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Augmented and *Unconstrained*: revisiting the Regional Knowledge Production Function

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Abstract

By adopting a semiparametric approach, the 'traditional' regional knowledge production function is developed in three complementary directions. First, the model is *augmented* with region-specific time trends in order to account for endogeneity due to *selection on unobservables*. Second, the nonparametric part of the model *relaxes* the standard assumptions of linearity and additivity regarding the effect of R&D and human capital. Finally, the assumption of homogeneity in the effects of R&D and human capital is also relaxed by explicitly accounting for the differences between developed and lagging regions. The analysis of the genesis of innovation in the regions of the European Union unveils nonlinearities and threshold effects, complex interactions, and shadows effects that cannot be uncovered by standard parametric formulations.

JEL classification: O32, R11, C14, C23

Keywords: Innovation, Europe, R&D, Regional knowledge production function, Semiparametric models.

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1 Introduction

Since the seminal contribution by Griliches (1979), the concept of knowledge production function (KPF) has become popular in the analysis of innovation. Two different and somewhat separate strands of literature have contributed to the popularity of this approach. First, micro-level studies - revamped by the increased availability of innovation survey data - have investigated the firm-level nexus between innovative input and output (Mairesse and Monhen, 2010). Second, the analysis of innovation at the regional level has made extensive use of regional KPFs (RKPFs) to assess the contribution of regional inputs to the generation of new local knowledge. This approach revisits the firm-level framework à la Griliches (1979 and 1986) to account for the role of territorial characteristics and spatial processes. The RKPF is therefore embedded into the geography of innovation literature, providing new insights into the territorial determinants of innovation (e.g., Coe, 2005; Howells and Bessant, 2012). In addition to meso-level RKPFs, empirical analyses of the geography of innovation have taken a micro-level perspective by explicitly accounting for firms' location and for their local environment as additional drivers for their innovation capabilities (for recent surveys see, e.g., Feldman and Avnimelech, 2011 and Howells and Bessant, 2012). Indeed, since Marshall, the role of firm location in the innovation process has been discussed at length by both geographers and economists (see, e.g., Rosenthal and Strange, 2004).

The influence of physical distance and accessibility on innovation performance is the result of the interaction of a complex set of factors. On the one hand, face-to-face contacts make it possible for innovative actors to exchange highly valuable non-codified (or not-yet-codifiable) knowledge (Leamer and Storper, 2001; Storper and Venables, 2004; Charlot and Duranton, 2004). On the other hand, market-mediated exchange mechanisms (e.g., linked to spatially segmented labour markets for scientists and other knowledge workers) are also facilitated by geographical proximity (Zucker et al. 1998; Singh and Agrawal, 2011). However, the transmission of localised knowledge flows remains a *'black box'* (Döring and Schnellenbach, 2006): relationally dense locations simultaneously benefit from the *'buzz'* of localised knowledge exchange mechanisms and *'global pipelines'* (i.e., communication channels formed by a differentiated set of 'global' actors, such as multinational firms, diasporic communities, universities, and 'star' scientists) that increasingly tap into pools of external knowledge while bearing the associated communication cost/effort (Bathelt et al. 2004; Breschi and Lissoni 2009; Malecki, 2010a,b) and developing alternative forms of proximity (social, institutional, organizational) to other innovative agents (Boschma 2005). In this context, geographical proximity and density are neither necessary nor sufficient conditions to promote regional innovation (Breschi and Lissoni 2001 and 2005). Many other factors, such as institutional context, non-spatial proximities, and networks, influence the ability of local firms to absorb knowledge and generate innovation (Shearmur, 2011 and 2012a).

Modelling the complexity of the innovation process is a relevant challenge for all empirical analyses of innovation and its geography, particularly those that adopt quantitative approaches. In response to this challenge, some scholars have taken a social network analysis perspective

(Maggioni et al. 2007), whereas others have developed the RKPF approach in different directions in order to explicitly include in the equation alternative non-spatial forms of proximity and disentangle their differential impacts (e.g., Breschi and Lenzi 2012; Marrocu et al. 2012). This paper aims to contribute to this second stream of literature by taking a different approach. The analysis is focused on the effect of the 'basic' innovation inputs (i.e., human capital (HK) and R&D spending as well as their intensity/accessibility in neighboring regions) while improving the specification of the RKPF in a number of directions. The approach proposed in the paper aims to disentangle the role of these inputs from other confounding factors. Whereas it would be very difficult in practice to directly estimate the contribution of all alternative innovation drivers (e.g., institutional conditions or alternative spillover channels), by 'controlling at best for them' the empirical results uncover a number of relevant human capital and R&D effects that are largely overlooked by the existing literature.

More precisely, the paper proposes an original semiparametric modelling, where the parametric part controls for the unobserved heterogeneity of the regions, which can affect innovation and be correlated with observable factors. Specifically, the model allows for this type of correlated unobserved heterogeneity to be time varying. This specific type of heterogeneity is introduced to account for unobserved time-varying regional conditions linked to institutional quality, organizational features, regional agglomeration economies, regional position in knowledge networks, and non-spatial proximities to other innovative regions. In so doing, the empirical model can also account for the non-random selection of location decisions of innovative agents. Compared with previous studies, this approach better accounts for the endogeneity of both R&D and HK. The nonparametric part of the model relaxes the linearity assumption regarding the functional relationship between patenting and its main determinants. Although a log-log specification is customary in the literature, alternative functional forms cannot be excluded a priori. This challenge was acknowledged, even at the firm level, in early work by Griliches (1990, p. 303) *"Given the nonlinearity and the noisiness in this relation, the finding of "diminishing returns" is quite sensitive to functional form, weighting schemes, and the particular point at which the elasticity is evaluated*'. However, this aspect of the KPF has not received much attention in subsequent empirical literature. Given that the precise functional form of this relationship has no straightforward theoretical foundations, we allow for an unconstrained nonparametric relationship, thereby preventing any functional form bias. Finally, the proposed model allows for the identification of heterogeneous relationships between innovative inputs and outputs in different groups of regions in order to test whether R&D and HK are equally conducive to innovation in all contexts. Simply, given the lack of a precise formalized theory and the complexity of this relationship, the model is estimated in the most general and unconstrained way possible both in terms of unobserved heterogeneity and functional form.

The analysis is performed using a sample of European regions from 1995 to 2004. All variables are measured using very simple indicators (e.g., patent intensity as a proxy for innovation output, which captures only patented product innovation) under the constraint of data availability at the sub-national level, as is customary in the RKPF literature. In addition, the paper relies on physical accessibility to extra-regional R&D and HK as the only additional sources of extra-regional innovation inputs (i.e., it does not explicitly control for other knowledge flow channels). This constraint leaves many limitations of the standard RKPF unresolved. These limitations relate to the scale at which the analysis should be deployed, the use of patents to measure innovation, and geography as a channel for spillovers (see, e.g., Griliches, 1990; Breschi and Lissoni, 2001; Shearmur, 2012a and c; Lundvall, 2007). Although these limitations should be considered when interpreting the results, the analysis provides relevant methodological insights and identifies a number of dynamics that are potentially relevant to (regional) innovation policies.

First, the paper shows that controlling for time-varying unobserved heterogeneity is crucial to properly assess the effect of R&D expenditure and human capital on regional patenting. The omission of time-varying unobservables would produce a severe bias in the estimation of the RKPF. R&D and HK exert a significant influence on innovation only when time-varying unobserved heterogeneity is fully controlled for. Second, the nonparametric part of the model highlights strong nonlinearities and threshold effects, complex interactions, and shadow effects in the impact of both R&D and HK. A critical mass of R&D or human capital is necessary to make such inputs truly innovative. Moreover, the results highlight a strong complementarity between these two factors. Investments in R&D can enhance regional innovation only when coupled with a supportive endowment of human capital. In this context, the richer regions of the EU benefit from a persistent advantage in terms of the innovativeness of their innovation inputs. Economically disadvantaged regions appear to be in an innovation trap in the sense that a marginal increase in R&D or HK would not increase their ability to innovate. The analysis also highlights the presence of shadow effects: high levels of external R&D are detrimental for regions with low levels of internal RD, and the highest joint impact of internal and external R&D is obtained in the correspondence of the highest level of both inputs. We also offer evidence that many relevant facts may be hidden by standard parametric formulations, which may ultimately provide misleading inference.

In summary, our findings have relevant methodological and policy-oriented implications. From a methodological point of view, the paper shows that properly accounting for unobserved factors and allowing for nonparametric effects and heterogeneous relationships are key components in assessing the effect of the main inputs on innovation. In terms of policy implications (bearing in mind the limitations underlined above), the results suggest that European policy makers should counteract a potential 'innovation trap' for their lagging regions. Public and private R&D investments may not pay off if they are not complemented by human capital and supported by favorable contextual conditions. This concern calls for balanced policies that are not only based on technological innovation but that also attempt to support the necessary conditions in terms of institutional and broader network conditions.

This paper is organized as follows. In the next section, the relevant background literature is reviewed to develop the foundations for an 'extended' regional knowledge production function approach and to identify the most suitable econometric approach for the empirical estimation.

Section 3 presents the database and discusses the empirical findings. Section 4 concludes with some tentative policy implications.

2 The regional knowledge production function

2.1 Micro-level foundations and regional mechanisms

The empirical literature on the RKPF (e.g., Bode, 2004; Crescenzi et al., 2007; 2012; Feldman et al. 2014; Ponds et al. 2010; Marrocu et al. 2011) is extensive and often estimates a reduced form equation that can be expressed as follows:

$$K_{r,t} = g(RD_{r,t}, HK_{r,t}, WRD_{r,t}, WHK_{r,t}, U_{r,t}), \tag{1}$$

where K is regional patent intensity, g is a real function (often assumed to be a Cobb-Douglas function), $r = 1, ..., N$ is an index of the regions, $t = 1, ..., T$ indicates time, $RD_{r,t}$ and $HK_{r,t}$ are R&D spending and human capital at the regional level, $WRD_{r,t}$ and $WHK_{r,t}$ are R&D and human capital levels in the regional neighborhood, respectively, and $U_{r,t}$ represents all unobservable factors that influence regional innovative performance.

As summarized by O hUallachain and Leslie (2007), this RKPF has micro foundations, relative to the innovation process at the firm level, and is based on additional regional mechanisms linked to the role of spatial spillovers and agglomeration economies in the innovation process.

The primary theoretical foundation comes from the firm-level study by Griliches (1979), who develops the conceptual KPF framework. This framework is suitable for explicitly examining the causal relationships among productivity, unobservable knowledge capital, and its observable input (i.e., R&D) and output (i.e., patents) after controlling for other relevant factors. Building upon this initial approach, KPF studies typically include additional formal (and informal) sources of knowledge and other firm-level characteristics that affect innovative capabilities (Cohen 2010). In this context, human capital plays a relevant role because highly specific skills are necessary to support and enhance the innovative process. In addition, the human capital endowment of individual innovative actors not only directly supports their ability to generate new ideas but also influences their capability to absorb external knowledge (absorptive capacity) in the form of knowledge spillovers. Moreover, innovative ability depends on observable human capital (such as the formal qualifications of workers or the number of researchers employed) and on intangible assets, including formal and informal exchanges of information through professional and social, local, and interregional networks (Ponds et al. 2010). Griliches (1992) suggests that firms must also be economically and technically close to benefit from one another's knowledge and to generate new innovations. The analysis of inter-firm knowledge spillovers has suggested that 'space' and geographical distance exert a relevant influence on these diffusion mechanisms (Jaffe 1989 and Acs et al. 1992). In a spatial context, the influence of knowledge spillovers on the innovative performance of firms has been linked to agglomeration economies (or 'second nature advantages' in Krugman 1992). Three key sources of agglomeration economies have been identified in the literature: pecuniary externalities linked to the proximity of customers and suppliers; labor market thickness conducive to better matching between employers and employees; and, most relevant to this paper, pure technological externalities.

The origin of knowledge flows can be local, but knowledge flows can also be generated outside of the borders of the region under analysis because *"there is no reason that knowledge should stop spilling over just because of borders, such as a city limit, state line or national boundary"*(Audretsch and Feldman, 2004, p.6). Knowledge that is produced in one region may spill over into another, influencing its innovative performance (Moreno et al. 2005), and proximity facilitates more rapid diffusion (Sonn and Storper 2008). This relationship motivates the inclusion of spatially lagged R&D and HK terms (WRD and WHK, respectively) in 'customary' RKPFs to proxy extra-regional innovation activities that might lead to knowledge flows towards neighboring regions.

