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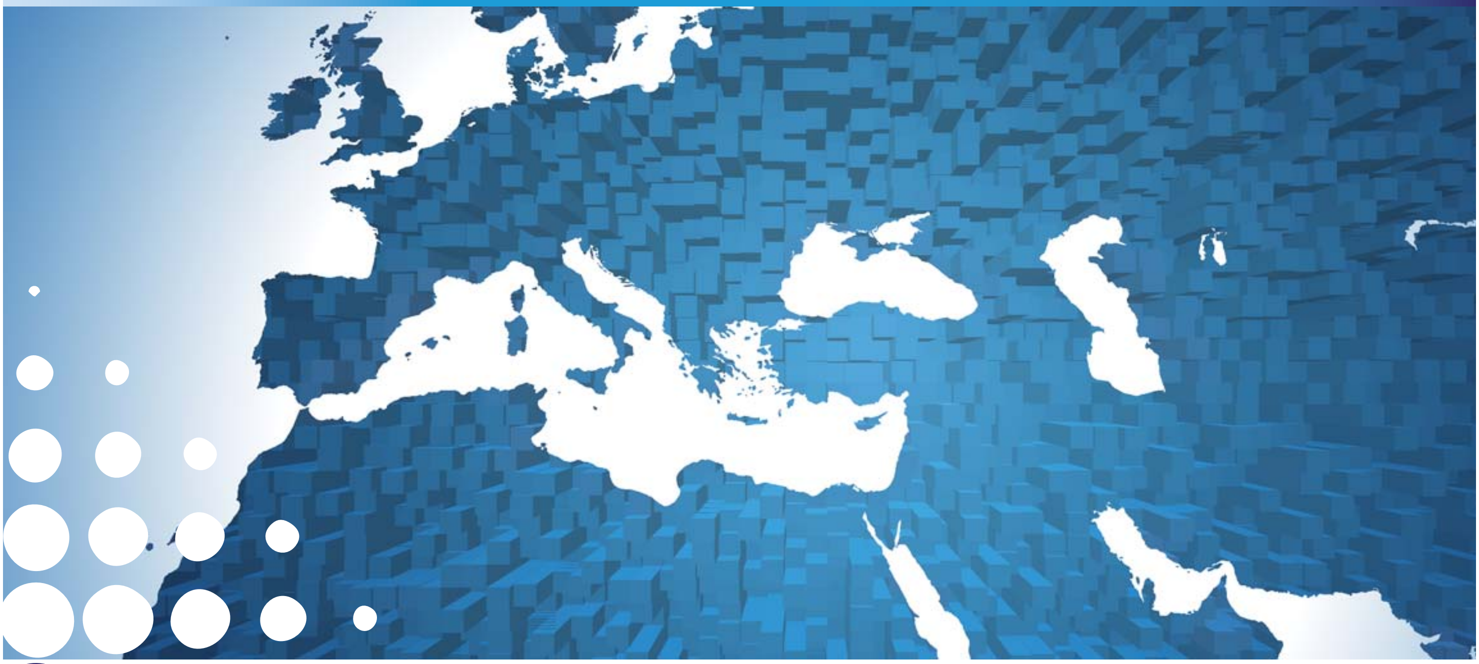

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The Effect of Spatio-Temporal Knowledge Flows on Regional Innovation Performance: the case of ICT patenting in Europe

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Abstract

In this study, we focus on the effects of external knowledge on regional innovation performance by considering that the neighborhood that supply a region with external knowledge might be relational as well as geographical, and it may evolve in time. Following Autant Bernard and LeSage (2011), and Lee and Yu (2012) we worked on a Spatial Durbin model, which includes time varying weight matrices, and space and time lagged variables. Our empirical application bases on European data in the field of ICT and aims at quantifying the effect of spatial, temporal and spatio-temporal flows on the inventive activity of 226 regions during 2003-2009. The results suggest that external knowledge emanating from geographical and relational neighbors play an equally important role on the regional inventive activity. The magnitude of contemporaneous flows from neighbors is small but they are in play in time because past inventive activity affects current inventive activity.

1 Introduction

External knowledge is considered to be a key input for innovation activities that take place both at the organizational and regional level (Chesbrough, 2003; Hagedoorn & Wang, 2012; Cassiman & Veugelers, 2006; Jensen et al., 2007). As a matter of fact, knowledge is not evenly distributed across

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regions, and hence knowledge flows are important for regions to fuel their economy with new products, processes, new ways of organizing work and new ways of marketing. It is also important from an economic convergence perspective concerning the theoretical findings suggesting that cross-regional knowledge flows leads to reducing uneven growth (Baldwin & Forslid, 2000; Baldwin et al., 2001).

