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Regional heterogeneity and interregional research spillovers in European innovation: modeling and policy implications

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Abstract

In agglomeration studies, the effects of various regional externalities related to knowledge spillovers remain largely unclear. To explain innovation clustering, scholars emphasize the contribution of Localized Knowledge Spillovers (LKS) and, specifically when estimating the Knowledge Production Function (KPF), of (interregional) research spillovers. However, less attention is paid to other causes of spatial heterogeneity. In applied works, spatial association in data is econometrically related to evidence of research spillovers. This paper argues that, in a KPF setting, omitting spatial heterogeneity might lead to biased estimates of the effect of research spillovers. As an empirical test, a spatial KPF is estimated using EU25 regional data, including a spatial trend to control for unexplained spatial variation in innovation. Accounting for geographical characteristics substantially weakens evidence of interregional research spillovers.

JEL: R12, R58

KEYWORDS: Generalized Additive Models, Knowledge Spillovers, Regional Innovation, European Union

1 Introduction

The knowledge economy and innovation play central roles in numerous contemporary theories on economic development in Europe and policy debates. The European Union's ambition to be among the most competitive and innovative regions in the world translates to national and regional "smart specializations" and place-based development strategies (BARCA et al., 2012). The geographical co-location of innovative actors has been acknowledged as a key driver of regional competitiveness and academic research has devoted substantial attention to Localized Knowledge Spillovers (LKS), in an attempt to explain the agglomeration and spatial concentration of innovative activities.

The relationship between agglomeration in cities and regions and innovation and economic development has been intensively studied in last decades. Since GLAESER et al. (1992), it has become common practice to analyze urban and regional growth variables using employment in cities and such efforts have suggested a relationship between agglomeration and economic growth, leading to the possibility that increasing returns to urbanization operate in a dynamic, rather than static, context. Sector-specific localization economies, stemming from input-output relationships and transport cost savings for firms, human capital externalities and knowledge spillovers, are generally compared to the formerly customary measures of general urbanization economies (HENDERSON, 2003). A substantial amount of literature builds on this conceptualization of agglomeration economies, which is reflected in three recent overviews and meta-studies (MELO et al., 2009; BEAUDRY and SCHIFFAUEROVA, 2009; DE GROOT et al., 2009). These studies reveal that the relationship between agglomeration and growth is ambiguous and inconclusive as to whether specialization or diversity is facilitated by (sheer) urbanization. This ambiguity is fuelled by measurement issues and heterogeneity in terms of temporal and spatial scales, aggregation, definitions of growth and the functional forms of the models applied. Based on an overview of historical and current conceptualizations of knowledge, knowledge diffusion and innovation in cities, several scholars call for conceptual and methodological renewal and rigor in future research to address this impasse in economic studies of agglomeration (VAN OORT and LAMBOOY, 2013). Only recently have various conceptualizations of distance and proximity been developed to empirically address the heterogeneity of the actors and processes involved and capture the role of cities and regions in this process. It is argued that research should more explicitly focus on both the transfer mechanisms of knowledge diffusion, such as spin-offs, research collaborations and social networks, and on the contexts that facilitate individual firms' familiarity with and diffusion of knowledge. New methodological perspectives also appear necessary, particularly modeling techniques that link appropriate levels of analysis, from the firm to regional contexts and agglomeration circumstances (VAN OORT et al., 2012).

An important issue in much econometric research is the need to address regional heterogeneity in analyses of (knowledge) productive relationships (BASILE et al., 2012b). This paper addresses this issue using Knowledge Production Function (KPF) approaches that attempt to econometrically estimate and assess interregional research spillovers. The KPF is widely employed to investigate innovation dynamics in regions and spatial econometrics has substantially contributed to reshape the scope of research emphasizing the contributions of interregional innovation spillovers (ANSELIN et al., 1997; 2000; PIERGIOVANNI and SANTARELLI, 2001; ACS et al., 2002; BOTTAZZI and PERI, 2003; DEL BARRIO CASTRO and GARCÍA-QUEVEDO, 2005; MORENO et al., 2005; FRITSCH AND SLAVTCHEV, 2007; PONDS et al., 2010). The principal argument in this paper is that the majority of contributions in this line of research overemphasize the role of interregional innovation spillovers while failing to optimally address the role of markets and spatial heterogeneity, thereby leading to biased estimates of the magnitude of interregional spillovers. In this respect the paper contributes to the empirical literature on KPF in Europe by discussing the indirect nature and potential overvaluation of the evidence obtained by commonly applied modeling strategies (BRESCHI and LISSONI, 2001; 2009) and linking results to an integrative academic and policy debate. The paper demonstrates that spatial data models can address spatial heterogeneity in an intrinsic manner (rather than by relying on entirely different data sources, concepts or methods per se), thereby demonstrating its value in the burgeoning discussion of innovation spillovers in a regional context.

Using data on high-tech patenting activity in EU25 NUTS II regions in 2007-2008, a KPF equation is estimated employing a negative binomial model. The standard specification adopted in the empirical literature is extended to account for the role of markets in prompting regional innovation and local characteristics generally unobservable by the econometrician. To do so, a spatial trend is introduced in the estimated KPF as a smooth function of geographical coordinates as in BASILE et al. (2012a), and a semi-parametric Generalized Additive Model (GAM) is estimated. The hypothesis is that, when heterogeneity is not observed, estimates of the interregional research spillover effect are biased by the omission of geographical variables.

The evidence presented in this paper provides useful insights for academic and policy discussions and implications for regional policies. If spatial heterogeneity affects the desired treatment of individual networks and knowledge transfer mechanisms, varied local development strategies could be more appropriate than generalized ones. More importantly, if research externalities are only characterized by an interregional geographical scope to a limited extent, as the evidence in this paper suggests, then the co-location of innovative activities and agglomeration will likely only produce benefits in selected regions, causing disparities to increase. A recent policy discussion on place-based (BARCA, 2009; OECD, 2009a, 2009b) versus place-neutral (WORLD BANK, 2009) development strategies in the European Union is highly relevant to the present topic and is summarized in BARCA et al. (2012). Place-neutral strategies rely on the agglomerative forces of the largest cities and metropolitan regions to attract talent and growth potential, further taking for granted the role of markets in the diffusion of the benefits of growth through the rest of the economy. Accordingly, agglomeration in combination with encouraging individual mobility not only allows individuals to live where they expect to be better off but also increases individual incomes, productivity, knowledge and aggregate growth (WORLD BANK, 2009). Advocates of place-based development strategies, in contrast, assert that the polycentric nature of a set of smaller and medium-sized cities in Europe, each with its own peculiar characteristics and specializing in the activities to which they are best suited, creates fruitful urban variety, which enhances optimal economic development, knowledge transfers and innovation. In fact, innovation and economic growth are not uniquely related to mega-city regions (BARCA et al., 2012) and the role of small and medium-size communities should be better addressed. This research confirms that innovation and economic growth are not uniquely related to mega-city regions (BARCA et al., 2012). Smart specialization, a policy tool for the division of money proposed for future EU cohesion policies, could direct the focus of regional innovation opportunities (EC, 2012).

The remainder of the article is organized as follows. The next section presents a critical review of the LKS theory. Criticisms of the theory are discussed and related to the limitations of empirical studies employing the KPF approach to address the role of interregional research spillovers. The empirical approach adopted in the analysis on European knowledge production is described in third section. Data and results are introduced and discussed in fourth section. The final section presents conclusions and connections to European innovation and cohesion policies.

2 Interregional Spillovers and Regional Heterogeneity in the Knowledge Production Function

The estimation of KPF at the territorial level dates back to JAFFE (1989). Its pervasiveness in the econometric literature on innovation dynamics is closely related to the ability to account for local externalities at the territorial level. Coefficient estimates of the relationship between patents and R&D are found to be larger when the relationship is estimated at the territorial level due to local externalities in innovation. In particular, the co-location of universities and firms in a given region improves the effectiveness of R&D investments.