In addition to spatially-mediated knowledge flows, local institutional factors and public policies are also key features of the regional ability to innovate because they enhance knowledge exchange locally and with universities and research centres. With regard to these localised institutional factors, universities and public research centres influence the productivity of local private R&D in 'science-based' sectors by means of localised spin-offs. There is consistent evidence that regional innovation policies influence the innovative performance of firms (Jaffe, 1989; Lundvall, 2001; Morgan 1997; O hUallachain et al. 2007).

Boschma (2005) argues that geographical proximity between firms is neither a necessary nor a sufficient condition to promote regional innovation. Many other factors, such as institutional context, cognitive proximity, and global networks, affect the ability of local firms to innovate. Furthermore, too much spatial proximity can lead to lock-in because innovation needs external exchange for new ideas to emerge. Finally, many mechanisms at work should be evaluated at different spatial scales. For instance, the role of scientist networks cannot be constrained to a geographical area (Breschi and Lissoni, 2001), whereas direct face-to-face exchanges may appear in a very close neighborhood. However, even at a very small regional scale, agglomeration effects are not always observed (Shearmur, 2012b), depending on the complexity of the information shared (Charlot and Duranton, 2006).

The regional innovation process therefore depends on the R&D and human capital observed in the region and its neighboring regions. More importantly, however, it depends on numerous unobservable factors linked to internal socio-institutional conditions as well as to organizational features or regional agglomeration economies, institutional quality, and the position of the region in global (non-spatially mediated/bounded) knowledge networks (Bathelt et al. 2004; Breschi and Lissoni 2009; Malecki, 2010a and b).

These unobservable characteristics are represented by the term $U_{r,t}$. Whereas some of these characteristics may affect knowledge and are uncorrelated with innovation inputs, most of them are likely to affect both knowledge and its primary inputs; for instance, the effects of inter-regional spillovers depend on local absorptive capabilities as well as the amount and nature of external innovation in terms of technological and cognitive congruence (Bode 2004), including sharing the same culture or language.

The correlation between some unobserved regional conditions and innovation inputs may also be the result of the non-random selection of the location of both R&D investments and human capital. In the same way that firms accurately select the location of their R&D investments, highly skilled workers non-randomly choose where to look for a job. They select the a priori most attractive regions where they can benefit from more opportunities and higher salaries. Consequently, although patenting depends on R&D spending, human capital, and unobservable (and possibly time-varying) characteristics, R&D spending and human capital also depend on the latter set of characteristics (e.g., agglomeration, regional industrial structure, infrastructure) because they determine location decisions.

2.2 A semiparametric model for regional knowledge production

To model the complex relationship between patents and observable and unobservable determinants of new knowledge at the regional level, we propose a generalized additive model (GAM) framework (Hastie and Tibshirani 1990; Wood, 2004, 2008) and begin by estimating the following specification:

$$K_{r,t} = f_1(RD_{r,t}) + f_2(HK_{r,t}) + f_3(WRD_{r,t}) + f_4(WHK_{r,t}) + \alpha_r + \lambda_t + \gamma_r t + u_{r,t}, \tag{2}$$

where $f_1, ..., f_4$ are smooth functions and $\alpha_r + \lambda_t + \gamma_r t + u_{r,t}$ account for unobservable $U_{r,t}$. The existing empirical literature on the RKPF has focused on more constrained linear (or log-log) relations, such as $K_{r,t} = \beta_1 RD_{r,t} + \beta_2 HK_{r,t} + \beta_3 WRD_{r,t} + \beta_4 WHK_{r,t} + \alpha_r (+\lambda_t) + u_{r,t}$. The primary advantage of the proposed GAM semiparametric approach, compared with the existing literature on the RKPF and with some competitive semi- or nonparametric approaches, is that it makes it possible to simultaneously address different types of econometric biases that are expected to affect the estimation of the RKPF. These are summarized below.

First, endogeneity bias is an important issue emphasized by the related empirical literature. This bias is primarily motivated by the omitted correlated variables problem. Indeed, as described in the previous subsection, in the RKPF framework, the endogeneity of R&D and/or HK may arise because of the omission from the patent equation of some relevant variables related to R&D and/or HK (see, e.g., Griliches, 1990, fig.3; Hall and Mairesse, 2006, fig.1; O hUallachain and Leslie, 2007 fig.1). Specifically, for the regional level, firms may locate their R&D activities in areas in which they can find all factors that support innovation and in which they can benefit from localised spillovers resulting from a concentration of other innovative firms, skills, and infrastructure. The existing literature on the RKPF has addressed such issues by exploiting the panel structure of the data (see, e.g., Crescenzi et al., 2007, 2012; Greunz, 2003; Moreno et al., 2005).[1] The panel structure is exploited by assuming that the unobservable term $U_{r,t}$ introduced in equation (1) can be described as $U_{r,t} = Z_t\theta_r + u_{r,t}$, where Z_t is a vector of non-random aggregate time variables that can be freely correlated with the explanatory variables; θ_r is the associated vector of coefficients;[2] and $u_{r,t}$ is an error term that is supposed to be uncorrelated with the knowledge inputs. At best, a two-way (individual and common time) fixed effects approach has been adopted to date.[3] Indeed, as shown by Mundlack (1978), Wooldridge (2005), and Hsiao (2011), the fixed effect approach is a very powerful means of managing endogeneity because it is valid in a variety of situations where endogeneity is important, such as selection bias (selection on both observable and unobservable characteristics). In particular, the ability of this type of model to address selection on unobservables (i.e., free correlation between unobservable variables and regressors; see for instance Heckman and Hotz, 1989) is particularly relevant in the spatial context. The regional fixed effect can capture both first- and second-nature advantages that are related to innovation output and to its observable inputs (R&D and HK). Aggregate time effects also account for the possible dependence between innovation inputs and unobserved time-related factors, such as general technological change, economic crises, and all common factors that affect the innovation process in all regions in the same way. However, the primary limitation of this two-way fixed effect model is that it imposes common time effects homogeneously upon all regions, whereas most of the unobserved global correlated factors are likely to affect heterogeneously different regions. Moreover, as detailed in the previous section, regions are likely to differ with respect to some unobservable time-varying regional-specific variables that are related both to the production of patents and to R&D and human capital. To address this issue, we adopt a random trend (or random growth) model originally proposed by Heckman and Hotz (1989), which was theoretically analyzed by Wooldridge (2005) and successfully applied in some empirical papers (see, e.g., Papke, 1994 or Friedberg, 1998).[4] The random growth model is motivated by a special case of a more general class of models in which $U_{r,t}$ has a factor structure (e.g. Pesaran, 2006). It introduces an individual time-varying (multiplicative) component, $\gamma_r t$, in addition to the individual, α_r, and time, λ_t, fixed effects. This model thus aims to control for all time-varying region-specific unobservable factors, simultaneously allowing these factors to be freely correlated with observable

[1]The firm-level literature most often focuses on cross-sectional data and has adopted equation systems or instrumental variables to address this issue (Mairesse and Monhen, 2002, 2010; Hall and Monhen, 2013, Musolesi and Huiban, 2010).

[2]Equation (2) corresponds to $Z_t = (1, \lambda_t, t)$ and $\theta_r = (\alpha_r, \delta, \gamma_r)$.

[3]Meaning $Z_t = (1, \lambda_t)$ and $\theta_r = (\alpha_r, \delta)$.

[4]The name "random growth" was originally introduced by Heckman and Hotz (1989) in a policy evaluation framework, in order to deal with the issue of selection (on unobservables) bias. However, as also discussed in Wooldridge (2010, p. 375), allowing $(\alpha_r, \lambda_t, \gamma_r)$ to be arbitrarily correlated with the explanatory variables makes the term 'random' in conflict with the standard use of random vs. fixed effects. This terminology, although now customary in the policy evaluation literature, may still cause some confusion.

innovation inputs. These include mobility factors, which could be relevant in this type of spatial context.

Because the precise functional form of the relationship between innovation and its inputs is not straightforwardly defined from a theoretical basis, a possible important bias may arise when imposing a parametric relationship, such as linear, log-log, or polynomial. As highlighted by Varga (2000), it can be expected, for instance, that a critical mass of R&D or human capital is necessary to make such inputs truly innovative. This requirement is allowed by the nonparametric part of the model $f_1(RD_{r,t}) + f_2(HK_{r,t}) + f_3(WRD_{r,t}) + f_4(WHK_{r,t})$. Moreover, the use of *'continuous-by-continuous interactions'* of the type $f(RD_{r,t}, HK_{r,t})$ makes it possible to relax the additivity assumption, which may also be too restrictive as suggested by Hall et al. (2010, p. 33): *'Because the additive model is not really a very good description of knowledge production, further work on the best way to model the R&D input would be extremely desirable'*.

Finally, European regions are known to be very heterogeneous, especially in their innovation systems but also in terms of development levels. The use of *'factor-by-continuous interactions'* (Ruppert et al. 2003) makes it possible to identify heterogeneous relationships between innovative inputs and outputs in different groups of regions, distinguishing lagging regions (identified as those belonging to the Objective 1 or 'Convergence Regions' group by the European Commission for the implementation of its regional policy) from all other regions.

Despite its appeal, our approach also requires some caveats. A first potential limitation is that it is less general than fully non-separable models. However, compared with these models, our approach presents some clear advantages in terms of interpretation, statistical feasibility (e.g., the curse of dimensionality) and identification (see e.g., Hoderlein and White 2012 and Evdokimov 2010). Appendix A includes further details on these issues. A second relevant issue is that the random growth parametric part of the model proxies time-varying (correlated) unobservable variables by means of individual linear trends while alternative specifications are more general and could also be suitable.[5] Third, it is useful to clarify the exogeneity assumptions underlying the proposed specification. The existing literature mainly proposed standard individual fixed effects estimates. The random growth model, adopted in this paper, identifies the parameters of interest under a "conditional" strict exogeneity assumption (Chamberlain, 1982; Wooldridge, 2005, 2010), i.e. $E\left(K_{r,t} \mid X_{r1}, ..., X_{rT}, \alpha_r, \lambda_t, \gamma_r\right) = E\left(K_{r,t} \mid X_{r,t}, \alpha_r, \lambda_t, \gamma_r\right)$, for $t = 1, ..., T$ and where $X_{r,t}$ is the vector of regional inputs of innovation (in our empirical model $X_{r,t} = (RD_{r,t}, HK_{r,t}, WRD_{r,t}, WHK_{r,t})$). The main appealing features of such a hypothesis, compared with that coming from the individual fixed effects model (i.e. $E\left(K_{r,t} \mid X_{r1}, ..., X_{rT}, \alpha_r\right) = E\left(K_{r,t} \mid X_{r,t}, \alpha_r\right)$) are that:

[5] A first alternative model could introduce the individual trends nonparametrically (see e.g. Mazzanti and Musolesi, 2013), while a second one could consider factor models (see e.g. Pesaran, 2006). Both these alternative specifications cannot to be straightforwardly applied to our analysis. The former requires a large time series dimension compared to the cross-section dimension for the estimation of N additional smooth functions, while the latter has been proposed in a linear panel data framework and future theoretical works may provide useful insights to adapt such a framework to a nonparametric setting. We ran some regressions adding individual quadratic trends to get more flexibility. The estimated models appeared to be overparametrised.

i) It allows for free correlation between $(\alpha_r, \lambda_t, \gamma_r)$ and $(X_{r1}, ..., X_{rT})$, thus aiming to account for the endogenous selection of innovation inputs with respect to both time-invariant and time varying unobservables. $\lambda_t + \gamma_r t$ broadly proxying this latter kind of unobservables such as agglomeration, regional industrial structure, and infrastructure which are correlated with both innovation output and inputs.

ii) Since the level of inputs possibly depends not only on α_r but also on (λ_t, γ_r), it is likely that shocks to patents today may influence some innovation inputs in the future if (λ_t, γ_r) is not controlled for. In such a case the strict exogeneity assumption underlying the individual fixed effects model will be violated and there is no identification of the slope parameters. This is why the conditional strict exogeneity assumption underlying the random growth specification is much more realistic than the standard individual fixed effects model.

However, our approach does not deal with other potential sources of endogeneity (e.g. reverse causality). To date, however, there are not attempts to deal with this issue in the RKPF literature. The complexity of the spatial mechanisms may require further theoretical studies and possibly econometric attempts to check if reverse causality may be relevant along with endogenous selection (i.e. even after introducing the random growth effects). Errors in variables (e.g. Griliches and Hausman, 1986) may also be another – but not yet addressed - problem with RKPFs requiring further investigation.