The literature suggests that knowledge might flow among regions via several mechanisms such as observing/imitating others, professional mobility, and networks (Andersson & Karlsson, 2005; Autant-Bernard et al., 2012). Some of these mechanisms are shown to be operating locally meaning that geographical proximity to sources of knowledge is important. Networks, however, enable regions to benefit from knowledge emanating from agents that are physically apart. This brings up two types of neighborhoods that might supply a region with external knowledge: the geographical neighborhood and relational neighborhood [1]. The former is either fixed or evolves slowly as a result of advances in the transportation technologies; whereas, the latter has a more dynamic nature as relations might be created or dissolved more quickly and easily. Then, from a temporal point of view how knowledge flows from these two neighborhoods affect a region's innovation performance involves two types of dynamism. On the one hand, the effects of external knowledge are not only immediate but also inter-temporal (Gleaser et al., 1992; Henderson, 1997). LeSage and Fischer (2012) show that the effect of dynamic externalities might be larger than the effect of static externalities. On the other hand, the neighborhoods, in particular the relational one, that supplies a region with external knowledge evolves in time.

Therein, this study aims at accounting for these two types of dynamism and investigating how contemporaneous and inter-temporal knowledge flows from geographical and relational neighborhoods differ from each other. The empirical literature so far mainly focuses on the geographical neighborhood (Caniels & Verspagen, 2001; Autant-Bernard, 2001; Greunz, 2003; Moreno et al., 2005). More recently, Maggioni et al. (2007) test the effects of flows through physical connections and relational connections on patenting activity of regions separately. Ponds et al. (2010), however, bring them together in a single model and conclude that academic knowledge spillovers do not only take place via physical connections but also through relational connec-

[1]These two dimensions of neighborhood may act as substitutes. Entering global networks can be seen as a way to benefit from distant knowledge and compensate for the absence of physical proximity (Amin & Cohendet, 2004). However geographical and relational neighborhood may also interact and complement each other. Physical proximity, in particular, has been shown to foster network relationship (Johnson et al., 2006). In this paper we do not investigate this aspect but rather we put emphasize on the respective role played by each neighborhood. Neglecting their potential interactions is not neutral, but the reasons behind this choice is detailed in the next sections.

tions. The recent methodological advancements in spatial econometrics now allow extending this stream of work, where a static approach is undertaken, by taking into account the evolution of the neighborhoods in time.

Towards this aim we employ a spatio-temporally extended Griliches-Jaffe KPF and quantify the effect of external flows on the inventive activity of 226 European Regions in the field of Information and Communication Technologies (ICT). We make use of a contiguity matrix to represent the pattern of geographical neighborhood. To represent the pattern of relational neighborhood we use the inter-regional R&D collaboration network created within the scope of European Union Framework Programs. Our results suggest that flows from both neighborhoods are affecting regional innovation performance, besides expenditure in R&D, specialization in the field, and the level of past inventive activity.

In the sequel, we will first review the literature to elaborate the link between regional innovation performance and knowledge flows in space and time. Next, we will provide the spatio-temporally extended KPF model that we used in our empirical analysis. In Section 4, we will present the empirical analysis by explaining the data sources and variables and discussing the estimation results, respectively. Finally we will provide concluding remarks in Section 5.

2 Innovation and Inter-Regional Knowledge Flows in Space and Time

A number of models or conceptions have acknowledged, either explicitly or implicitly, that external knowledge plays a role in the innovation process. The linear innovation model (Bush, 1945), which represents the dominant conception during 1940's, assumes that innovations occur as knowledge flows linearly and in one way from performers of basic research to performers of applied research. More recent and holistic approaches emphasize the role of knowledge flows in an innovation system that take place through interaction among actors, which perform different functions in the system (Lundvall, 1992; Hekkert et al., 2007). Open innovation model (Chesbrough, 2003) and concepts like democratizing innovation (vonHippel, 2005) focus on organizations' innovation performance and argue that higher permeability of organizational boundaries to inflows and/or outflow of ideas and knowledge results in higher innovation performance.

Knowledge might flow intentionally or unintentionally and through different mechanisms. Andersson and Karlsson (2005) classify knowledge flows under two headings: knowledge spillovers vs transaction based flows. The former connotes involuntary flows which are classified further into two: those mediated by market mechanisms (pecuniary) vs. pure (technological) externalities. While pecuniary knowledge spillovers take place via the labor market or purchasing and selling of goods; pure externalities arise from observing and imitating others. Whereas the latter refers to the case where there is a formal agreement among partners showing the monetary payments for knowledge (or division of work) and the rights of partners conducting collaborative research. Indeed, intentional access to knowledge might not always be transaction-based in the form of formal collaborations such as making use of information disclosed by patents or scientific papers and intentional flows might be accompanied with unintentional flows. Therein, in a more general sense Autant-Bernard et. al. (2012) identify networks as another mechanism for knowledge flows.

