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Spatial Effects of Innovation Variety and Trade Openness on Innovation Outputs

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Abstract

The paper analyzes the spatial effects of innovation variety and trade openness on innovation performance using a data set for 30 European countries during 2007-2017. The estimations illustrate the presence of spatial dependencies that affect the mechanisms of knowledge distribution and the magnitude of the effects of the various determinants of innovation. Considering spatial dependence, diversified agglomerations (urbanization economies) can induce important inferences to improve the innovation outputs. So, related innovation activities based on technology fields are a real, constant and significant support for better innovation outcomes. A key role can likewise play the R&D expenditures within the business sector. A high share of engineers and scientists in science and technology also contribute to innovation enhancement, but the general level of tertiary educated labor force do not have a uniform positive effect, contrary to expectations. Regarding the spatial effects, the results are relevant especially concerning the direct effects and less through indirect (*spillovers*) effects. Including more open services imports can induce a some positive direct influence on the international patent applications. In the empirical assessments, we used spatial econometric procedures that take into account the spatial dependencies, as weights matrices and specific tests prove.

Keywords: patent applications, unrelated and related variety, direct and spillovers effects, export and import openness, diversification and concentration

1. Introduction

The knowledge economy receives a special importance not only through the dynamic innovation activity in all countries, but also by the special interest in understanding the determinants and mechanisms in innovative process as well as its impact on the development of societies and people wellbeing. This is highlighted in the theoretical literature on the innovation drivers or its impact on macroeconomic aggregates. Many empirical studies, on different territorial areas and periods, using approaches, models, and various methods have contributed to the development of knowledge, with evident statements views on the cause-effect relationship between innovation and the other economic activities. Innovation has become an essential link in increasing productivity, output of production process, or better insertion into the labor market and the quality of life.

2. Literature review

A very large literature underlines the impact of activities agglomeration on macro or micro results.
Griliches [1], Pakes and Griliches [2], Jaffe [3] or Hall, Griliches and Hausman [4] are among the first authors who, based on a knowledge production function, analyzed patenting activity in relation to company performance. They have highlighted that the level of knowledge of an individual, firm, society is not only the result of one's own effort but also of external knowledge through effects related

to the accumulated experience of other actors, without thereby diminishing the value of transferred knowledge.

Analyzing the relationship between the public research benefits and the location of different firms, Jaffe [3] integrates a geographical correlation index between company and university locations into the knowledge production function, as well as an inter-firm correlation index. He considers that, given the evidence of a high geographic correlation, it can be assumed that supporting local research activities (universities, research centers) has external effects on innovation activity in other firms.

Thus, the results of knowledge activity (such as patents) increase with R & D expenditure of firms and universities research centers. In parallel, it becomes obvious that large firms tend to internalize the knowledge they have acquired in their research centers, and small firms exploit the earnings from university research centers.

Innovative developers, through collaborative systems and networks, transfer information from one domain to another and where they can be applied, linking innovative clusters and firms and making possible knowledge and technology recombinations, and thus lead to new innovations [5], [6]. As a result, effective knowledge dissemination may occur, given a geographical proximity, influenced by labor mobility or direct contact possibilities. Feldman and Kogler [7] argue that the geographic dimension of innovation activity produces effects in terms of promoting economic growth as well as technological change and physical proximity is of particular importance in understanding the dynamics of innovation.

We find in literature more and more approaches to macroeconomic processes, in which a special place is due to the experience and skills acquired by individuals or various entities. Over time, a number of elements of the evolutionary economy and other areas of science have been integrated into the models of the new economic geography. A central principle of evolutionary theory is diversity [8], which could mean the quantification of regional technological knowledge, by combining existing and new knowledge, actually contributing to the generation of others (Schumpeter’s innovation idea, by recombining previous ideas). When a region has a variety of related technologies, connections are more efficiently established, making these technologies easier to recombine. At the same time, when knowledge comes from technologies that are very different from each other (reflected by the *unrelated variety*), regional actors may encounter difficulties in integrating them and benefiting from spillovers, respectively, developing interactions leading to new ideas, and improving innovation outcomes.

