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Knowledge Spillovers: An Evidence from The European Regions

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Abstract: The article deals with the issue of knowledge spillovers in the European regions. For this purpose, a standard Knowledge Production Function (KPF) approach was extended by the application of spatial econometrics methods. Our analysis started from the construction of the alternative structures of the spatial weight matrices. These matrices were based on technological and institutional proximities, which represent compelling alternatives to geographic proximity regarded as a kind of all-encompassing connectivity measure. The next step in our analysis was the modeling of regional knowledge generation processes. We treated R&D expenditures and human resources in science and technology as the input measures and patent applications to the European Patent Office as the output measure in our basic and extended models. The results show that the scope and direction of knowledge spillovers are sensitive to the type of knowledge (tacit vs. codified) and proximity dimension engaged. These findings contribute to the current debate in the geography of innovation and economics of knowledge literature.

Keywords: region; knowledge spillovers; innovation; R&D; patent; human capital

1. Introduction

Initially, the geographical proximity between firms or regions has been considered as a main transmission channel of innovation and knowledge. This idea assumes that knowledge and innovation spillovers are bounded in space and the economic entities may benefit from close location to other economic entities generating innovations [1]. The recent ideas, beyond spatial dimensions, emphasize the greater role of other proximity dimensions in innovation spillovers [2].

The most comprehensive approach to knowledge externalities takes into account all aspects of distance between firms or regions, i.e., geographical, social, institutional, technological, and organizational [3]. This procedure is also consistent with spatial econometric contribution, which often gives up geographical distance in regional studies and takes economic variables to measure distance between spatial units. It better reflects the structure of connections between regions because the country boundaries and geographic distance plays a decreasing role in these relationships [4].

Moving beyond the previous research on innovation and knowledge spillovers, this work used modified versions of spatial model for intensity of patent applications. First, to study the effect of R&D expenditures and human resources on the number of patent applications per million of inhabitants in EU regions we employed two spatial matrices. The first of them reflected technological proximity, and the second showed institutional proximity. Contrary to previous studies that measure technological proximity on the basis of the sectoral distribution of regional patenting activity or the distribution of regions' production structures, we applied the similarity matrices based on total factor productivity (TFP) level. The second proposition was the inclusion of interactions between R&D expenditures or human resources in the spatial models. This solution contributed to the verification of relationships between R&D and human resources in the context of innovation efforts in the regional European area. This approach also allowed us to portray the complexity of knowledge spillovers in the context of non-linear effects. To the best of our knowledge, there are few empirical studies on the non-linearity of knowledge spillovers.

The aim of this article is to provide a detailed-ranging answer of knowledge production and spillovers among EU regions. The specific research questions, anchored in the regional knowledge production function framework, are as follows:

- What is the role of R&D and human capital in the knowledge production processes in the EU regions?
- What specific types of knowledge spillovers occur in the knowledge production processes?

The research employs data for NUTS2 (Nomenclature of Territorial Units for Statistics) EU regions. The spatial models for these regions allow us to study the role of knowledge and human capital spillovers diffused through various proximity links. We analyse the impact of R&D expenditures and human capital, and interactions between them on the effects of innovation activity in NUTS2 regions.

The next section includes the literature review on mechanism of knowledge spillovers and regional knowledge production function. The following parts of the paper consist of a presentation of data and methods, and the results and discussion, followed by the conclusions.

2. Literature Review

2.1. Mechanism of Knowledge Spillovers and Externalities

In line with the Marshallian tradition externalities are regarded as 'untraded' interdependencies among firms [5]. An externality does exist when one producer takes the advantage (or disadvantage in the case of a negative externality) of the action of other producer. Such an interpretation of externalities allowed the neoclassical economists to explain the existence of increasing returns without violating the assumption of constant returns to scale at the firm level. It means that output can rise more, proportionally, than inputs when the effect of the production process of one firm depends on the production activities of another firm. As suggested by Antonelli and Ferraris [6], the concept of externalities plays a central role in economics of technological knowledge. Due to well-known features of technological knowledge, i.e., non-divisibility, non-appropriability, non-excludability, and non-rivalry, the exogenous growth theory assumes that knowledge spills freely (involuntarily) in the economic system and firms can take advantage of it without any costs [7,8]. In other words, knowledge spillovers generate positive externalities. The explicit effect of such an approach is applying knowledge externalities to the investigation of the impact of knowledge generating activities on economic growth [9]. In particular, knowledge is the engine of economic growth in the endogenous growth theory or new growth theory (NGT). Knowledge externalities play a central role in NGT models. For example, Grossman and Helpman [10] state that imitators can use technological knowledge produced by innovators freely. When knowledge enters the public domain, it becomes immediately available to all researchers. In similar vein, Jones [11] highlights that free spillovers of knowledge lead to increasing returns to scale and imperfect competition. NGT models also assume the existence of human capital externalities. Specifically, human capital externalities occur when the stock of human capital in an economy is supposed to have the impact on a typical firm's productivity in the economy. Lucas [12] argues that human capital spillovers lead to a gap between the social marginal product of human capital and the private one.