As knowledge and innovation are difficult to appropriate, their production often generates unintended benefits for agents (positive externalities) through several mechanisms. These benefits are deemed as "localized" and hence are assessed as a cause of the geographical co-location of innovative activities. In the Geography of Innovation literature, particular attention is devoted to knowledge spillovers (AUDRETSCH and FELDMAN, 2004). Knowledge spillovers are broadly characterized as *pure* externalities and are related to the transfer of *tacit* knowledge between firms -and institutions- in non-market transactions. Understanding the geographical structures that underlie these spillover benefits is necessary for any evidence-based innovation policy to stimulate a region's (or collection of regions, such as Europe) transition towards a knowledge-based society. BOSCHMA and FRENKEN (2006) argue that tacit knowledge diffusion relies on specific transfer mechanisms such as labor mobility, spin-offs and inter-organizational networks, implying that the spillover effect is subject to distance decay. In recent years, numerous macro studies on the effect of knowledge spillovers on innovation have been conducted, and there is consensus that the strength of interregional knowledge flows decreases rapidly with geographical distance (ACS, 2002). The distance effect has been shown to exist even when spillovers are directly measured using patent citations (BRESCHI and LISSONI, 2009) using the approach initially proposed by JAFFE et al. (1993). As previous research has produced a certain degree of empirical agreement (FRITSCH and SLAVTCHEV, 2007), the *local* spatial dimension has been commonly acknowledged as a characteristic feature of such mechanisms. Recent applications at the regional and urban levels indicate that this line of reasoning is useful for explaining urban growth differentials (ACS, 2002). As a source of positive externalities, knowledge spillovers are theoretically capable of influencing the innovative behaviors of firms and, consequently, of determining regional disparities in the level of innovative activity and, eventually, economic performance (JAFFE et al., 1993).

The approach is becoming increasingly sophisticated by incorporating interregional externalities conveyed through either the spatial structure or network structures of economies and scientists (MORENO et al., 2005; BASILE et al., 2012b; PONDS et al., 2010; VARGA et al., 2012). Geographical and relational externalities between regions are generally measured in an econometric sense, by estimating spatial lag and/or spatial error specifications, indicating potential spatial and relational diffusions of knowledge. This modeling framework is put forward incorporating the opportunity to include links between regions by using contiguity or other matrices that map relationships assumed to represent the infrastructure for the diffusion of externalities.

With the introduction of spatial econometric methods (ANSELIN, 1988a; 1988b), increased attention has been devoted to interregional innovation spillovers, examining the effect of R&D expenditures made in neighboring regions on innovation. In an attempt to consider interregional externalities' contributions to innovation, the original cross-regional KPF, a linear relationship between innovative outputs and inputs, proxied by patents and R&D, respectively, has been extended by either including spatially lagged variables in the model or attributing a spatial structure to the error term. More precisely, the spatially lagged R&D variable is frequently included to account for the contribution of research performed in neighboring regions (interregional spillovers in research). A substantial econometric literature based on spatial KPF has provided evidence supporting the existence of interregional innovation spillovers (ANSELIN et al., 1997; 2000; PIERGIOVANNI and SANTARELLI, 2001; ACS et al., 2002; DEL BARRIO CASTRO and GARCÍA-QUEVEDO, 2005; FRITSCH AND SLAVTCHEV, 2007). In addition, certain studies have more specifically investigated the geographical scope of knowledge spillovers in research by either testing the hypothesis at different distances (BOTTAZZI and PERI, 2003) or considering different distance bands (MORENO et al., 2005). In a similar vein, this empirical framework has also been adapted to test the importance of spillovers mediated by technological proximity (GREUNZ, 2003) or institutional proximity, as proxied by scientific collaboration (PONDS et al., 2010). Reduced geographical distance is necessary but not sufficient for knowledge diffusion (BOSCHMA, 2005). In general, there is econometrical evidence that innovation spillovers have a localized character.

Despite the large consensus achieved through the spatial econometric approach to the KPF, the identification of interregional innovation spillovers is liable of criticisms from both theoretical and empirical perspectives. From the theoretical perspective, the *pure* character of knowledge externalities cannot be easily identified (GEROSKI, 1995); however, this characteristic is frequently taken for granted in innovation studies, under the assumption that externalities originate from the informal transmission of tacit knowledge. Although informal knowledge exchange is very important for successful knowledge diffusion (DAHL and PEDERSEN, 2004), a consistent share of knowledge is generated through formal collaboration agreements between institutions (HAGEDOORN et al., 2000) and unintended knowledge flows might only be complementary to the knowledge exchange mediated by market agreements. BRESCHI and LISSONI (2001), elaborating on these notions, suggest that the tacitness of knowledge is clearly not the only explanation for the clustering of innovative activities, as many studies on regional KPF seem to suggest. The presence of a market for technologies and specialized technology suppliers at the local level may promote spatial clustering among innovative firms potentially to a greater extent than pure knowledge spillovers (HENDERSON 2003). A well-developed market for technology likely increases the market value of patents by aligning the demand for and supply of technologies, making it more convenient for innovative firms to locate within short distances from markets (LAMOREAUX and SOKOLOFF, 1999). Furthermore, the presence of specialized technology suppliers is expected to encourage the co-location of innovative firms, as a consequence of the resulting reduced complexity of innovative processes, provided that new technologies can be more easily acquired in the market than produced internally. Once innovative clusters begin to develop at the local level, this increases the likelihood that local firms will engage in R&D collaborations, and this might eventually produce spillovers. Accordingly, spillovers in research, both within the region and between regions, could be considered a consequence of the geographical co-location of firms rather than a cause.

Critiques have also been advanced concerning the empirical application of the KPF model. BOTTAZZI and PERI (2003) argue that coefficient estimates for the patent-research relationship are biased due to the omission of relevant variables that are highly related to both research investments and patenting activity. This is, for instance, the case for the market potential of a region, a variable which is likely to affect the R&D productivity of firms in the region and, consequently, their decision on the level of R&D investments. Market potential, a measure of the market available to firms in a region, is expected to be positively correlated with patents, as innovative firms might be willing to locate near to the market in which innovations are to be sold (VARGA et al., 2012) term these the Edison-type of innovations). Similarly, a positive correlation can be expected between market potential and investments in research, as greater market opportunities indicate that a larger share of a firm's budget is committed to research. The findings reported in

BOTTAZZI and PERI (2003) suggest that interregional innovation spillovers in research contribute little to regional innovation after accounting for R&D endogeneity.

Omitted variable bias and unobserved heterogeneity are both substantially important issues in the empirical estimation of the KPF and, to an even greater extent, when the model also accounts for interregional research spillovers. In summarizing the motivations for the use of a spatial econometric model, LESAGE and PACE (2009) highlight three central explanations for the evidence of spatial correlation in the data, namely omitted spatially correlated variables, unobserved spatial heterogeneity and externalities between units. Of these motivations, only the last resembles the argument for interregional innovation spillovers. In contrast, spatial autocorrelation in the model's residuals is likely related to the other two arguments in the case of a standard KPF. Variables commonly omitted from the model specification might exhibit a high degree of spatial association. This likely represents the case of market potential. Similarly, region-specific characteristics related to the demand for and supply of innovation are also frequently absent in the specification, due to their non-observability, causing unobserved spatial heterogeneity. Spatial model estimates do not allow the researcher to distinguish the spatial autocorrelation caused by unobserved spatial heterogeneity or omitted variables from that resulting from spatial interactions, and consequently it is possible to characterize as interregional knowledge spillovers what in reality is the effect of unobserved spatial heterogeneity and omitted variables.

The conceptual weaknesses of the LKS rationale for innovation clustering are closely related to the empirical issues arising in the spatially extended KPF. The mutual transfer of tacit knowledge via frequent interactions is clearly not the sole motivation for the spatial concentration of innovative activities. Market opportunities, on the one hand, determine regional innovation and attract innovative firms and stimulate the investments of existing firms; on the other, regional and local characteristics drive investments by providing an innovation-friendly environment for local firms (VARGA et al., 2012). A failure to include these elements in the empirical specification produces an estimation bias that eventually results in incorrect inferences in favor of the LKS rationale. In support of this hypothesis, the results in TAPPEINER et al. (2008), based on 51 NUTS I EU regions, seem to indicate that evidence of spillovers is weakened by the inclusion of social capital variable in the model.

