Threshold Effects From Absorptive Capacity and the Effectiveness of Innovation Policy

Daniela Strube

Department of Economics, Johannes Gutenberg University Mainz,
Jakob-Welder-Weg 4, 55128 Mainz, Germany; Telephone: +49 6131 3923232;
Email: daniela.strube@uni-mainz.de

Abstract

In this paper, absorptive capacity effects of human capital on innovation are introduced into the endogenous growth model. In order to empirically test their relevance, a spatial endogenous sample splitting estimator is proposed. With the help of the proposed model and estimation strategy, we are able to empirically demonstrate the relevance of absorptive capacity effects on innovation controlling for the direct impact of human capital. Accounting for threshold effects sheds lights on relevant absorptive capacity-induced differences in R&D productivity patterns across Europe which would be masked by standard estimation procedures. Moreover, absorptive capacity significantly affects the geographical impact and the relative magnitude of the spatial effects from regional R&D policy. These results suggest consequences for the economic viability of R&D in lagging areas and the spatial configuration of relative regional development patterns.

1 Introduction

Economic theory suggests that the effectiveness of pecuniary R&D policy and knowledge spillover absorption is associated with a series of structural characteristics of a region, in particular relating to human capital endowments (Rodríguez-Pose, 2001). This function of human capital facilitating the productive transformation of R&D inputs into innovation outcomes is generally referred to as absorptive capacity. While the instrumental role of regional absorptive capacity in fostering innovation performance is widely acknowledged, little attention has been paid to modelling the mechanism of how absorptive capacity stimulates innovation.

The principal contribution of this paper refers to suggesting a simple approach for explicitly introducing absorptive capacity into the endogenous growth model. This is done in a theoretically consistent way by taking account of the sequential nature of the relationship between absorptive capacity and other R&D

inputs. In this way, it also allows for separating the absorptive capacity effect of human capital from its direct impact on innovation. In order to empirically test the role of indirect human capital effects, an intuitive and robust estimation strategy is suggested by means of a spatial endogenous sample splitting estimator.

With the help of the proposed model and estimation strategy, we are able to empirically demonstrate the relevance of absorptive capacity effects on innovation controlling for the direct impact of human capital. The estimation results show that the absorptive capacity channel matters for innovation performance by stimulating the productivity of R&D investment and knowledge spillover assimilation. Hence, absorptive capacity endowments may have significant consequences for the economic viability of R&D in lagging regions.

Secondly, accounting for threshold effects sheds lights on relevant absorptive capacity-induced differences in R&D productivity patterns across Europe which would be masked by standard estimation procedures. The results add to the existing literature in demonstrating that the relatively low absorptive capacity endowments in Eastern and Southern European regions are not only a descriptive property of these areas, but have a causal effect on innovation by triggering lower productivity rates of R&D investment and knowledge spillover assimilation.

Finally, it is found that absorptive capacity significantly affects the geographical impact and the relative magnitude of the spatial effects from regional R&D policy. Hence, location in the vicinity of regions which themselves are better equipped for absorbing external knowledge increases both the likelihood of being exposed to spillovers as well as their magnitude. Consequently, not only a region's internal endowment, but also the level of absorptive capacity of its neighbouring areas, matter for effective spillover assimilation. These findings suggest consequences for the spatial configuration of regional development patterns.

This paper proceeds as follows. In Section 2, the theoretical model of absorptive capacity effects of human capital is introduced. The empirical model and the data are presented in Section 3. Section 4 outlines the estimation strategy and the econometric method while Section 5 presents the estimation results focusing on spatial dynamics and providing s series of robustness checks. Section 6 concludes.

2 Theoretical model

A major development in the study of innovation policy refers to the recognition of the role of geography (Audretsch and Feldman, 2003; Krugman, 1991a) which has led to an increasing focus on the regional level, both in theoretical and empirical analysis (Cooke et al., 2007). It has been discovered that innovative activity is path-dependent and strongly clusters in space (Redding, 2002). Empirically, this is evident from the clear core-periphery pattern of innovation performance in Europe (Table 1 on page 7).

Economic theory suggests that structural characteristics of a region are instrumental in explaining its innovation performance (Rodríguez-Pose, 2001). The latter are conventionally subsumed under the heading of absorptive capacity. Different forms of human capital are most frequently associated with generating such absorptive capacity (Cohen and Levinthal, 1990). The theoretical concept of absorptive capacity has been prominently brought forward by Cohen and Levinthal (1990), originally as a contribution to firm organization theory. Later it has been applied to more aggregate contexts, including regions (Caragliu and Nijkamp, 2011; Roper and Love, 2006; Kallio et al., 2010). Because of its function of linking R&D inputs to innovative outcomes, it seems crucial to understand the determinants and effects of absorptive capacity. While it is rather intuitive that sufficient and suitable human capital is necessary for transforming R&D investment into innovation, effectively making use of knowledge spillovers may equally depend on specific complementary knowledge embodied in human capital (Cohen and Levinthal, 1990).

Hence, the theoretical proposition of absorptive capacity facilitating the effectiveness of R&D inputs is theoretically appealing and firmly based in the academic literature and in policy-making. Little attention, however, has been paid to formally modelling the mechanism of how absorptive capacity stimulates innovation. This paper offers a simple extension of the knowledge production function that explicitly introduces absorptive capacity into the endogenous growth model.

While endogenously accounting for human capital has been a central advance in growth theory, conventional endogenous growth models typically consider human capital only as a direct determinant of the knowledge stock and through the latter, as a driver of economic growth. The theoretical framework of this paper offers a conceptually relevant addition to the standard framework by allowing for indirect effects of human capital via its impact on the productivity of R&D inputs.

Following Romer (1990), a simple output function, for region j[1],

$$Y_j = A_j K_j^{\alpha} L_j^{1-\alpha}, \tag{1}$$

is considered. Capital, K, and labour, L, are characterised by constant returns while knowledge production A is subject to increasing returns. Moreover, in contrast to traditional growth models, it refers to an endogenous determinant of output. In his original model, Romer (1990) proposes a linear relationship between technological progress and the R&D inputs, human capital, H, and the existing knowledge stock, A,

$$\dot{A} = \delta H A. \tag{2}$$

An increase in the number of researchers or in the stock of knowledge available to a region leads to a proportional rise in knowledge production and, thus, in economic growth. However, Jones (2005) demonstrated that this proposition is incompatible with empirical evidence and modified Romer's model accordingly to account for the productivity parameters of H and A.

[1] The subscript is suppressed in the following.

Hence, growth of the stock of knowledge in Jones' model is given by

$$\dot{A} = \delta H^{\beta} A^{\rho} R^{\lambda} \tag{3}$$

with β, ρ and λ denoting the productivity parameters of the R&D inputs respectively. In Eq. (3), physical R&D inputs R are considered in addition to human capital and the knowledge stock.

In this paper, an alternative specification of the knowledge production function is proposed that explicitly models absorptive capacity within an endogenous growth framework and thus, postulates indirect effects of human capital on the productivity parameters of R&D inputs. In particular, we suggest lifting the constraint of constant returns to R&D inputs and allowing them to be affected by absorptive capacity, as constituted by human capital, H,

$$\dot{A} = \delta H^{\beta} A^{\rho} R^{\lambda} \tag{4}$$

with

$$\rho = \rho(H) \tag{5}$$

and

$$\lambda = \lambda(H), \tag{6}$$

and thus, contrasting this absorptive capacity function of human capital from its direct innovation effect, β.

