REGIONAL GROWTH, INNOVATION AND LATENT NONLINEAR EFFECTS*

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Abstract

This paper studies the link between knowledge, innovation and growth in European regions using nonparametric methods. Our findings suggest that knowledge inputs and the share of innovative firms have a heterogeneous and nonlinear relationship with growth. This evidence has been exploited to examine the consequences of alternative policies using a counterfactual estimation setup, the results of which imply that increasing the formal knowledge base may be optimal in most regions. Less knowledge and innovation intensive regions will also benefit from a higher innovation potential and from a trustworthy and entrepreneurial economic environment.

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1 INTRODUCTION

A fundamental premise of endogenous growth models is that deliberate decisions of rational economic agents may increase the productivity of labour which, in turn, promotes economic growth. A prominent role in these productivity increments is played by decisions regarding research and development (R&D) expenditures because they generate knowledge and innovation[1]. The "Lisbon Agenda" established the objective of making the European Union (EU) *"the most competitive and dynamic knowledge-based economy in the world",* explicitly considering innovation as the driving force of economic growth. The importance of entrepreneurship, R&D and innovation has subsequently been emphasized by the "Europe 2020" strategy for smart, sustainable and inclusive growth.

Key incentives for R&D and innovation should be addressed at the regional level because that is where knowledge is generally transferred. The competition to attract talent and investments also takes place at this geographical level. Therefore, the growth experienced by a given region depends, to a great extent, on its ability to innovate and transform. This explains why the EU Cohesion Policy has increased the percentage of its total funds devoted to R&D and innovation from nearly 25 percent in the previous programming period (2007-2013) to 30 percent in the present one (2014-2020). A major element of this new Cohesion Policy agenda is to give regional innovation strategies a central role, supported by a smart specialization logic (McCann and Ortega-Argilés, 2013; 2015).

Following the "place-based" approach to regional development intervention (Barca, 2009; Barca, McCann, and Rodríguez-Pose, 2012), smart specialization strategies allocate resources to each region's relative strengths[2], tailoring policies to the local context. The implementation of smart innovation policies - that consist of enhancing regional innovative capability and expertise in knowledge production and use - has been advocated by Camagni and Capello (2013). In order to make the "place-based" approach operative, Capello and Lenzi (2013a, 2013b) exploit the different ways in which knowledge and innovation can occur in a region. More specifically, these authors acknowledge that it is the complex set of interactions between innovative agents and the socio-economic and institutional environment that enables some regions to translate knowledge and innovation efforts into growth more efficiently than others. That is to say, there are territorial pre-conditions that make the response of growth to knowledge and innovation spatially heterogeneous in European regions (Capello and Lenzi, 2014).

Apart from these complex interactions and spatial heterogeneity, Charlot, Crescenzi, and Musolesi (2015) show that innovation in European regions is also characterized by the presence of nonlinearities and threshold effects that cannot be uncovered by standard parametric formulations. In line with this argument, the present paper tries to contribute to the literature on the relationship between knowledge, innovation and regional growth in the EU through the application of nonparametric methods[3]. These estimation techniques will not only allow us to consider a heterogeneous effect of knowledge and innovation on growth, but also a nonlinear influence. As a byproduct of our study, it will be shown that the geographical distribution of the estimated partial effects from kernel regressions can be explored through spatial analysis techniques (Anselin, 1995; Fischer and Getis, 2010). Last, but not least, the presence of heterogeneity and nonlinearities will be exploited to discuss optimal research and innovation policies in a counterfactual estimation setup (Cohen-Cole, Durlauf, and Rondina, 2012; Henderson, Papageorgiou, and Parmeter, 2013).

The rest of the paper is structured as follows. Section 2 briefly reviews the empirical literature on the link between knowledge, innovation and growth in EU regions and motivates the introduction of nonlinearities when studying this relationship. Section 3 describes the nonparametric kernel regression methods on which our analysis is based. Section 4 discusses the empirical framework and related econometric issues. Section 5 presents the results on the relevance of knowledge and innovation in explaining regional growth in Europe. This section also explores the presence of nonlinearities, threshold effects and spatial patterns in the heterogeneous partial effects. Section 6 analyzes optimal research and innovation policies, taking into account the evidence obtained on the presence of heterogeneous and nonlinear effects. Finally, Section 7 concludes. Tables and Figures are compiled in the Appendix.