Despite the substantive contribution of NGT to the endogenization of technical progress, the endogenous growth theorists make misleading assumptions about knowledge spillover. First of all, it is not true that knowledge is freely available. This argument has been raised for the first time by Nordhaus [13] who stated that much of the difficulty of using external knowledge might not involve transmission lines with a great deal of resistance, but rather faulty receivers. It results from the fact that identification, access and exploitation of external knowledge by a receiver require dedicated resources and generate additional costs. As suggested by Cohen and Levinthal [14], absorptive capacity allows firms to absorb and appropriate "outside" knowledge. This absorptive capacity depends on the firm's level of prior R&D related knowledge and the employment of skilled and highly educated individuals. The observation that the firm's knowledge base creates a capacity to assimilate and exploit new knowledge provides a convincing explanation of why some firms may not gain benefits from external knowledge which spills out into the public domain. Finally, imitation costs are typically substantial relative to innovation costs in a number of industries [15]. For example, Mansfield et al. [16] find that imitation costs average about 65 per cent of the cost incurred during innovation process.

Another issue which is extremely important from the perspective of knowledge spillovers is the form of diffused knowledge. Thus, knowledge spillovers are considerably more significant in the case of pure "codified" knowledge (e.g., manuals, hard data, scientific formulae, codified procedures, or scientific principals) as compared to tacit knowledge consisting of know-how and practical experience [17]. The former includes inter alia knowledge embedded in patent which provides a legal title protecting an invention. In line with formal requirements inventions must be described in patent documents in a way which makes them accessible to third parties who want to use technical details on new knowledge. It is worth noting that patents are a double-edged sword with regard to the diffusion of knowledge. On the one hand, patents erect barriers to the use of knowledge. On the other hand, the publication of patents makes technological knowledge public, which can contribute other researchers [18]. It can support future research by helping to better define an enquiry that remains open. Moreover, patent disclosure can also open the fields for research that are directly related to the initial invention and that would not have been considered otherwise. Denicolò and Franzoni [19] draw the conclusion that patents can promote the diffusion of technological knowledge in early disclosure stage. For example, the Cohen–Boyer patent application describing gene coding of proteins unlocks many directions of university research in genetic biology. A similar situation is reported in industrial companies where patent departments actively analyse patents filed by competitors. It allows for avoiding entering into research that would duplicate already patented inventions of other firms.

While explicit knowledge can be expressed in a systematic and formal way, tacit knowledge is personal and difficult to formalize. Nonaka [20] stresses that tacit knowledge is hard to transfer, since it is grounded in the specific context of action and commitment. Contrary to the assumptions on human capital spillovers presented in NGT models, tacit knowledge needs proximity (geographical and cognitive) or face to face contact for its diffusion [21]. Howells [22] argues that tacit knowledge flows more easily across shorter distances, since it needs a direct contact between individuals to be decoded and understood. What is more, tacit knowledge by its nature often requires non-verbal communication [23]. Thus, the spillover of tacit knowledge requires institutions in the form of common cultural values, informal codes, and routines. These institutions are geographically localized, giving the diffusion process of tacit knowledge a strong local dimension [24]. The fact that tacit knowledge spillover has spatial dimension is non-controversial. It is well accepted that the marginal cost of transmitting tacit knowledge across space diminishes as frequency of contact increases [25]. The costs of moving employees are still very high. As von Hippel [26] expressed it, tacit knowledge is sticky. Stickiness leads to a number of issues in terms of the knowledge diffusion. These issues are involved with knowledge characteristics (e.g., casual ambiguity) and situational characteristics (e.g., source, recipient, practice, and context) [27,28].

From the previous discussion, it is possible to argue that the diffusion of codified knowledge requires technological proximity in a way that technological capacities are required to exploit new knowledge [29]. On the other hand, learning that improves one technology may have little effect on technologies from other domains. Such situation is explained by Marshall–Arrow–Romer (MAR) externalities. In line with the MAR perspective, externalities take place among similar units sharing common knowledge [30]. Contrary to the MAR externalities, Jacobs [31] believes that the diversity of knowledge sources leads to knowledge externalities and ultimately affects innovation performance.