This general proposition a priori accomodates any theoretically consistent functional form for ρ and λ. Introducing a threshold effect in the impact of human capital on the productivity parameters of R&D inputs and knowledge resources explicitly embraces the sequential logic of absorptive capacity by postulating that first a minimum level of human capital is required for allowing a region to efficiently transform R&D and knowledge inputs into innovation. Hence, the productivity parameters of the available knowledge stock and R&D inputs are allowed to vary depending on a critical level of absorptive capacity endowments. We obtain the following functional form from applying a threshold condition to a log-transformed version of Eq. (4),

$$\begin{aligned} \log \dot{A} &= \log \delta + \beta \log H + \rho_{H \le \gamma} \log A_{H \le \gamma} + \rho_{H > \gamma} \log A_{H > \gamma} \\ &\quad + \lambda_{H \le \gamma} \log R_{H \le \gamma} + \lambda_{H > \gamma} \log R_{H > \gamma}, \end{aligned} \tag{7}$$

with γ denoting the threshold value.

As stated in Eqs. (4-6) or Eq. (7) when relying on the threshold assumption, the model allows human capital to influence innovation both directly via β and indirectly via its effect on the productivity parameters of other R&D inputs and the knowledge stock, λ and ρ. If $\rho_{H \le \gamma}$and $\rho_{H > \gamma}$ as well as $\lambda_{H \le \gamma}$and $\lambda_{H > \gamma}$ in Eq. (7) were equal, the indirect effect of human capital would not be relevant and Jones' original model would be obtained. Hence, the proposed model nests the conventional specification of the knowledge production function and is, thus, compatible with existing theory.

By analysing human capital from an absorptive capacity perspective, any singular focus on a concept of human capital as a complementarity to other R&D inputs is challenged. Rather it is suggested to extend this standard framework by adding a sequential relationship of human capital being a prerequisite for the effective employment of R&D inputs and knowledge resources. In this way, we suggest a simple approach for modelling absorptive capacity explicitly and consistently with its theoretical concept in the endogenous growth framework. In Section 3.1, an empirical approach for estimating the impact of the proposed absorptive capacity channel is offered.

3 Empirical model and data

3.1 Empirical model

The empirical model is directly derived from the theoretical framework. The empirical approach departs from several related contributions (i.e. Akcomak and ter Weel, 2009) by explicitly accounting for knowledge spillovers. Since such a spatially interdependent modelling approach is often absent from empirical papers drawing on structural endogenous growth models and since knowledge spillovers might in practice be of particular relevance to lagging areas, we will focus on estimating the productivity parameter for those parts of the knowledge stock, A, that stems from knowledge spillovers. The productivity parameter ρ for knowledge spillovers is modelled in terms of the spatial dependence parameter of the spatial lag of innovation activity, $W\dot{A}$. A useful feature of this approach refers to the parameter space for ρ being bound between 0 and 1 for row-normalised weights matrices. This is consistent with the standard assumptions for the productivity parameter in the knowledge production function (Abdih and Joutz, 2006). Other R&D inputs are proxied by focusing on R&D investment.

The suggested modelling approach allows for testing for threshold effects in the impact of human capital on the productivity of R&D inputs and knowledge spillovers. Hence, the empirical model is based on the threshold specification of the structural model as stated in Eq. (7) in Section 2. It explains innovation outcomes, $\dot{A}$, in terms of R&D investment, R, and knowledge spillovers, $W\dot{A}$, which are conditioned by the level of absorptive capacity, L_A, as well as a set of control variables, C,

$$\begin{aligned} \log \dot{A} \quad = \quad & \alpha + \beta \log H + \rho_{H\leq\gamma} \log W\dot{A}_{H\leq\gamma} + \rho_{H>\gamma} \log W\dot{A}_{H>\gamma} \\ & + \lambda_{H\leq\gamma} \log R_{H\leq\gamma} + \lambda_{H>\gamma} \log R_{H>\gamma} + \log C\theta + u. \end{aligned} \tag{8}$$

Hence, the two R&D input variables are split into two regimes, each based on whether absorptive capacity is below or above the endogenously estimated threshold value, γ.

3.2 Data and choice of variables

The data comprises 251 European regions covering the 27 members of the European Union, hence including the 10 New Member States that joined the Union in 2004. The regions are defined according to the Nomenclature of Territorial Units for Statistics (NUTS) at the second highest level of aggregation (NUTS 2) except for Belgian regions and London which are aggregated to the highest level (NUTS 1). The data has been obtained from the Statistical Office of the European Communities, Eurostat. All data refers to the year 2007[2], except indicated otherwise.

For calculating the spatial lag, a weights matrix has been employed that attributes equal weights to the 11 nearest neighbours of a region. The latter are obtained from calculating inverse distances between centroids of the regions in the sample. This procedure was chosen since it minimises the impact of location at the borders of the sample. It implies that an epidemic model of knowledge diffusion is assumed. However, criticism voiced by advocates of hierarchical models (Caniels, 1996) is accounted for by including absorptive capacity in the model and thus, explicitly considering the readiness of regions for using knowledge spillovers. According to the convention, the weights matrix has been row-normalised.

Innovation outcomes are measured by means of patents per capita. Patent data refers to a very common proxy for innovation output (Griliches, 1990). Nonetheless, it is an intrinsically imperfect measure due to its narrow focus on innovation output that can be standardised (Griliches, 1990). Often this kind of innovation is conducted by relatively sizable firms (Caragliu and Nijkamp, 2011). Moreover it is much more common in manufacturing than in services (Hipp and Grupp, 2005). However, it may be argued that patents constitute the best available measure of innovation that is firmly grounded in economic literature. In order to smoothen the data and to avoid capturing outliers, we calculated an average of patents per million inhabitants from 2006 and 2007. Table 1 indicates the existing disparities in innovation performance among European regions.

R&D investment is measured by gross expenditure on R&D as a percentage of GDP and thus, covers all sectors: business, government, higher education and private non-profit R&D. It is a standard measure, widely applied in academic literature as well as in policy-making. It has been lagged by two years in order to account for time lags in the R&D process.

Knowledge spillovers are measured in terms of the spatial lag of patenting outcomes in neighbouring regions. Credibly measuring knowledge spillovers has been a profound challenge ever since the onset of the related literature (Krugman, 1991b). Drawing upon the spatial lag refers to an alternative that is measuring knowledge which is theoretically available to a region. It is precisely not capturing externally generated knowledge that is actually used by the recipient region. However, not accounting for the actual use of knowledge

[2] Since the estimation approach is essentially cross-sectional, potential cyclical effects cannot be accounted for. Extending the framework to longitudinal data would be an interesting area for future research, but might be severely restricted by data shortages.