2 RELATED LITERATURE

Knowledge, Innovation and Growth in European Regions

The study of growth determinants in European regions has attracted a great deal of attention (Crespo-Cuaresma, Doppelhofer, and Feldkircher, 2014) because their economic cohesion and convergence were two key policy goals during the EU integration and enlargement processes. The Barca (2009) report proposed to reform European Cohesion Policy - intended to make cities and regions more competitive, fostering growth and creating jobs - adopting a "place-based" approach. Emphasizing the geographical (social, cultural and institutional) context and the importance of knowledge, this report established that regional development strategies should move away from convergence issues and focus instead on the mechanisms that encourage local capabilities and promote innovative ideas (Barca, McCann, and Rodríguez-Pose, 2012).

There are a number of different theories on the mechanisms that link the innovation process to regional economic performance (Capello, Caragliu, and Nijkamp, 2011). Neoclassical growth models consider technological knowledge as freely available and exogenously determined. These assumptions and the presence of decreasing returns lead to long-run convergence. Given the complex role that innovation plays in the promotion of regional growth, this linear view has limited explanatory power. The endogenous growth theory considers that new knowledge is produced through R&D

investments using existing knowledge and human capital. Therefore, regions with better endowments will obtain a competitive advantage. The neo-Schumpeterian strand of the literature has established that the relationship between R&D investments and growth is not linear. In addition, the "innovation systems" approach recognizes that there are other factors - such as institutions, human and social capital and geography - that cause regions to have a different capacity to transform available knowledge into economic growth.

Combining these theoretical approaches, and building on previous studies, Crescenzi and Rodríguez-Pose (2011) analyze the influence of socio-economic conditions and geography on the process by which innovation is translated into growth in European regions. Their results suggest that an increase in the innovative efforts of a region may boost its economic performance, but in different ways depending on contextual factors like educational achievement, productive employment and the demographic structure. Similarly, Capello, Caragliu, and Nijkamp (2011) show that intangible factors (also called "territorial capital") affect the relationship between knowledge creation and growth. Although Crescenzi and Rodríguez-Pose (2011) conclude that peripherality is an intrinsic source of regional competitive disadvantage, Camagni and Capello (2013) establish that the geography of innovation in the EU is more complex than a core-periphery distinction.

The heterogeneous response of growth to innovation in European regions implies that policy-makers should avoid adopting a "one-size-fits-all" approach and act on the local conditions that reinforce regional innovation processes (Barca, 2009; Barca, McCann, and Rodríguez-Pose, 2012). Making this alternative "place-based" approach operative requires a classification of innovative regions. Capello and Lenzi (2013a) propose a new taxonomy based on the "territorial patterns of innovation" paradigm that departs from the knowledge-innovation equivalence. By considering that knowledge and innovation are neither necessarily overlapping processes in space nor necessarily sequential at the local level (Capello, 2012), this conceptualization refers to combinations of context conditions and ways of developing the different phases of the innovation process (knowledge creation, knowledge diffusion and commercialization of a new idea). The main idea of this conceptual framework is that innovation is not always derived from locally created formal knowledge. In fact, regions with a weak formal knowledge base can successfully achieve innovation and growth by exploiting local informal knowledge capabilities and/or knowledge spillovers from other regions.

Applying cluster analysis methods to regional knowledge and innovation intensities and territorial pre-conditions, Capello and Lenzi (2013a) identify five innovation patterns in EU regions: "European science-based area" (ESBA), "applied science area" (ASA), "smart technological application area" (STAA), "smart and creative diversification area" (SCDA) and "imitative innovation area" (IIA). Broadly speaking, the first three are more intensive in knowledge and innovation and rely on scientific and technological knowledge. The last two are less knowledge and innovation intensive and characterized by exploiting the knowledge embedded in the human capital of specialized workers.