3 Econometric strategy

When estimated at the regional level, the KPF describes a linear relationship between patenting activity, a measure of the regional capacity to produce innovative output, and the R&D-to-GDP share, a measure of the innovative efforts made by firms and public institutions located in the region (JAFFE, 1989). This basic framework is extended by accounting for spatial relationships and spatial interactions between regions using spatial econometric techniques (ANSELIN et al., 1997; ACS et al., 2002; FISCHER and VARGA, 2003).

More recently, a number of studies (BOTTAZZI AND PERI (2003) for EU15 regions; FISCHER AND VARGA (2003) for Austria; DEL BARRIO-CASTRO and GARCÍA-QUEVEDO (2005) for Spain; FRITSCH and SLAVTCHEV (2005) for Germany; GUMBAU-ALBERT and MAUDOS (2009) for Spain; PONDS et al. (2010) for the Netherlands; AUTANT-BERNARD and LESAGE (2011) for France and GRIMPE and PATUELLI (2011) for Germany) have concentrated in modeling the number of patents instead of the patenting rate (i.e., patents normalized per million inhabitants) in an attempt to maximize the informational content of the variable which is, by definition, discrete and positively defined. The analysis in this paper continues this line of research, and, accordingly, distributions for count data are used to model the number of patent applications. In the majority of cases, interregional research spillovers are accounted for by including spatially lagged R&D; hence the R&D variable is pre-multiplied by a row-standardized spatial weight matrix (DELTAS and KARKALAKOS, 2013).

For the set of 250 NUTS II regions belonging to EU25 (Iceland and overseas territories excluded), regional innovation (PA_i) is measured as the average number of patent applications to the European Patent Office during the period 2007-2008. Applications are only considered if made in high-tech industries, in which the diffusion of tacit knowledge is expected to play a crucial role for innovation at both the firm and regional levels (KEEBLE and WILKINSON, 1999). More generally, evidence suggests that the diffusion of both formal and informal knowledge contributes to firm performance, especially in high-tech and science-based industries (PONDS, 2008). The definition adopted by Eurostat and based on IPC classes is employed to classify patents in the high-tech category. The geographical distribution of total patents and patents in the high-tech sector is presented in the appendix alongside a more detailed description of the approach to patent classification.

The expected value of regional innovation is a function of (private) R&D expenditure by business enterprises (*BESRD*), university R&D (*UNIRD*) and government R&D (*GOVRD*), all relative to regional GDP. Private R&D investments primarily occur in regions with larger multinational enterprises, such as Eindhoven (Philips), Stockholm (Ericsson), Helsinki (Nokia), Leverkusen (Bayer), Stuttgart (Bosch, Porsche , Mercedes) and Toulouse (Airbus). University R&D is more associated with regions with technological universities and regions with alliance between universities and firms, such as Cambridge, Leiden, Braunschweig and Rome (DOGARU et al., 2011). Additionally, the human capital available in the region, proxied by the share of regional employees with tertiary degrees (*TEREDUC*), is considered another input in the knowledge production process. Workforce education rather than tertiary education attainment data is used speculating that the former best represents the actual employment of high-skilled workers in economic and innovation production. The contribution of interregional externalities in research is estimated by including the spatially lagged R&D to GDP ratio (*WBESRD*). These investments in innovation are hypothesized to have a positive correlation with innovation output, as much of the empirical literature also seems to suggest. The matrix W is defined as a positive definite weight matrix, the single element of which equals the squared inverse of the distance between regional centroids if this distance is lower than 500 km and zero otherwise[i]. The decision to rely on the 500 km cut-off is motivated by the observation that 492 km is the distance value at which no region has no neighbors and, accordingly, each row of the matrix has at least one non-zero element. In addition, the share of employees in high and medium/high-tech manufacturing (*HTMAN*) was included to control for sources of unobserved heterogeneity related to the industrial composition of the regional economy. The definition of NACE sectors used to identify high and medium/high-tech manufacturing industries is taken from Eurostat and reported in the appendix. All right-hand-side variables are averaged over the period 2004-2006 in an attempt to mitigate simultaneity bias. Finally, regional variation in economic size is captured by including a variable for average population of the period 2007-2008 with a unity-constrained coefficient (offset). A complete description of the dataset is provided in the appendix.

Two indicators are included among explanatory variables to account for market factors that may influence the innovative activity of regions. Market potential (*MPOT*) is a measure of the size of the market that is potentially accessible from within the region. Data for this variable at the regional level is only available for the year 2006 and, in contrast to the other covariates, are not averaged over past years. The measure was created by the ESPON project and is available for download at the project website[ii]. Based on ESPON's definition, it is a proxy *'for the potential for activities and enterprises in the region to reach markets and activities in other regions'*. Specifically, it is based on the average distance separating the region of origin from all other potentially accessible regions, and Gross Domestic

Product (GDP) values are used as weights. Accordingly, it is exogenous, while it is also appropriate to capture a measure of the potential markets of innovative firms, provided that distances are weighted by the respective GDP. In addition to the market potential indicator, an indicator of market size is included in the analysis, namely the gross value added per employee *(GVAPE)*. The indicator is expected to account for the size of internal market at the regional level and is, simultaneously, expected to explain variation in regional innovation related to the development of the region. As current values of the variable may induce endogeneity in the estimation, the value for the year 1991 is used, under the assumption that the lag is long enough to avoid any endogeneity.

Unobserved spatial heterogeneity is undoubtedly the most demanding of the specification problems. At the European regional level, the lack of sufficient regional data impedes the observation of relevant variables that likely affect the patenting activity of firms. In addition, many aspects influencing innovation in firms are not observable or measurable. This might be the case, for instance, when regional variation in innovation is related to the presence of regional markets for technologies and of specialized technology suppliers. Unobserved heterogeneity could be addressed by estimating model parameters using panel data techniques. It is plausible that most unobserved spatial heterogeneity would disappear after a within transformation. While longitudinal data on innovation are available for some European countries, this is unfortunately not the case for Europe as a whole. Although the patent database available at the European Patent Office is among the most complete collections of data at the NUTS II level, a complete longitudinal dataset on R&D expenditures at the same level cannot be easily created due to limited data availability for certain regions. Accordingly, the use of longitudinal data would force the exclusion of certain regions from the dataset.

In the absence of an available panel dataset, the issue of unobservable heterogeneity can be addressed by including geographical variables. Unobservable regional characteristics are likely related to the business and institutional environments and hence non-randomly distributed in space. Among several alternatives, the inclusion of geographical dummy variables among the covariates would be the simplest and most intuitive solution. Nevertheless, this would require an ex ante division of the geographical space using a set of dichotomous variables, which, in turn, presumes knowledge on the way in which unobservable characteristics are distributed in space. Very common and easily interpretable choices include the use of country-specific dummy variables and, in the European case, dummy variables for regions in New Member States and regions in Cohesion Countries. Particularly in the first case, research indicates that structural differences in economic environments may induce differentiated growth and innovation patterns (MARROCU et al., 2012; DOGARU et al., 2011).

A more direct approach to including unobserved spatial heterogeneity relies on the inclusion of regional geographical coordinates among the covariates. The relationship between innovation and geographical coordinates is expected non-linear, although the degree of non-linearity is unknown a priori. The linear hypothesis cannot be appropriately considered as long as it would imply that the number of patents increases (decreases) with increasing (decreasing) latitude or longitude. The most common non-linear specification, the quadratic hypothesis, can be considered more appropriate. Nonetheless, the specification is a only valid alternative when the spatial distribution of innovation exhibits a core-periphery pattern. The quadratic hypothesis suggests that innovation is increasing up to a certain threshold of longitude after which it begins decreasing. The same is expected to hold in case of latitude. Using parameter values to identify thresholds, it is possible to delineate a core area. Obviously, this impedes studying more complex patterns and might eventually result in misleading inferences in the latter case. To identify the functional form we rely on the *spline* fitting method, on the basis of which the degree of non-linearity is selected by optimizing the informational content available in the data. Thus an isotropic thin plate regression spline, a non-linear function of joint longitude and latitude, is added to the linear predictor. The smoothed spatial trend is expected to account for the spatial variation in innovation explained by the geographical concentration of unobserved characteristics (BASILE et al., 2012a).