	Mean	Standard deviation	Minimum	NUTS code and name of region (minimum)	Maximum	NUTS code and name of region (maximum)
Patents per capita (million inhabitants)	78.948	99.806	0.181	RO31 - Sud-Muntenia	530.184	DE11 - Stuttgart
R&D investment	1.372	1.557	0.080	BG32 - Severen tsentralen; PL33 - Swietokryzskie	5.760	DE91 - Braunschweig
Knowledge spillovers	100.854	90.790	1.300	RO32 - Bucuresti - Ilfov	408.672	DE14 - Tübingen
Labour in research	0.425	0.431	0	GR22 - Ionia Nisia; GR25 - Peloponnisos; GR42 - Notio Aigaio	2.490	DK01 - Hovedstaden
Higher education	73.402	13.310	21.470	PT16 - Centro (PT)	96.690	CZ01 - Praha
High-tech manufacturing	6.459	3.619	0.760	ES70 - Canarias (ES); GR41 - Voreio Aigaio; GR42 - Notio Aigaio; GR43 - Kriti	21.220	DE11 - Stuttgart
GDP per capita	18331.871	7383.025	3400.000	RO21 - Nord-Est	48800.000	BE1 - Région de Bruxelles-Capitale / Brussels Hoofdstedelijk Gewest

Table 1: Descriptive statistics.

spillovers is explicitly intended in this framework since the latter would already convey information about a region's capacity to benefit from externally generated knowledge. Hence, it would measure both available knowledge and absorptive capacity while the analysis in this paper endeavours to single out the influence of the latter. Another advantage of this measure is that it is more direct in nature than looking at spatially lagged R&D investment, which is also frequently used for capturing externally generated knowledge. The spatial lag is calculated from lagged values of patenting referring to an average of the years 2004 and 2005, since it is considered intuitive that knowledge spillovers only affect innovation with a time lag. Similarly to innovation, R&D investment and knowledge spillovers are also characterised by significant heterogeneity between European regions (Table 1).

In terms of control variables, sectoral structure and the stage of economic development of a region are considered. Accounting for sectoral structure is important in order to disentangle the innovation performance of a region from economic structures that tend towards more innovation-prone and in particular, more patent-intensive sectors. Employment in high and medium high-technology manufacturing as a percentage of total employment is used as a measure of sectoral structure. This segment of the economy is expected to generate a relatively large share of patents compared to other sectors. The stage of economic development of a region is captured by including GDP measured in purchasing power parities per capita in 2000 among the control variables. It is firmly established that innovative capacity is dependent on the stage of development (Audretsch, 1998). Hence, accounting for the latter is important, since we would like to empirically model the impact of the determinants of innovation, independently of the stage of development of the respective region.

Absorptive capacity is intrinsically hard to measure. Human capital is widely acknowledged as an influential factor contributing to the absorption of knowledge (Rodríguez-Pose, 2001). We use two standard measures of human capital. Drawing on labour in research for capturing human capital has explicitly been suggested in theory (Romer, 1990) and is also frequently used in applied work. It is measured in terms of R&D personnel (in full-time equivalents) as a percentage of the active population. Due to better data availability, we focus on R&D personnel in the business sector. Schooling refers to a widely acknowledged constituent of human capital (Lucas, 1988). We measure schooling in terms of the percentage of the active population who pursued higher education (ISCED level 3 to 6). Table 1 on page 7 shows that the sample is strongly heterogeneous regarding human capital.

The decision to use two different human capital measures is based on theoretical uncertainties regarding the behaviour of the applied sample splitting estimator when the threshold variable is included among the regressors. Hansen (2000) remarked that the latter might behave in a way that is comparable to the impact of trends in changepoint models and that the distribution for such estimates has not been determined yet. In explorative analyses, we find that human capital variables that tend to be strongly related to each other, both regarding their substance and statistical properties, i.e. correlation, tend to produce insignificant direct human capital effects when being applied as threshold variables. Due to the mentioned theoretical uncertainties, we are, however, not sure whether the latter refers to a substantial result or only a statistical artefact. For prudence, we use two different measures for capturing the direct and indirect human capital effect that are not characterised by excessive correlation.

4 Estimation strategy and econometric method

For estimating the model, the endogenous sample splitting framework developed by Hansen (1999, 2000) is applied to a spatial autoregressive model structure. The general version of Hansen's threshold model allows for one or several regressors, here x_1, to affect the dependent variable in a regime-specific fashion. The sample split depends on whether another variable q, henceforth threshold variable, exceeds a certain value,

$$y_i = \theta_0 + \theta_{1,q_i \leq \gamma} x_{1,i} I(q_i \leq \gamma) + \theta_{1,q_i > \gamma} x_{1,i} I(q_i > \gamma) + X_{ji}\theta_j + \varepsilon_i, \qquad (9)$$

for observation i with $j = 2, ...$ This threshold value γ is not arbitrarily chosen ex-ante, but estimated endogenously according to the following minimisation criterion

$$\hat{\gamma} = \arg \min_{\gamma \in \Gamma_n} S_n(\gamma), \qquad (10)$$

with $S_n = \hat{\varepsilon}(\gamma)'\hat{\varepsilon}(\gamma)$ and $\Gamma_n = \Gamma \bigcap \{q_1, ..., q_n\}$. The threshold estimate refers to the value of the threshold variable that minimises the concentrated sum of squared errors function obtained by least-squares regression of y on X conditional on the threshold value.

Hansen (2000) developed the asymptotic distribution theory for the threshold and slope estimates. The threshold estimate asymptotically follows a non-standard distribution and requires the assumption that the difference between the coefficients of the split variables decreases to zero as the sample size approaches infinity. Once the threshold estimate has been determined, Hansen (2000) shows that the slope coefficients can be estimated by standard estimation techniques as if the estimated threshold value was the true threshold. As suggested by Hansen (1999, 2000), the sample is trimmed to ensure that at least 20% of the sample, i.e. 25 regions, fall inside any regime in order to avoid capturing outliers.

Determining the statistical significance of the threshold estimate involves testing the hypothesis

$$H_0 : \theta_{q_i \leq \gamma} = \theta_{q_i > \gamma}. \qquad (11)$$

Doing this is complicated by the fact that the threshold value is not identified under H_0. Hansen (1999) suggests a bootstrap procedure based on a simple likelihood ratio (LR) statistic,

$$F_1 = n \frac{(S_0 - S_1(\hat{\gamma}))}{S_1(\hat{\gamma})} \qquad (12)$$

with S_0 denoting the sum of squared errors of the null model and $S_1(\hat{\gamma})$ representing the sum of squared errors from of the alternative model. It follows a non-standard distribution. Bootstrapped p-values are asymptotically valid. The procedure is implemented by fixing the explanatory variables and then, sampling residuals from the alternative model. These draws are used for creating a bootstrap sample under the null hypothesis. The parameters from the null model are used for generating the bootstrap dependent variable, although the test statistic does not dependent on these values. On the basis of the estimated null and alternative model, the test statistic is calculated and simulated 1000 times. The bootstrapped p-value under H_0 refers to the percentage of draws for which the simulated statistic exceeds the true value.

In a similar fashion, a single threshold model can be evaluated against a multiple split alternative. The only difference involves that the test statistic depends on the parameters used for constructing the bootstrap sample and thus, Hansen (1999) cautions against placing undue confidence in its results. A graphical indication of the relevance of an additional sample split may also be obtained from the plot of the true LR statistic.