As stressed by Beaudry and Schiffauerova [32], the debate on the MAR or Jacobs externalities is still unsolved. It is important to note that the geographical dimension plays less of a role in codified knowledge diffusion. It results from the potential of ICT to reduce spatial constrains. Foray [17] argues that ICT allows codified knowledge to travel efficiently and knowledge spillover is not influenced by the distance from the knowledge source. Similar arguments are presented by Mokyr [33] who believes that clusters of activities are less necessary to absorb knowledge spillovers in the case of intensive use of new ICT.

2.2. Knowledge Spillovers and The Regional Knowledge Production Function

The regional development literature shows that the accumulation of knowledge is related to region's internal ability to generate innovation as well as to its capacity to obtain and use the stock of knowledge produced in other regions [34–36]. In the case of a relation between innovation input and invention output, knowledge production function—KFP is widely used to find the impacts of research and development (R&D) on innovation performance at the regional level. The concept of KPF was introduced by Griliches [37]. His approach allows for studying the impact of R&D (i.e., observable input of unobservable knowledge capital) on patents (i.e., inventive output) considering other important factors. The inclusion of additional formal (and informal) sources of knowledge results from recognition that R&D investments alone do not govern useful knowledge production in a region [38]. In the regional analysis, this approach assumes that there is some function:

$$P = f(RD, KS, \varepsilon) \quad (1)$$

where P is patent production, RD is the level of R&D, KS is the set of other knowledge sources, ε embodies all unobservable factors that affect patent production.

The regional KPF is usually anchored into the geography of innovation literature [39]. As mentioned previously, the impact of physical distance on invention achievement is extremely important for non-codified (or not-yet-codifiable) knowledge which is exchanged by face-to-face contacts. Storper and Venables [40] show that the face-to-face contacts among economic agents improve coordination and reduce the incentives issue, resulting in spillovers and greater innovation activity. There are many empirical studies which apply the KPF approach to find how the spatial external spillovers from neighboring regions influence the knowledge production process of a specific region. Table 1 shows the results of selected studies in this field. To ensure the comparability of results, all the presented studies relate to European regional area and use the intensity of patent applications to the European Patent Office (EPO) as a proxy of innovation performance.

On the one hand, the results show that the spatial knowledge spillovers from neighboring regions are important in affecting invention performance of the specific region. On the other hand, they also prove that other kinds of proximity stimulate the transfer of knowledge among regions. Specifically, technological proximity plays an important role in explaining interregional knowledge spillovers. According to Caragliu and Nijkamp [23], technological proximity means a similar technological specialization and development of regions, which may foster knowledge spillovers by increasing the chance of the cross-fertilization of inventions. The high explanatory power of technological proximity among other types of proximity studied in the knowledge spillovers literature may be explained by the absorptive capacity concept [14], which suggests that entities/regions with a similar knowledge base exchange information more effectively.

Table 1. Results of studies on regional knowledge production processes with spatial spillovers.

Author	Sample		Main Findings
	Number of Regions	NUTS Level	
Bottazzi and Peri [41]	86 European regions	1, 2	There are small positive externalities accrue to regions within 300 km from the region that employs the R&D resources.
Moreno, Paci, and Usai [42]	175 regions of 17 countries in Europe	0, 1, 2	Spillovers are mostly constrained by national borders within less than 250 km.
Parent and LeSage [43]	323 regions in 9 European countries	1, 2	The largest spillovers are for the most part taking place between a limited set of highly developed regions in Europe.
Autant-Bernard and LeSage [30]	94 metropolitan French “d´epartements”	-	The spatial spillover effects from cross-industry private research are larger than spatial spillover effects from other types of R&D activity.
Paci, Marrocu, Usai [44]	276 regions in 29 countries (EU27 plus Norway, Switzerland)	2	Geography is not the only dimension which may help knowledge diffusion. Technological proximity is the most important one.
Charlot, Crescenzi, Musolesi [45]	169 EU regions	1, 2	Geographical links matter for knowledge spillovers. R&D expenditure of neighboring regions have a positive impact on a region’s invention performance for the central part of R&D distribution.

Source: Own elaboration.