Supporting the goal of strengthening the knowledge base established in the "Lisbon Agenda" and the "Europe 2020" strategy, Capello and Lenzi (2013b) show that both knowledge and innovation promote regional growth and point out that the existence of different territorial patterns of innovation in EU regions questions the invention-innovation equivalence. These authors also study how each area translates knowledge and innovation into growth and conclude that growth benefits from innovation are of a greater magnitude than those from knowledge. The analysis of the effects that knowledge and innovation exert on growth for an average region is not really informative in a context of regionally-focused policies. In this line, and confirming previous results, Capello and Lenzi (2014) show that growth advantages from knowledge and innovation are spatially heterogeneous and do not always match. More specifically, while the effects of knowledge on growth are shown to be spatially concentrated, those generated by innovation are more widespread.

Nonlinearities and Growth Determinants

Along with heterogeneity, the analysis of growth should take into account the possible presence of nonlinearities (Temple, 2001). Their introduction is necessary to determine the relevant variables that explain growth and to uncover key mechanisms for the growth process (Henderson, Papageorgiou, and Parmeter, 2012). Several studies have revealed the presence of nonlinear relationships between growth and its determinants in EU regions. Azomahou et al. (2011) provide evidence of a nonlinear convergence process that depends on national characteristics. The existence of nonlinearities related to the initial level of income per capita and self-employment rates has also been reported by Fotopoulos (2012). Similarly, Basile and Gress (2005), Basile (2008) and Basile, Capello, and Caragliu (2012) find nonlinear effects of the initial GDP per capita level and physical and human capital endowments. Sanso-Navarro and Vera-Cabello (2015) conclude that nonlinearities mainly affect the initial productivity of labour, human capital and the level of infrastructures. Adopting a distributional approach, Basile (2009) only assigns a marginal role to nonlinearities in the accumulation of physical capital while Fiaschi and Lavezzi (2007) find that the sectoral composition induces nonlinear growth patterns.

These contributions rely on the application of semiparametric and nonparametric estimation methods. Hence, they reinforce the increasing consensus in the related literature that empirical growth studies should be based on functional forms beyond linear parametric models (Henderson, Papageorgiou, and Parmeter, 2012). In spite of potential specification errors, parametric models offer greater accuracy with less data. On the other hand, nonparametric models alleviate misspecification concerns at the expense of larger data requirements and lower estimator convergence rates. Semiparametric estimators may be an alternative but, unless the structure imposed is correct, the subsequent estimation will be inconsistent (Henderson and Parmeter, 2015).

The studies reviewed in the previous subsection impose a linear structure on the relationship between knowledge, innovation and growth[4]. Nonetheless, the "territorial innovation patterns" paradigm considers that the complexity of the link between the innovation process and territorial conditions gives feedback, spatial interconnections and nonlinearities a prominent role. With the purpose of deepening our understanding of the knowledge-innovation-regional growth relationship, the objective of this paper is to uncover whether it is characterized by the presence of nonlinearities. With this aim, nonparametric kernel regression methods that do not require a priori assumptions on the underlying functional form will be applied. An advantage of these techniques is that they avoid using a misspecified model that would lead us to incorrect parameter estimates and inferences as well as to misleading policy prescriptions. Another benefit of nonparametric kernel estimation methods is that they provide observation-specific estimates that will allow us to deal with parameter heterogeneity. Finally, one more virtue of kernel regressions is that, although they do not explicitly control for spatial dependence across observations, their estimates can be consistent and asymptotically normal in the presence of this data feature[5] (Robinson, 2011; Jenish, 2012).