The confidence interval for the threshold estimate can be derived from a similar LR statistic,

$$LR_1(\gamma) = n\frac{(S_1(\gamma) - S_1(\hat{\gamma}))}{S_1(\hat{\gamma})}. \tag{13}$$

Since its distribution is non-standard, critical values $c(\alpha)$ are not tabulated and have to be calculated from the distribution of the LR statistic. The 5% critical value is 7.35. The confidence interval at the $1 - \alpha$ confidence level includes all values of the threshold estimate for which $LR_1(\gamma) \leq c(\alpha)$.

For the intended application, Hansen's threshold estimation approach is subjected to a spatial autoregressive model structure. From a methodological point of view, the inclusion of Hansen's threshold condition in Eq. (10) into spatial econometric estimation techniques requires, inter alia, splitting the spatial dependence parameter in two (or more) regimes, $\rho_{H\leq\gamma}$ and $\rho_{H>\gamma}$. Since we use a non-standard methodology, the behaviour of the spatial threshold estimator was simulated. The simulations were conducted using the empirical weights matrix and a parameter space that corresponds to the empirical reality. Contrary to the intuition from the generic spatial autoregressive model, the first simlation results as well as theoretical deliberations cast doubt on the appropriability of the standard estimators, spatial two-stage least squares (S-2SLS) and spatial maximum likelihood (S-ML).

S-2SLS implies large biases in the threshold estimate for high levels of spatial dependence. This bias in S-2SLS becomes significantly more serious for smaller sample sizes. In order to explain these findings, it is conjectured that the instrumentation stage of S-2SLS does not fully capture the implied spatial dynamics which causes the error term to be biased. The endogenous estimation of the threshold estimate, however, crucially relies on the error to reflect the degree to which the sample split reflects the true data structure. The biased first stage of S-2SLS precisely implies that the size of the overall error is not proportional to the sample split error anymore.

Similarly, S-ML is found to be a less suitable estimator, both on the basis of theoretical deliberations and the simulation results. Recent findings suggest a potential inconsistency of the S-ML estimator in the presence of heteroskedasticity (Lin and Lee, 2010). Sources of heteroskedasticity in a spatial context include heterogeneity of the spatial units, i.e. regarding their size, as well as the dependence of the error term on the sample size due to the presence of the spatial multiplier, $u = (1 - \rho W)^{-1}\varepsilon$. It might be intuitive that such spatial heteroskedasticity issues might even be aggravated by sample splitting. With the help of an adapted version of White's test (White, 1980), the relevance of heteroskedasticity can, indeed, be shown in simulations.

A potential remedy might be found in adapting Lee (2003)'s best spatial 2SLS estimator (BS-2SLS) to account for Hansen's sample splitting criterion. Hence, the following instrument matrix is used,

$$H = [\alpha, X, WS]$$

with $S = \begin{cases} (1 - \tilde{\rho}_{q_i \leq \gamma} W)^{-1} X & \text{if } q_i \leq \gamma \\ (1 - \tilde{\rho}_{q_i > \gamma} W)^{-1} X & \text{if } q_i > \gamma \end{cases}$ and $\tilde{\rho}$ being an estimate from a preliminary S-2SLS regression. It captures the full spatial dynamics and should therefore avoid a spatial omitted variable bias in the error term. Consistency is not affected by potential heteroskedasticity. Nonetheless, we use Huber-White variance estimators (White, 1980) for prudence. It is, indeed, found that the BS-2SLS estimator effectively minimises bias in the estimation of the threshold value. Moreover, it provides for precise estimates of the spatial dependence parameters and control variable coefficients.

Interestingly, the simple spatial ordinary least-squares (S-OLS) estimator is characterised by a very favourable performance in estimating the threshold value, in particular regarding its root mean squared error. Its drawbacks result from the conventional endogeneity issue of S-OLS resulting in overestimation of the spatial dependence parameters. However, in this paper's application, endogeneity might be mitigated by the fact that the spatial lag is calculated from time-lagged values of the dependent variable. Nonetheless, significantly higher estimates of the spatial dependence parameters are observed for S-OLS compared to the BS-2SLS estimates suggesting potential overestimation. In Section 5, only the results from BS-2SLS estimation are reported. S-OLS estimates are provided in column (1) in Table 7 on page 27 in the appendix. Detailed simulation results can be obtained upon request from the author.

Calculating standard errors for the estimated spatial effects requires approximating the nonlinear function which arises from the presence of the spatial multiplier. This is done by applying the delta method which is based on determining the asymptotic variance of a first-order Taylor series approximation around the estimated parameter values (Franzese and Hays, 2007).

5 Estimation results

This section will provide an overview of the estimation results. It is structured as follows. Section 5.1 analyses and derives the main insights from the coefficient estimates. True spatial effects are treated in Section 5.2. The sample split is discussed in Section 5.3. Section 5.4 derives policy implications from the findings of the previous sections. Finally, Section 5.5 considers multiple thresholds while Section 5.6 provides additional robustness checks.

5.1 Analysis of the coefficient estimates

The estimated coefficients suggest that R&D investment and knowledge spillovers have a significant impact on innovation performance, independently of the absorptive capacity regime. Moreover, the estimated threshold value is significant. These results are shown in column (1) in Table 2. Hence, human capital seems to not only influence innovation as a direct determinant, but also indirectly via its absorptive capacity character which impacts on the productivity of R&D investment and knowledge spillover assimilation. This finding suggests the empirical relevance of indirect human capital effects.

The size of the parameter estimates in column (1) in Table 2, however, strongly depends on the absorptive capacity regime. They are significantly higher for advanced absorptive capacity areas than for those regions lacking strong absorptive capacity endowments. Hence, innovation outcomes will also be stimulated by increases in R&D inputs in low absorptive capacity regions, albeit much less effectively than in more advanced areas. This may negatively affect the economic rationale for conducting R&D in regions with inadequate absorptive capacity endowments. Policy intervention targeting improvements in absorptive capacity may, thus, be more beneficial in lagging regions than heavily committing to direct R&D investments. As soon as a critical level of absorptive capacity is attained, R&D investments and knowledge spillovers are likely to yield significantly higher returns. Hence, improvements in absorptive capacity may have significant consequences for making R&D investment, particularly in lagging areas, economically more attractive.