3 Data and econometric analysis

3.1 Data

The analysis covers the entire EU-25 for the 1995-2004 period. Data on innovative output (patents) and all explanatory variables are available from Eurostat. The analysis is based on a combination of NUTS1 and NUTS2 regions that were selected to maximize homogeneity in terms of the relevant governance structure under the constraint of data availability. For each country, a unit of analysis was selected that had the greatest relevance in terms of the institutions supporting the process of innovation and its diffusion and that could be considered a target area for innovation policies by the national government and/or the European Commission. Consequently, the analysis is based on NUTS1 regions for Belgium, Germany,[6] and the United Kingdom and NUTS2 regions for all other countries (Austria, Czech Republic, Finland, France, Greece, Hungary, Italy, the Netherlands, Poland, Portugal, Slovakia, Spain, and Sweden). Countries without equivalent sub-national regions (the Baltic states, Cyprus, Denmark[7], Ireland,

[6]The NUTS2 level corresponds to *Provinces* in Belgium and to the German *Regierungsbezirke*. In both cases, these statistical units of analysis have little administrative and institutional meaning. For these two countries, the relevant institutional units are *Régions* and *Länder*, respectively, codified as NUTS1 regions. The lack of correspondence between the NUTS2 level and the actual administrative units accounts for the scarcity of statistical information pertaining to many variables (including R&D expenditure) below the NUTS1 level for both countries.

[7]Although Denmark introduced regions above the local authority level on 1 January 2007 in accordance with the NUTS2 classification, regional statistics are not available from Eurostat.

Luxembourg, Malta and Slovenia) are excluded a priori from the analysis.[8]

Regarding the exact definition of the variables, we closely follow the recent literature on RKPF to maximize the comparability of our results with the existing literature (e.g., Crescenzi et al., 2007; 2012; Crescenzi and Rodriguez-Pose 2011; Dettori et al. 2012; Feldman et al. 2014; Marrocu et al. 2011; Paci and Marrocu 2013; Ponds et al. 2010). We measure the regional innovation output, K, using the regional number of patents per million inhabitants. The analysis is based on homogenous comparable data for regions belonging to all EU countries and relies on European Patent Office data as recorded by Eurostat in its regional database. This measure of innovation has many limitations, as extensively discussed by Griliches (1990) and (in a city-regional context) by Shearmur (2012c). Patent intensity accounts only for a small share of total innovation output for a number of reasons. First, only product innovation can be patented, whereas in many regions and sectors (in particular, in the service sector), process and organizational innovations can be the most relevant forms of innovation. These other forms of innovation cannot be captured by means of patent counts but can only be captured by micro-level survey data which are, however, often not representative at the sub-national level. Second, even when addressing product innovation, firms of different sizes and in different sectors of activity might decide to rely on alternative forms of IPR protection, sometimes favouring secrecy (or trademarks) over patenting (Breschi and Lissoni, 2001). Furthermore, patented inventions vary in their technical and economic value. Patent applications tend to be clustered geographically in a limited number of regions, and this is especially true for high-tech activities. Regional statistics for patent applications to the European Patent Office (EPO) build on information from the inventors' address; this may not represent the location where the invention is developed because inventors do not necessarily live in the location where they work. This discrepancy is likely to be higher when smaller geographical units are used. However, given the size of the selected units of analysis, it is reasonable to assume (as in much of the existing literature on innovation in Europe) that the selected combination of NUTS1 and NUTS2 regions can be a good approximation for 'functional areas' (i.e., geographical units self-containing a large share of commuting flows and encompassing both residence and workplace of the corresponding population). This assumption should ensure that the regional patent count can accurately reflect the number of patented inventions actually developed within the boundaries of a region. In addition, it is important to recall that recent research on the topic has highlighted that the geographical mobility of EU inventors is very limited (Miguélez et al. 2012). Unfortunately, regional patent intensity is currently the most widely used and the only widely available indicator of regional innovation for the entire EU. We are confident that the proposed methodology, as discussed above, can correct potential regional biases generated by the poor quality of this indicator in a much more convincing fashion than previous empirical works.

The innovation inputs, RD and HK, are defined as follows. The regional R&D variable is

[8]With respect to specific regions, no data are available for the French Départments d'Outre-Mer (FR9). Trentino-Alto Adige (IT31) has no correspondent in the NUTS2003 classification. Because of the nature of the analysis, the islands (PT2 Açores, PT3 Madeira, FR9 Départements d'Outre-mer, and ES7 Canarias) and Ceuta y Melilla (ES 63) were not considered as a result of problems with the computation of the spatially lagged variables.

provided by Eurostat and corresponds to the share of regional GDP spent on R&D by public and private institutions, regardless of the sector. Human capital is proxied by the regional share of workers with tertiary education or higher (ISCED76 classification levels 5-7).

It is worth noticing that both innovation output and input as defined above are positive real variables, thus explaining why previous work at the regional level has adopted standard linear (panel data) estimators (Audretsch and Feldman 1996; Crescenzi et al. 2007 and 2012; O hUallachain and Leslie 2007; Ponds et al. 2010). Conversely, in firm-level analyses, the use of the number of patents as dependent variable requires the adoption of count data models (Crépon et al. 1998).

The dataset covers 169 regions over 10 years. The variables have few missing values and the size of the econometric sample depends on the explanatory variables included in the regression function.

The average EU regional patent intensity is 67.3 patents per million inhabitants. The EU regional average has increased over time: from 43.7 in 1995 to 79.7 in 2004. This trend is the result of the combination of a generalised increase in patenting activity (in line for example with the USA or Japan – see Crescenzi et al. 2007 for an in-depth comparative analysis) and technological catch-up in 'core' regions of the Central and Eastern European countries. However, the EU-wide increase in average patent intensity is accompanied by an upsurge in its heterogeneity across regions (the standard deviation of regional patent intensity has also increased). Similar dynamics are in place as far as R&D (sample average 0.69, increasing from 0.65 in 1995 to 0.73 in 2004) and Human Capital (average 20.6; 17.9 in 1995 up to 22.7 in 2004) are concerned: an upward trend in the sample average over time is accompanied by an increase in the corresponding regional dispersion. The group of the most innovative regions (in terms of both patent intensity and innovation inputs) includes: the German Berlin, Baden-Württemberg, Bayern and (to a lesser extent) Bremen regions, the entire South East England, the Île de France and Midi-Pyrénées regions in France. At the opposite end of the spectrum the lowest innovation dynamism is recorded in the Portuguese Algarve and Centro regions, the Greek Anatoliki Makedo and in all Eastern regions in Poland. Between these two groups it is possible to observe a variety of intermediate possible combinations of local R&D and Human Capital associated with very different innovation outcomes.

Finally, in order to assess R&D and human capital spillovers in neighboring regions, spatially lagged variables are computed by means of inverse Euclidian distance matrices, as is customary in the literature on spatially mediated knowledge flows (Moreno et al. 2005; Crescenzi et al., 2007, 2012; Crescenzi and Rodriguez-Pose 2011). This geographical criteria for the identification of each region's neighborhood is based on a smooth distance decay, with weights w_{rj} that depend on the Euclidean distance between region r and j. These weights have been standardized in such a way that for each region, WRD (WHK) is a weighted average of the RD (HK) of the other regions:

$$WRD_{r,t} = \sum_j w_{rj} \times RD_{j,t} \quad and \qquad WHK_{r,t} = \sum_j w_{rj} \times HK_{j,t},$$
$$with \ : \ w_{rj} = \begin{cases} 0 \text{ for } r = j \\ \frac{\frac{1}{d_{rj}}}{\sum_j \frac{1}{d_{rj}}} \text{ for } r \neq j \end{cases}$$

In this case, the influence of one region on its neighbors decreases with Euclidian distance. The contiguity matrix is another frequently used distance matrix, but it is more constrained and does not allow for long-distance interactions, which are highly relevant in the EU regions as extensively discussed in the existing literature.

3.2 The role of unobserved factors and preliminary quantile regression estimates

We first adopt a log-log specification (called "Cobb-Douglas" to recall the production function), as is customary in existing regional-level studies. In this preliminary specification, the set of explanatory variables is constrained to include only R&D and Human Capital (HK):

$$\log(K_{r,t}) = Z_t\theta_r + \beta_1 \log(RD_{r,t}) + \beta_2 \log(HK_{r,t}) + u_{r,t}$$

We compare the results based on alternative definitions for the deterministic component $Z_t\theta_r$:

- $Z_t = 1$, "one-way fixed effects"
- $Z_t = (1, \lambda_t)$, $\theta_r = (\alpha_r, \delta)$, "two-way fixed effects"
- $Z_t = (1, \lambda_t, t)$, $\theta_r = (\alpha_r, \delta, \gamma_r)$, "random growth".

The estimation results are shown in Table 1, which reports robust standard errors. Columns (1), (2), and (3) report 'one-way', 'two-way', and 'random growth' coefficients, respectively. Because the three specifications discussed above are nested, we sequentially use the F-test to choose among them. The F-test strongly supports the random growth specification.

TABLE 1

The results show significant discrepancies in the estimated coefficients for different specifications of the unobservable part of the model (columns (1)-(3)) in terms of both magnitude and significance of the estimated coefficients. When controlling only for time-invariant regional characteristics (column (1)), the generation of innovation is dominated by human capital endowment, which has an estimated coefficient of 1.40 and is highly significant, whereas regional R&D investment does not appear to play a significant role. Regional fixed effects control for the time-invariant structural regional conditions of the local economy. When introducing common time effects affecting all regions homogeneously (two-way model, column (2)), the effect of both RD and HK is close to zero and no longer significant. However, after controlling for time-varying unobservable factors, as in the random growth specification (column (3)), the picture changes substantially: both R&D and human capital are significant and show elasticities of a similar magnitude (0.60 and 0.51, respectively). The random growth specification is the most suitable for fully controlling not only for the role of first-nature geography, which is stable over time, but also for the effects of other time-varying factors, related to the second-nature geography, such as agglomeration, regional industrial structure, and infrastructure, that may affect both the production of patents and location decisions, concerning both R&D and HK. This is the first relevant result we provide, showing empirically that the omission of time-varying unobservables produces a severe bias in the estimation of the RKPF.

It is interesting to note that with the random growth specification, the elasticity of patents with respect to R&D is estimated at 0.6, which is consistent with firm-level analyses. Indeed, summarizing previous results, Griliches (1990) reports that the elasticity of patents with respect to R&D is between 0.3 and 0.6, whereas Blundell et al. (2002) report a preferred estimate of 0.5. Concerning regional-level studies based on the KPF, there is a large and rapidly increasing amount of empirical literature whose results are difficult to summarize. Some of these studies have produced comparable results (e.g., OhUallachain and Leslie, 2007; Ponds et al., 2010; Foddi et al., 2012). However, the comparison with such studies is not straightforward because they use different econometric specifications, such as cross-sections (OhUallachain and Leslie, 2007), pooled panel data (Ponds et al., 2010), or one-way fixed effects models (Foddi et al., 2012).

Columns (4) to (7) focus on more complex specifications, including spillover effects, interaction terms, and some degree of heterogeneity in the effects of the primary knowledge inputs, respectively. The results from these specifications will be compared with those obtained from less constrained semiparametric specifications in the following section.

Finally, it is worth to note that another appealing but complementary approach with respect to GAMs for estimating a RKPF could be the quantile regression. This approach allows a conditional quantile function (rather than the conditional mean function as for GAMs and (G)LMs) to be estimated. Quantiles of the conditional distribution of the response variable are expressed as a function of observed covariates. In a panel data setting with individual fixed effects and nonlinear effects of the explanatory variables, the conditional quantile function is $Q_{Y_{r,t}}(\tau \mid X_{r,t}) = f_\tau(X_{r,t}) + \alpha_{r,}$, with $\tau \in (0,1)$. Unfortunately these models have not yet been fully developed in a panel data framework (Koenker, 2005, Ch. 7, reviews nonparametric quantile regression for cross-sections). As a preliminary analysis, we provide the results obtained from the pooled panel data quantile regression $Q_{Y_{r,t}}(\tau \mid X_{r,t}) = c(\tau) + X_{r,t}\beta(\tau)$, with $\tau \in (0,1)$, $Y_{r,t} = \log(K_{r,t})$ and $X_{r,t} = (\log(RD_{r,t}), \log(HK_{r,t}), \log(WRD_{r,t}), \log(WHK_{r,t}))$. Figure 1 presents estimates of the effects of the main covariates (elasticities) as a function of the quantiles τ (using percentiles) of the conditional distribution of $\log(K_{r,t})$. Two key insights come from these results: i) looking at the mean effect, it can be noticed that, as expected, the pooled model suffers from a severe omitted variables bias when compared with all the fixed effects specifications presented above; (ii) for all the explanatory variables, the corresponding elasticity varies greatly with τ. However, the direct comparison between this pooled quantile with the GAM specification adopted in this paper, $E\left(K_{r,t}\right) = f_1(RD_{r,t}) + f_2(HK_{r,t}) + f_3(WRD_{r,t}) + f_4(WHK_{r,t}) + \alpha_r + \lambda_t + \gamma_r t$, is not straightforward: only the GAM specification makes it possible to introduce unobserved heterogeneity and nonlinearities and focuses on the mean effect. Very recently, Harding and Lamarche (2014) proposed a linear quantile regression estimator for a panel data model with interactive effects (factor model) potentially correlated with covariates (see also Koenker, 2004 and Lamarche, 2010 for quantile regression models with individual fixed effects). This approach could possibly be applied in the near future to account for time-varying unobservables. In a longer run perspective, quantile panel data models allowing for nonlinear effects and unobserved (possibly time varying) heterogeneity could be a very promising line of investigation to complement our work on RKPFs.