In a recent related study, Charlot, Crescenzi, and Musolesi (2015) analyze the contribution of regional inputs in a knowledge production function framework using semiparametric estimation techniques. These authors conclude that the generation of innovation in European regions is characterized by nonlinearities, threshold effects, complex interactions and shadow effects, none of which can be uncovered by parametric methods. They also find that R&D and human capital are highly complementary and that there exists an innovation trap of economically disadvantaged regions. These results suggest that policy-makers should also focus on the institutional conditions that will support innovation. Although the present paper does not explicitly account for time-varying regional unobserved heterogeneity and spatial processes, it improves the analysis carried out by Charlot, Crescenzi, and Musolesi (2015) in several dimensions. First, a fully nonseparable nonparametric model is adopted. Second, the presence of heterogeneity is introduced in a more flexible way than merely distinguishing between developed and lagging ("Objective 1") regions. Third, the proxy for innovation that we use captures both product and process innovations. Finally, the evidence of heterogeneity and nonlinearities in the knowledge-innovation-growth relationship is exploited to carry out a counterfactual optimal policy analysis.

3 NONPARAMETRIC ESTIMATION METHODS

Kernel Regression and Bandwidth Selection

In a linear empirical growth model, all explanatory variables enter the conditional mean linearly and each of them is separable without theoretical justification. A nonparametric specification of a growth model does not make any assumption about the functional form of the conditional mean or the distribution of the error term. Furthermore, a nonparametric model neither assumes that the variables enter linearly nor that they are separable one from another.

A fully nonparametric specification of a growth regression admits nonlinear effects for all the variables in the model:

$$y_i = \mathrm{m}\left(\mathbf{X}_i\right) + \epsilon_i, \quad i = 1, \ldots, n; \tag{1}$$

where y_i denotes the growth rate in region i, $\mathbf{X}_i = (X_{i1}, X_{i2}, ..., X_{iq})$ is a vector of q variables related to growth, ϵ_i is a zero-mean additive error and n is the number of regions. Further, $\mathrm{m}(\cdot)$ is the smooth unknown function for the conditional mean:

$$\mathrm{m}(\mathbf{x}) = \mathrm{E}[y_i|\mathbf{X}_i = \mathbf{x}], \tag{2}$$

with $\mathbf{x} = (x_1, x_2, ..., x_q)$ denoting the vector of growth determinants at which the conditional mean is evaluated.

An estimator of the conditional mean function in Equation (2) consists of locally averaging the growth rates of the regions that are similar in terms of the values taken by their growth determinants. This method is known as the local-constant (or Nadaraya-Watson) kernel estimator:

$$\hat{\mathrm{m}}\left(\mathbf{x}\right) = \sum_{i=1}^{n} w_i y_i.$$

Weights are non-negative, their sum is equal to one and they are given by

$$w_i = \frac{\mathrm{K}(\frac{\mathbf{X}_i - \mathbf{x}}{\mathbf{h}})}{\sum\limits_{j=1}^{n} \mathrm{K}(\frac{\mathbf{X}_j - \mathbf{x}}{\mathbf{h}})},$$

with

$$\mathrm{K}(\frac{\mathbf{X}_i - \mathbf{x}}{\mathbf{h}}) = \mathrm{k}(\frac{X_{i1} - x_1}{h_1}) \cdot \mathrm{k}(\frac{X_{i2} - x_2}{h_2}) \cdot ... \cdot \mathrm{k}(\frac{X_{iq} - x_q}{h_q}),$$

and $\mathrm{k}(\cdot)$ being a kernel function.

That is, the local-constant kernel estimator at $\mathbf{x}$ takes the average of the y_i values for the regions such that their $\mathbf{X}_i$ are in the neighborhood of $\mathbf{x}$. The amount of information used to calculate the local average is determined by the bandwidths $\mathbf{h} = (h_1, h_2, ..., h_q)$. A data-driven method for selecting these smoothing parameters is least-squares cross-validation (LSCV), which consists of choosing $\mathbf{h}$ to minimize

$$\mathrm{CV}(\mathbf{h}) = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{\mathrm{m}}_{-i}(\mathbf{X}_i))^2 \mathrm{M}(\mathbf{X}_i), \quad 0 \leq \mathrm{M}(\cdot) \leq 1; \tag{3}$$

where $\mathrm{M}(\cdot)$ is a weighting function and

$$\hat{\mathrm{m}}_{-i}(\mathbf{X}_i) = \frac{\sum_{l \neq i}^{n} y_l \mathrm{K}(\frac{\mathbf{X}_i - \mathbf{X}_l}{\mathbf{h}})}{\sum_{l \neq i}^{n} \mathrm{K}(\frac{\mathbf{X}_i - \mathbf{X}_l}{\mathbf{h}})}.$$

In other words, the criterion minimized by the cross-validation bandwidth selection in Equation (3) is a trimmed version of the sum of squared residuals from a leave-one-out estimator of the conditional mean function. Following Li and Racine (2004), we have set $\mathrm{M}(\cdot) = 1$.