Moreover, we can show that indirect absorptive capacity-induced human capital effects are empirically relevant, controlling for the direct impact of human capital. The latter is substantially lower for the proposed model than in the non-split specification without absorptive capacity effects in column (2) in Table 2. This finding may suggest that, in such standard specifications, the absorptive capacity function of human capital effect is at least partly subsumed into the direct human capital effect without, however, revealing the mechanism of its impact via influencing the effectiveness of knowledge spillover assimilation and R&D investment. Hence, the proposed model allows for demonstrating that these two structurally different human capital effects empirically exist next to each other and are of significant relevance. Moreover, the estimation approach ascertains that absorptive capacity is a prerequisite and not only a complementary asset for achieving improvements in R&D productivity and innovation

	(1) Knowledge spillovers and R&D investment subject to sample splitting	(2) Non-split model	(3) Knowledge spillovers subject to sample splitting	(4) R&D investment subject to sample splitting	(5) Threshold variable: schooling
Knowledge spillovers - low absorptive capacity regime	0.213 (0.072)***		0.267 (0.060)***		0.300 (0.048)***
Knowledge spillovers - high absorptive capacity regime	0.368 (0.049)***		0.368 (0.048)***		0.410 (0.052)***
R&D investment - low absorptive capacity regime	0.301 (0.101)***			0.437 (0.098)***	0.380 (0.091)***
R&D investment - high absorptive capacity regime	0.521 (0.067)***			0.542 (0.069)***	0.401 (0.100)***
Knowledge spillovers - entire sample		0.335 (0.049)***		0.371 (0.045)***	
R&D investment - entire sample		0.504 (0.063)***	0.462 (0.059)***		
Human capital	0.599 (0.200)***	0.731 (0.165)***	0.666 (0.184)***	0.708 (0.165)***	0.111 (0.061)*
High-tech manufacturing	0.237 (0.067)***	0.260 (0.066)***	0.223 (0.070)***	0.239 (0.066)***	0.192 (0.096)**
Initial GDP per capita	1.437 (0.158)***	1.463 (0.160)***	1.363 (0.162)***	1.410 (0.152)***	1.389 (0.174)***
Constant	-14.823 (1.882)***	-15.565 (1.806)***	-14.305 (1.899)***	-15.070 (1.728)***	-11.503 (1.667)***
Threshold estimate	0.110**		0.160[a]	0.140[b]	76.400[c]
Confidence interval - lower bound	0.090		0.10	0.09	75.900
Confidence interval - upper bound	0.170		0.260	0.650	78.900
Observations - low absorptive capacity regime	63		79	71	134
Observations - high absorptive capacity regime	188		172	180	117
Observations - entire sample	251	251	251	251	251
R-squared	0.894	0.891	0.895	0.895	0.895

[a]Significance tests have not been performed for these estimates.
[b]Significance tests have not been performed for these estimates.
[c]Significance tests have not been performed for these estimates.

Table 2: Coefficient estimates. Standard errors in parentheses; *** Significance at the 1% level; *** Significance at the 5% level.

performance.

The coefficient estimates for the control variables are highly significant in all specifications in Table 2, as well, and carry the expected signs and magnitudes.

These findings are confirmed when knowledge spillovers and R&D investment are split in separate regressions. As expected, the direct human capital effect is once again stronger picking up part of the indirect effect that the respective specification does not account for. In column (3) of Table 2, for example, the effectiveness of R&D investment is not conditioned on absorptive capacity endowments and we observe a direct human capital effect that is more than 10% higher than for the reference specification in column (1). Moreover, the non-split coefficient estimate for R&D investment in column (3) is much closer to the parameter estimate for the high absorptive capacity regime in column (1). This is intuitive, since the latter is substantially bigger than the low absorptive capacity regime. Hence, the sample is driven by regions with relatively strong absorptive capacity endowments. If the threshold effect was not accounted for, divergent R&D productivity patterns in the European periphery would, thus, be masked. The estimated threshold values as such are very similar for the specifications in columns (1), (3) and (4), although confidence intervals tend to be wider when sample splitting is performed separately for knowledge spillovers and R&D investment.

Furthermore, we can confirm the substantive results when the human capital measures that are used for capturing the direct and indirect effects are interchanged (column (5) in Table 2). The estimated threshold values are again very similar to the original specification, although we observe that the differences between the resulting regimes are less pronounced, in particular for R&D investment.

For all the models, we cannot observe any significant differences in R-squared. However, it is conjectured that the threshold models in columns (1), (3), (4) and (5) extend the results from the non-split specification in column (2) and thus, help providing a more informative approximation of the empirical reality of knowledge production.

It has to be taken into account that all the results that have been discussed so far characterise the prespatial impetus of R&D investment and knowledge spillovers on innovation only. True spatial effects will be presented in the next section.

5.2 Analysis of the spatial effects

Spatial effects estimates do not only consider the immediate internal impact of a policy change in a certain region, but capture the spatial feedback through spillovers from direct and indirect neighbouring areas into region i. As already described in Section 2, theory suggests that absorptive capacity is crucial for being able to benefit from such spatial dynamics. The spatial sample splitting model allows for testing this theoretical proposition empirically. The relevance of spatial interdependence is suggested, inter alia, by the fact that the average spatial effects of an increase in R&D spending exceed the coefficients of the

	(1) Average effect	(2) Minimum effect	(3) Maximum effect	(4) Average effect - low absorptive capacity regime	(5) Average effect - low absorptive capacity regime
Spatial effects on region i	0.472	0.302	0.531	0.303	0.527
Region i		ITG2 - Sardegna	UKD3 - Greater Manchester		
Prespatial coefficient				0.301	0.521

Table 3: Spatial effects on region i.

prespatial impetus. This is the case independently of the absorptive capacity regime (column (4) and (5) in Table 3). Hence, a positive impact of spatial spillovers can be confirmed.

The spatial effects of R&D investment tend to be lowest in the geographic periphery of Europe, i.e. in Sardinia in Italy (column (2) in Table 3). The highest ceteris paribus impact from increased R&D spending is reaped in the Greater Manchester region (column (3) in Table 3). This result is intuitive since Manchester region represents both a relatively strong innovator itself and may also strongly benefit from significant positive spillovers from surrounding regions, in particular from London.

In the next step, the size of the spatial effects of changes in region i on its neighbouring regions and in particular, on the most strongly affected neighbouring region j, are analysed. The estimation results in column (1) in Table 4 suggest that spatial dynamics cause about 4.3% of a given rise in R&D investment in region i to spill over to region j on average. This figure includes spatial feedback on region i. This spillover effect, however, notably depends on absorptive capacity endowments. The average effect on region j corresponds to 2.5% of the original spatial effect on region i if the latter belonged to the low absorptive capacity regime (column (2) in Table 4). This number rises to 4.6% of the impact on region i if the latter was characterised by absorptive capacity levels exceeding the critical threshold value (column (3) in Table 4). Since relative magnitudes are considered, this observation abstracts from the fact that the original spatial effect on region i tends to be lower in regions with weak absorptive capacity endowments.

Finally, the geographical reach of spatial spillovers is analysed by examining the number of region i's neighbouring regions that are affected by a change in R&D investment in region i and where this spillovers effect is statistically significant at the 5% level. On average, the latter refers to 19 regions (column (1) in Table 4) confirming that also indirect spillovers exceeding a region's direct vicinity are of importance, since the spatial weights matrix considers only 11

	(1) Average effect	(2) Average effect - low absorptive capacity regime	(3) Average effect - high absorptive capacity regime	(4) Minimum effect	(5) Maximum effect
Ratio of spillover effect to region j to original spatial effect on region i	4.285%	2.525%	4.613%		
Number of significantly[a] affected regions	18.896	3.431	24.074	0	39
Region i				Several Bulgarian, Greek and Slovak regions[b]	FR51 - Alsace

[a] P-value ≤0.05

[b] Specifically, BG31 – Severozapaden; BG32 - Severen tsentralen; BG34 – Yugoiztochen; BG42 - Yuzhen tsentralen; GR11 - Anatoliki Makedonia, Thraki; GR22 - Ionia Nisia; SK03 - Stredné Slovensko; SK04 - Východné Slovensko

Table 4: Spatial effects on neighbouring region j.

direct neighbours. Traditionally peripheral regions in Bulgaria, Greece and Slovakia do not affect other areas in a significant fashion via spatial spillovers (column (4) in Table 4) while in comparison, policy changes in very centrally located and more innovative regions such as Alsace in France spill over much more widely. The latter significantly influence 39 direct and indirect neighbours (column (5) in Table 4).