The degree of non-linearity is selected by an algorithm minimizing $\sum_i \left(y_i - f(x_i)\right)^2 + \lambda \int f''(x)^2 dx$, where y is the dependent variable and x is the set of independent variables (WOOD, 2006). The first term represents the residual sum of squares (RSS) and the second is a penalty term based on the second derivative of the smooth function $f(\cdot)$. The penalty approaches zero as the smooth function becomes linear. Conversely, a high degree of non-linearity produces low RSS values but high penalty values. Therefore, the algorithm is demonstrably appropriate for weighting goodness of fit, on the one hand, and model complexity, on the other. In this respect, the choice of smoothed splines of geographical coordinates favors the more flexible non-linear specification for the spatial trend to the simple linear or quadratic specifications by correcting for the excess of non-linearity potentially caused by excessive unobserved heterogeneity.

The resulting model can be characterized as a Generalized Additive Model (GAM) in which a non-parametric trend based on geographical coordinates $s(long, lat)$ is added to a parametric (exponential) specification of the mean function. The estimation is performed using methodologies described by WOOD (2003, 2006) and BIVAND et al. (2008) and available in the R package *mgcv*. The final model is presented in equation (1). As explained, the dependent variable used in this model is obtained by averaging the values of patent applications over two consecutive years. No assumption is made about the distribution of the original variable. Instead, the appropriate model is selected relying on statistical tests conducted to explore which distribution best fits the dependent variable. Shapiro-Wilk normality tests were conducted, and the hypothesis that the distribution is normal or even log-normal is strongly rejected. As non-normality is likely the result of the high skewness of the distribution, an attempt was made to fit in the data up to the fourth quintile to the normal distribution, hence excluding the most patent-productive 20% of regions. While normality and log normality are also rejected in this case, the likelihood ratio statistic indicating the goodness of fit of the Negative Binomial distribution does not reject the null at a 5% significance level[iii]. A negative binomial distribution is preferred to the more restrictive Poisson distribution, as the former relaxes the demanding assumption of mean-variance equality required by the latter with the introduction of the over-dispersion parameter θ. Furthermore, a plot of the Pearson residuals against fitted values of a Poisson distribution confirms that the variance increases with the expected value of the outcome variable, strengthening the preference for the Negative Binomial model against the Poisson model (a formal test for overdispersion is also conducted and the result is presented in the next section). Of the 250 observations in the dataset, only 4 regions contain zero applications. This suggests that the application of econometric procedures suitable to control for the abundance of zeroes is unnecessary.

$$\begin{aligned} PA_i &\sim NB(\mu_i, \theta) \\ \mu_i &= \exp\left(a + \sum_{k=1}^{K} b_k X_{k,i} + s(long_i, lat_i)\right) \end{aligned} \qquad (1)$$

In the specification, the log link is used to relate the dependent variable to predictors. The exponential function[iv] is a common specification for the mean function in GLMs in general, and in count data models in particular. Interpretation of coefficients is straightforward: holding constant other variables, a unit change in the predictor k^{th} multiplies the number of patents by e^{b_k} (FOX, 2008). Predictors in the X matrix include the research variables (*BESRD*, *UNIRD* and *GOVRD*), controls (*HTMAN* and *TEREDUC*), market indicators (*MPOT* and *GVAPE*) and, finally, private research in neighboring regions (*WBESRD*). All of these effects are expected to be positive and significant. More specifically, a positive and significant coefficient on *BESRD* confirms the previous results regarding the validity of the KPF approach at the territorial level in Europe. Positive and significant estimates of coefficients related to *UNIRD* and *GOVRD* indicate the relevance of universities and government institutions, respectively, in shaping the geography of patenting activity in Europe. Evidence of interregional research spillovers is associated with an estimate of the *WBESRD* coefficient that is statistically greater than zero, as is standard in this literature (DELTAS and KARKALAKOS, 2013). Here it is argued that the evidence related to the last coefficient is biased if spatial heterogeneity is not taken into account. The magnitude and statistical significance of this coefficient is expected to decrease once the spatial trend is included in the specification. Dummy variables for regions in New Member States and Cohesion Countries are also included in the regressions.

4 Results

Table 1 provides a summary of the descriptive statistics for the variables in the model. By analyzing the correlations, a positive relationship between patents and research conducted by private firms, universities and government institutions is detected, although to a lesser extent in the latter cases. All covariates exhibit a relatively low degree of correlation, both with patents and one another. A negative correlation is detected between the indicator of industrial composition (share of high and medium/high-tech employment) and research in universities and human capital. This negative relationship may be due to the extent to which service industries and entrepreneurship are taken into account in the industrial composition indicator. In VAN OORT and BOSMA (2013) a similar negative relation is found in European regional data.

Table 1: Summary Descriptive Statistics of variables (EU 25 NUTS II regions)

	Cross-correlations							
	HTPC	*BESRD*	*UNIRD*	*GOVRD*	*HTMAN*	*TEREDUC*	*MPOT*	*GVAPE*
HTPC	-							
BESRD	0.5461	-						
UNIRD	0.2451	0.3286	-					
GOVRD	0.3273	0.3177	0.3813	-				
HTMAN	0.2302	0.4573	-0.0340	0.1050	-			
TEREDUC	0.2314	0.2877	0.2692	0.1910	-0.1190	-		
MPOT	0.3533	0.4258	0.2042	0.2845	0.3471	0.2978	-	
GVAPE	0.3675	0.4269	0.3331	0.0917	0.1205	0.3650	0.5346	-
	Descriptive Statistics							
	HTPC	*BESRD*	*UNIRD*	*GOVRD*	*HTMAN*	*TEREDUC*	*MPOT*	*GVAPE*
Min	0.0000	0.0000	0.0000	0.0000	0.8170	13.3000	30.3000	1.9130
Mean	36.1800	0.8922	0.3615	0.1812	6.3900	25.1400	97.9300	32.8050
St Dev	76.488	0.8870	0.2438	0.2025	3.4439	7.2848	35.2484	13.6234
Max	706.0000	4.9100	1.5900	1.1130	21.0730	50.2000	201.1000	64.4450
	Moran Test for Spatial Correlation							
	HTPC	*BESRD*	*UNIRD*	*GOVRD*	*HTMAN*	*TEREDUC*	*MPOT*	*GVAPE*
I	0.0781	0.2679	0.1230	0.0846	0.3925	0.5367	0.6099	0.6387
E(I)	-0.0040	-0.0040	-0.0040	-0.0040	-0.0040	-0.0040	-0.0040	-0.0040
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes to table 1:
p-values related to Moran's I are computed under randomization and one-tail hypothesis.

All average, minimum and maximum values suggest the absence of outliers in the data. As mentioned previously, the minimum value of applications equals to zero in certain – limited – cases, with a maximum of 706 and an average value of 36. As the standard deviation substantially excides the mean, the mean-variance equality of the Poisson distribution may prove an unsuitable hypothesis in this case. On the contrary there is evidence of overdispersion, which in turn suggests once again the use of a negative binomial distribution. The average R&D-to-GDP ratio is 0.89% in the case of expenditures by business enterprises, and 0.36% and 0.18% for university and government expenditures, respectively. Workers employed in high and medium/high-tech manufacturing industries represent, on average, 6.39% of the total employment and 25% of workers hold a tertiary education degree[v].

Turning to the spatial descriptive statistics, the Moran's Index *I*, computed on the basis of the 500 km inverse squared distance weight matrix, is consistently positive, indicating spatial association for all variables. More specifically, large values of Moran's Index are reported for variables included to control for regional variation in high-tech patents not explained by R&D investments. In particular, the market potential and market size variables exhibit substantial spatial association and hence are expected to capture spatial heterogeneity to a large extent.

Before introducing geography into the econometric specification of the regional KPF, baseline results are presented and discussed in table 2. Four models are presented, a baseline model *(a)* that does not include market potential and market size indicators, a model in which the only market potential is included *(b)* and a model in which the market size is included jointly with market potential *(c)*. Finally an attempt is made to mitigate the bias from unobserved heterogeneity by capturing country-specific effects through a set of dummy variables *(d)*.