Least-squares cross-validation bandwidth selection, in conjunction with the local-constant kernel estimator, is capable of automatically reducing the dimension of the problem when some of the regressors are irrelevant[6]. More specifically, the irrelevant variables will be smoothed out as

$$\mathrm{k}(\frac{X_{is} - x_s}{h_s}) \rightarrow \mathrm{k}(0) \quad \text{when} \quad h_s \rightarrow \infty; \quad s = 1, 2, ..., q.$$

Instead of the local-constant approximation, a linear regression can be fitted for regions with growth determinants in the same neighborhood. When a weighting function is included with this purpose, the estimation method is known as the local-linear kernel regression. The aim is to estimate an expression that is derived from a first-order Taylor expansion of Equation (1) around $\mathbf{x}$:

$$y_i = a + \mathbf{b}'(\mathbf{X}_i - \mathbf{x}) + e_i, \quad i = 1, \ldots, n.$$

As $(\mathbf{X}_i - \mathbf{x})$ is used as the regressor, the intercept equals the conditional mean in Equation (2). The estimation is based on solving the following optimization problem:

$$\min_{a,\mathbf{b}} \sum_{i=1}^{n} (y_i - a - \mathbf{b}'(\mathbf{X}_i - \mathbf{x}))^2 \mathrm{K}(\frac{\mathbf{X}_i - \mathbf{x}}{\mathbf{h}}).$$

It has been demonstrated that the solutions $\hat{a} = a(\mathbf{x})$ and $\hat{\mathbf{b}}$ =b($\mathbf{x}$) are consistent estimators of the conditional mean function and of its partial derivative ($\mathbf{m}^{(1)}(\mathbf{x}) = \partial \mathrm{m}(\mathbf{x})/\partial \mathbf{x}$), respectively (Li and Racine, 2007). In addition, the local-linear estimator has desirable theoretical and applied features as it measures the conditional mean more accurately and permits the estimation of its first derivatives, commonly referred to as partial effects or gradients.

The local-linear kernel regression nests the least-squares estimator as a special case for sufficiently large values of the bandwidth parameters. Moreover, the least-squares cross-validation bandwidth selection rule in the local-linear framework has the ability to select a large value of h_s when the conditional mean function is linear in x_s. On the contrary, it will select small values of the bandwidth parameter for variables that have a nonlinear relationship with regional growth.

To sum up, the least-squares cross-validation bandwidth parameters for the local-constant regression will be used to draw conclusions regarding the relevance of regional growth determinants. The bandwidths for the local-linear estimation will allow us to determine their nonlinear influence. Given that the kernel function considered in the empirical analysis is the Gaussian one, we will conclude that a continuous growth determinant enters the conditional mean in an irrelevant fashion (local-constant regression) or linearly (local-linear) if its corresponding bandwidth parameter is greater than twice its sample standard deviation. Nonparametric estimation requires the use of appropriate kernels to smooth discrete variables. As will be explained in the next section, we are dealing with categorical information, so the versions of the methods that have been applied in this paper are those that allow us to handle both continuous and discrete variables. In the latter case, the upper bound for the corresponding least-squares cross-validation bandwidths is unity (Hall, Li, and Racine, 2007).