Moreover, by comparing the figures in column (2) and (3) in Table 4 we can see that regions which are characterised by strong absorptive capacity endowments significantly influence a substantially higher number of neighbouring areas on average than regions in the low absorptive capacity regime. The latter impact only 3 neighbouring regions on average while spillovers from high absorptive capacity areas significantly affect 24 regions on average.

Hence, Table 4 shows that both the substantive magntitude (first row) and the geographical impact (second row) of spillovers strongly depend on absorptive capacity. Consequently, it is suggested that location in the vicinity of regions which themselves are better equipped for absorbing external knowledge increases both the likelihood of being exposed to knowledge spillovers as well as their magnitude. Consequently, not only a region's internal endowment matters for the effective assimilation of spillovers, but also the level of absorptive capacity of its neighbouring areas.

5.3 Analysis of the sample split

The estimated spatial threshold model predicts a typical core-periphery split. It is depicted in the left-hand map in Figure 4. The light grey colour depicts those regions falling into the low absorptive capacity regime while the dark grey colour indicates regions that are characterised by absorptive capacity endowments above the critical threshold. What is conventionally denoted to be the core of Europe largely overlaps with the high absorptive capacity regime that implies high R&D productivity rates. The European periphery, on the other hand, constitutes the low absorptive capacity regime, including mainly Eastern and Southern European regions, except capital areas.

These results are robust to dropping those observations from the sample that fall inside the confidence interval around the threshold estimate which are indicated by the light grey colour in the right-hand map in Figure 1. Moreover, the findings can be confirmed when splitting R&D investment and knowledge spillovers separately. In this case, a very similar core-periphery pattern will be obtained if only knowledge spillovers assimilation is conditioned on absorptive capacity endowments (Figure 2). As shown in Figure 3, the high absorptive capacity regime for the case in which only the productivity of R&D investment is subject to sample splitting seems to be larger compared to the reference model depicted in Figure 1. When considering the bounds of the confidence interval around the threshold estimate, however, we obtain a very similar sample split again (right-hand map in Figure 3).

This geographical pattern highlights not only the significant disparities between Northern and Western Europe on the one hand and Eastern and Southern

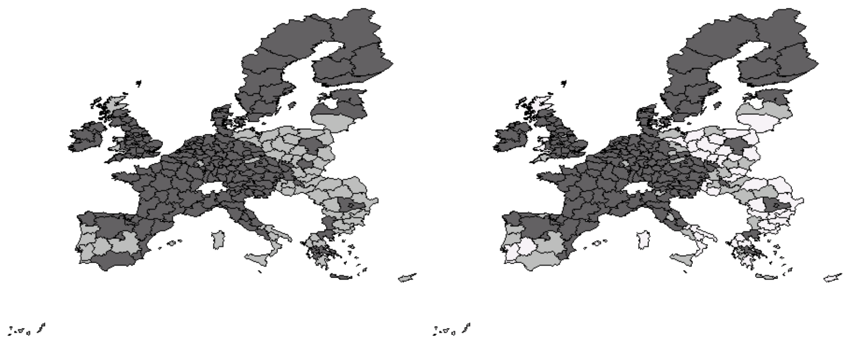

Figure 1: Maps of the sample split.

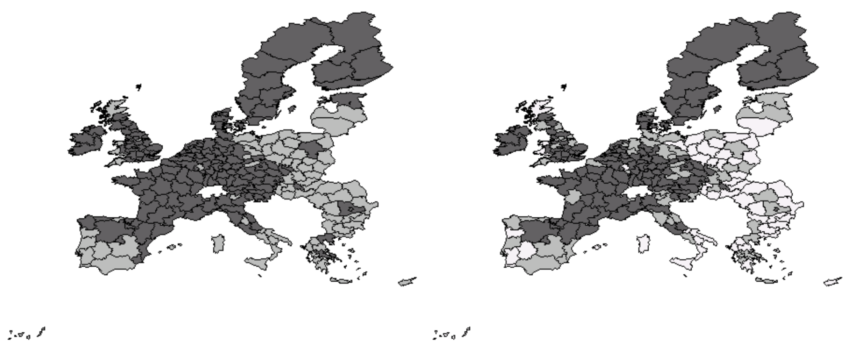

Figure 2: Maps of the sample split - knowledge spillovers s.t. sample splitting.

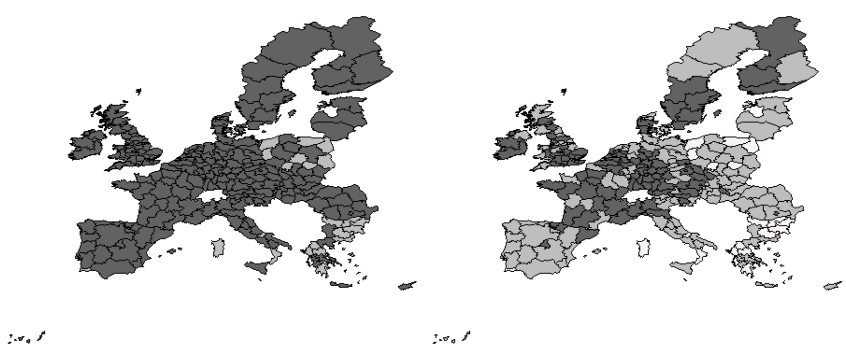

Figure 3: Maps of the sample split - R&D investment s.t. sample splitting.

Europe on the other hand, but also confirms the substantial internal heterogeneity of lagging areas. The capital cities of Eastern and Southern European countries, in particular, tend to perform significantly better than the rest of these countries. These results add to the existing literature in demonstrating that the relatively low absorptive capacity endowments in Eastern and Southern European regions are not only a descriptive property of these areas, but have a causal effect on innovation by triggering lower productivity rates of R&D investment and knowledge spillover assimilation.

5.4 Policy implication

If cohesion was a political objective, the policy implication from these findings fundamentally suggests a sequential strategy favouring investments aiming at fostering absorptive capacity for lagging regions. The latter does not only enhance the productivity of making use of knowledge spillovers, but also raises the effectiveness of current and future R&D investments. However, a complete focus on only stimulating absorptive capacity might imply foregoing innovation output based on internal R&D efforts and might risk brain drain of the existing, though relatively small research community in peripheral regions. The latter is also consistent with propositions by Cohen and Levinthal (1990) who argue that R&D investment may not only benefit from higher absorptive capacity levels, but may itself contribute to increasing absorptive capacity. In particular, R&D funding might involve the opportunity for well-trained researchers to learn and further specialise in a learning-by-doing process. The latter may endow them with an even greater capacity to transform future R&D investment into innovative output. Moreover, they might be able to assimilate more sophisticated and cutting-edge external knowledge. However, it has to be kept in mind that the existing research community might be rather small in peripheral areas, possibly too small for being able to achieve sufficient productivity for guaranteeing economic viability of large-scale R&D efforts at the aggregate level. The latter relates to notions of scale effects in R&D. Hence, an intermediate sequential strategy might involve discriminating against R&D investment in relatively early stages of regional human capital development in order to use these resources for fostering absorptive capacity. Only once human capital levels would be sufficiently elevated for the research community to be well endowed with absorptive capacity would it be efficient for a region to start investing in R&D at a larger scale in order to enhance the sophistication of its research endeavours and to decrease its dependence on external knowledge inputs.