FIGURE 1

3.3 A non-constrained regional knowledge production function

The next step of our analysis estimates the model by adopting the proposed semiparametric specification, as detailed in section 2.2, that relaxes the restrictive assumptions on the shape of the RKPF. The goal of this section is twofold. First, from a methodological perspective, by comparing our results with those obtained using the standard parametric model presented above, we will shed new light on the practical advantages of the proposed semiparametric approach and uncover relevant innovation dynamics that have been overlooked in previous studies. Second, we will stress the novel policy insights that can be drawn from such results. Concerning the parametric part of the model, for all estimated specifications, the results of the tests clearly favour the random growth specification. Thus, in the following, we set $Z_t = (1, \lambda_t, t)$, $\theta_r = (\alpha_r, \delta, \gamma_r)$.[9]

The effect of human capital and R&D The effects of regional human capital and R&D expenditure on regional innovation are first estimated by the following model:

$$K_{r,t} = Z_t\theta_r + f_1(RD_{r,t}) + f_2(HK_{r,t}) + u_{r,t}$$

.

Figure 2 represents the estimated functions with their confidence bands.

FIGURE 2

[9]We follow Wood (2006a) and use an approximate F-test.

The left-hand section of Figure 2 shows the effect of R&D expenditure on patenting, with the black line depicting the estimated smooth function and the dotted line representing the corresponding confidence bands. Plots are presented in a mean-centered fashion (see Wood, 2014 for details). What therefore matters for interpreting the results from the proposed level equation is the shape of the estimated smooth (without looking at its level with reference to the y axis) and the p-value associated to the test that the whole function is zero. In Figure 2, both smooths are highly significant (p-value < 0.001). For reasons of identification detailed in appendix A, we follow many previous works and do not adopt neither a within nor a first difference transformation and estimate the level equation.[10] For very low levels of regional R&D expenditure, the patent-R&D relationship is flat, suggesting that a minimum level of R&D in necessary to produce innovation. Then, after reaching a threshold (when the share of regional GDP spent on R&D is equal to 0.4-0.5%), this relationship becomes positive but relatively weak: 'average' levels of R&D positively affect innovation, but only to a limited extent. There is a second threshold (i.e., above 1.5%) at which the effect of additional investments becomes much less significant and potentially detrimental for innovation. This threshold effect is very limited over the range of R&D expenditure because after a third threshold (above approximately 2%), R&D expenditure maximizes its effect on innovation. This positive and significant relationship holds true until an additional threshold is reached (slightly below 3%). Finally, after this threshold, there are few observations, and the confidence interval becomes too broad. It should be stressed that some unobservable factors may be correlated with R&D expenditure, which can explain the success of the top innovative EU regions in which, for instance, institutional conditions have been shown to be of paramount importance for the innovativeness of R&D activities (Crescenzi et al. 2007 for the EU and the US and 2012 for emerging countries; Iammarino 2005; Lundvall 2001). This correlation is allowed for by the random growth parametric component of the model.

For human capital (the right-hand part of Figure 2), the function highlights a single fundamental threshold when the regional share of workers with tertiary education or higher is equal to approximately 20%. Below this threshold, there is no significant effect from human capital on innovation because the relationship is completely flat. Above this level, the effect becomes highly positive and significant. It is only for very high levels of human capital intensity (above approximately 35% of workers with tertiary education or higher), where only few observations are available, that the relationship becomes slightly less sloping and the confidence interval broadens again.

In summary, these results clearly suggest that parametric estimates conceal an important part of the story regarding the relationship between innovation and its key inputs (R&D and human

[10] P-values for smooth terms are based on a Wald test statistic, motivated by an extension of Nychka's (1988) analysis of the frequentist properties of Bayesian confidence intervals for smooths (Wood 2013). They are p-values associated with Wald test that the whole function equals zero, $f(.) = 0$. Low p-values indicate low likelihood that the splines of the function are jointly zero. Component smooths are shown with confidence intervals that include the uncertainty about the overall mean. Marra and Wood (2012) suggest that this approach results in better coverage performance. In order to identify the model, the smooth functions have to be constrained to have zero mean (usually taken over the set of covariate values).

capital). This link is not linear and presents relevant thresholds, and it could not be correctly approximated using the variables' transformation within a parametric framework.[11]

Relaxing additivity Innovation theory suggests that R&D investments and human capital are strongly complementary in their contribution to innovation. As a consequence, we adopt a *continuous-by-continuous* interaction between R&D and HK that partially relaxes additivity (see, e.g., Ruppert et al., 2003, Ch. 12):

$$K_{r,t} = Z_t\theta_r + f(RD_{r,t}, HK_{r,t}) + u_{r,t}$$

The estimation generates the results depicted in Figure 3.

FIGURE 3

The results are presented using a surface 3-D plot (Figure 3) showing how the innovative output (Z-axis) responds to simultaneous changes in R&D (Y-axis) and human capital (X-axis).[12] The estimated bivariate smooth function is highly significant (p-value < 0.001). For low levels of regional human capital endowment, the patent-R&D relationship is flat, whereas for higher levels of human capital intensity (after an initial threshold located at slightly less than half in the range of human capital), the influence of R&D investments on innovation is positive and increases sharply with a higher level of HK.

Looking at the effect of HK on innovation, for low levels of R&D, the patent-HK relationship is completely flat until it reaches a threshold and then becomes positive. For a higher level of R&D, this relationship is different: the flat part of the relationship between innovation and HK is significantly reduced, and the positive part of the relationship becomes increasingly steeper when R&D increases.

This finding confirms the risk of the 'cathedrals in the desert' scenario (Crescenzi and Rodriguez-Pose 2011; Midelfart-Knarvik and Overman 2002), in which R&D investments are concentrated (for example, because of policy incentives in favour of lagging areas) in regions that lack the appropriate receptive environment in terms of human capital. The local mismatch between R&D and skilled labour persistently hinders innovation. This finding suggests that R&D investments can boost innovation only in locations in which appropriate complementary skills are available locally to support knowledge generation and absorption.

From a methodological perspective, this figure indicates the relevance of allowing for nonparametric effects, because this type of picture cannot be identified using parametric models. Indeed, the standard Cobb-Douglas function has a very different shape compared with the estimated function plotted in Figure 3. Moreover, even parametric specifications including interaction terms can,

[11] Results, available upon request, using various parametric formulations support this conclusion.

[12] In appendix B, we also provide the corresponding contour plot for all the bivariate smooth functions presented in the main text, using a surface plot representation.

at best, suggest whether two inputs are complementary or substitutable but cannot uncover relevant threshold effects. Columns (5) and (6) in Table 1 consider parametric specifications with interaction terms. In column (5), an interaction term is added to the Cobb-Douglas specification, as in many empirical investigations, whereas in column (6), a translog specification, originally introduced by Christensen et al. (1973) for analyzing value-added production functions, is estimated.[13] In both cases, the estimated coefficient of the interaction term is close to zero and not significant, confirming that a non-parametric approach provides us with a more nuanced and realistic picture of the geography of innovation in Europe [14].

Regional spillovers A further step is to focus on regional spillover effects and estimate the following equation:

$$K_{r,t} = Z_t\theta_r + f_1(RD_{r,t}) + f_2(HK_{r,t}) + f_3(WRD_{r,t}) + f_4(WHK_{r,t}) + u_{r,t}$$

which provides us with results that are graphically summarized in Figure 4.[15]

FIGURE 4

Figure 4 shows the estimations for spillovers generated by R&D activities (WRD - left-hand side) and human capital (WHK - right-hand side) in neighboring regions. The first relevant result that is worth noting is that such a graph provides a much richer information than the parametric estimation (Table 1, Column (4)), in which neither WRD nor WHK are significant.

In the proposed semiparametric approach, the estimated function concerning the effect of WHK is significant: the p-value associated with the Wald test that the whole function $f(.) = 0$ is lower than 0.001. Regions surrounded by a neighborhood that is poorly endowed in terms of human capital (low levels of WHK) are not affected by this external factor (negative effect but large confidence bands). Conversely, for higher levels of external human capital, the effect on internal innovation becomes positive and significant. This suggests that peripheral regions (with limited access to a human capital abundant neighborhood) may not be able to rely on inter-regional human capital spillovers to reinforce their innovative performance. In this sense, peripherality may become a source of structural disadvantage for innovative performance (Crescenzi, 2005). However, above another threshold, the confidence interval broadens again: the effect tends to wane with proximity to the largest centres of human capital accumulation (high values of WHK). These hotspots may tend to generate a shadow effect in their neighborhood, absorbing its human

[13]The translog form can be interpreted as a second order Taylor series approximation of an unspecified underlying production function and achieves local flexibility (also called Diewert flexibility) implying that the approximating functional form provides perfect approximation for the underlying function and its first two derivatives at a particular point (Fuss et al., 1978). It has also been shown that it outperforms other Diewert-flexible forms (Guilkey et al., 1983).

[14]The calculated average elasticities of R&D and HK are, respectively, 0.598 and 0.486 for the equation estimated in column (5) and 0.835 and 0.612 for column (6).

[15]Because the estimated smooth functions f_1 and f_2 addressing the effect of R&D and human capital are very similar to those shown in Figure 1, we focus attention only on spillover effects, i.e., f_3 and f_4.

capital. For the highest levels of WHK, indeed, the effect on innovation seems to be non-significant and tends to become negative. The estimated smooth function concerning WRD does not appear to be significant (p-value = 0.313). This p-value seems to suggest that the splines that make up the function may be jointly zero, even if, when looking at the plot and its confidence interval, the estimated smooth for WRD (although less statistically significant) appear to have a similar functional shape than the one obtained for WHK. Only over a limited range of the distribution of WRD (the central part), R&D expenditure in neighbouring regions may exert a positive influence on innovation while for both low and high levels of WRD it does not affect the genesis of new knowledge.

Finally, the partially non-additive specification presented in the previous section is re-estimated by interacting local R&D and human capital, respectively, with R&D and human capital in neighboring regions:

$$K_{r,t} = Z_t\theta_r + f_1(RD_{r,t}, HK_{r,t}) + f_2(RD_{r,t}, WRD_{r,t}) + f_3(HK_{r,t}, WHK_{r,t}) + u_{r,t}$$

This enlarged set of interactions is particularly relevant on both analytical and policy grounds. Although there is consensus in the literature regarding the relevance of spatially bound inter-regional spillovers for the genesis of innovation in the EU, the analysis of the indigenous factors that condition their effects remains to be further explored. These interaction terms make it possible to test the indirect effect of both R&D and human capital investment as components of the regional economy's ability not only to produce (directly affect) but also to absorb (indirectly affect) external knowledge flows and 'translate' them into innovation.

FIGURE 5

All the estimated bivariate smooth functions are again highly significant (p-value < 0.001). The first graph (left-hand side) of Figure 5 depicts the results for spillovers from R&D activities and suggests that the effect of localised knowledge spillovers is highly differentiated depending on the local level of R&D spending.[16] For (very) low levels of internal R&D expenditure, external R&D activities do not appear to play a compensatory role; they do not exert a positive influence on local innovation. However, for intermediate levels of internal spending, WRD has a local positive effect on innovation until a certain threshold (of WRD). After this threshold is reached, a negative effect prevails. Finally, when internal R&D is sufficiently large, the WRD-innovation relationship changes again. It is flat for low/average levels of WRD and then increases sharply. Highly innovative regions surrounded by other technologically dynamic regions maximize innovative output because of strong complementarities between internal and external knowledge flows.

For human capital (right-hand side of the graph), the results are as follows. A 'critical mass' of external human capital is necessary to produce a positive effect on innovation when the internal

[16] Again, the estimated interaction term f_1 is not reported here because it is very similar to the estimation reported in the previous section.

endowment of human capital is limited. Conversely, for high levels of internal human capital, external human capital exerts a positive and monotonic effect on innovation. In addition, the effect of internal human capital changes with the level of human capital in neighboring regions. Although internal human capital does not affect innovation for low levels of WHK, it has a positive effect for intermediate levels of WHK. Finally, for higher levels of external human capital, the effect of internal human capital again becomes flat and does not affect innovation, suggesting that when the total availability of human capital (both internal and external) is very high, qualitative considerations (in terms of typologies of formal and informal skills) become more relevant drivers for innovation.