However, as suggested by Gertler [46], technological fixes alone may not be sufficient to facilitate knowledge flows in fundamentally different institutional environments. It is quite obvious that institutions, such as language, routines, expectations, laws and norms, shape the processes of knowledge sharing in the national and regional context. In the case of innovation processes institutional proximity is formally created by regional innovation systems—RIS. The RISs are generally regarded as subsystems linked to the national innovation system—NIS in which firms and other organizations are systematically engaged in interactive learning through an institutional milieu characterized by embeddedness [47]. The crucial role of institutional proximity in explaining knowledge spillovers results from the similarity logic introduced by the "Proximity Dynamics" group made of French economists. Gilly and Tore [48], who are the members of this group, argue that the institutional dimension matters for entities that have the same representations and functioning modes. As such, one can expect that country and regional level institutional elements, e.g., the type of the schooling system or innovation policy, affect the interregional knowledge flows. What is important, the similarity logic can be complemented by the adherence logic. The latter suggests that entities with the same space of relations, e.g., RIS and NIS, interact actively in various dimensions. These arguments suggest that there is the need to focus on an alternative interconnectivity structure. In this vein, Boschma [2] argues that the spatial dimension is neither a necessary nor a sufficient condition to promote knowledge spillovers and should be extended by other dimensions of proximity formed by links of technological, institutional, and social nature.

Another issue that needs greater attention from regional economists is the occurrence of externalities related to human capital. In the conventional approach human capital has both a productive and absorptive function in knowledge production processes. The former is grounded in the endogenous growth models where human capital is regarded as the input into the production of ideas [49,50]. According to these models, the skills of employees increase their ability to produce ideas. What is important, human capital is assumed to be complementary to R&D investments in their contribution to innovation [51,52]. The latter relates to the absorption capacity concept [14]. Besides these two functions of human capital it may also generate positive or negative externalities among regions. According to a theoretical explanation proposed by Sanso-Navarro et al. [53], an increase in the stock of human capital in a region leads to both a higher technological level of this region, and further technological knowledge flows into neighboring regions. From the point of view of a migration framework, the positive effect of inter-regional flows of knowledge may be eliminated by the regional rivalry for highly qualified people and inter-regional migration of the skilled workforce. On the other hand, Saxenian argues that the "brain drain" process may be transformed into the "brain circulation" process when skilled immigrants maintain their professional ties to the home countries/regions [54].

Finally, it is worth to note there is a need for going beyond spatial dimension of knowledge spillovers and studying how the type of knowledge (i.e., tacit knowledge vs. explicit knowledge) affects its diffusion paths in the regional area.

3. Data and Methods

This study used the most recent data published by the Quality of Government Institute of University of Gothenburg. Due to missing data the real problem was to ensure their comparability. Moreover, we wanted to note that the limitation of data availability at the regional level is a common problem in the regional knowledge production function literature. For this reason, we selected the years 2009–2012 as the research period ($T = 4$) and excluded the regions from Belgium, Estonia, Slovenia, Spain, and the Portugal and French islands ($N = 187$).

To fulfil the aim of the article, we employed a spatial model. The spatial model allowed researchers to study the relationships between variables taking into account different spatial patterns [55].

Our model was used to describe the number of patent applications per million inhabitants to the EPO in NUTS2 regions. Human capital and expenditures on R&D at the regional level were applied as independent variables. Table 2 contains the description of variables and methods of their measurement.

Table 2. Description of variables.

Variable	Description	Method of Measurement
European Patent Office (EPO)	Patent applications to the EPO	Number of patent applications per million inhabitants
RD	Total intramural R&D expenditure in all sectors	Expenditure on R&D as % of GDP
HR	Human resources in science and technology	Scientists and engineers as a share of the active population in the age group 15–74

Source: Own elaboration.

In our study we use the model, specified as follow:

$$\begin{aligned} \text{EPO} = \alpha + \lambda_1 W_1\text{EPO} + \lambda_2 W_2\text{EPO} + \beta_{10}\text{RD} + \beta_{20}\text{HR} + \beta_{30}\text{RD} \times \text{HR} \\ + \beta_{11} W_1\text{RD} + \beta_{21} W_1\text{HR} + \beta_{12} W_2\text{RD} + \beta_{22} W_2\text{HR} + u \end{aligned} \quad (2)$$

$$u = \rho_1 W_1 u + \rho_2 W_2 u + \varepsilon,\ \varepsilon \sim N\left(0,\ \sigma^2 I_n\right) \quad (3)$$

This model describes EPO variable with lagged dependent variable (W_1EPO, W_2EPO), RD and HR variables, their interaction (RD·HR) and spatially lagged independent variables (W_1RD, W_2RD, W_1HR, W_2HR). It contains two spatial matrices. This is due to the assumption that knowledge spillovers between NUTS 2 regions depend on technological proximity and institutional proximity. The first type of proximity determines the structure of matrix W_1. Proxies for technological proximity are usually basis for the so-called techno-economic weights, where the difference between two locations on the values of economic or technological variable can be used as the distance metric. Our measure of technological proximity is related to the total factor productivity (TFP) index. According to the standard interpretation, the TFP represents the level of disembodied technological knowledge and is defined as the aggregated output–input ratio. To calculate TFP, we use the multiplicatively-complete Färe–Primont index, which meets all economically-relevant requirements from the index number theory [56].