Moreover, the dependence of the spatial effects from R&D investment on both internal and neighbouring areas' absorptive capacity endowments might have significant consequences for the spatial configuration of relative regional development patterns. If the latter turn out to favour divergence between innovation centres and lagging areas which would be suggested by the economic intuition from the results, this might be perceived to be a political issue, depending on whether political agendas focus on cohesion or efficiency only.

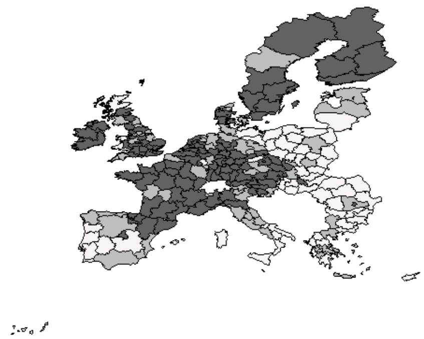

Figure 4: Maps of the sample split - double split model.

5.5 More than one threshold

We might be interested in examining the effect of more than one critical threshold. Indeed, a second sample split is found to be significant. The resulting intermediate regime is characterised by an R&D investment coefficient in column (1) in Table 5 that comes close to the estimate for the low absorptive capacity regime in the single split case in column (2) in Table 5. The coefficient for knowledge spillover assimilation, however, almost equals the parameter estimate of the single split high absorptive capacity regime. Hence, this intermediate regime is constituted by regions that are relatively inefficient in internal knowledge production from R&D investment, but that are relatively advanced in effectively absorbing external knowledge and transforming it into innovation output. The light grey colour in Figure 4 corresponds to this regime. It shows that it is made up by coastal and Northern Spanish regions except Catalunya and the Basque country, central Italy, Greek regions surrounding Athens, Greater Sofia and Bratislava, the regions around Warsaw and Krakow, Latvia, Estonia, Eastern Slovenia and a few lagging regions in Western European countries. These largely correspond to the emerging dynamic part of the European periphery.

However, as already outlined in Section 4, the significance test for multiple thresholds is subject to theoretical uncertainties. Further, graphical evidence from the plot of the LR statistic in Figure 5 on page 28 in the appendix suggests a good fit of the single split model, since the curve does not show any second major dip besides its tangent point at zero corresponding to the value of the first threshold estimate. We might also question the practical usefulness of the additional information that can be derived from multiple split models, especially when considering more than two thresholds. In fact, it is found that the additional regime that results from a triple split model further splits the intermediate regime which has already been rather small in the double split case resulting in an insignificant coefficient for R&D investment (Table 9 on page 29 in the appendix). This might be attributed to capturing outliers. Moreover, changes in R-squared are negligible when moving from the single to multiple-split models. Hence, we find a maximum of two useful threshold values and

	(1) Double split model	(2) Single split model
Knowledge spillovers - low absorptive capacity regime	0.235 (0.073)***	0.213 (0.072)***
Knowledge spillovers - intermediate absorptive capacity regime	0.368 (0.051)***	
Knowledge spillovers - high absorptive capacity regime	0.395 (0.049)***	0.368 (0.049)***
R&D investment - low absorptive capacity regime	0.298 (0.102)***	0.301 (0.101)***
R&D investment - intermediate absorptive capacity regime	0.360 (0.146)**	
R&D investment - high absorptive capacity regime	0.519 (0.085)***	0.521 (0.067)***
Human capital	0.593 (0.194)***	0.599 (0.200)***
High-tech manufacturing	0.218 (0.067)***	0.237 (0.067)***
Initial GDP per capita	1.390 (0.161)***	1.437 (0.158)***
Constant	-14.374 (1.889)***	-14.823 (1.882)***
First threshold estimate	0.110**	0.110**
Second threshold estimate	0.310***	
Observations - low absorptive capacity regime	63	63
Observations - intermediate absorptive capacity regime	66	
Observations - high absorptive capacity regime	122	188
Observations - entire sample	251	251
R-squared	0.897	0.894

Table 5: Coefficient estimates for double split model. Standard errors in parentheses; *** Significance at the 1% level; *** Significance at the 5% level.

would have a preference for the simpler model. Abstracting from the exact number of thresholds, the main message that can be derived from the suggested model refers to the causal relevance of regional differences in absorptive capacity endowments for efficient regional innovation systems which can be empirically demonstrated by means of the suggested spatial endogenous sample splitting estimator.

5.6 Robustness and adequacy of the model specification

A critical argument for demonstrating model adequacy refers to the significance of the threshold estimate. For this purpose, the bootstrap significance test as described in Section 4 is applied. It tests the null hypothesis of a linear, non-split specification. As denoted in Table 2 on page 13, the estimated threshold value is found to be statistically significant. Hence, the hypothesis of a linear model of innovation performance is rejected.

Since the proposed model nests the conventional specification considering only direct human capital effects, it allows for obtaining the standard results regarding the role of human capital. Furthermore, it offers additional information about the determinants of innovation and in particular, about the channels of how they impact on innovation output.

Moreover, the endogenous sample splitting regression method provides for identifying the model specification that implies the smallest sum of squared errors compared to sample splits based on any other observations of the threshold variable. This refers to an important strength of the approach, since any other way of splitting the sample based on the same threshold variable in an empirically reasonable range would result in explaining less of the observed pattern of innovation performance. Hence, if the objective was to provide a model that explains empirically observed innovation outcomes and their geographical pattern as precise as possible, we would be confident of having identified a strong model.

Finally, the specification of the spatial weights matrix refers to the principal exogenous choice related to the model setup. Moreover, it cannot be strictly guided by theoretical deliberations which distinguishes it from other modelling decisions such as choice of variables. However, the results are very robust against the choice of the spatial weights matrix. The principal alternative to using equal weights for n nearest neighbours as in the proposed specification refers to defining the size of the weights directly in terms of inverse distances and applying a maximum distance threshold for region j to qualify as region i's neighbour. The latter is set to imply an average number of 14 neighbours per region. Column (1) in Table 6 shows that replacing the original spatial weights matrix by the suggested inverse distance matrix only marginally affects the coefficent estimates.

