influencing this survival also target neighboring regions. The second affirmation was verified several times in the study, through tests, significance of the spatial autocorrelation parameter ($\lambda \neq 0$) and the significance of indirect impacts. Moreover, it was shown that there are four regions which present significant spillover effects to surrounding regions: Iasi, Bacau, Galati and Bucharest. This detail is interesting due to the lower economic level of the Moldova region – efficient investment can be done in the three Moldavian counties, with the expectancy that economic growth can flow to their neighbors.

Other significant variables in the study are the percentage of new business in the total business population and the population of immigrants. Unexpectedly, based on previous studies, the analysis found insignificant relations between startup survival and Baccalaureate promotion rates, unemployment and number of R&D employees per capita. By combining all these results, we can say that a startup culture is important for new businesses to thrive, while the flow of foreign capital and foreign residence add to this culture with new perspectives, technology and market openness. This can also explain why there aren't many R&D employees – foreign companies export knowledge obtained from their local R&D departments. Unemployment is insignificant, meaning that people don't start a business due to necessity-driven reasons, but rather because they see opportunities. This can be linked to the high-level perception Romanians have on the entrepreneurial career.

This paper is the first to discuss the influence of FDIs on entrepreneurial success from a spatial perspective. The case for this type of analysis is made by reflecting on efficient methods of regional investments: spillover effects can be of key importance to share economic prosperity between neighboring sub-regions. This type of strategy is of even more importance now, as the Start-Up Nation program was launched in Romania two years ago. A well-constructed mixed strategy of foreign investment and government spending could bring impressive results in Romania's economy.

Major limitations of this study include the narrow time period of the data panel, the specificity of using a spatial model in the case of Romania that might bring difficulty in replicating the study in other countries, or choosing to use the model employed. There might be much better spatial models to describe the data.

For further direction, researchers can begin with the last discussed limitation – they could verify how other spatial models perform for this data. Other data can be added to the model, such as the source of foreign capital, the breakdown of industries that are most affected by foreign investment, or behavior and perception factors that contribute to an entrepreneur's success. Another interesting analysis would be to also look more in-depth to the region of Moldova – especially around the three regions which present most significant spillover effects. Finally, the future studies should also take into account the implementation of the Start-Up nation program and suggest better strategies for the Romanian government's budget.

References

Albulescu, C., & Tamasila, M. (2014). The impact of FDI on entrepreneurship in the European Countries. *Procedia - Social and Behavioral Sciences 124*, 219-228.

Anselin, L. (2003). *An Introduction to Spatial Autocorrelation Analysis with GeoDa.* Chicago.

Baltagi, B. H., Song, S. H., & Koh, W. (2003). Testing panel data regression models with spatial error correlation. *Journal of Econometrics*, 123-150.

Baumol, W., Panzar, J., & Willig, R. (1988). *Contestable markets and the theory of industry structure, revised edition.* San Diego: Harcourt Brace Jovanovich.

Berry WD, F. S. (1985). Multiple Regression in Practice (Quantitative Applications in the Social Sciences). *SAGE Publications*.

Borensztein, E., De Gregorio, J., & Lee, J.-W. (1998). How does foreign direct investment affect economic growth? *Journal of International Economics*, 115-135.

Elhorst, J. P. (2014). *Spatial Econometrics - From Cross-Sectional Data to Spatial Panels.* Springer.

Espinoza, C., Mardones, C., Saez, K., & Catalan, P. (2019). Entrepreneurship and regional dynamics: the case of Chile. *Entrepreneurship & Regional Development*.

Fahed, W. (2013). The Effect of Entrepreneurship on Foreign Direct Investment. *International Journal of Economics and Management Engineering Vol 7 No 6*, 1346-1358.

Fritsch, M. (2008). How does new business formation affect regional development?

Introduction to the special issue. *Small Business Economics*, 245-260.
Fritsch, M., & Mueller, P. (2007). The effect of new business formation on regional development over time: The case of Germany. *Small Business Economics*.
GEM. (2015-2016). *Global Report.*
GEM. (2018-2019). *Global Report.*
Ghani, E., Kerr, W., & O'Connell, S. (2014). Spatial Determinants of Entrepreneurship in India. *Regional Studies 48, no. 6*, 1071-1089.
Kalantaridis, C., & Bika, Z. (2006). In-Migrant Entrepreneurship in Rural England: Beyond Local Embeddedness. *Entrepreneurship & Regional Development 18*, 109-131.
Kalyanasundaram, G. (2018). Why Do Startups Fail? A Case Study Based Empirical Analysis In Bangalore. *Asian Journal of Innovation and Policy*, 79-102.
Kerr, W., Nanda, R., & Rhodes-Kropf, M. (2014). Entrepreneurship as Experimentation. *Journal of Economic Perspectives - Volume 28, Number 3*, 25-48.
Khelil, N. (2015). The many faces of entrepreneurial failure: Insights from an empirical taxonomy. *Journal of Business Venturing*, 72-94.
Kim, W., & Mauborgne, R. (2004). *Blue Ocean Strategy: How to Create Uncontested Market Space and Make the Competition Irrelevant.* Boston: Harvard Business School Press.
Klepper, S., & Sleeper, S. (2005). Entry by spinoffs. *Management Science*, 1291-1306.
Koster, S., van Stel, A., & Folkeringa, M. (2010). Start-ups as drivers of market mobility: An analysis at the region-sector level for the Netherlands. *Scientific Analysis of Entrepreneurship and SMEs*.
LeSage, J., & Pace, R. K. (2009). *Introduction to Spatial Economentrics.* Boca Raton: CRC Press.
Millo, G., & Piras, G. (2012). splm: Spatial Panel Data Models in R. *Journal of Statistical Software*.
Nanda, R., & Rhodes-Kropf, M. (2017). Innovation Policies. *Working Paper 13-038 Harvard Business School*.
Okrah, J., Nepp, A., & Agbozo, E. (2018). Exploring the Factors of Startup Success and Growth. *The Business and Management Review, Volume 9, Number 3*, 229-237.
OUG-3. (2017, January). *Emergency ordinance for stimulating the creation of new small and medium enterprises.* Preluat de pe gov.ro: http://sgg.gov.ro/new/wp-content/uploads/2017/01/OUG-3.pdf
Pace, R. k., & LeSage, J. P. (2008). A spatial Hausman test. *Economics Letters*, 282-284.
Ross, A. (2011). Regional Determinants of Entrepreneurship in a Small Economy: Panel Data Evidence from Scotland. *The European Regional Science Association.*
Silva, D., Cerqueria, A., & Brandao, E. (2016). Portugese Startups: a success prediction model. *FEP Working Papers*.
Valliere, D., & Peterson, R. (2009). Entrepreneurship and economic growth: Evidence from emerging and developed countries. *Entrepreneurship & Regional Development*, 459-480.
Zamfir, C. (2017, December 15). *Start-Up Nation 2018: How many firms could be financed by a new programme.* Preluat de pe Startup Cafe:
https://www.startupcafe.ro/finantari/start-nation-2018-firme.html