One of the first approaches to the differentiation of the sectors variety belongs to Frenken, Van Oort and Verburg [9], who have shown that the related variety contributes to regional economic growth in the Netherlands. The study validated the relevance of the diversity of regional knowledge stocks to the outcome of regional innovation, employment or productivity [10], [11], [12]. Instead, Bishop and Gripaios [13] find that unrelated variety affects more employment growth in British industries than related varieties.

Tavassoli and Carbonara [14] or Castaldi, Frenken and Los [15] analyzed the role of the unrelated and related variety on innovation output in Sweden and the USA. Their findings suggest that in case of knowledge variety within American states, unrelated variety does not affect production of regional innovation in general, while the impact is robust and positive in terms of related variety. However, Castaldi, Frenken and Los [15] show that a high degree of unrelated variety increases technological progress – i.e., innovation with a high technological and economic impact.

Starting from a knowledge production function, Miguélez and Moreno [16] investigate the effects of the distribution of innovation activity on innovation performance in 261 European regions. They use entropy indicators as unrelated and related varieties, based on the Frenken, Van Oort, and Verburg model [9], but based on patents applications, and not on the most commonly used measure of employment. Miguélez and Moreno [16] estimate a positive relationship between the variety of knowledge stocks at regional level and the output of innovation, as well as employment and productivity.

We also find in more recent literature studies on the link between trade policy, international trade and innovation. Analysing the effects of tarrif cuts and company patenting activity on a sample of 60 and 100 countries, Coelli, Moxnes and Ulltveit-Moe [17] estimate significant effects of promoting innovation and growth. Based on the new theory of growth and firm heterogeneity, Aghion, Bergeaud, Lequien and Melitz [18] establish a strengthened patenting activity in direct relation with exports of firms with high productivity (using data for French firms between 1994 and 2012).

3. Methodology

Assessing the role of diversification of exports/imports, trade opening and variety in innovation, we estimated a knowledge production function on a sample of 30 European countries (between 2007-2017), aiming to highlight the connections between the results of the innovation activities and some diversified agglomerations economies. Spatial dimensions were taken into account by a series of econometric models that use as a tool the weighted distance matrices.

Spatial estimation methods are diverse, connecting spatial correlation to the dependent variable, independent variables, or error patterns. Based on diagnostic tests, considering the lowest value of the Akaike Information Criterion and Schwarz Criterion, and the highest probability of the *log-likelihood* function, as a prime choice, we could appreciate the Durbin spatial model (SDM) as the most appropriate fit in achieving consistent results. This is a special model involving consideration of the lagged endogenous variable, explanatory variables, and all of the exogenous regressors (WX).

Thus, the dependent variable, Y, will depend on the characteristics of its own region (matrix vector X) and the same variables of neighboring regions.

The linear logarithm specification of the basic parametric model (SDM type) with spatially lagged dependent variable has the form (spatial autocorrelation effect, λ=0):

$$Y_{it} = \rho W Y_{it} + \beta X_{it} + \theta X_{it} WX + \varepsilon,$$

where:

Y_{it} indicates the number of European patent applications per field of technology and per country of residence of the applicants or the intensity of innovation, expressed by reporting patent applications to the number of inhabitants;

W_{it} is the inverse matrix of distances for country *i* in year *t*:

X_{it} is the set of potential determinants of innovation (β and θ are their elasticities) considering, as the main inputs, R & D expenditures (total – *gerd*, or in the business area – *berd*), labor market indicators (share of scientists and engineers, 25-74 years, employed in scientific and technological activities), to which we added measurement variables for the size of the economies (*gdp per capita in pps*), demographic characteristics (*population density*) as well as indicators like concentration and diversification exports and imports, and also the international trade openness.

At the same time, at this stage of analysis, we could include as variables of interest not only the total number of patents filed, but also measures of the unrelated (*uv_patents*) and related (*rv_patents*), built on the basis of European patent applications by 35 fields of technology (based on WIPO IPC technology concordance, associated with the CAEN economic sections, divisions, groups). The indicators have been calculated using Frenken, van Oort and Verburg [9] formula. The sources of the data are EPO for the patent applications [19] and Eurostat [20].

The cartographic distribution of European patent applications and un/related variety calculated on the basis of technology fields is also eloquent (EPO data for 2017).