A similar observation can be made if the two aforementioned methods for constructing the spatial weights matrix are combined. Therefore, inverse distance weights are used, but their number is conditioned to be equal for all regions. Moreover, we vary the scenario even further by choosing only three

	(1) Model with inverse distance weights matrix	(2) Model with n nearest neighbours inverse distance weights matrix	(3) Original model with n nearest neighbours equal weights matrix
Knowledge spillovers - low absorptive capacity regime	0.219 (0.078)***	0.221 (0.089)**	0.213 (0.072)***
Knowledge spillovers - high absorptive capacity regime	0.368 (0.050)***	0.348 (0.056)***	0.368 (0.049)***
R&D investment - low absorptive capacity regime	0.315 (0.106)***	0.333 (0.107)***	0.301 (0.101)***
R&D investment - high absorptive capacity regime	0.508 (0.066)***	0.473 (0.070)***	0.521 (0.067)***
Human capital	0.506 (0.188)***	0.529 (0.191)***	0.599 (0.200)***
High-tech manufacturing	0.248 (0.066)***	0.254 (0.067)***	0.237 (0.067)***
Initial GDP per capita	1.416 (0.172)***	1.472 (0.193)***	1.437 (0.158)***
Constant	-14.227 (1.955)***	-14.818 (2.130)***	-14.823 (1.882)***
Threshold estimate	0.110[a]	0.110[b]	0.110**
Confidence interval - lower bound	0.090	0.090	0.090
Confidence interval - upper bound	0.170	0.170	0.170
Observations - low absorptive capacity regime	63	63	63
Observations - high absorptive capacity regime	188	188	188
Observations - entire sample	251	251	251
R-squared	0.894	0.890	0.894

[a]Significance tests have not been performed for these estimates.
[b]Significance tests have not been performed for these estimates.

Table 6: Coefficient estimates for model with alternative spatial weights matrices. Standard errors in parentheses; *** Significance at the 1% level; *** Significance at the 5% level

and hence, a substantially smaller number of direct connections per region than in the original spatial weights matrix which specifies 11 nearest neighbours. Results on the basis of this combined inverse distance-n nearest neighbours matrix (column (2) in Table 6) are also remarkably similar to the reference case using the original spatial weights matrix. The estimates of the threshold value are even identical, independently of which spatial weights matrix is applied.

Hence, the proposed model provides additional information regarding the human capital- innovation nexus and its spatial implications while allowing for the standard specification of the knowledge production function to emerge as the optimal model. Besides this inherent flexibility, we show that the results from the proposed model are characterised by a remarkable degree of robustness.

6 Conclusion

In this paper, an indirect absorptive capacity-induced channel for explaining the impact of human capital on innovation is proposed and embedded into the endogenous growth model. This approach nests the traditional way of modelling the human capital-innovation link in terms of direct effects of human capital. Beyond that, it allows human capital to assume an absorptive capacity function by influencing the productivity of R&D inputs and knowledge spillovers. In order to empirically test the relevance of absorptive capacity effects of human capital, a spatial version of endogenous sample splitting is proposed. Moreover, a series of robustness and model adequacy checks are performed.

The estimated model predicts a typical core-periphery split. The traditional core of Europe largely overlaps with the high absorptive capacity regime. The European periphery, on the other hand, constitutes the low absorptive capacity regime, including mainly Eastern and Southern European regions, except capital areas. These results add to the existing literature in demonstrating that the different absorptive capacity endowments across Europe have a causal effect on innovation outcomes by affecting the productivity of R&D investment and knowledge spillover assimilation.

It is shown that these absorptive capacity-induced differences in R&D productivity patterns in Europe are subject to threshold effects. This concerns in particular the role of absorptive capacity for explaining the relatively weak innovation performance of peripheral areas. The estimation results specifically highlight that innovation outcomes will also be positively stimulated by increases in R&D inputs in low absorptive capacity regions, albeit much less effectively than in more advanced areas. This may negatively affect the economic rationale for conducting R&D in regions with inadequate absorptive capacity endowments.

Finally, it is found that the spatial effects from R&D depend on absorptive capacity, both concerning their geographical reach and their relative magnitude. Hence, regions do not only benefit from elevated internal levels of absorptive capacity, but also from favourable absorptive capacity characteristics of neighboruing areas. This might have important consequences for relative regional development patterns. If cohesion was a political objective, the policy implication from these findings would fundamentally suggest sequencing of policy intervention favouring investments aimed at fostering absorptive capacity in early stages of development of regional innovation systems.

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Appendix

	(1) S-OLS estimates	(2) BS-2SLS estimates
Knowledge spillovers - low absorptive capacity regime	0.299 (0.051)***	0.213 (0.072)***
Knowledge spillovers - high absorptive capacity regime	0.430 (0.042)***	0.368 (0.049)***
R&D investment - low absorptive capacity regime	0.315 (0.087)***	0.301 (0.101)***
R&D investment - high absorptive capacity regime	0.532 (0.065)***	0.521 (0.067)***
Human capital	0.597 (0.170)***	0.599 (0.200)***
High-tech manufacturing	0.189 (0.064)***	0.237 (0.067)***
Initial GDP per capita	1.280 (0.140)***	1.437 (0.158)***
Constant	-13.436 (1.616)***	-14.823 (1.882)***
Threshold estimate	0.110**	0.110**
Confidence interval - lower bound	0.090	0.090
Confidence interval - upper bound	0.170	0.170
Observations - low absorptive capacity regime	63	63
Observations - high absorptive capacity regime	188	188
Observations - entire sample	251	251
R-squared	0.910	0.894

Table 7: S-OLS estimates. Standard errors in parentheses; *** Significance at the 1% level; *** Significance at the 5% level.

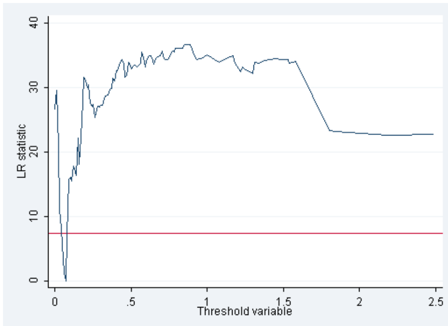

Figure 5: Plot of the LR graph of the single split model (entire sample).

	(1) Triple split model
Knowledge spillovers - low absorptive capacity regime	0.224 (0.071)***
Knowledge spillovers - first intermediate absorptive capacity regime	0.391 (0.050)***
Knowledge spillovers - second intermediate absorptive capacity regime	0.336 (0.054)***
Knowledge spillovers - high absorptive capacity regime	0.387 (0.047)***
R&D investment - low absorptive capacity regime	0.303 (0.097)***
R&D investment - first intermediate absorptive capacity regime	0.636 (0.156)***
R&D investment - second intermediate absorptive capacity regime	-0.360 (0.279)
R&D investment - high absorptive capacity regime	0.517 (0.085)***
Human capital	0.581 (0.190)***
High-tech manufacturing	0.214 (0.066)***
Initial GDP per capita	1.408 (0.159)***
Constant	-14.467 (1.861)***
First threshold estimate	0.110**
Second threshold estimate	0.190
Third threshold estimate	0.310***
Observations - low absorptive capacity regime	63
Observations - first intermediate absorptive capacity regime	31
Observations - second intermediate absorptive capacity regime	35
Observations - high absorptive capacity regime	122
Observations - entire sample	251
R-squared	0.900

Table 9: Coefficient estimates - triple split model. Standard errors in parentheses; *** Significance at the 1% level; *** Significance at the 5% level.