Following Hoekman et al. [57], we have created a weight matrix, whose elements take the value of techno-economic weight, if regions belong to the same country and zero otherwise, to measure institutional proximity.

4. Results and Discussion

The first step consists in creating a matrix reflecting technological proximity. The weights are determined based on techno–economic distances between regions. We apply the TFP level as techno-economic weights. For this purpose, the inverse of absolute values of the differences between values of these variables are used. The intensities of techno-economic variable is presented in Figure 1. This figure shows that the TFP levels tend to be highest along London, Düsseldorf and Liguea corridor and lowest in the Eastern Europe regions. Such distribution of the TFP levels may result from regional specialization. For instance, Evangelista et al. [58] stress that the regional productivity growth is closely related to technological specialization. It is assumed that regional knowledge-intensive specialization, which tends to cluster in dense urban areas, positively affects the TFP growth.

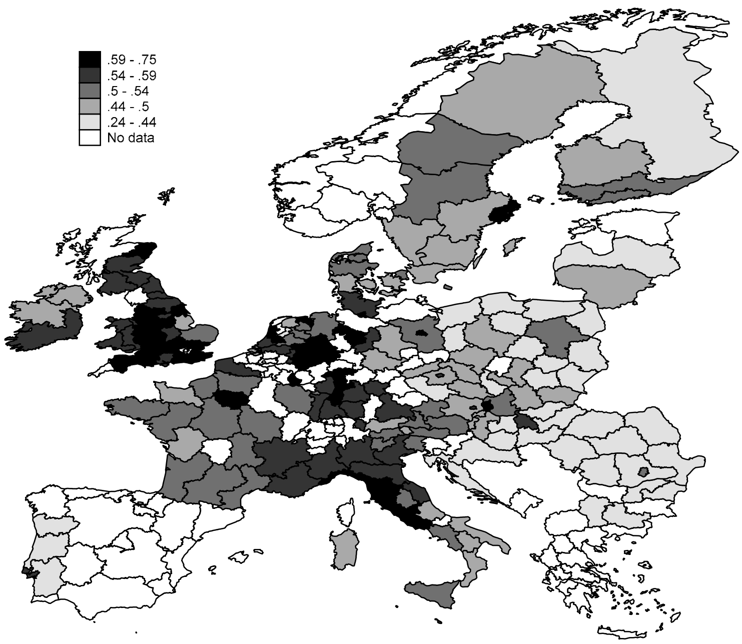


Figure 1. Total factor productivity (TFP) level in NUTS2 (Nomenclature of Territorial Units for Statistics) EU regions. Source: Own elaboration.

The matrices W_1 and W_2 for the TFP level are row-standardized (i.e., each row of the matrix is divided by the row's sum). In consequence, the technologically lagged variables are the mean values of them in similar regions.

The second step involves estimating the spatial model parameters for number of patent applications per million inhabitants (EPO) for the EU NUTS2 regions using the generalized spatial two-stage least squares. We employ two kinds of models: without and with interaction between explanatory variables. Introducing interaction to the model can result in the numerical instability for estimation associated with multicollinearity. To solve this problem, we use variable centering [59]. In order to separate the effect of institutional proximity between regions in the same countries, the models without spatially lagged explanatory variables (W_1X) are applied. The results of the estimation of the models with spatial matrices based on the TFP level are shown in Table 3.

The results of our models, i.e., direct effects, confirm a strong and positive impact of R&D expenditures and human capital on patent intensity at the regional level. The findings are consistent with the results of other studies in this field. For example, Diebold and Hippe [60] show that human capital, measured by literacy and numeracy, is the most important historical factor affecting current patent applications per capita in the regions of Europe. This outcome corresponds with the endogenous growth models initiated by Lucas [12]. These models regard human capital as an important factor for economic growth. On the other hand, the theoretical explanation for positive R&D effects on patent application can be found in R&D-based growth models. In his seminal paper, Romer [49] predicts that new knowledge is generated in the R&D sector and it is linear in the existing stock of knowledge. It is worth noting that human capital can interact with an economy's R&D activity. For example, Redding [51] shows that human capital composition is important in determining the probability of innovation. He applies a formal model in which workers invest in human capital, while firms invest in R&D. These two forms of investments are strategic complements and interdependent.

Table 3. Estimates of model parameters and effects of explanatory variables (EPO equation spatial with matrices based on the TFP level).