External knowledge might effect innovation performance along two dimensions: static and dynamic (Gleaser et al., 1992; Henderson, 1997). Among these static dimension refers to the effects of knowledge on the innovation performance in the current period. In other words, static effects are contemporaneous effects. Whereas dynamic effects are inter-temporal as they refer to the effects of prior accumulated knowledge on the current innovation performance. LeSage and Fischer (2012) provides empirical evidence on the dynamic effects of knowledge spillovers on regional factor productivity. Their results show that dynamic externalities may have a higher impact than static externalities.

Organizations do not equally benefit from such effects of external knowledge due to several reasons. First of all organizations differ in their "ability to recognize the value of new information, assimilate it, and apply it to commercial ends" (Cohen & Levinthal, 1990). This ability, called the absorption capacity, is cumulative as some absorptive capacity accumulated earlier enables more efficient accumulation of absorption capacity in the succeeding periods (Ibid.). In this regard, it is closely related to the dynamic effects of external knowledge. Second, knowledge is not diffusing uniformly in space (Caniels & Verspagen, 2001; Autant-Bernard, 2001; Greunz, 2003; Moreno et al., 2005), meaning that organizations are not breeding their innovative activities with a single, homogeneous pool of external knowledge.

One of the factors that hinders homogeneous spatial distribution of external knowledge is that there exists a tacit component of knowledge (Polanyi, 1966) which requires face-to-face-interaction in order to be transmitted. As another factor Sorenson et al. (2006) argue that complexity of knowledge matters and in the case of moderate knowledge complexity being spatially proximate to the knowledge source becomes advantageous. Finally, different mechanisms through which knowledge flows get affected by spatial constraints in different extents.

Among these pure externalities depend highly on physical proximity to the source as by definition they refer to the externalities arising from being physically close (like buzz or ability to observe). Knowledge spillovers via labor market have also been shown to be localized due to spatially constrained mobility of individuals (Zucker et al., 1994; Almeida & Kogut, 1999; Balconi et al., 2004). On the other hand, empirical evidence has shown that spatial distance is less restrictive on intentional knowledge flows. Analyzing patent citations Agrawal et al. (2008) and Singh (2005) conclude that it is social proximity that facilitates knowledge flows and the additionality that arise from geographical proximity is low. Hoekman et al. (2010) study European co-publication networks and suggest that although physical distance dampens co-publication intensity, its effect is decreasing over time. For the case of R&D project networks empirical evidence is mixed. Autant-Bernard et al. (2007) report that physical distance has no effect on collaboration choices for micro and nanotechnologies field. Conversely, Paier and Scherngell (2008) report a negative role played by physical distance but they state that there are more important determinants of partner choice like joint history or similarity in knowledge bases. Finally, Lata and Scherngell (2012) conclude that country border effects are decreasing over time.

In the light of these findings one might consider two types of neighborhoods that might supply an organization or a region region with external knowledge: the geographical neighborhood versus relational neighborhood. The former stems from the fact that some knowledge flows occur locally and geographical proximity to sources of knowledge is important and refers to geographically proximate neighbors. The latter involves deliberate actions of agents to benefit from knowledge emanating from others and refers to relational neighbors. When considered at the organizational level both might change as organizations might change their locations as well as their interactions. However, for the case of regions geographical neighborhood is less dynamic. Either it remains the same or changes slowly due to advances in the transportation technologies. Whereas the relational neighborhoods both for organizations and regions has a more dynamic nature since starting or ending relationships is much easier and quicker.

Therein, from a temporal point of view the relationship between external knowledge and innovation performance involves two types of dynamism: dynamism stemming from the changes in the topology of connections through which knowledge flows and dynamism resulting from the effects of prior of accumulated knowledge on the current innovation performance. In the sequel, we will present a spatio-temporal extension to the Griliches-Jaffe knowledge production function (KPF) approach to study the effect of knowledge flows through physical and relational connections over time on innovation performance.

3 A Spatio-Temporal Extension to KPF Approach

Griliches-Jaffe knowledge production function (KPF) provides a framework to relate inputs to innovation process to innovation outputs. Autant Bernard and LeSage (2011) show that the theoretical reasoning that neighbor effects might occur on both observable and unobservable inputs, results in a spatial extension to KPF in the form of a Spatial Durbin model. Concerning that knowledge flows involve a dynamic component and due to the time varying nature of neighborhoods of a region (the relational one in particular), following (Lee & Yu, 2012) we work on the following Spatial Durbin model, which includes time varying weight matrices and time lagged variables, expressed in the log-linear form [2]:

$$\begin{aligned}\mathbf{y_t} = \lambda \mathbf{W_t y_t} + \gamma \mathbf{y_{t-1}} + \rho \mathbf{W_{t-1} y_{t-1}} + \mathbf{X_t}\boldsymbol{\beta} + \mathbf{W_t X_t}\boldsymbol{\delta} + \mathbf{X_{t-1}}\boldsymbol{\tau} \\ + \mathbf{W_{t-1} X_{t-1}}\boldsymbol{\phi} + \mathbf{c} + \alpha_t \mathbf{l} + \mathbf{v_t}\end{aligned} \quad (1)$$