For all models, the results are also presented when the spatial lags of university research and human capital are included. Although the primary focus of this paper is the incidence of unobserved spatial heterogeneity in the estimation of private research spillovers, according to the geography of innovation literature, university research and the mobility of highly skilled workers are also important sources of knowledge spillovers that likely extend beyond regional borders (AUDRETSCH and FELDMAN, 2004). Accordingly, the spatial lags of both university research and tertiary education are included in all models to account for additional sources of interregional spillovers in innovation.

Baseline estimates of the regional KPF extended to account for interregional spillovers are presented in column *(a)*. All coefficients related to research exhibit positive and highly significant values. The contribution of the share of high-tech employees in manufacturing is also positive and significant, as is the share of labor force with tertiary education. As expected, the coefficient associated with the dummy for regions in NMS is negative and significantly different from zero. The same result is found for the dummy for regions in COHESION countries. Concerning interregional spillovers, the spatial lag of private research is the only variable with a significant coefficient. Conversely, coefficients related to lagged university research and lagged human capital are both not significantly different from zero.

The value of θ is estimated at 2.082, and this value is consistently greater than one in all specifications. In addition to the difference between the mean and variance observed in the summary statistics for the dependent variable, this value of θ is considered clear evidence of overdispersion. Nonetheless, for this specification only, a formal test of overdispersion was conducted and definitively favors the negative binomial specification. The likelihood ratio statistic used to compare the Poisson with the negative binomial distribution takes a value of 3168, which is statistically significant at the 0.1% level.

Table 2: Patent Equation – Generalized Linear Model (EU25 NUTS II regions)

	(a)	*(b)*	*(c)*	*(d)*
Intercept	-6.7577***	-7.3525***	-7.9210***	-7.2186***
	(0.3506)	(0.3744)	(0.4211)	(1.2443)
BESRD	0.5108***	0.4706***	0.4396***	0.4452***
	(0.0725)	(0.0701)	(0.0700)	(0.0732)
UNIRD	0.7400***	0.8144***	0.7412***	0.5430**
	(0.2368)	(0.2309)	(0.2281)	(0.2420)
GOVRD	0.7704***	0.6118**	0.8034***	0.7393***
	(0.2660)	(0.2587)	(0.2585)	(0.2673)
HTMAN	0.0408**	0.0231	0.0284	0.0140
	(0.0188)	(0.0186)	(0.0183)	(0.0211)
TEREDUC	0.0304**	0.0227*	0.0205*	0.0245**
	(0.0126)	(0.0124)	(0.0123)	(0.0121)
MPOT		0.0078***	0.0055***	0.0033
		(0.0018)	(0.0020)	(0.0023)
GVAPE			0.0204***	0.0165*
			(0.0079)	(0.0084)
NMS	-1.2866***	-1.0480***	-0.5096*	
	(0.1885)	(0.1923)	(0.2828)	
COHESION	-0.8535***	-0.4699**	-0.3881*	
	(0.1989)	(0.2155)	(0.2153)	
AT				0.4326
				(0.3540)
BE-NL-LU				0.3919
				(1.2300)
CZ-HU-SK-SI				-0.5769
				(1.2086)
DE-DK				0.4257
				(1.2114)
ES-PT				-0.6770
				(1.2279)
FR				0.1520
				(1.2235)
GR-CY				-1.1348
				(1.2568)
IT				-0.0467
				(1.2036)
PL-EE-LV-LT				-0.8462
				(1.2183)
SE-FI				0.4234
				(1.2654)
UK				-0.1694
				(1.2186)
W_BESRD	0.5463***	0.6416***	0.6096***	0.4032**
	(0.1629)	(0.1569)	(0.1548)	(0.1723)
W_UNIRD	-0.1563	0.2732	0.2985	-0.5145
	(0.4934)	(0.4983)	(0.4920)	(0.5918)
W_TEREDUC	0.0005	-0.0075	-0.0043	0.0010
	(0.0166)	(0.0162)	(0.0159)	(0.0183)
theta	2.0820	2.2550	2.3300	2.5967
AIC	1758.5000	1742.0000	1736.7000	1733.8000
LZI	0.0686	0.0425	0.0380	0.0298
[p-value]	[0.0070]	[0.0571]	[0.0754]	[0.1259]

Notes to table 2:
SE in parenthesis. ***, ** and * indicate significance at 1%, 5% and 10% respectively. LZI is the value of the Moran's Index for residual autocorrelation adapted by LIN and ZHANG (2007) for GLM residuals. Since in all cases the value of the LZI statistic exceeds the expected values, the one side test for the "greater" alternative hypothesis is conducted.

The market potential indicator (*MPOT*) is added to the model in column *(b)*. The inclusion of this variable leaves all previous result unchanged with the only notable exception being the HTMAN coefficient, which is now insignificant.

The estimated coefficient related to market potential follows expectations and is positive and significant. The model in column *(c)* also includes gross value added per employee, a measure of market size (*GVAPE*). Although the market potential coefficient marginally decreases after the inclusion of market size, both coefficients are positively sloped and significant. Therefore, the two variables are able to effectively account for various aspects related to the potential and actual size of the regional market. As shown in table 1, both the market potential and the market size variables exhibit very high degrees of spatial association and their omission from the model specification would likely result in substantial residual autocorrelation (MCMILLEN, 2003), which would eventually affect estimation. In the case of interregional innovation spillovers, the introduction of market potential and market size affects the estimation of private research spillovers but not the significance level, while neither of the other two coefficients (on university research and tertiary education) becomes significant.

The results of LIN and ZHANG's (2007) test reject the null hypothesis of absence of spatial association in the residuals of models *(a)* (at a 5% significance level*), (b)* and *(c)* (but only at a 10% significance level). Notably, the degree of spatial association diminished after the introduction of market size and potential, indicating the effective contribution of the two variables in accounting for spatial heterogeneity. Nonetheless, unexplained spatial variation in the innovative activity of EU regions still characterizes residuals, although to a narrowed extent only. Thus, country-specific dummy variables expected to capture unobserved heterogeneity at the country level are added to the model in column *(d)*. Adopting a conservative approach in terms of degree of freedom, countries comprising either a single or a small number of NUTS II regions have been aggregated. The variables NMS and COHESION were excluded to avoid perfect multicollinearity. Only small changes can be observed in the regression results, specifically concerning the effect of research in the region and neighboring regions. The human capital variable continues to exhibit a positive and significant coefficient. In contrast, the market potential and market size coefficients turn both less significant, and even insignificant in the case of market potential. However, none of the dummy is statistically significant, and the utility of such a specification is thus questionable. To obtain a measure of the accuracy of the model, the estimates of the models in columns *(c)* and *(d)* were compared, using ANOVA analysis, with the null hypothesis of a model excluding both the NMS and COHESION dummy variables and country-specific dummy variables. As the model under the null hypothesis is nested in both alternatives, it is possible to compare alternatives. According to the results of the test, the restricted model is rejected in both cases but the associated p-value is lower in the case of model *(c)*[vi]. Based on this result, the model with dummy variables for new member states and cohesion countries is preferred to the model with country dummy variables, which, most important, may not lead to insightful policy results. Finally, evidence of spatial association in the residuals disappears in model *(d)*.

Geographical information is included in the specification of the patent equation to account for unobserved spatial heterogeneity, and the results are presented in table 3. A basic generalized linear model (GLM) is first estimated as a reference model *(e)*. Based on the evidence in table 2, dummy variables for new member states and cohesion countries are included instead of country-specific dummy variables and spatial lags of university research and human capital are removed because these are never significant. Comparing estimates of this baseline model in column *(e)* of table 3 with the estimates in table 2, it appears that the decision to simplify the specification is effective in terms of both parameter estimates and significance.