In summary, despite the complexity of the picture presented so far, these results suggest that by reinforcing both R&D and human capital investments, regions can not only reach the internal critical mass necessary to make these inputs fully productive but can also support the absorption of external knowledge. Another relevant insight is that when internal R&D expenditure is too small, shadow effects may prevail, and a very high level of extra-regional R&D may be detrimental for local innovation, diverting resources away from the regional economy.

3.4 Developed versus lagging regions

It is possible that the EU RKPF shows heterogeneous effects of R&D (and HK) on innovation. By testing this potential heterogeneity on the basis of a priori knowledge of the structural features of the regions, we can estimate a more realistic KPF model. Following this line of reasoning, the final section of the analysis aims to test whether regions that are eligible for the highest level of support from EU structural funds (i.e., the most disadvantaged regions in Europe whose GDP per capita is below 75% of the EU average[17]) show heterogeneous dynamics with respect to the other, historically richer and more developed, regions. Let us define

$$O1_r = \begin{cases} 1 \text{ if region } \in \text{ objective 1 group} \\ 0 \text{ if region } \notin \text{ objective 1 group} \end{cases},$$

and then the following model is estimated:

$$K_{r,t} = Z_t\theta_r + f_1(RD_{r,t}, O1_r) + f_2(HK_{r,t}, O1_r) + f_3(WRD_{r,t}, O1_r) + f_4(WHK_{r,t}, O1_r) + u_{r,t}.$$

This is a *binary-by-continuous* interaction model, allowing us to obtain two distinct non-parametric functions (one for Objective 1 and the other for non-Objective 1 regions) for each

[17]This group has historically identified the most backward and structurally disadvantaged regions of the European Union. The regions belonging to this category have remained the same since 1994. In fact, the lack of upward mobility for Objective 1/Convergence regions is one of the key criticisms for the EU Regional Policy. However, this categorisation of the EU regions offers an easy and straightforward means for identifying historically disadvantaged areas in Europe.

explanatory variable.[18]

FIGURE 6

Figure 6 confirms the hypothesis that R&D and HK produce very heterogeneous effects when comparing developed and disadvantaged EU regions. The estimated results show that the evidence discussed thus far is fundamentally unchanged when examining the most dynamic regions of the EU (left-hand section of figure 5). For these regions, all the smooth functions but that of WRD are again highly significant (p-value < 0.001) and the estimated functional forms are similar to those estimated above for all the regions. Conversely, the empirical evidence is completely modified for the sub-group of less developed regions (right-hand section). For these lagging regions, the only driver that remains statistically significant is external human capital (WHK). Internal human capital is almost significant (p-value$= 0.15$); it shows a threshold effect that is less accentuated than for the other regions, as the increasing part of the curve is flatter. Internal and external R&D, in contrast, do not appear to play any significant role (p-value equals to 0.28 and 0.78 respectively, and the shape is very flat and linear).[19] In this case, the proposed approach not only provides us with results with relevant policy implications but it is also much more informative than the corresponding parametric specification (Table 1, column (7)).[20] The most deprived and less developed regions of the European Union deserve special attention in the design of innovation policies given that some key 'regularities' in the genesis of regional innovation might not hold in these highly differentiated regional contexts.

4 Conclusions

This paper proposed an innovative approach to the estimation of RKPFs based on a semiparametric version of the random growth model. The 'random growth' parametric component of the model improves upon the standard fixed effects specifications (customary in the existing literature) by better accounting for endogeneity, especially as related to the endogenous selection of R&D and human capital into the most attractive areas (e.g., in terms of agglomeration, regional industrial structure, and infrastructure). The nonparametric part of the model makes it possible to estimate the unconstrained patent-inputs relationships and, to some extent, to relax additivity, uncovering relevant aspects and complexities of the genesis of innovation.

[18]Sometimes, in literature such kind of interactions are noted as $K_{r,t} = Z_t\theta_r + f_{1O1_r}(RD_{r,t}) + f_{2O1_r}(HK_{r,t}) + f_{3O1_r}(WRD_{r,t}) + f_{4O1_r}(WHK_{r,t}) + u_{r,t}$, (see e.g. Ruppert et al. 2003).

[19]These smooths are estimated to be straight lines and their confidence intervals vanish where they pass through zero. This is why smooths are subject to sum-to-zero identifiability constraints. If a smooth is estimated to be a straight line then it consequently has one degree of freedom, and there is no uncertainty where it passes through zero, so that the confidence interval must vanish at that point.

[20]Other answers for the lagging EU regions may come from the complementarities between the various innovation inputs and their interactions. A more general model can be for instance obtained by interacting the binary variable $O1_r$ with the two-dimensional splines previously introduced $f_1(RD_{r,t}, HK_{r,t})$, $f_2(RD_{r,t}, WRD_{r,t})$ and $f_3(HK_{r,t}, WHK_{r,t})$, i.e. $K_{r,t} = Z_t\theta_r + f_1(RD_{r,t}, HK_{r,t}, O1_r) + f_2(RD_{r,t}, WRD_{r,t}, O1_r) + f_3(HK_{r,t}, WHK_{r,t}, O1_r) + u_{r,t}$. Results from this specification are available upon request.

The empirical approach adopted in the paper, however, shares a number of relevant limitations with other similar work in the same stream of literature. First, it relies on patent intensity as a measure of innovation. This can only capture patented product innovation and completely overlooks innovations that are protected by secrecy (or other means) and all other (equally relevant) forms of process or organizational innovation. Second, the paper looks at geographical links as the key source of extra-regional knowledge flows and does not explicitly assess the role of alternative non-spatial proximities and networks in the genesis of innovation. These limitations should be kept in mind when interpreting the empirical results. However, the reliance on customary proxies and the inclusion of 'traditional' spatial channels of knowledge transmission maximize the comparability of our results with other pre-existing papers and clearly evidence the methodological improvements we provide. Even when based on 'standard' data and 'customary' innovation drivers, the proposed approach can reveal relevant dynamics previously overlooked in the empirical quantitative literature.

The paper has provided relevant insights, primarily from a methodological perspective. We first show that the random growth specification is not only statistically superior to the one- and two-way fixed effect model but also that it provides much more credible results. The omission of time-varying unobservables would produce a severe bias in the estimation of the RKPF. Second, concerning the nonparametric relationship between patents and their inputs, many relevant results have been provided. These results involve strong nonlinearities and threshold effects, complex interactions, and shadow effects that cannot be uncovered using standard parametric formulations. Third, we show the importance of allowing for heterogeneous relationships and, in particular, distinguishing between developed and lagging regions.

Keeping in mind the limitations underlined above, the empirical analysis also includes a number of results potentially relevant to EU policy makers. Perhaps the clearest result concerns the existence of an innovation trap for regions with very low levels of human capital and R&D. For these regions, investing marginally in such inputs would be wasting money. In particular, the return to R&D expenditure is maximized between 2% and 3% of regional GDP, whereas HK has a positive effect when at least 20% of the regional population has completed tertiary education. Moreover, R&D expenditure and human capital are highly complementary. Both are needed simultaneously to boost innovation, and investing in R&D does not appear to produce a positive effect on innovation for low levels of HK. These results appear to support the shift in the EU innovation strategy from an almost exclusive focus on R&D in the Lisbon Strategy to the Europe 2020 Strategy, which covers a broader set of dimensions such as the objective to increase the share of people aged 30-34 with a tertiary degree to 40% by 2020.[21] In addition, the debate on the reform of the EU Cohesion Policy for the 2014-2020 period, informed by the Barca Report (Barca 2009), has increased the policy emphasis on the socio-institutional framework conditions

[21] The Lisbon Strategy was launched in the year 2000 with 3% of the EU GDP as an overall target for R&D expenditure in all countries and regions. See e.g., http://ec.europa.eu/growthandjobs/pdf/COM2005_330_en.pdf http://ec.europa.eu/europe2020/index_en.htm.

that need to be in place to support innovation, particularly in lagging regions. The empirical results also shed new light on the relevant spatial effects. The exposure to inter-regional knowledge flows generated by R&D activities and HK is only beneficial after a certain threshold of such external knowledge, suggesting that peripheral regions might be at a disadvantage when it comes to relying on extra-regional resources. At the same time, however, shadow effects have also been documented since after another and higher threshold, external knowledge may be no more effective or even may be detrimental for innovation. In particular, the results suggest that largest concentrations of human capital in Europe may 'suck' resources away from their neighbors. This evidence has important implications because it supports the link between EU labour mobility and innovation policies, which the European Commission has only recently incorporated into its long-term strategies for growth and innovation (European Commission 2012).

Future works could adopt our approach and our primary ideas in order to explicitly account for additional knowledge-transmission mechanisms (alternative spillovers' channels) or more sophisticated measures of innovation (including both product and process innovation) by means of micro-data, for instance. Other methodological improvements in the estimation of a RKPF could consider fully non-separable nonparametric panel data models or semiparametric quantile models, both of which are ongoing theoretical lines of research.

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Appendix

A The econometric approach

This appendix details the identification and estimation of the semiparametric approach adopted in the paper. Let us consider the semiparametric model:

$$K_{r,t} = Z_t\theta_r + f_1(RD_{r,t}) + f_2(HK_{r,t}) + u_{r,t}$$

where f_1 and f_2 are smooth functions. This model can be viewed as a Generalised Additive Model, which was initially developed by Hastie and Tibshirani (1990). It is worth to note that, to date, there is an increasing amount of theoretical literature on non-parametric panel data estimators that aims to provide very general econometric set-ups such as the fully non-separable model (i.e., models of the type $Y_{i,t} = f(X^1_{i,t}, ..., X^k_{i,t}, \alpha_i, u_{i,t})$, where i is a generic index for the cross sectional units). However, despite the appeal of these models, they present substantial theoretical and computational difficulties, and the identification conditions arising in such models can be difficult to maintain. Indeed, Hoderlein and White (2012) focus on the identification of fully non-separable models. Although they find that a generalised version of differencing identifies local average responses, they also find that such a result is confined to the subpopulation of 'stayers' (Chamberlain, 1982), the population for which the explanatory variables do not change over time. This case does not correspond to our empirical framework. On the contrary, GAMs avoid the curse of dimensionality because each of the individual additive terms is estimated using a univariate smoother. GAMs are also easily interpretable, whereas fully non-separable models present problems of interpretability and do not present difficult identification problems (see below). Finally, and perhaps most importantly in the context of this paper, adopting a GAMs framework has a comparative advantage with respect to other semi-/non-parametric approaches in that it allows the straightforward introduction of the 'random growth' parametric part ($Z_t = (1, \lambda_t, t)$, $\theta_r = (\alpha_r, \delta, \gamma_r)$) to account for time-varying endogenous unobserved variables, while simultaneously allowing for the unconstrained effect of the main knowledge inputs.