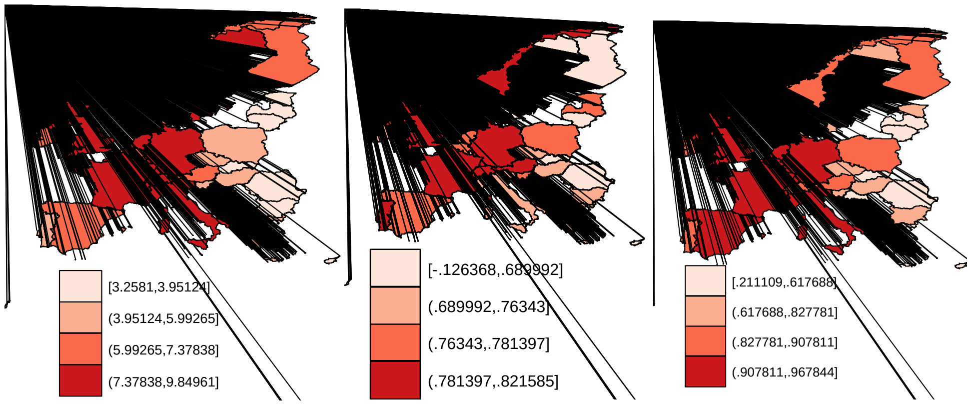

Fig. 1. Spatial distribution of patents applications by filing date and technological un/related variety

Clusters with low levels of innovation intensity are represented by countries such as Romania and Bulgaria (modest innovators), in the moderate category being 14 old and new member states [21], the rest being the strong and the top innovators.

4. Results and effects

4.1. Exploratory Data Analysis

The first step was the exploratory data analysis, i.e., spatial autocorrelation on a panel of 30 European states (European Union, Norway and Switzerland) over a 11-year time span (2007-2017).

Spatial autocorrelation can be examined using statistical significance tests on which the spatial dependence structure is established, and then it is incorporated into spatial econometric models. Once the inverse matrix of distances was established, we used the *I'* Moran (and *c* Geary) statistical tests to detect spatial autocorrelation of the variables according to Table 1.

Table 1. Measures of global spatial autocorrelation – *Moran's I*

Variables	I	E(I)	sd(I)	z	p-value
log_patent_applications	0.373	-0.034	0.082	4.994	0.000
log_gdp_per_cap_pps	0.424	-0.034	0.079	5.771	0.000
log_urban_population	0.359	-0.034	0.081	4.843	0.000
log_uv_patents	0.011	-0.034	0.045	1.011	0.156
log_rv_patents	0.304	-0.034	0.079	4.276	0.000
log_export_openness_goods	0.117	-0.034	0.081	1.873	0.031
log_ import_openness_goods	0.143	-0.034	0.081	2.184	0.014
log_scientists_engineers_pop_74	0.468	-0.034	0.081	6.225	0.000
log_gerd_gdp	0.232	-0.034	0.081	3.287	0.001

**** Weights matrix. Type: Distance-based (binary). Row-standardized: Yes*
Source: own elaboration in Stata

The index has values ranging from -1 (indicating perfect dispersion) and 1 (perfect correlation) also being able to have higher values. A null value means that the spatial distribution of the considered variable is perfectly random in the space. Positive values of the index indicate positive spatial autocorrelation, implying that the values of each observation (countries) resemble those of the neighbors. A negative index involves negative autocorrelation; neighbor's values (for a specific variable) are raised when the observation (the country in our case) is low and if it is high, its neighbors have low values.

The data on patent applications show a very large variation in country distribution, but I Moran's average of 0.373 indicates a certain concentration of high/low values.

4.2 Main results (elasticities)

The presence of a process of spatial dependence by relating similar values in neighboring areas and the persistence of the process throughout the period allows for a more detailed analysis of the innovation determinants. Detecting spatial autocorrelation may be real and due to the spreading of the variable structure, or it may be apparent due to the existence of other variables that can explain the spatial dependence. The estimated results are illustrated in Table 1 (*Spatial Durbin Model* models).