Table 3: Patent Equation – Generalized Linear and Additive Models (EU 25 NUTS II regions)

	(e)	*(f)*	*(g)*	*(h)*
Intercept	-7.8680***	-8.4191***	-14.3600***	-7.8651***
	(0.3562)	(0.7231)	(4.4520)	(0.4184)
BESRD	0.4384***	0.4383***	0.4232***	0.4825***
	(0.0700)	(0.0699)	(0.0702)	(0.0683)
UNIRD	0.7439***	0.6444***	0.7413***	0.7528***
	(0.2272)	(0.2379)	(0.2410)	(0.2249)
GOVRD	0.8167***	0.8584***	0.8665***	0.4413*
	(0.2534)	(0.2575)	(0.2556)	(0.2500)
HTMAN	0.0280	0.0286	0.0268	0.0005
	(0.0180)	(0.0180)	(0.0186)	(0.0209)
TEREDUC	0.0189**	0.0165*	0.0153*	0.0293***
	(0.0083)	(0.0093)	(0.0092)	(0.0103)
MPOT	0.0053***	0.0056***	0.0051**	0.0063**
	(0.0019)	(0.0020)	(0.0022)	(0.0026)
GVAPE	0.0205***	0.0215***	0.0241***	0.0229**
	(0.0079)	(0.0080)	(0.0082)	(0.0091)
NMS	-0.5273*	-0.5971**	-0.7037**	-0.4228
	(0.2776)	(0.2919)	(0.2948)	(0.3374)
COHESION	-0.4201**	-0.3121	-0.2815	-0.7418*
	(0.2051)	(0.2396)	(0.2720)	(0.4239)
W_BESRD	0.6300***	0.5590***	0.5770***	0.3291*
	(0.1445)	(0.1576)	(0.1576)	(0.1850)
LONG		0.0046	-0.0074	
		(0.0074)	(0.0161)	
LAT		0.0121	0.2525	
		(0.0146)	(0.1781)	
LONG^2			0.0011	
			(0.0009)	
LAT^2			-0.0024	
			(0.0018)	
	Non parametric terms			
s(LONG,LAT) – χ^2				51.7700
[p-value]				[0.0014]
theta	2.3280	2.3500	2.3910	3.1310
AIC		1736.0000	1737.2000	1708.5940
LZI	0.0383	0.0360	0.0338	-0.0115
[p-value]	[0.0739]	[0.0853]	[0.0978]	[0.3992]

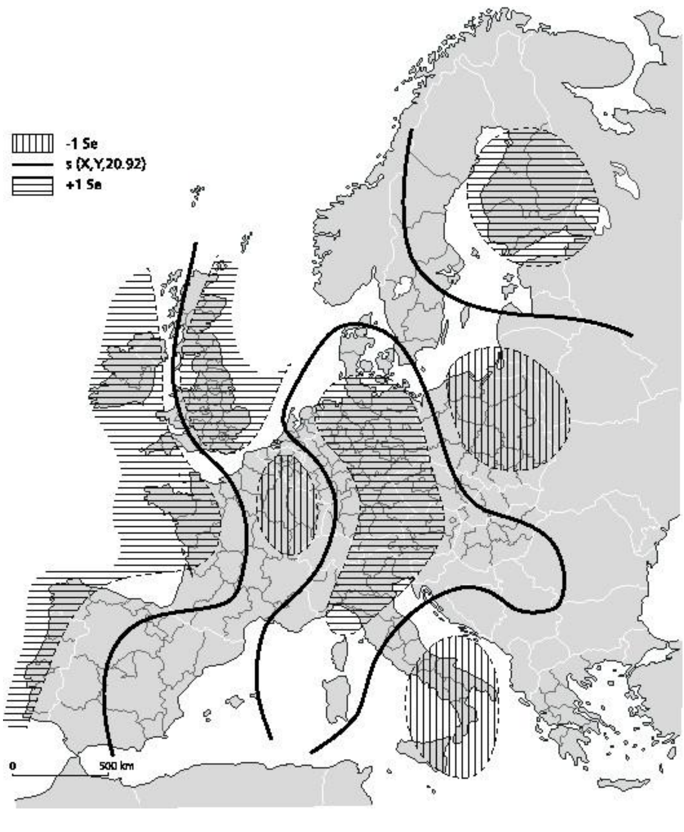
Notes to table 3:
SE in parenthesis. ***, ** and * indicate significance at 1%, 5% and 10% respectively. LZI is the value of the Moran's Index for residual autocorrelation adapted by LIN and ZHANG (2007) for GLM residuals. Significance is calculated based on the one-side alternative hypothesis. The selected alternative depends on whether the LZI statistic exceeds or not the expected value. The approximate significance of the s(LONG,LAT) term is evaluated using the χ^2 statistic test suggested by WOOD (2006). The value of the statistic is reported in the table alongside with the p-value associated with the null hypothesis of the term's statistical insignificance.

An initial attempt to introduce space in the regional KPF is made by adding geographical coordinates to the functional specification of the mean of patent counts. This is done in model *(f)*, and related coefficients are reported. The coefficients for the two geographical variables are not significant. All other coefficients except for that associated to the dummy for cohesion countries are not affected by the change in the mean specification. Similarly, no significant changes emerge when the squared values of the coordinates are included in the specification. All coefficients, except that for cohesion countries, maintain their original signs, size and significance. Again, the coefficients for geographical variables are not significant.

The GAM estimates are reported in column *(h)*. The test statistic concerning the significance of the spatial trend indicates that, in this case, geographical information significantly contributes to explaining variation in regional innovation. Coefficients related to private and university research continue to be highly significant and positive. The size of the coefficient associated with government research decreased and becomes less significant. Results indicate also a positive contribution of human capital to regional innovation and a positive relationship among high-tech patents, market potential and market size. Concerning the coefficient for research spillovers, its magnitude changes after the introduction of the spatial trend, and overall, the coefficient is now only significant at the 10% level.

Figure 1 maps the values of the estimated trend in the geographical space of EU regions. The estimated value of the trend is indicated by a black line, while vertical and horizontal lines indicate the lower and upper bounds of the confidence level, respectively, set at minus/plus one of the standard error. In area below the lower bound (above the upper bound), the geographical position of the region contributes less (more) than expected to regional innovation, all other predictors being constant. Accordingly, it is unsurprising that regions in southern Italy and in certain NMS exhibit poor performance, while in contrast, regions in northern Italy, Germany and Denmark and Sweden perform very well. Values below the lower bound are also detected in eastern France. As this area is located between important technological poles in Europe (such as Eindhoven in the north and Toulouse in the south), this area performs worse than its geographical position would lead to expect. Finally, a similar situation is detected in the northern and eastern UK, although in this case there is no similar locational explanation for this evidence. This trend measures, to some extent, our ignorance of the phenomenon and it might not be a simple matter to find a detailed explanation for the evidence.

Figure 1: Estimated spatial trend in innovation



The last part of table 3 concerns the test for autocorrelation in the residuals. LIN and ZHANG (2007) statistic applied to the residuals of models *(e)* to *(g)* indicates that the null hypothesis of absence of spatial association can be rejected at a 10% significance level. The low level of significance of the statistic shows that the residual autocorrelation is substantially mitigated by the inclusion of linear and squared geographical coordinates. Nonetheless the null hypothesis of absence of spatial correlation in the residuals can only be rejected completely with the inclusion of the spatial trend.

The evidence in table 3 indicates that the contribution of interregional research spillovers, measured on regional scale in Europe and while controlling for spatial heterogeneity, is limited. Prior research suggested that geographical spillovers have a positive effect on innovation. This effect is also observed in these results, but in conclusion, it appears less relevant than previously suggested. Overall, innovation in European regions is driven by several different factors, some of which are clearly unobservable by the econometrician. After including geographical coordinates, in an attempt to control for geographical heterogeneity not captured by other covariates, evidence of interregional research spillovers is weakened considerably. This indicates evidence of spatial correlation that is caused, in this case, by model misspecification, the omission of relevant variables and unobserved spatial heterogeneity, thereby assigning only a secondary role to geographically localized knowledge spillovers.

Robustness checks

In the remainder of this section, the validity of this result is assessed by comparing GLS (without trend) estimates with GAM (with trend) counterpart estimates against changes in the specification of the spatial weight matrix used to construct the spatial lag of private research expenditures.