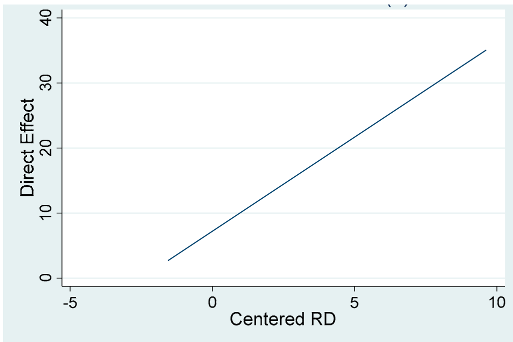
Variables/Spatial Matrices	(1)	(2)	(3)	(4)
RD	30.87 ***	29.19 ***	26.31 ***	24.39 ***
HR	9.162 ***	9.716 ***	8.501 ***	9.016 ***
RD·HR	x	x	2.721 **	2.677 **
CONST	66.35 ***	41.30 ***	52.05 ***	16.83
W_1				
EPO	−0.083	0.151	−0.035	0.309 ***
RD	x	−20.31 *	x	−29.01 ***
HR	x	0.598	x	1.772
W_2				
EPO	0.381 ***	0.404 ***	0.439 ***	0.458 ***
RD	33.81 ***	32.78 ***	29.91 ***	28.29 ***
HR	−13.44 ***	−13.36 ***	−12.59 ***	−12.57 ***
Pseudo R^2	0.539	0.533	0.538	0.518
Wald test of spatial terms (p-value)	278.65 (0.000)	272.17 (0.000)	286.82 (0.000)	329.34 (0.000)
Effects of Explanatory Variables	**(1)**	**(2)**	**(3)**	**(4)**
direct				
RD	36.09 ***	35.04 ***	32.27 ***	30.58 ***
HR	8.003 ***	8.402 ***	7.195 ***	7.665 ***
indirect				
RD	54.38 ***	56.137 ***	56.00 ***	65.60 ***
HR	−13.72 ***	−14.67 ***	−13.62 ***	−13.72

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, x—not included in the model. Source: Own elaboration.

In order to test the relationship between human capital and R&D, we adopt a direct test for complementarity or substitutability between two or more practices based on the estimation of pair-wise interaction effects [61]. Complementarity is understood in this approach to exist if the implementation of one practice increases the marginal return to other practices. In turn, substitutability relates to the situation when the implementation of one practice decreases the marginal return to other practices. As suggested by LeSage and Pace [62], the interpretation of the parameter estimates in spatial autoregressive models may result in erroneous conclusions. This can be explained by the non-linear character of these models that include a spatial lag in the input and output variable. So, we decide to analyze not only parameters for pair-wise interaction terms, but also the impact of human capital on the direct effect of R&D and vice versa. Figure 2 and coefficients for the interaction terms in model 3 and model 4 suggest that human capital and R&D are complementary inputs into inventions discovery processes. In other words, we confirm that two sources of knowledge, i.e., R&D and human capital, reinforce each other. In this context, the regions with the abundance of human capital possess a sustainable advantage over the regions with low levels of human capital in terms of the productivity of their innovation inputs.

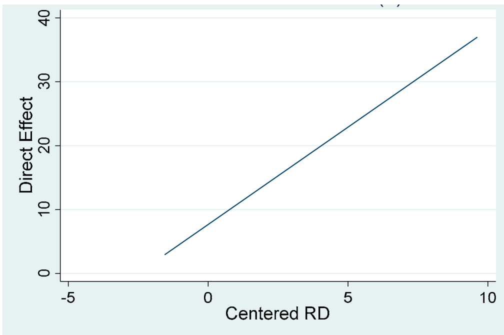
As regards spillovers of knowledge embedded in patents, the results reveal significant differences in the coefficients for the EPO variable. When controlling for institutional proximity and technological proximity, the applications for patent in the region is positively affected by the applications for patent in technologically similar regions when the interaction term is included in the model. This finding may indirectly suggest that the absorption of external (codified) knowledge requires the sufficient stocks of internal human capital and R&D. It confirms the arguments that codified knowledge described in patent documents may travel efficiently between regions with similar technological profiles, but effectiveness of knowledge flows is directly shaped by institutional proximity. Institutions, such as patent laws, are different in each country. So, there is a set of standard national procedures and mechanisms for assessing, granting and publishing patents, which are common to all agents. Using a region-by-region citation frequency matrix, Maurseth and Verspagen [63] prove that patent citations happen more frequently among EU regions within the same country. They also show that technological specialization affects knowledge spillovers.