$\mathbf{y_t}$ is a column vector of size $N \times 1$ with entries showing the innovation output in region n at time t. $\mathbf{W_t}$ is an $N \times N$ row-normalized matrix of spatial weights at time t. $\mathbf{X_t}$ is a $N \times k$ matrix of individually and time varying non-stochastic regressors representing regional inputs to innovation. $\mathbf{c}$ is an $N \times 1$ column vector of individual effects. α_t is the t^{th} element of the $T \times 1$ column vector of fixed time effects. $\mathbf{l}$ is an $N \times 1$ column vector of ones. Finally, $\mathbf{v_t}$ is an $N \times 1$ column vector of i.i.d error terms with zero mean and variance σ_0^2.

By backward substitution Equation (1) can be re-written as in Equation (2). Lee and Yu (2012) show that provided that $\mathbf{W_t}$'s are all row-normalized, if $\mid \alpha \mid< 1$ and $(\mid \gamma \mid + \mid \rho \mid)/(1- \mid \alpha \mid) < 1$ then eigenvalues of $\mathbf{A_t}$ are less than 1 and then the process is stationary.

$$\mathbf{y_t} = \sum_{t=0}^{\infty} A_t^{(h)} S_t^{-1} (\mathbf{c} + \mathbf{B X_{t-h}} + \mathbf{D X_{t-h-1}} + \alpha_{t-h}\mathbf{l} + \mathbf{v_{t-h}}) \quad (2)$$

where $\mathbf{S_t} = \mathbf{I_n} - \lambda \mathbf{W_t}$, $\mathbf{A_t} = \mathbf{S_t^{-1}}(\gamma \mathbf{I_n} + \rho \mathbf{W_{t-1}})$, $\mathbf{A_t^{(h)}} = \prod_{i=0}^{h} A_{t-i}$ with $\mathbf{A_t^{(0)}} = \mathbf{I_n}$, $\mathbf{B} = \boldsymbol{\beta} + \mathbf{W_{t-h}}\boldsymbol{\delta}$, $\mathbf{D} = \boldsymbol{\tau} + \mathbf{W_{t-h-1}}\boldsymbol{\phi}$.

To eliminate individual and time fixed effects Lee and Yu (2012; 2010) uses a three stage process. First, they transform relevant variables into deviations from the group means by using $\mathbf{J_{N\times N}} = \mathbf{I_{N\times N}} - \mathbf{(1/N) l_{N\times 1} l'_{N\times 1}}$ as in Equation (3) , and thus eliminate time effects (as $\mathbf{J_{N\times N} l_{N\times 1}} = \mathbf{0}$).

$$\begin{aligned}(\mathbf{J y_t}) = \lambda(\mathbf{J W_t})(\mathbf{J y_t}) + \gamma(\mathbf{J y_{t-1}}) + \rho(\mathbf{J W_{t-1}})(\mathbf{J y_{t-1}}) + (\mathbf{J X_t})\boldsymbol{\beta} \\ + (\mathbf{J W_t})(\mathbf{J X_t})\boldsymbol{\delta} + (\mathbf{J X_{t-1}})\boldsymbol{\tau} + (\mathbf{J W_{t-1}})(\mathbf{J X_{t-1}})\boldsymbol{\phi} + (\mathbf{J c}) + (\mathbf{J v_t})\end{aligned} \quad (3)$$

[2] We dropped the index n in the variables and the index 0 in parameters in the original notation (Lee & Yu, 2012) for simplicity of the notation. Also, as we do not give the derivation of the likelihood in detail we made some minor changes in the notation.

Second, letting $\mathbf{F_{N\times N-1}}$ denote the matrix corresponding to $N-1$ eigenvectors of J with a value 1, they further transform $(\mathbf{Jy_t})$ to $(\mathbf{F'_{N\times N-1}Jy_t})$ to eliminate linear dependence in $(\mathbf{Jv_t})$. Third, they concentrate out the transformed individual effects. In the end they express the concentrated log likelihood function as follows (the derivation is available in Appendix A of Lee and Yu (2010) for a spatial autoregressive model):

$$lnL_{N,T}(\theta) = -\frac{1}{2}(N-1)Tln2\pi - \frac{1}{2}(N-1)Tln\sigma^2 - Tln(1-\lambda) + \sum_{t=1}^{T} ln \mid \mathbf{S_t}(\lambda) \mid - \frac{1}{2\sigma^2}\sum_{t=1}^{T}\hat{\mathbf{V}}_\mathbf{t}(\theta)\mathbf{J_{N\times N}}\hat{\mathbf{V}}_\mathbf{t}(\theta) \quad (4)$$