Results are reported in the appendix for four values of the critical distance used to construct the contiguity matrix. Weights are then computed consistent with the previous definition; hence the inverse of squared distance among centroids is used as a weight and row-standardization is applied.

All coefficients related to research have the expected sign and are statistically significant. The change in the critical cut-off distance does not affect the size or the significance level of the estimated coefficients. A change in significance is only observed in the case of the share of the HTMAN variable, which consistent with previous evidence, is not significant when a value of the cut-off distance greater than 500 km is used. Conversely, coefficients related to human capital, market potential and market access and the two dummies for new member states and cohesion countries exhibit the correct signs and high significance levels for all values of the critical distance. Finally, the results indicate, at least those of GLM estimates, the positive contribution of interregional research spillovers to regional innovation. In addition, the estimated effect of research in neighboring regions is not constant becomes larger at higher values of the critical distance.

By focusing on the model specification, residual autocorrelation is detected in all models, providing confirmation that dummy variables, market potential and market access may not be sufficiently able to account for spatial heterogeneity.

Comparing GLM and GAM estimates, the latter including the smooth trend, the only significant change in coefficient estimates concerns the government R&D variable. As expected, the two geographical dummy variables for new member states and cohesion countries are no longer significant. Focusing on the variable of interest, interregional research spillovers, the associated coefficient is lower in magnitude and less significant in all models with the spatial trend. The difference between the GLM and GAM estimates is large and evident in all models, independent of the critical cut-off value. For distance values below 500 km, the coefficient becomes insignificant after the inclusion of the trend, while for values greater than 500 km it is only weakly significant. All tests on the GAM residuals fail to reject the null of absence of spatial correlation, while the χ^2 statistic related to the spatial trend is always significant.

To conclude, changes in the critical cut-off distance used to construct the weight matrix do not significantly affect the main evidence in this paper, as evidence of interregional research spillovers appear less relevant for regional innovation when spatial heterogeneity is accounted for in the model specification.

5 Conclusion and discussion

Research spillovers have received increasing attention in the empirical literature on regional innovation, as they have been indicated as one of the most important vehicles for regional growth. Studies seeking evidence of research spillovers have argued that such spillovers are localized, as tacit knowledge cannot be codified and requires face-to-face contacts to be exchanged. Using a spatially extended KPF, this paper examined the contribution of interregional research spillovers to regional innovation in the European Union, with particular focus on spillovers between neighboring regions. This paper argued that when studying the spatial clustering of innovative activities, past research has overemphasized the local knowledge spillover (LKS) argument both theoretically and empirically, and less attention has been devoted to the geographical characteristics of the region. This emphasis on innovation spillovers has been empirically supported by spurious results, which are often biased by the omission of geographical variables from the econometric specification. At the regional aggregate level, innovative output is not caused by R&D alone. Rather, output relates to region-specific characteristics such as the industry-mix, market opportunities, the innovative environment, and social capital. Some of these characteristics can be observed, while others cannot. Each of them, however, also relates to R&D to the extent that it affects the productivity of R&D investments, and consequently, to the R&D investment decision of local firms. Their omission from the econometric specification introduces bias in the R&D-related coefficients. Finally, if these variables have a specific spatial structure, similar to that of R&D-investments, their omission is also likely to bias the lagged R&D coefficient, causing incorrect inferences regarding interregional research spillovers.

The evidence provided in this paper nuances and, to some extent, contradicts results presented in previous empirical contributions. However our analysis does not contradict LKS theory in general or the potential relevance of knowledge spillovers in particular. Rather, this paper suggested that methods currently employed to address the issue of interregional spillovers in research collaborations risk producing biased results. This, in turn, requires researchers to improve the conceptualization and econometric specification of the KPF, including the introduction of multilevel interaction scales, ranging from the very local to the regional, as well as network measures of spatial interaction and the specific multilevel interaction. Knowledge spillovers are likely to be either highly localized, and hence evidence of interregional spillovers should be sought at a low geographical scale, or captured in (social and cooperation) network relationships. Assessing this in specific technology fields, in panel data settings and controlling for additional regional heterogeneity variables is essential.

The results presented in this paper have important policy implications. It appears that excessive emphasis has likely been placed on the local knowledge spillover theory in explaining spatial patterns of innovation, and attention should be refocused on what actually motivates innovative investments. At the regional aggregate level, our evidence suggests that innovation is led by existing market opportunities and regional innovative environments. Spillovers are thus likely also the consequence of innovation clustering, rather than merely the cause. Findings in this paper therefore also contribute to the recent discussion on place-based or place-neutral development strategies in the European Union (BARCA et al., 2012). The conceptual discussion of development oscillates between, on the one hand, spatially blind approaches arguing that intervention without respect to context ("people-based policy") is the best approach and, on the other hand, place-based approaches assuming that interactions between institutions and geography are critical for development. Research results discussed in this paper indicate a substantial heterogeneity in regional and urban conditions that influence patenting activity in Europe, suggesting that micro-economic processes and network alliances operate differently in different regions. This supports European place-based policy strategies *alongside* place-neutral (people-based) policy strategies. Both types of strategies are important for innovation policies intended to promote research cooperation and dissemination. Clearly, this research indicates that a more careful analysis of individual and network level innovation processes in a multilevel spatial framework is needed to capture the full advantages of the two policy strategies.

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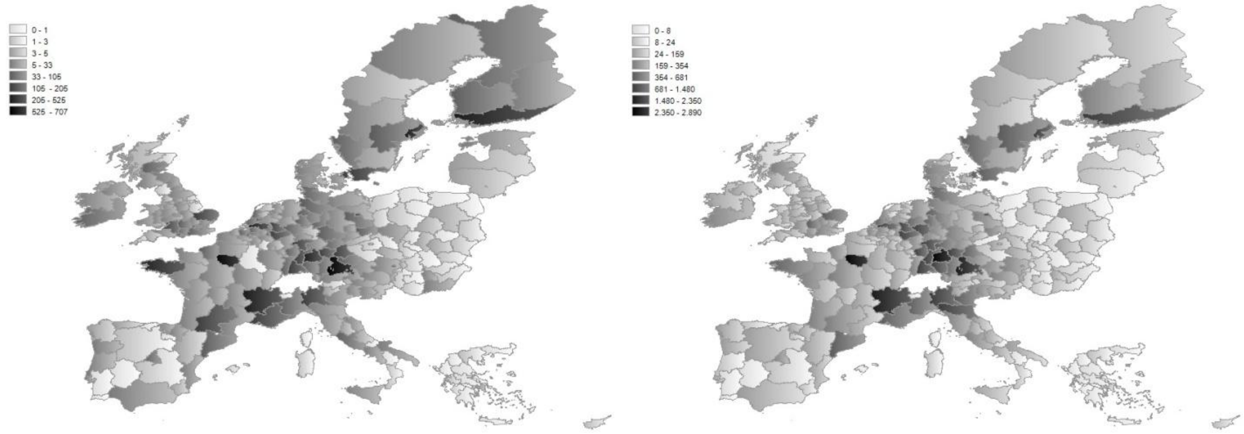
Appendix

A1: Distribution of patent applications to EPO, 2007-2008: total patents on the left and high-tech patents on the right