(**a**) Direct Effects of RD in model (3)



(**b**) Direct Effects of HR in model (3)

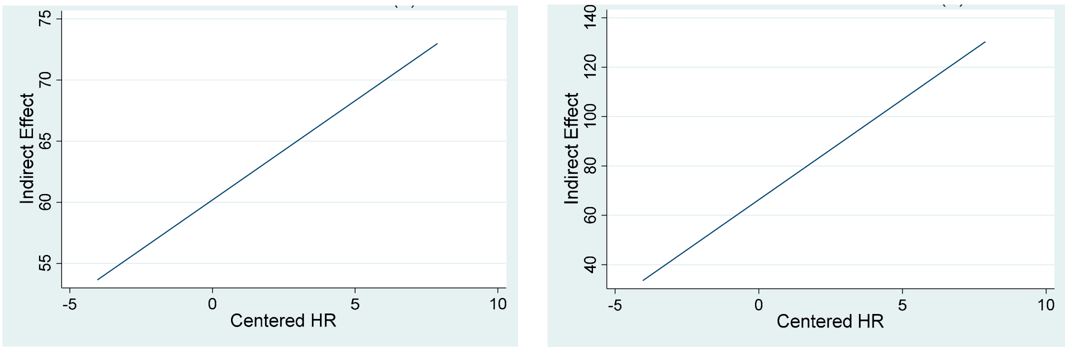
(**c**) Direct Effects of RD in model (4)



(**d**) Direct Effects of HR in model (4)

Figure 2. Average marginal direct effects of explanatory variables in models with interactions. Source: Own elaboration.

Concerning the R&D spillovers, our study produces consistent outcomes. The indirect effects of R&D are positive and highly significant in all models. According to our expectations, coefficients are positive and significant when we control for institutional proximity. It may be argued that common language, norms, values and expectations allow knowledge to flow easily between regions. The crucial role of institutions in interpreting the complexity of innovation development and diffusion is highlighted in a service ecosystems approach [64,65]. According to this approach, institutional arrangements formed by interrelated institutions lead to the establishment of the domain of ecosystem and innovation structures at the macro level. This argumentation is partially in line with the National Innovation System—NIS perspective. The NIS is the set of distinct institutions which contribute to the creation and diffusion of innovation and which constitutes the framework within which governments set and implement policies to affect the innovation process [66]. In such context our findings prove the effectiveness of the European NIS policies and programs that are aimed at facilitating the creation of positive external economies in the form of an exchange of knowledge. We also try to verify the absorptive capacity hypothesis. As can be seen at Figure 3, the increase in human capital leads to the increase in indirect effects of R&D. It means that labor market characteristics of the region shape its ability to absorb and use external R&D. Similar results are reported by Roper and Love [67] who state that high-tech employment may help with the absorption of knowledge from the public sector R&D. They conclude that improvements in the supply side of the labor market seem to have the potential to contribute to regions' ability to use external knowledge.



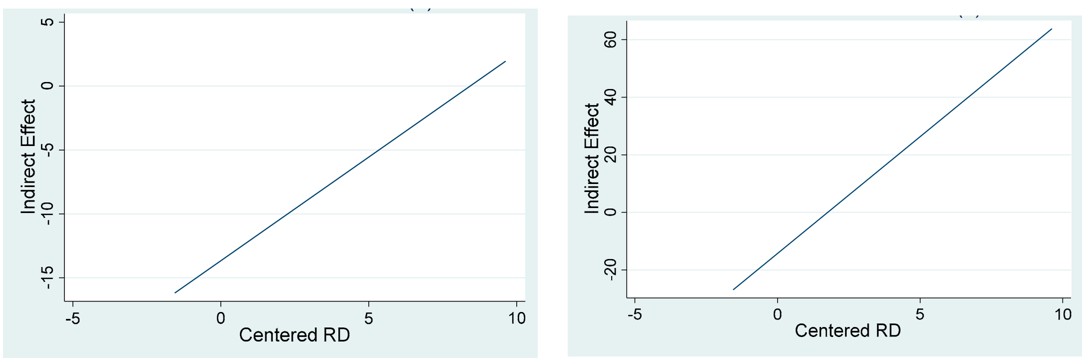
(**a**) Indirect Effects of RD in model (3) (**b**) Indirect Effects of RD in model (4)

Figure 3. Average marginal indirect effects of R&D in models with interactions. Source: Own elaboration.

Finally, the indirect effects of human capital are negative and significant in all models besides model 4. It seems partially surprising, because knowledge embodied in human brains flows less easily than codified knowledge due to its tacit character. This kind of knowledge is difficult to transfer without moving people. On the other hand, it should be stressed that we measure human capital as the share of scientists and engineers in the active population of the region. As proved by Giannetti [68], higher-skilled workers are more likely to migrate than low-skilled workers.