where $\mathbf{S_t}(\lambda) = \mathbf{I_{N\times N}} - \lambda\mathbf{W_t}$, $\hat{\mathbf{V}}_\mathbf{t}(\theta) = \mathbf{S_t}(\lambda)\mathbf{y_t} - (1/T)\sum_{t=1}^{T}\mathbf{S_t}(\lambda)\mathbf{y_t} - \mathbf{Z_t}\psi$ with $\mathbf{Z_t} = (\hat{\mathbf{y}}_\mathbf{t-1}, \widehat{\mathbf{W_{t-1}y_{t-1}}}, \hat{\mathbf{X}}_\mathbf{t}, \hat{\mathbf{X}}_\mathbf{t-1}, \widehat{\mathbf{W_t x_t}}, \widehat{\mathbf{W_{t-1}x_{t-1}}})$, $\hat{\mathbf{y}}_\mathbf{t-1} = \mathbf{y_{t-1}} - (1/T)\sum_{t=1}^{T}\mathbf{y_{t-1}}$, $\widehat{\mathbf{W_{t-1}y_{t-1}}} = \mathbf{W_{t-1}y_{t-1}} - (1/T)\sum_{t=1}^{T}\mathbf{W_{t-1}y_{t-1}}$, $\hat{\mathbf{X}}_\mathbf{t} = \mathbf{X_t} - (1/T)\sum_{t=1}^{T}\mathbf{X_t}$, $\hat{\mathbf{X}}_\mathbf{t-1} = \mathbf{X_{t-1}} - (1/T)\sum_{t=1}^{T}\mathbf{X_{t-1}}$, $\widehat{\mathbf{W_t x_t}} = \mathbf{W_t x_t} - (1/T)\sum_{t=1}^{T}\mathbf{W_t x_t}$, $\widehat{\mathbf{W_{t-1}x_{t-1}}} = \mathbf{W_{t-1}x_{t-1}} - (1/T)\sum_{t=1}^{T}\mathbf{W_{t-1}x_{t-1}}$.

Following the discussion in Section 2 the neighborhoods of regions at time t could be expressed as the weighted sum of two neighborhoods, geographical (W_{t_g}) and relational (W_{t_r}), which are also row-standardized:

$$\mathbf{W_t} = \omega_g\mathbf{W_{t_g}} + \omega_r\mathbf{W_{t_r}} \quad (5)$$

While maximizing the log likelihood in Equation (4), we add the following constraint so that the sum $(\mathbf{W_t})$ still remains row-standardized.

$$\omega_g + \omega_r = 1 \quad (6)$$

4 The Effect of Spatio-Temporal Knowledge Flows on ICT Patenting in European Regions

As an empirical application, we implemented the above-mentioned modeling approach to quantify the effect of spatio-temporal knowledge flows on inventive activity of European regions in the field of ICT. As a matter of fact, inventive activities are not representative of all innovation activities for several reasons. First, not all innovations are preceded by inventions. Second, even if they start with an invention phase, the scope of innovation activities is broader as it includes further steps that are essential for transforming inventions into new goods, services, processes, etc. Hence, all inventions do not necessarily end up with successful innovations, for some reason some innovations are abandoned after the invention phase. Despite these well-known limitations, we use inventive activities as a proxy for innovative activity as frequently encountered in the literature. One reason for it is that even if they do not capture a full-fledged view of the innovation process, they still reflect the activities undertaken to come up with a novel, non-obvious and useful outcome. Also, in terms of measurement and data availability, the focus on inventive activities comes as a natural choice as existing databases on outputs of invention process enable analysis with considerable temporal and spatial scope.

4.1 Data and Variables

The empirical analysis covers the inventive activity of 226 regions located in 25 members of the European Union (Bulgaria and Switzerland omitted due to missing data) and Norway during 7 years from 2003 to 2009. The definition of regions follows the usual NUTS-2 classification except for the fact that we excluded some NUTS-2 regions (the islands far from the mainland) and replaced a number of NUTS-2 regions with their NUTS-1 counterparts (only for Belgium, Denmark and United Kingdom) in order to get more homogeneous spatial areas. In the sequel, we will explain the definition of variables in detail.

(a) **The Dependent Variable:** The dependent variable represents the level of inventive activity of a region at point in time and named as "*Patents*"[3]. It is measured by the number of patent applications to the European Patent Office (EPO)[4] (localized with respect to the inventor(s)'s country of residence) in the field of ICT.

(b) **The Weight Matrices:** The geographical neighborhood at time t, $\mathbf{W_{t_g}}$, is build on the basis of 1st order rook contiguity among regions. Since contiguity does not evolve in time, $\mathbf{W_{t_g}}$'s are identical $\forall t$.

    On the other hand, we approximate the relational neighborhood at time t, ($\mathbf{W_{t_r}}$) by means of the R&D project network that is created through European Commission (EC) support within the scope of the Framework Programs (FP). This choice stems from the fact that this data source has a better representativity as compared to co-invention or co-publication networks as it covers the collaborative research activity of all types of organizations; i.e. universities, private enterprises, public research bodies, non-profit organizations. Yet, it is not free of limitations. Although not as severe as in the case of co-invention networks, the structure of R&D project networks is not totally exogenous to the level of inventive activity. However, as we explain below the way $\mathbf{W_{t_r}}$ is build tries to minimize a possible endogeneity problem.