A2: Description of the dataset

Variable	Description	Source	Year
PA	Number of High-Tech patent applications to the EPO by priority year	Eurostat [pat_ep_rec]	2007-2008 (average)
BESRD	Total intramural R&D expenditure performed by the Business Enterprise Sector – percentage of GDP	Eurostat [rd_e_gerdreg]	2004-2006 (average)
GOVRD	Total intramural R&D expenditure performed by the Government Sector – percentage of GDP	Eurostat [rd_e_gerdreg]	2004-2006 (average)
UNIRD	Total intramural R&D expenditure performed by the Higher Education Sector – percentage of GDP	Eurostat [rd_e_gerdreg]	2004-2006 (average)
HTM	Workers in High and Medium High technology manufacturing – percentage of total employment	Eurostat [htec_emp_reg]	2004-2006 (average)
TEREDUC	Workers having completed first and second stage of tertiary education (levels 5 and 6 of ISCED97) – percentage of total employment	Eurostat [htec_emp_risced]	2004-2006 (average)
MPOT	Multimodal Potential Accessibility Index – ESPON average = 100	Espon	2006
GVAPE	Per-capita Gross Value Added at 2000 prices – euros	Cambridge Econometrics	1991
NMS	Dummy (=1 if region belongs to one of the EU10 countries)		
COHESION	Dummy (=1 if region belongs to either Portugal, Ireland, Greece, Spain)		
AT	Dummy (=1 if region belongs to Austria)		
BE-NL-LU	Dummy (=1 if region belongs to either Belgium, Netherlands or Luxemburg)		
CZ-HU-SK-SI	Dummy (=1 if region belongs to either Chez Republic, Hungary, Slovakia or Slovenia)		
DE-DK	Dummy (=1 if region belongs to either Germany or Denmark)		
ES-PT	Dummy (=1 if region belongs to either Spain of Portugal)		
FR	Dummy (=1 if region belongs to France)		
GR-CY	Dummy (=1 if region belongs to either Greece o Cyprus)		
IT	Dummy (=1 if region belongs to Italy)		
PL-EE-LV-LT	Dummy (=1 if region belongs to either Poland, Estonia, Latvia or Lithuania)		
SE-FI	Dummy (=1 if region belongs to either Sweden of Finland)		
UK	Dummy (=1 if region belongs to either the UK or Ireland)		
Long	Longitude, defined on the base of ETRS89 coordinate system	Eurostat-GISCO	
Lat	Latitude, defined on the base of ETRS89 coordinate system	Eurostat-GISCO	

A3: Definition of high-tech industries

Two different definitions of high-tech industries are used in this paper, and both are adopted by Eurostat for the classification of innovation data in Europe. The first, and certainly the most important, is related to the classification of patents, the dependent variable in the KPF estimated in this work. This definition uses specific subclasses of the International Patent Classification (IPC) as defined in the trilateral statistical report of the EPO, JPO and USPTO. More detailed information on this classification can be found on the web site http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Glossary:High-tech. A brief list of relevant sectors includes the following:

- computer and automated business equipment;
- micro-organism and genetic engineering;
- aviation;
- communication technology;
- semiconductors;
- lasers.

The second definition concerns the classification of manufacturing industries. This definition includes the following sectors of the manufacturing industry, based on NACE_R1 classification:

- DG (Manufacture of chemicals, chemical products and man-made fibers);
- DK (Manufacture of machinery and equipment n.e.c.);
- DL (Manufacture of electrical and optical equipment);
- DM34 (Manufacture of motor vehicles, trailers and semi-trailers);
- DM35.2 (Manufacture of railway and tramway locomotives and rolling stock);
- DM35.3 (Manufacture of aircraft and spacecraft);
- DM35.4 (Manufacture of motorcycles and bicycles);
- DM35.5 (Manufacture of other transport equipment n.e.c.).

A4: robustness check – specification of the contiguity matrix (EU 25 NUTS II regions)

	300 km		***400 km***		***600 km***		***700 km***	
	GLM	***GAM***	***GLM***	***GAM***	***GLM***	***GAM***	***GLM***	***GAM***
Intercept	-7.7378***	-7.6799***	-7.8061***	-7.7402***	-7.9162***	-7.9323***	-7.9448***	-7.9286***
	(0.3589)	(0.4033)	(0.3578)	(0.4102)	(0.3572)	(0.4295)	(0.3583)	(0.4343)
BESRD	0.4598***	0.4876***	0.4423***	0.4846***	0.4460***	0.4844***	0.4499***	0.4851***
	(0.0720)	(0.0687)	(0.0712)	(0.0687)	(0.0694)	(0.0682)	(0.0693)	(0.0682)
UNIRD	0.8252***	0.7494***	0.8066***	0.7468***	0.7166***	0.7507***	0.7324***	0.7544***
	(0.2312)	(0.2260)	(0.2293)	(0.2255)	(0.2270)	(0.2247)	(0.2269)	(0.2249)
GOVRD	0.7412***	0.4391*	0.7678***	0.4394*	0.8397***	0.4438*	0.8285***	0.4402*
	(0.2569)	(0.2511)	(0.2553)	(0.2508)	(0.2533)	(0.2500)	(0.2533)	(0.2502)
HTMAN	0.0411**	0.0042	0.0345**	0.0030	0.0268	0.0003	0.0276	0.0013
	(0.0181)	(0.0210)	(0.0181)	(0.0210)	(0.0180)	(0.0209)	(0.0180)	(0.0209)
TEREDUC	0.0250***	0.0292***	0.0224***	0.0294***	0.0180**	0.0296***	0.0183**	0.0297***
	(0.0083)	(0.0104)	(0.0083)	(0.0104)	(0.0083)	(0.0103)	(0.0083)	(0.0103)
MPOT	0.0044**	0.0063**	0.0047**	0.0063**	0.0054***	0.0062**	0.0053***	0.0062**
	(0.0020)	(0.0026)	(0.0020)	(0.0026)	(0.0019)	(0.0026)	(0.0019)	(0.0026)
GVAPE	0.0219***	0.0225**	0.0212***	0.0225**	0.0202***	0.0233***	0.0199**	0.0231**
	(0.0080)	(0.0092)	(0.0080)	(0.0092)	(0.0079)	(0.0091)	(0.0079)	(0.0091)
NMS	-0.5932**	-0.4312	-0.5428**	-0.4249	-0.5298*	-0.4304	-0.5318*	-0.4341
	(0.2810)	(0.3406)	(0.2797)	(0.3393)	(0.2773)	(0.3371)	(0.2773)	(0.3375)
COHESION	-0.6098***	-0.7491*	-0.5260***	-0.7453*	-0.3871*	-0.7430*	-0.3795*	-0.7426*
	(0.2020)	(0.4311)	(0.2034)	(0.4288)	(0.2070)	(0.4234)	(0.2084)	(0.4245)
W_BESRD	0.2956***	0.1110	0.4655***	0.1827	0.6961***	0.3859*	0.7207***	0.3756*
	(0.1155)	(0.1311)	(0.1325)	(0.1574)	(0.1542)	(0.2068)	(0.1624)	(0.2170)
	Non parametric terms							
s(LONG,LAT) - χ^2		***61.8200***		***58.1200***		***50.5300***		***51.2800***
[p-value]		***[0.0001]***		***[0.0002]***		***[0.0020]***		***[0.0017]***
theta	2.2430	3.1160	2.2820	3.1200	2.3660	3.1330	2.3340	3.1300
AIC	1742.2000	1709.8150	1738.3000	1709.5520	1732.0000	1708.5070	1732.5000	1708.8530
LZI	0.0548	-0.0104	0.0424	-0.0099	0.0327	-0.0143	0.0358	-0.0120
[p-value]	[0.0537]	[0.5679]	[0.0738]	[0.4280]	[0.0889]	[0.3529]	[0.0631]	[0.3798]

Notes to table A4:
SE in parenthesis. ***, ** and * indicate significance at 1%, 5% and 10% respectively. LZI is the value of the Moran's Index for residual autocorrelation adapted by LIN and ZHANG (2007) for GLM residuals. Significance is calculated based on the one-side alternative hypothesis. The selected alternative depends on whether the LZI statistic exceeds or not the expected value. The approximate significance of the *s(LONG,LAT)* term is evaluated using the χ^2 statistic test suggested by WOOD (2006). The value of the statistic is reported in the table alongside with the p-value associated with the null hypothesis of the term's statistical insignificance.

Notes

[i] As usual, the matrix is row standardized.

[ii] http://www.espon.eu

[iii] The variable is rounded to the integer. Detailed results of these tests are not presented but are available from the authors upon request.

[iv] The mean function is the inverse of the link function.

[v] The market potential variable has an average value of 97. 93. This differs from the value of 100, which is expected because the indicator is measured as the deviance from the EU mean (EU=100), as the Atlantic Islands were not considered in the dataset used for the analysis.

[vi] Specifically, the p-value of the ANOVA test when model (c) is considered as the alternative is 4.2188E-15, while when model (d) is considered, the alternative the p-value decreases to 0.2054E-15.