It is important to note that differences in language, culture, and values translate into higher cross-country migration costs as compared to within country migration cost. Moreover, we may conclude that regional technological specialization affects migration choices of human resources in science and technology. As such our results suggest that there is a fierce competition for highly qualified employees among EU regions. According to European Committee of the Regions, a distribution of highly skilled migrants at the NUTS2 level shows that these migrants prefer the countries located in the north of Europe (e.g., Denmark, Sweden, and Ireland) and urban areas [69]. In turn, Italian regions seem to be the less attractive regions for highly skilled migrants.

What is important, we find that negative externalities of human capital can be reduced by regional investments in R&D. Moreover, Bana [70] argues that the brain drain may bring the positive effects for sending regions in the form of return migration, inward investment, and technology transfer. According to Figure 4, the indirect effects of R&D depend on the human capital endowments of the region. These effects become positive after reaching a threshold of the HR variable.



(**a**) Indirect Effects of HR in model (3) (**b**) Indirect Effects of HR in model (4)

Figure 4. Average marginal indirect effects of human capital in models with interactions. Source: Own elaboration.

5. Conclusions

This paper examines knowledge spillovers using the KPF at the regional level for Europe. Its main contribution is the investigation of the role of technological and institutional proximity in shaping knowledge diffusion. Although some previous empirical papers have focused on these kinds of proximities, we take into account the alternative structure of the spatial weight matrix by applying techno-economic weights based on the TFP level. Moreover, we try to provide an empirical evidence on whether there is complementarity or substitutability between human capital and R&D at the regional level. For regional economists an important task is to understand how regions integrate these two knowledge sources and if such activities increase their innovation performance.

We find a positive impact of regional R&D expenditures and human capital on patent intensity. As regards knowledge spillovers, our study proves that institutional proximity captures channels through which the diffusion of knowledge embedded in patents takes place within the European regions. We also confirm that there are positive externalities generated by R&D when controlling for institutional proximity and technological proximity. These positive externalities are additionally reinforced by the human capital endowments of the region. Moreover, we reveal that there are negative externalities of human capital, but they can be reduced by regional R&D investments. Finally, the results confirm complementarities between human capital and R&D.

Our findings have a few policy implications. The first one relates to the importance of regional policies focusing on investing in R&D and human resources in science and technology, given their role in local creation of inventions. Moreover, R&D and human capital appear to be complementary, which means that both are required to boost inventions. These results confirm the need for keeping the right balance between two flagship initiatives within the Europe 2020 Strategy, i.e., "Innovation Union" and "Youth on the move". At the regional level the complementarity of the European Research Area instruments and the Structural Funds is the crucial issue. It should be noted that regional policies to trigger R&D may be in the form of fiscal incentives or public funding of private R&D as well as public performed R&D. However, R&D incentives will work sub-optimally when the number of scientists and engineers is rigid. So, regional authorities should increase the supply of scientists and engineers, for instance by providing fellowships to students in engineering or generous grants for scientists. This in turn ought to be supplemented by regional mechanisms preventing high skilled labor from migration. According to European Committee of the Regions, the possible prevention mechanisms of brain drain may include, inter alia, stimulating regional labor market by applying online tools to tie the labor demand with talent supply, achieving synergies among creative industries and ICT and providing information to highly educated people interested in coming back to their home region [69]. The next policy implication is a necessity for promoting institutions in the form of laws, common values, codes and routines of knowledge sharing, which should be inherent elements of the RIS and NIS, particularly in lagging regions/countries. Moreover, Research and Innovation Strategies for Smart Specialisation (RIS3) ought to focus on building capacities in R&D in regional and interregional dimensions. In the case of the interregional dimension, cooperation between regions should be based on technological proximity, since regions with the similar technological level are more willing to exchange knowledge. Our results show that the positive effect of R&D and patent information spillovers are realized in a specific institutional framework which may lower transaction costs and, finally, stimulate cooperative behaviors.

Apart from the obtained results, there are different avenues of future research. It would be appealing to assess the role of other non-spatial proximities (e.g., social and organizational ones) in the production of knowledge in the regional context. Our approach applies patent intensity as a proxy of innovation performance, which is an undeniable limitation. Firstly, patent applications relate only to technical inventions that meet the patent eligibility requirements and it is obvious that our depended variable misses many non-patentable inventions. Secondly, patent is an intermediate output measure of innovation. As such, future research ought to use commercialized outputs of innovation (e.g., innovative sales—a measure of innovation success). As regards other methodological improvements of our research, it would be interesting to apply semi-parameter varying-coefficient spatial panel data models to estimate the regional knowledge production function. Finally, it seems desirable to take into account the differences between public and private R&D spillovers and study the spillover effects of foreign direct investment.

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