[3]Patents as indicators of inventive activity have also advantages and disadvantages, see Griliches (1990) and Kleinknecht et al. (2002)

[4]Source: OECD Regpat Database (June 2012)

To build the network we made use of all collaborative projects supported by the EC via FP5 to FP6. We obtained the raw data from the French Ministry of Higher Education and Research and have it processed by EuroLIO. For projects that are funded by the Commission during FP5 and FP6 the address of the applicant organization is available. Indeed starting from FP7 both the address of the applicant organization and the department at which the research is conducted are available in the database. A comparison of these two addresses reveal that they are not necessarily the same in all cases; yielding two different spatial distribution of innovative activity. Although geo-localization with respect to the place where R&D is carried out is more relevant for the aim of our study, our study bases on a geo-localization with respect to the address of the applicant organization as the information at the department level is not available fo FP5 and FP6. Nevertheless, regarding endogeneity concerns, this definition might also be advantageous as the dependent variable is measured in terms of the inventors' location.

Before row-normalization the matrix $\mathbf{W_{t_r}}$ in our analysis is the valued representation of the one-mode network representation of the inter-regional collaboration in ICT. The value of a link between two regions is calculated by counting the number of running projects between a pair of organizations (one located in the first region and the other in the second) at time $t-3$ and then taking the sum over all such unique pair of organizations. This time lag can also be considered as another factor alleviating endogeneity concerns.

Table 1 summarizes the temporal dynamics of the contiguity network and the collaboration network. While at the beginning of FP5 few regions are connected to each other, in 2006 we observe a dramatic decrease in the number of isolated regions and a significant increase the network density. Nevertheless, these changes do not happen in a gradual and linear fashion as we observe oscillations in these statistics over the years.

(c) **The Explanatory Variables:** The explanatory variables include inputs to the innovation process (three year time lag is assumed). Among these the variable "*BERD*" shows the amount of gross regional R&D expenditure performed by the business enterprise sector in ICT [5]. The variable "*HRST*" stands for the human resources in science and technology [6]. The variable "*Specialization*" stands for the degree of specialization of a region in ICT. It is an index that is calculated by EuroLIO

[5] Since data is not available on sectoral breakdown of regional R&D expenditures, we used an approximation by multiplying the R&D expenditures performed by the business enterprise sector (in million PPS) by the ratio of ICT publications to publications in all domains. Source: EUROSTAT, PASCAL (INIST-CNRS)

[6] In thousands. Source: EUROSTAT

on the basis of PASCAL (INIST-CNRS). This index is obtained by taking the ratio of two shares: the share of ICT publications of a region in its overall portfolio of publications, and the share of ICT publications in total number of publications for all regions. When the index is greater than one this means that the regions is more specialized in ICT as compared to the average.

Table 1: Temporal Dynamics of the Inter-Regional Contiguity and the Collaboration Networks

Network	**Measures**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**
Contiguity	Density	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019
	Avg. degree	4.4	4.4	4.4	4.4	4.4	4.4	4.4	4.4
	Max. degree	11	11	11	11	11	11	11	11
	No. of isolates	11	11	11	11	11	11	11	11
Collaboration	Density	0.004	0.243	0.323	0.369	0.243	0.404	0.382	0.404
	Avg. degree	0.1	109.4	73.0	83.0	54.7	90.8	86.4	90.8
	Max. degree	2	160	179	187	186	187	189	197
	No. of isolates	209	35	16	14	16	18	18	16

4.2 Results

Table 2 presents the coefficients estimates[7] for three model specifications obtained by using STATA. Among these Model 1 includes all the elements of the model presented in Equation 1. This model bases on the conception that current level of inventive activity does not only get affected from past inventions (own or neighbors') but also from the inputs of the invention process in the past period (own and neighbors'). Hence it considers that knowledge can flow temporally, spatially, and spatio-temporally by means of both outputs and inputs. On the other hand, Model 2 omits spatio-temporal flows via inputs and Model 3 omits both spatio-temporal and temporal flows via inputs. The reason for these restrictions is to avoid the adverse effects that arise from the correlations between current and past levels of inputs on the one hand and from the correlations between neighboring inputs and outputs on the other. The unexpected negative coefficient estimates for hrst in (both) neighborhoods in the past period and hrst in the past period in Model 1 and Model 2, respectively, might be considered as an indication of such adverse affects.

The three models corroborate each other in a number of aspects. First of all, once individual fixed effects and time effects are singled out, two important explanatory factors for the level of regional inventive activity in ICT in

[7]Estimates statistically significant at 90% and 95% are indicated by * and **, respectively.