A.1 Identification

The fixed effects parameters α_r can be treated as nuisance terms to be eliminated with a transformation or as parameters to be estimated. Considering the α_r as nuisance terms allows the number of parameters to be estimated to be significantly reduced. At the same time, this can produce serious identification problems. Consider, for example, the one-way fixed effects specification. By differencing, we obtain

$$(K_{r,t} - K_{r,t-1}) = f_1(RD_{r,t}) - f_1(RD_{r,t-1}) + f_2(HK_{r,t}) - f_2(HK_{r,t-1}) + (u_{r,t} - u_{r,t-1}) .$$

Azomahou and Mishra (2008) argue that differencing may be useful if the researcher is interested in estimating a feedback effect through the functions $f_1(RD_{r,t-1})$ and $f_2(HK_{r,t-1})$, and they estimate such an equation directly using GAM. There are some difficulties, however, with this approach, which are discussed in Su and Ullah (2010). The first difficulty is that, by definition, the smooth function of the contemporaneous term $f_1(RD_{r,t})$ is equal to that of the lagged term $f_1(RD_{r,t-1})$. We thus have two estimators for the same function arousing the difficulty to choose the good one. Often this problem has been handled by using the simple average of the two estimators, possibly providing the best approximation for the true function. Secondly, by differencing doubles the nonparametric components to be estimated. A third difficulty derives from the fact that some components of the functions f_1 and f_2 may not be fully identified. As argued by Su and Ullah (2010), if, for example,

$$f_1(RD_{it}) = a + m(RD_{r,t}),$$

then differencing does not allow for the identification of $f_1(RD_{it})$. Eventually, only $m(x_{it})$ can be identified. Adopting a fixed effects transformation to remove the individual effects, as is standard in the linear panels, is even more problematic:

$$\begin{aligned}\left(K_{r,t} - \frac{1}{T}\sum_{t=1}^{T} K_{r,t}\right) &= f_1(RD_{r,t}) - \frac{1}{T}f_1(RD_{r,1}) - \frac{1}{T}f_1(RD_{r,2})+, ..., -\frac{1}{T}f_1(RD_{r,T}) + \\ & f_2(HK_{r,t}) - \frac{1}{T}f_2(HK_{r,1}) - \frac{1}{T}f_2(HK_{r,2})+, ..., -\frac{1}{T}f_2(HK_{r,T}) + \\ & + \left(u_{r,t} - \frac{1}{T}\sum_{t=1}^{T} u_{r,t}\right).\end{aligned}$$

A possible way to estimate the random growth model $Z_t = (1, \lambda_t, t)$, $\alpha_r = (\alpha_{r1}, \alpha_2, \alpha_{r3})$ for the linear model is to combine the first difference transformation and the (two-way) within transformation. First differences are initially applied to obtain a two-way fixed effects model, and then the fixed effects transformation is used to obtain the differenced equation (Wooldridge, 2010, p. 376-377). In the semiparametric framework presented above, this approach does not appear to be directly applicable while a feasible approach consists of estimating $K_{r,t} = Z_t\alpha_r + f_1(RD_{r,t}) + f_2(HK_{r,t}) + u_{r,t}$ directly by including the fixed effects parameters in the parametric part of the level equation, as in Mammen et al. (2009), Ordás Criado et al. (2011), Mazzanti and Musolesi (2013), and Longhi et al. (2013). This approach allows the identification of all of the components of $K_{r,t} = Z_t\theta_r + f_1(RD_{r,t}) + f_2(HK_{r,t}) + u_{r,t}$, and the relatively high number of time series observations (T=10) in our data set allows for the recovery of all parameters (and functions) of interest.

A.2 Estimation

The estimation is performed by adopting a method recently developed by Simon Wood using the GAM ( ) function of the mgcv R package (Wood, 2014). The estimation is based on the maximisation of a penalised likelihood by penalised iteratively reweighted least squares (P-IRLS) (Wood, 2004). This method provides an optimally stable smoothness selection method that presents some advantages compared with previous approaches, such as modified backfitting (Hastie and Tibshirani, 1990) or the Smoothing Spline ANOVA. Smoothing parameter estimation and reliable confidence interval calculation are difficult to obtain with modified backfitting, whereas Smoothing Spline ANOVA provides well-founded smoothing parameter selection methods and confidence intervals with good coverage probabilities, but at high computational costs. To avoid these problems, Wood (2000), among others, suggests representing GAM using penalised regression splines but leaves unresolved a number of practical problems, including convergence and numerical stability. Wood (2004) further provides an optimally stable smoothness selection method. The choice of the basis to represent the smooth terms and the selection of the smoothing parameters is presented in Wood (2003, 2006a, 2008). Penalised Regression Splines are adopted as a basis to represent the univariate smooth terms (Wood, 2003, 2006ab), whereas for bivariate smooth functions such as $f(RD_{r,t}, HK_{r,t})$, we use the scale-invariant tensor product smooths proposed by Wood (2006c) (see also Augustin et al., 2009, Longhi et al. 2014). The smoothing parameters are selected directly using the so-called outer iteration (Wood, 2008), which has been shown to be computationally efficient and stable. The smoothing parameter values are selected by the GCV (Generalised Cross validation) criterion,[22] and the statistical inference is made by computing 'Bayesian p-values'. These values appear to have better frequentist performance (in terms of power and distribution under the null hypothesis) than the alternative strictly frequentist approximation (Wood, 2006ab).

[22]Because the GCV may present a tendency to over fit, we have increased the amount of smoothing by correcting the GCV score by a factor $\delta = 1.4$, which can correct the over-fitting without compromising model fit (Kim and Gu, 2004).

B Contour plots for the bivariate smooth functions

The estimated bivariate smooth functions (depicted with 3d surface plots in Figures 3 and 5 above) can be also represented using contour plots. A countour plot is a graphic representation of the relationship among three numeric variables in two dimensions. Two variables are for X and Y axes, and a third variable Z is for contour levels. It is possibly less intuitive than a surface 3d plot but allows, for instance, the visualisation of confidence bands. These contour plots are obtained by using the plot.gam() function available in the *mgcv* R routine. The left-hand side of the figures below gives a heatmap, with overlaid contours. Contour plots are produced with the X axis labelled with the first covariate name and the Y axis with the second covariate name. The main title of the plot is something like *te(var1,var2,edf)*, *te* indicating the estimated tensor product smooth, *var1,var2* are the variables of which the smooth is a function, and the *edf* are estimated degrees of freedom for the estimated smooth term. The *edf* measures the degree of nonlinearity of the estimated smooth function, and when it is equal to 1, this corresponds to a linear relationship.The right-hand side of the figures is a contour plot which provides information on the estimator variability by overlaying contour plots with their confidence bands. The black dots in both plots represent the scatterplot of the observations on the *var1* - *var2* plane.

FIGURE 7
FIGURE 8
FIGURE 9

Table 1: Parametric estimation of the RKPF

Patents per capita	(1)	(2)	(3)	(4)	(5)	(6)	(7)
R&Dspending	0.260	0.00481	0.600***	0.5834**	1.088	1.857	0.309
	(0.183)	(0.206)	(0.208)	(0.201)	(1.469)	(1.346)	(0.287)
Human capital	1.397***	0.0382	0.508***	0.529**	0.560**	-0.768	0.546**
	(0.195)	(0.204)	(0.162)	(0.171)	(0.260)	(0.826)	(0.246)
Neighborhood R&D				2.740			2.356
				(1.858)			(2.240)
Neighborhood HK				-0.855			-0.573
				(1.327)			(1.772)
HK/R&D interaction					-0.163	0.094	
					(0.477)	(0.500)	
Square R&D						-2.864***	
						(0.680)	
Square HK						0.446	
						(0.343)	
R&D Objective 1							1.188***
							(0.206)
HK Objective 1							0.437
							(0.142)
Neigh. R&D Obj. 1							2.677
							(3.032)
Neigh. HK Obj. 1							-1.609
							(1.115)
Adj. R^2	0.909	0.925	0.948	0.948	0.948	0.948	0.948
Number of obs.	1638	1638	1638	1632	1638	1638	1632
Individual FE	X	X	X	X	X	X	X
Indiv. and time FE		X	X	X	X	X	X
Random growth			X	X	X	X	X

All variables in log. Driscoll and Kraay's (1998) standard errors, robust to heteroscedasticity and serial and spatial correlation, between brackets. $^*: p-value < 0.1$, $^{**}: p-value < 0.05$, $^{***}: p-value < 0.01$. F-test statistics testing individual fixed effects (column (1)) versus individual and time fixed effects (column (2)): 36.483^{***} ($p-value < 2.2e-16$). Individual and time fixed effects (column (2)) versus random growth model ((column (3)): $F = 4.7767^{***}$ ($p-value < 2.2e-16$). SquareR&D$= 0.5 * (\log(R\&D_{r,t}))^2$; SquareHK$= 0.5 * (\log(HK_{r,t}))^2$.

Column (7): VAR Obj.1 $= VAR * O1_r$ while VAR indicates $VAR * (1 - O1_r)$.

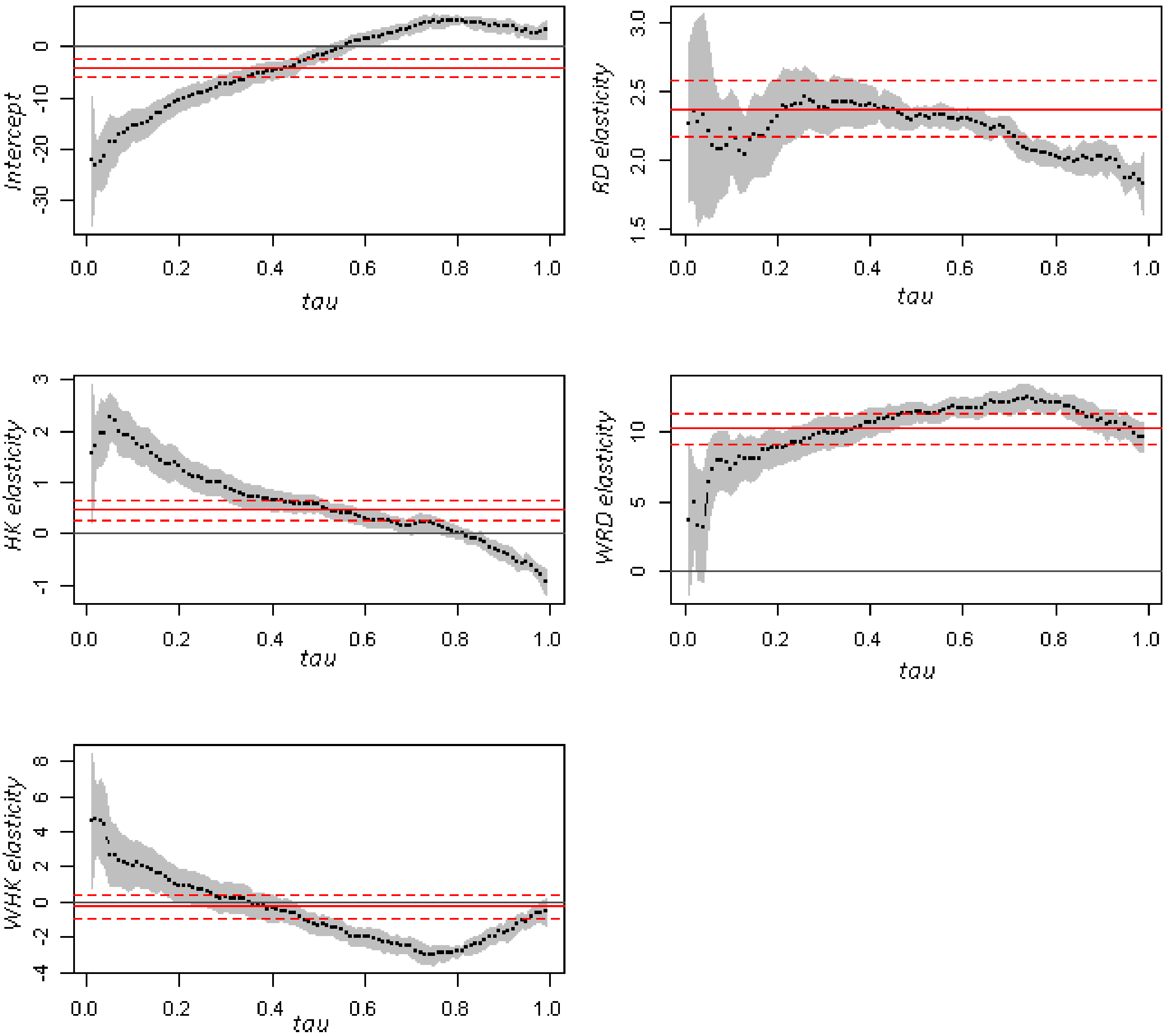

Figure 1: Quantile regression. Estimates of the effects of the main covariates (elasticities) as a function of the quantiles τ (using percentiles) of the conditional distribution of patents per capita. The dotted line shows quantile regression estimates with 95% confidence bands. The horizontal line shows the least square estimates with 95% confidence bands (dashed lines).