Table 2. Estimation of spatial autoregressive parameters of innovation determinants

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
log_gdp_per capita_pps	0.879***	1.070***				
log_gross_fixed_capital_forma-tion (*fbkf*)	-0.182	-0.453**	-0.0644		-0.0949	-0.122
log_business_expenditure_R&D (*berd*)	0.172**	0.161*			0.163*	0.152*
log_scientists_engineers_15_74			0.522***		0.492***	0.468***
log_population_density					0.544	0.648
log_inward_FDI_stock_%						-0.134*
log_import_openness_services	0.145	0.0456	0.0940	0.0127	0.136	0.194
log_import_openness_goods	-0.662***	-0.165	-0.586***	-0.508**	-0.691***	-0.674***
log_export_concentration_index	-0.0649	-0.00510				
log_import_concentration_index	0.110	0.121				
log_export_diversification_index	-0.401	-0.449				
log_import_diversification_index	-0.187	-0.167		-0.206	-0.165	-0.166
log_export_openness_goods		-0.563***				
log_export_openness_services		0.253				
log_related_variety_patents	0.0961	0.0930	0.237**	0.252**	0.230**	0.229**
log_unrelated_variety_patents	0.00342	-0.00975	0.0639	0.0631	0.0719	0.0774
Spatial rho	-0.596*	-0.605*	-0.630*	-0.631*	-0.493	-0.472
Observations no.	330	330	330	330	330	330

** $p<0.05$, ** $p<0.01$, *** $p<0.001$*
Source: own elaboration in Stata

The rho coefficient reflects the influence of the dependent variable in a country on the dependent variable in neighboring countries. The *ρ (rho)* parameters in the all models have a minus sign and a statistical significance of 90% in *models 1-4*, indicating a purely spatial effect of patent applications in one country on the same indicator in neighboring countries, which is not a positive one.

The results confirm expectations for the estimated elasticity coefficients (mostly), showing real, constant and consistent effects of the size of the economic activity: the higher the GDP per capita and the patent activity is more important. In all specifications, we obtained a positive and statistically significant coefficient for the dependent variable in relation to the related variety of the entire innovation activity. The *related variety* contribution can be understood as evidence for intensifying innovation activity, a trend observed in most countries. At the same time, the development of innovation by large types of innovative activities (*unrelated variety*) cannot be a support for improving innovation patenting activity, being obvious the importance of its development on related fields, as the premise of a potential multiplier effect on total activity. Our results are in line with the findings of Miguélez and Moreno [16], that also conclude on a positive relationship between the output of innovation and RV (*related variety*) and an insignificant relationship with the UV (*unrelated variety*). However, the elasticity values obtained with respect to RV are on average 0.540 [16], compared to about 0.240 on our examples. However, we have to take into account the differences of territorial units, the period and the econometric technique used.

Miguélez and Moreno [16] confirm the role of the variety in the regional knowledge stocks on improving performance in innovation, and Boschma and Iammarino [9] reach the same conclusions regarding the effects on employment and productivity. Thus, the effect induced by urban agglomeration appears as predominantly at the expense of localization (specialization). Castaldi, Frenken and Los [15] or Autant-Bernard and LeSage [22] also highlight the benefits of diversifying activities in sectors with related technologies for better economic and innovative performance.

Findings on the role of research activity (*berd*) through financial expenditures confirm the results in literature, reflecting the need to support the work as a key prerequisite for innovation. The coefficients of elasticity of the number of patent applications in relation to research expenditure are within the limits found in the literature, although in some models these are still higher. Thus, the values obtained by us are on average of 0.155, similar to the estimations of Bottazzi and Peri [23], of 0.10-0.20. In terms of increasing employment, this is compatible with a shift towards more sophisticated, intensive technology sectors. Including the variable for the employment in science and technology with tertiary education (scientists and engineers), the positive effect seems to be a substantial one. A significant but negative influence is the return of trade opening for exports and imports of goods, which could be explained by the fact that a significant part of these do not belong to the high technology ones. However, as we will see below, there is some positive direct influences of trede openness.