Europe seem to be financial resources devoted to R&D, and specialization of the region in the field. Of course, this is consistent with the observation that regions with advanced levels of technology often have strongly invested in R&D and have been able to create a comparative advantage in the field. Thus, more R&D and more specialization should lead to higher rates of technological progress via improvements in specific research infrastructures and skills.

Table 2: Estimation Results

Variables	**Model 1**	**Model 2**	**Model 3**
Berd	0.3381**	0.3313**	0.3314**
Hrst	0.1126	0.1224	0.0326
Specialization	0.0582**	0.0575**	0.0597**
Berd in Geog. Neighb.	0.0016	0.0021	0.0023
Berd in Relat. Neighb.	0.0016	0.0021	0.0023
Hrst in Geog. Neighb.	0.3183**	0.1151	0.0835
Hrst in Relat. Neighb.	0.3183**	0.1151	0.0835
Specialization in Geog. Neighb.	-0.0266	-0.0244	-0.0256
Specialization in Relat. Neighb.	-0.0266	-0.0244	-0.0256
Berd in prev. period	-0.0066	-0.0060	
Berd in Geog. Neighb. in prev. period	0.0065		
Berd in Relat. Neighb. in prev. period	0.0065		
Hrst in prev. period	-0.1626	-0.2262*	
Hrst in Geog. Neighb. in prev. period	-0.2923**		
Hrst in Relat. Neighb. in prev. period	-0.2923**		
Patents in Geog. Neighb.	0.0012**	0.0013**	0.0013**
Patents in Relat. Neighb.	0.0012**	0.0013**	0.0013**
Patents in prev. period	0.1038**	0.1000**	0.0780**
Patents in Geog. Neighb. in prev. period	-0.0165	0.0026	0.0019
Patents in Relat. Neighb. in prev. period	-0.0165	0.0026	0.0019
Log likelihood	**-204.6**	**-207.9**	**-209.9**
AIC	**451.3**	**449.9**	**449.8**

Second, past level of inventive activity appears as a major driver of current technological capacities. This is in accordance with the theoretical analysis on the cumulative aspect of the knowledge production process. The ability to learn depends on past knowledge and skills, as it allows better assimilation of new ideas (Cohen & Levinthal, 1990). This result is also in line with the assumption of inter temporal knowledge externalities used in ideas-based growth literature.

Third, since the spatial dependence parameter estimate is positive and significant, this provides evidence that spillover effects are significantly related to the presence of knowledge stocks in both neighboring and partner regions. Model 3 and Model 2 suggest that these effects are created by means of outputs; i.e. patents. Whereas Model 1 shows that both neighborhoods might affect patenting via inputs (hrst) and outputs. Nevertheless, as mentioned above the unexpected negative coefficients of hrst in neighborhoods in the past period might be signaling a possible multicollinearity problem. Spatial dependence also suggests an immediate response to a change in the level of neighboring and partner regions innovative activities. To this regard, our results differ from (Parent, 2012), who finds a positive impact of past innovation and R&D activities and no significant impact of their current values. In addition, the geographical and the relational neighborhoods are found to be equally affecting the regional inventive activity. This result points out that interactions between regions are mediated by both relational and spatial proximity. To this regard, our results corroborate past studies on the role played by space in knowledge diffusion. In addition, it shows that the EU policy implemented through the Framework Programme appears as an effective way to diffuse knowledge among European regions. Some regions remain however weakly integrated into these global networks. Peripheral regions (in geographical terms as well as in relational terms) may thus suffer from a difficulty to access external knowledge.

Moreover, it has to be noticed that this observed cross-sectional spatial and relational dependences however arise from knowledge diffusion over both time and space. Two mechanisms are at play here. Firstly, a time lag is considered between the R&D inputs and the dependent variable, inputs at neighbors impact the innovative outputs after few years only. Secondly, the coefficient of the temporally lagged dependent variable includes direct as well as indirect impacts. It therefore reflects the direct effects of y at $t-1$ and the indirect effects that Wy at $t-1$ produces on y at $t-1$.

Finally, our results point to a stronger time than spatial and relational dependence. The effects of inventions in both neighborhoods are small in magnitude (0.0013) whereas the magnitude of the effect of past inventions on current inventions is much larger (the second largest). This is consistent with past observations (Parent, 2012). This highlights the necessity of considering dynamic effects for a more a proper assessment of the importance of flows from neighborhoods. This means that the weak cross-sectional dependence may prove to have important impacts on the long run, due to the temporal dependence. This can therefore explain the existence of regional clusters with persistently different levels of innovative activity.

Concerning Akaike information criterion, there is not much difference among the models yet Model 3 is the best. In order to verify the results we have also run the specification in Model 3 by using alternative variable definitions. The results are presented in the appendix together with explanations on variable definitions. The comparison reveals that the results of Model 3 is quite robust with respect to changes in the variable definitions.