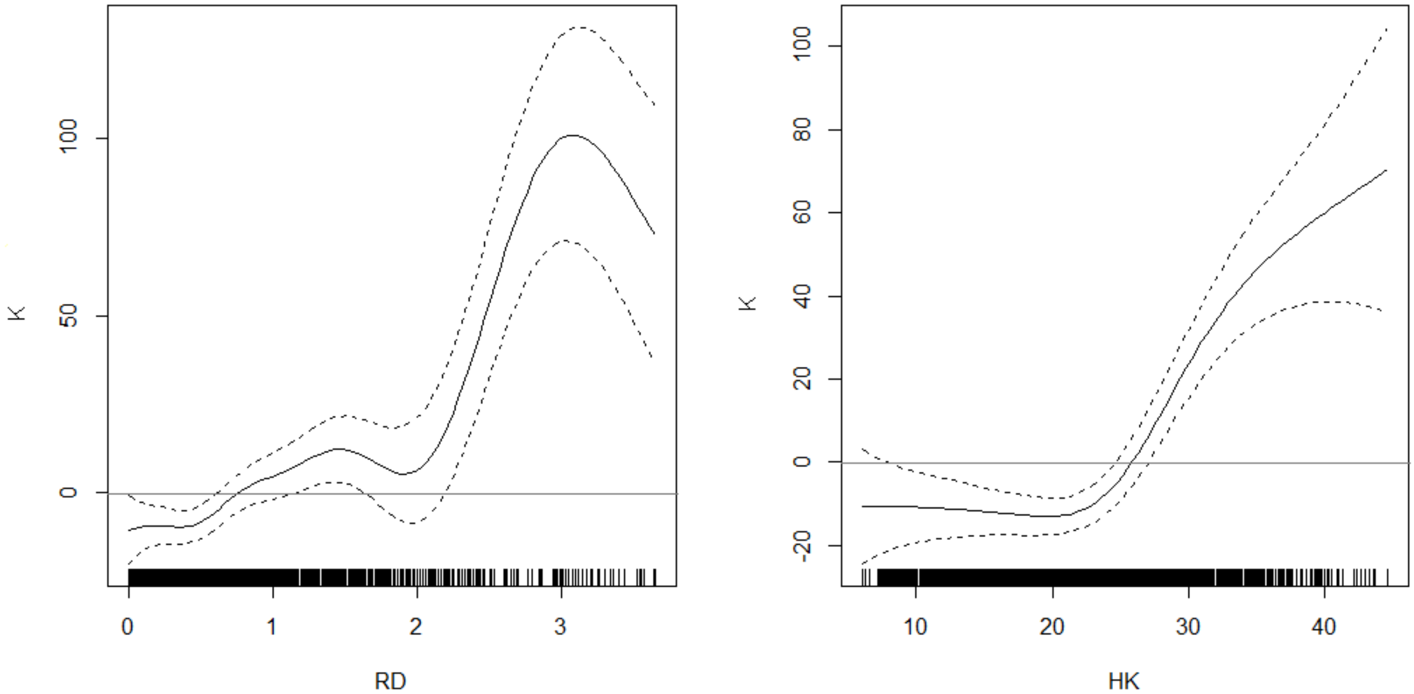

Figure 2: The effect of R&D (RD) and Human Capital (HK) on regional patent intensity (K). The continuous line shows the estimate of the smooth; the dashed lines represent 95% confidence bands. The black box at the bottom of the plots represents the frequency of the observations over the range of the explanatory variable. This allows to identify ranges with sparse observations.

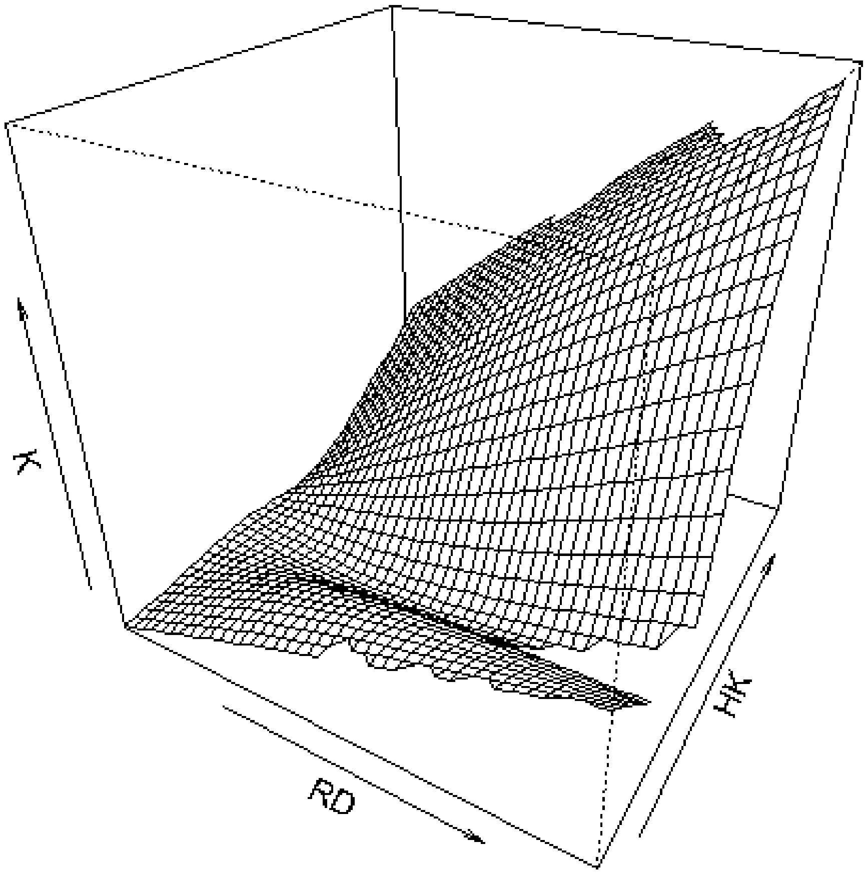

Figure 3: The joint effect of R&D and HK on regional patent intensity K, $f(RD_{r,t}, HK_{r,t})$. 3D surface plot.

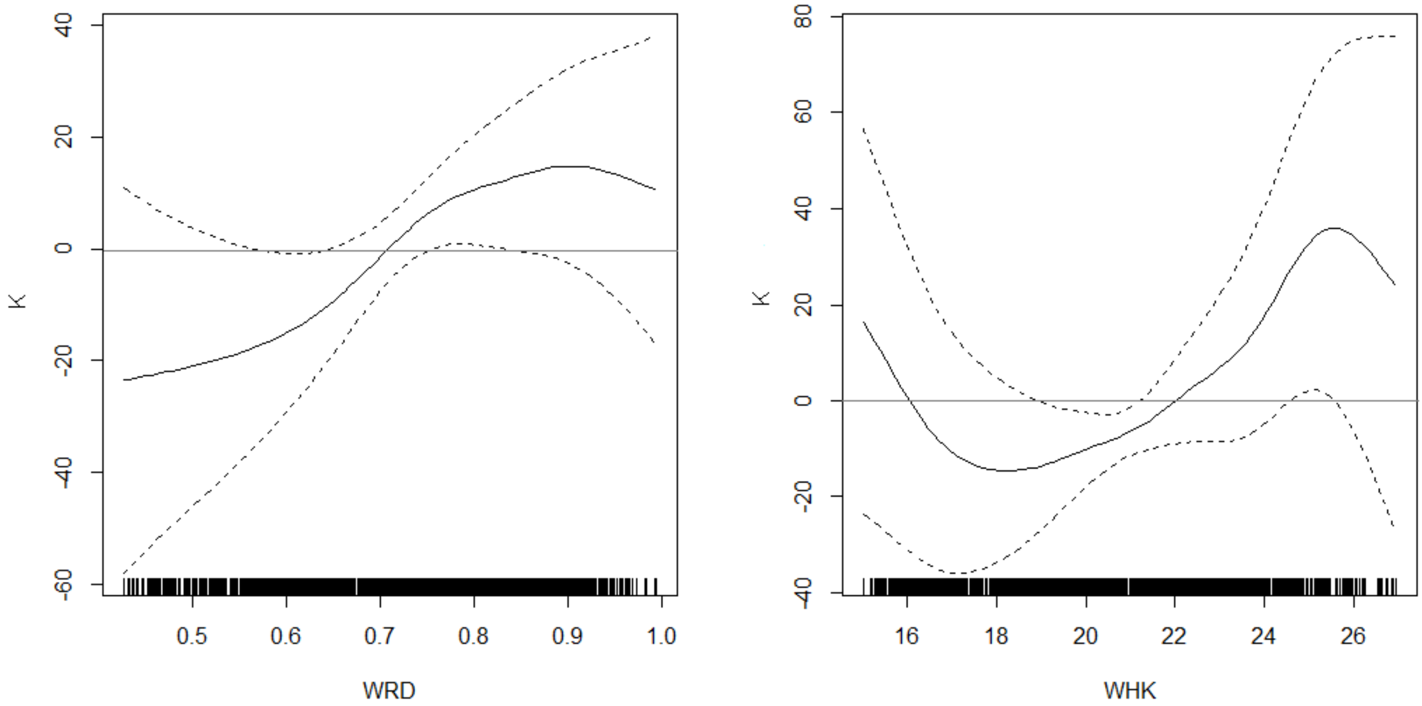

Figure 4: Geographic spillovers from R&D (WRD) and Human Capital (WHK) on regional patent intensity (K). The continuous line shows the estimate of the smooth; the dashed lines represent 95% confidence bands. The black box at the bottom of the plots represents the frequency of the observations over the range of the explanatory variable. This allows to identify ranges with sparse observations.

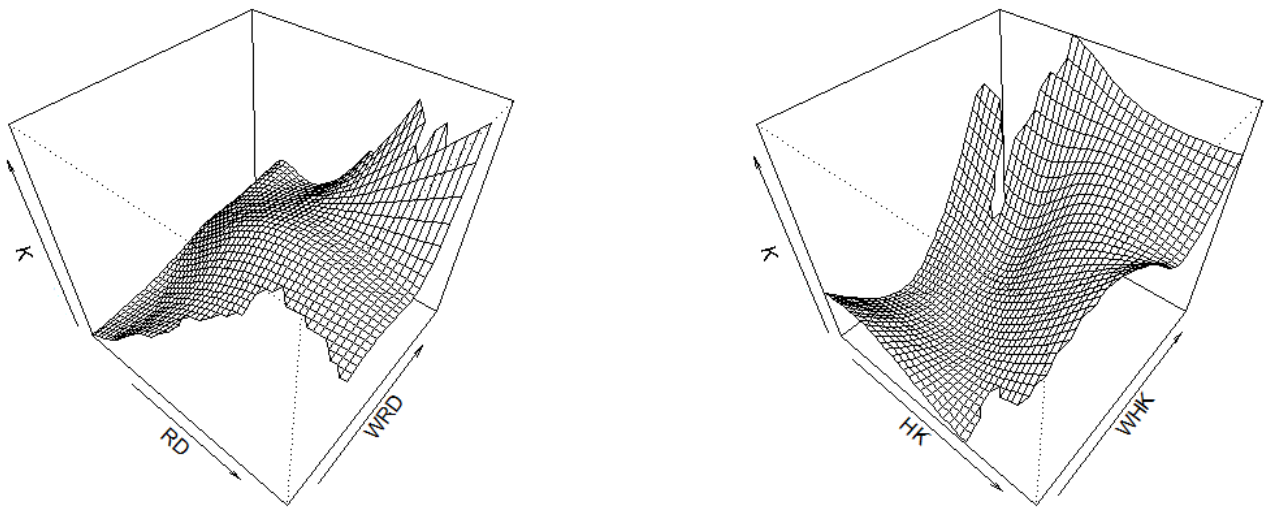

Figure 5: Interaction between internal R&D (RD) and spillovers from neighbouring regions R&D (WRD) on regional patent intensity (K), $f_2(RD_{r,t}, WRD_{r,t})$ [left] and interaction between internal human capital (HK) and spillovers from neighbouring regions human capital (WHK) on regional patent intensity (K) $f_3(HK_{r,t}, WHK_{r,t})$ [Right]. 3D surface plots.