4.3 Direct, indirect and total effects

The interpretation of the estimation parameter in spatial models is not the same as for models without space connections. The direct effect is the classical impact of a variation in an independent variable on the dependent variable and is measured by the estimated coefficient β_i. Indirect effects are the consequence of space-labeled variables introduced into patterns, these effects also being called spatial *spillovers* that measure the impact of a change in a variable in the region *i* and on the other regions. In other words, spatial *spillover* effect occurs at the same time as a causal relationship between the characteristics of the observations (countries in this case). Both types of effects depend on the spatial model and the spatial matrix used. In SDM models (similar to autoregressive *Spatial Autoregressive Model* (SAR) and *Spatial Autocorrelation Model* (SAC), the effects may be/are different due to the effects of endogenous interaction [24], which causes feedback effects in the sense that the impact (the change) that occurs on the intensity of innovation in some neighboring countries passes over to other countries and then back to those that have caused that impact (change).The empirical results in Table 3 comprise only the spatial effects resulting for three selected models (of the estimated ones), retaining only variables whose coefficients have statistical significance.

Table 3. Direct, indirect and total effects

Effects	**Model number**	**log_gdp_ per capita_pps**	**log_berd**	**log_ scientists _engineers_15_74**	**log_import_ openness_services**	**log_import_ openness_goods**	**log_export_ openness_goods**	**log_related_ variety_patents**
Direct	1	0.900***	0.184**		0.105	-0.646***		-0.547***
	2	1.088***	0.179**		-0.0227	-0.184	-0.547***	0.0908
	5		0.183**	0.496***	0.102	-0.682***		0.231**
Indirect	1	0.476	-0.515*		1.171**	0.145		-0.0732
	2	0.820	-0.487		1.835*	0.853	-0.830	0.0346
	5		-0.794**	-0.322	1.251***	0.426		-0.174
Total	1	0.476	-0.332		1.275**	-0.501		0.0233
	2	0.820	-0.308		1.812*	0.669	-1.377	0.125
	5		-0.611*	0.174	1.352***	-0.256		0.0571

Source: own elaboration in Stata

Direct effects: We can see that there are no big differences between the elasticity coefficients in the results table and the direct effects. Thus, calculating the feedback effects on the RV variable on *Model 5*, we obtain: 0.231-0.230 = -0.001, which totally corresponds to the estimated coefficient; the case is similar in terms of the influence of the proportion of *scientists and engineers* in science and technology activity, and it cannot be emphasized that this direct influence is due to a *feedback* process.

This means that the influence of the related variety and of the engineers employed in science and technology is solely due to the characteristics of the respective countries and does not bear any external influence. A positive feedback effect is exerted by the increase in the business sector of spending for research activity, about 14.5% (0.174-0.152, which represents 14.5% of the estimated coefficient) of the estimated elasticity coefficient due to a higher financial support of research in neighboring countries. In this sense, we can observe the direct effects of more open services imports, perhaps due to those who are intensive in knowledge.

Indirect effects: Differences between indirect effects are quite high, with high order sizes. Thus, there are positive spillovers induced by the increase in the share of imports of services made by neighboring countries (including intensive services in knowledge), with similar effects arising from the increase in imports of goods (in Model 4, the spillover effect is 1,079**). However, a higher share of engineers in a country does not have a positive influence on innovation in neighboring countries (in Model 3, i.e., the spillover effect on innovation of scientists and engineers has a value of - 594**, including statistical significance).

Statistically significant *total effects* are found in those induced by greater openness in imports of services (all models), but potential negative impact of business expenditures on research from other countries (the major contribution being the one resulting from their increase in each observation-country).

5. Conclusions

These results provide support for the research on the spatial effects of innovation activity (performance). We can summarize the main conclusions as follows. An intense innovation activity in some countries does not have a positive impact on this activity in other countries, suggesting the competitive nature of innovative products (the estimated *rho* coefficient is negative and significant in all models assessing these effects). Our results confirm the impact of technological variety in improving the performance of innovation activity. The estimated coefficient of the innovation output in relation to related variety (RV) has the expected positive sign in all models, but a same role of the uncorrelated variety (UV) cannot be demonstrated. Also, the direct role of R&D expenditures as a key factor for innovation is checked: the elasticity of innovation in relation to the *berd* variable is positive and statistically significant in all models that take this into account). There is a real and expected influence of the scientists and engineers (employees with tertiary education) share in science and technology in the relationship with the intellectual assets (patents), the elasticities being positive and statistically significant.

Some direct spatial effects that correspond to theoretical predictions may be highlighted, but under the circumstances, the estimation of indirect ones (of spillovers) proves to be more difficult (under the given conditions).

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