5 Conclusion

In this study, we studied the effects of external knowledge on a region's inventive activity by taking into account two facts. First, knowledge can diffuse in space not only though localized mechanisms but also though networks, which allow long-distance exchanges. Second, the neighborhood that supply a region with external knowledge may evolve in time, and especially for the relational neighborhood the evolution can be quick and significant (See Table 1). Bringing together the theoretical reasoning suggested by Autant Bernard and LeSage (2011) and methodological advancements by Lee and Yu (2012) we worked on a Spatial Durbin model, which includes time varying weight matrices, and space and time lagged explanatory and dependent variables. We conducted an empirical analysis using European data in the field if ICT to identify the role of spatial, temporal and spatio-temporal knowledge flows on the inventive activity of 226 regions during 2003-2009.

Our results corroborate the literature that external knowledge matters for innovation and additionally it shows that two different types of neighborhoods play an equally important role as a source of external knowledge. Hence, concerning the criticism on excessive focus on localized spillovers, this finding suggests the neglected mechanisms through which knowledge flows might be as important as the spatially localised mechanisms. Note that this finding bases upon a more proper quantification of geographical flows as it is obtained by demarcating flows through collaboration relations, controlling for the dynamism in the neighborhoods, and accounting for the temporal and individual effects. The study also reveals that although the effect of contemporaneous flows from neighbors is small in magnitude, they are in play in time because evidence is found on the effect of past inventive activity on the current inventive activity.

Nevertheless, these results are not free of limitations. First, due to data availability constraints we could be able to study a period of seven years. As addressed by Lee and Yu (2012) through a simulation analysis, as the number of observations in time decreases the bias in the estimates increases. Second, the conclusions that we abridged above base on a study conducted for a single technological domain, and hence more evidence is necessary to make generalizations. Third, the results might have a bias due to endogeneity of the weight matrix showing the relational neighborhood as the level of inventive active might have an impact on the configuration of the relational neighborhood. In this study we could not eliminate this totally but we tried to minimize it (see Section 4.1). Finally, our parameter estimates include both direct and indirect effects. Indeed, a change in a single region associated with any given explanatory variable will affect the region itself and potentially affect all other regions indirectly. Therefore, models containing spatial lags of the dependence variable require a special interpretation of the parameters and the computation of marginal impacts. As computation of these impacts in the case of our extended spatial Durbin panel model is not trivial, this will be dealt with in a further step of our research.

Still we would like to conclude by making some reflections on policy implications. From a policy making perspective, these findings affirm the rationales for promoting inter-regional research collaborations and provides additional support in the sense that it shows the existence of the dynamic effects. The positive effect of neighbors inventive activity on patenting suggests that a region can benefit from more external knowledge by increasing the number of inter-regional collaborations and/or by getting connected to regions with higher inventive activity. Therein findings in another strand of research that focuses on identifying the factors affecting the structure of inter-regional networks become key.

Appendix

To check the robustness of the results of Model 3, we have estimated the same specification by using alternative variable definitions. Among these, Alternative 1 refers to the case where we only changed the definition of berd and instead of berd in ICT we used total berd. Whereas in Alternative 2 we expressed patents, berd, and hrst in growth rates, and rather than approximating berd in ICT, we used total berd.

Table 3: Model 3 Results Under Alternative Variable Definitions

Variables	**Model 3**	**Altern. 1**	**Altern. 2**
Berd	0.3314**	-0.0009	-0.0390
Hrst	0.0326	0.0515	0.0091
Specialization	0.0597**	0.0515*	0.0695**
Berd in Geog. Neighb.	0.0023	0.0290	0.0011
Berd in Relat. Neighb.	0.0023	0.0290	0.0011
Hrst in Geog. Neighb.	0.0835	0.1661	0.4721**
Hrst in Relat. Neighb.	0.0835	0.1661	0.4721**
Specialization in Geog. Neighb.	-0.0256	-0.0264	-0.0266
Specialization in Relat. Neighb.	-0.0256	-0.0264	-0.0266
Patents in Geog. Neighb.	0.0013**	0.0017**	0.0013**
Patents in Relat. Neighb.	0.0013**	0.0017**	0.0013**
Patents in prev. period	0.0780**	0.1690**	-0.5036**
Patents in Geog. Neighb. in prev. period	0.0019	0.0414	0.0309
Patents in Relat. Neighb. in prev. period	0.0019	0.0414	0.0309
Log likelihood	**-209.9**	**-770.6**	**-1047.8**

Comparing of Model 3 and Alternative 1 we see that the results are stable under changes in the definition of berd. When we use the total berd, this variable becomes statistically insignificant but the effect of investment in ICT research is captured by means of outputs of ICT research in the previous period. Hence we observe an increase in the coefficient of patents in the previous period. The same observation holds for Alternative 2, where patents, berd, and hrst are expressed in growth rates. However, in this specification we also see that hrst in both neighborhoods become statistically significant. The results of alternative specifications are in line with the conclusions that relational neighborhood and geographical neighborhood are playing equally important roles and flows from neighbors take place also over time.

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