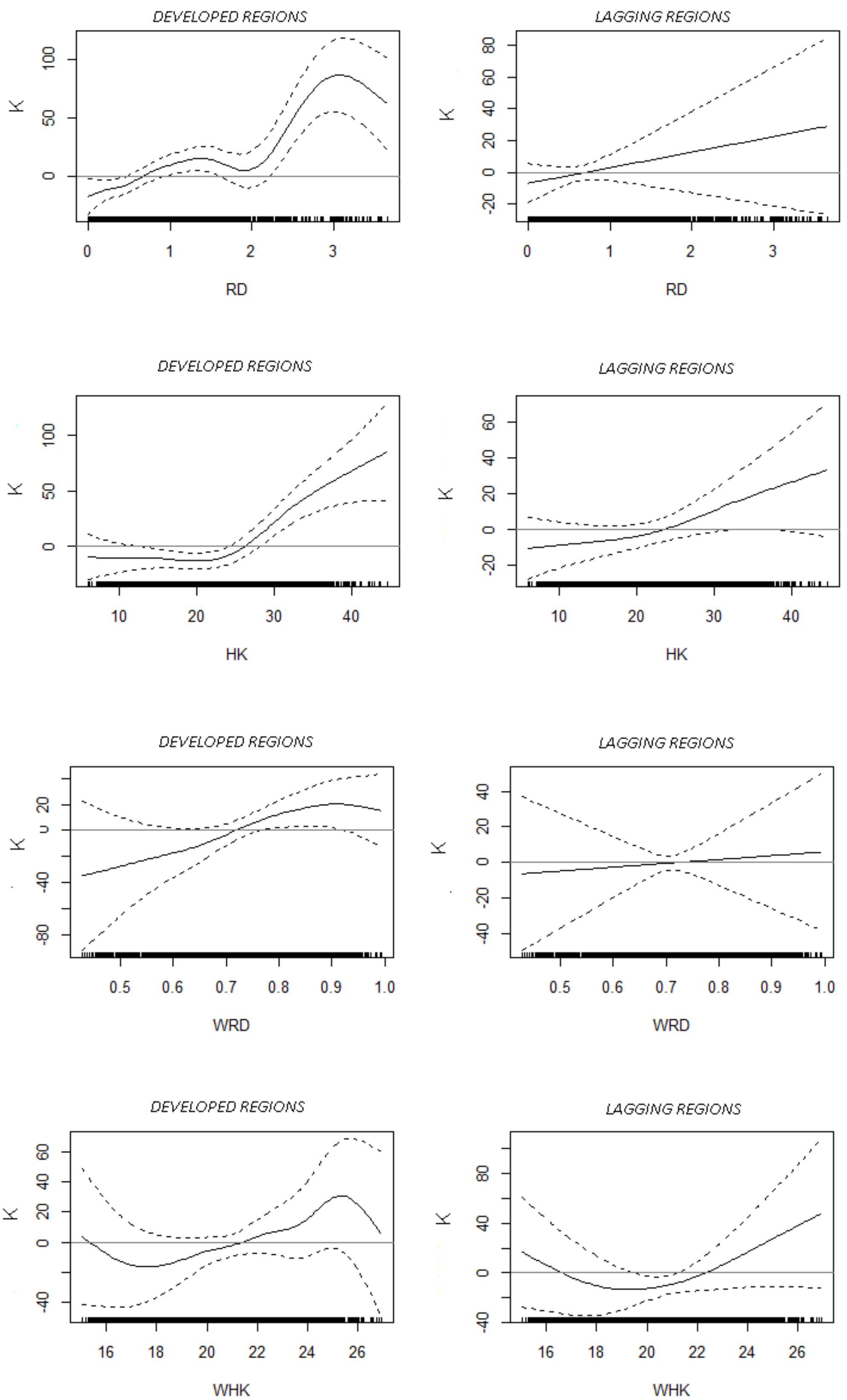

Figure 6: Developed vs. lagging regions. The continuous line shows the estimate of the smooth; the dashed lines represent 95% confidence bands. The black box at the bottom of the plots represents the frequency of the observations over the range of the explanatory variable. This allows to identify ranges with sparse observations.

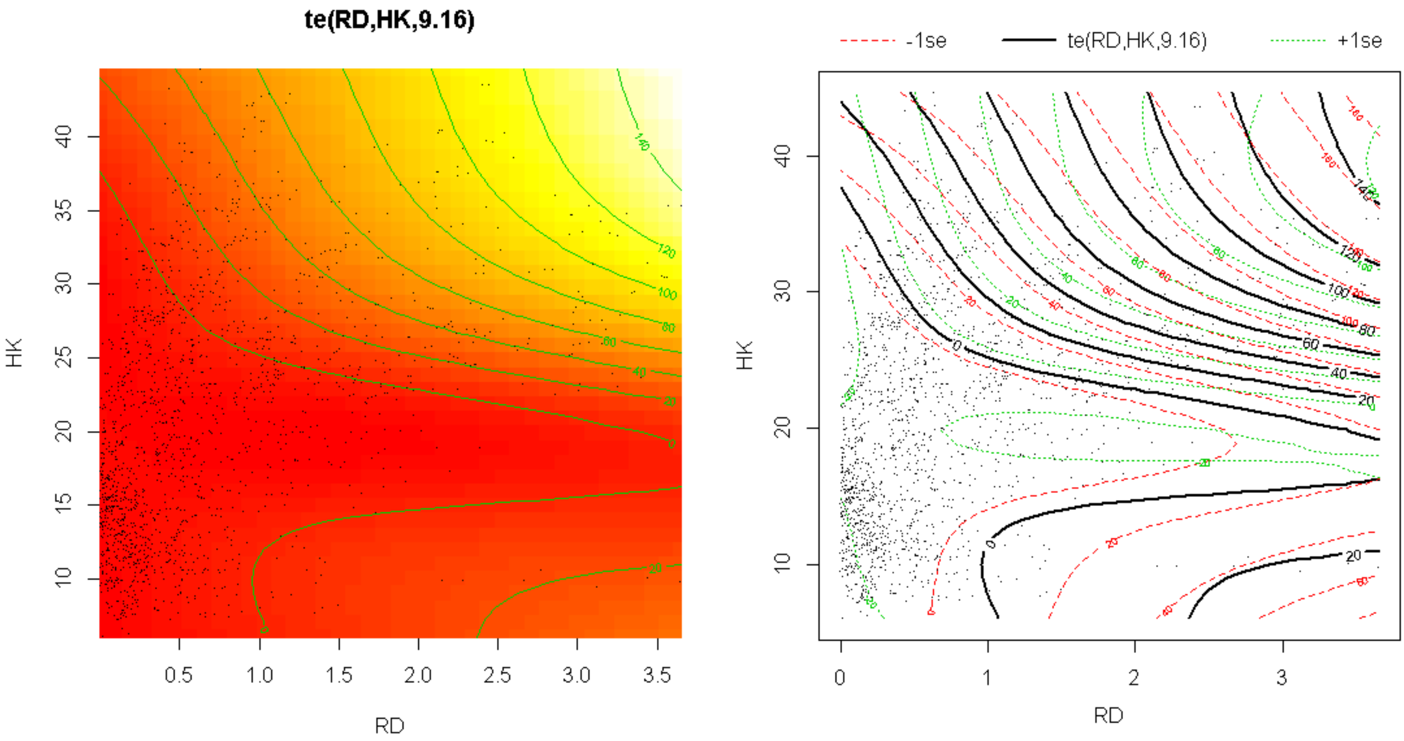

Figure 7: The joint effect of R&D and HK, $f(RD_{r,t}, HK_{r,t})$. Contour plots.

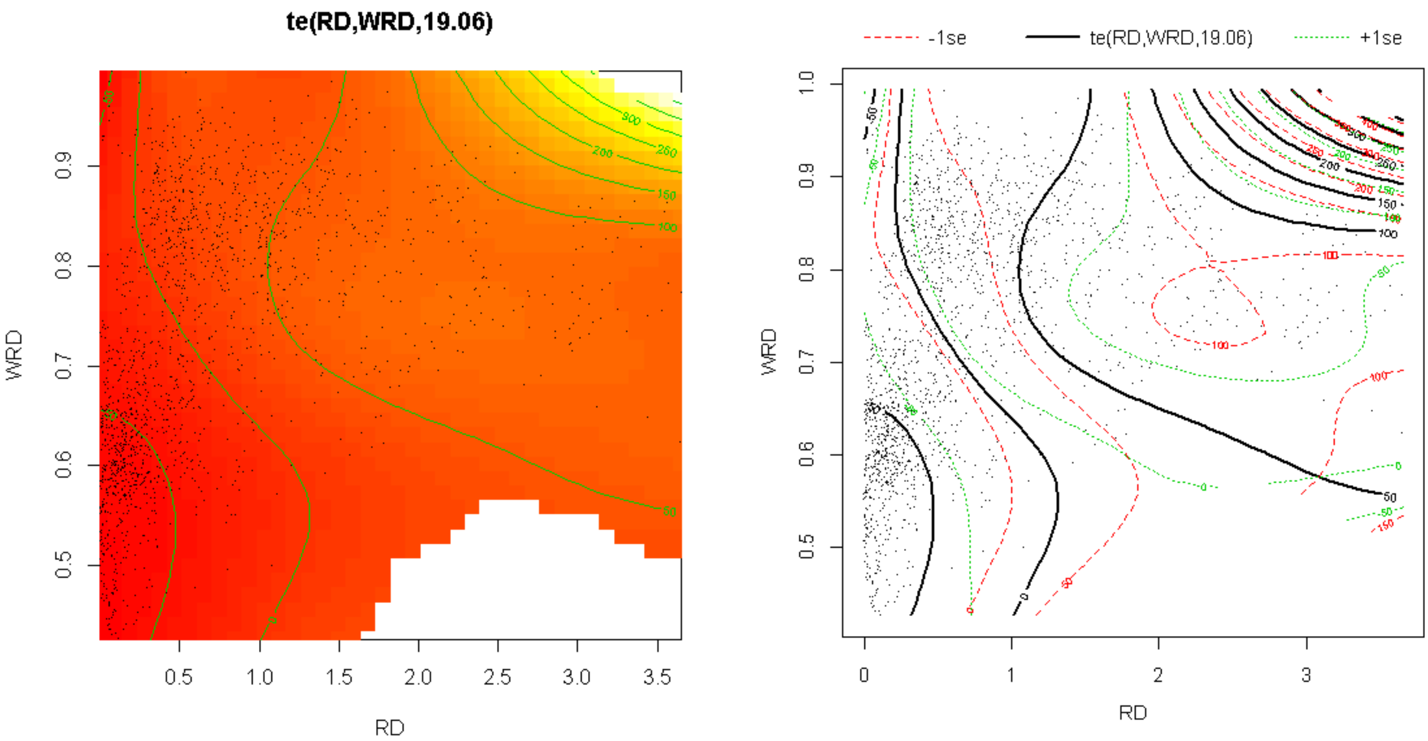

Figure 8: Interactions: $f_2(RD_{r,t}, WRD_{r,t})$. Contour plots.

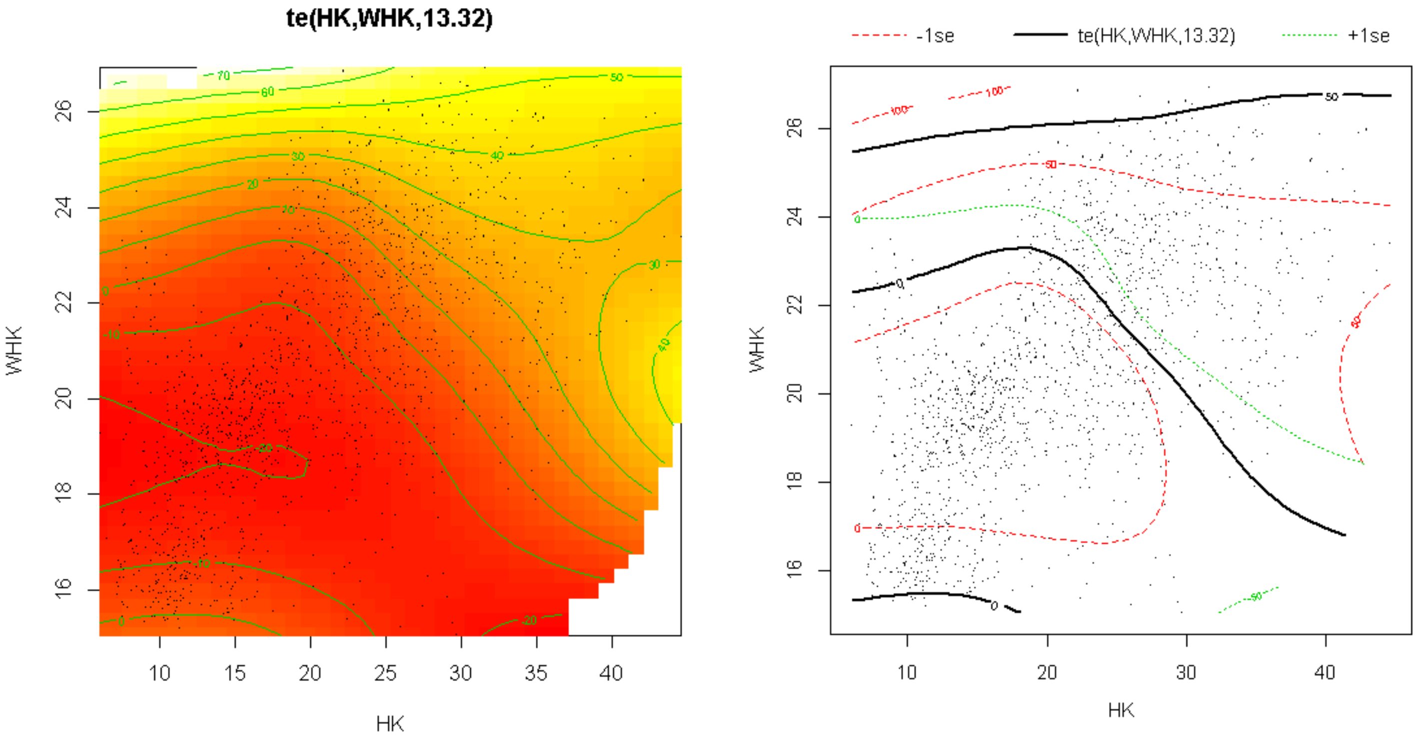

Figure 9: Interactions: $f_3(HK_{r,t}, WHK_{r,t})$. Contour plots.