Nonparametric Methods and Spatial Dependence

The geographic dimension of the data began to attract greater attention in empirical growth studies when theoretical models shifted their object of analysis from countries to regions (Barro and Sala-i-Martín, 1991). Given that existing growth theories did not account for the spatial patterns present in the data, López-Bazo, Vayá, and Artís (2004) propose a model with regional spillovers caused by physical capital investment and where the initial level of productivity and its growth in neighboring regions also play an important role. In this same line, Ertur and Koch (2007) develop a model that explicitly accounts for technological interdependence across economies as well as for physical and human capital externalities. This necessity of addressing spatial dependence between regions in empirical growth analyses led to an upsurge in the application of spatial econometrics techniques (Fingleton and López-Bazo, 2006).

As Rey and Janikas (2005) point out, spatial dependence may result in misguided inferences and interpretations when using standard parametric regression methods. Estimation results from parametric spatial models also depend, to a great extent, on the way this feature is modelled (Halleck Vega and Elhorst, 2015). Nevertheless, this is not necessarily the case for the local-constant and local-linear kernel regressions because their estimates can be consistent and asymptotically normal in the presence of spatial dependence, even if they do not explicitly control for it (Robinson, 2011; Jenish, 2012).

While parametric models employ global estimators that use all data points, nonparametric kernel regressions use a local sample of nearby data points to fit a specific parametric model and, then, smooth each local fit to construct the global function. That is, nonparametric methods do not make any choice about the functional form given their focus on the local peculiarities of the data. Their consistency in the presence of spatial dependence is related to the fact that physical distance is only one dimension of proximity. Cognitive, social and institutional factors are other dimensions of proximity (Boschma, 2005) reflected in the regressors. Therefore, kernel estimations will be able to control for spatial dependence when the regressors are close both in the variable and geographical spaces. Further, Sanso-Navarro and Vera-Cabello (2015) have shown that the local-linear kernel estimator is more efficient than the alternative geographically-weighted regression method (Brunsdon, Fotheringham, and Charlton, 1996). These arguments can be added to those in McMillen (2010, 2012) to advocate the use of nonparametric methods when dealing with spatial data and motivate their use to analyze the link between knowledge, innovation and growth in European regions.

4 EMPIRICAL FRAMEWORK

Variable Description

The data analyzed in the present paper correspond to NUTS2 regions, that is, the level at which European regional policy, in general, and smart specialization strategies, in particular, are addressed in most countries. Our final sample covers a cross-section of 252 regions (20 EU countries). Regional growth has been measured as the average annual growth rate of real GDP, calculated with data from the European Regional Database (Cambridge Econometrics). In order to provide some insights on regional growth determinants before and after the crisis, two time periods have been considered in the analysis: 2005-2007 and 2005-2012.

Our study will be based on an empirical framework similar to that used by Capello and Lenzi (2014). Neoclassical growth variables like initial income level, physical capital investment and population growth will not be included because we are interested in looking for the determinants of regional competitiveness rather than those of the steady-state equilibrium. The empirical model includes variables that capture knowledge and innovation intensities, socio-economic factors and regional economic dynamism. A description of the variables, their corresponding sample periods and data sources is shown in Table A1 in the Appendix.

Formal knowledge has been measured using R&D expenditures (both private and public) as a percentage of GDP (R&D). Human capital is commonly proxied by the percentage of the labour force with tertiary education. The underlying assumption is that a well-educated workforce will enhance productivity which, in turn, will promote economic growth. Although there exists a wide consensus about this premise, the occupations of the so-called "creative class" (Florida, 2002; Florida, Mellander, and Stolarick, 2008) are considered as a better measure of high-skilled workers and, hence, set a new standard for measuring human capital. Accordingly, informal knowledge embedded in human capital has been proxied by a variable (CAPABILITIES) that is constructed using a factor analysis[7] on the shares of production and specialized service managers (ISCO code 13) and of science and engineering associate professionals (ISCO code 31) over total employment[8]. This variable tries to establish the extent to which the regional knowledge base depends on scientific or non-scientific capabilities and, therefore, is not directly linked to innovative activities[9]. In line with the "territorial innovation patterns" paradigm, the present framework supposes that innovation has additional explanatory power to that of knowledge. For this reason, a categorical variable that reflects the share of firms that develop product and/or process innovation (INNOV) has been included in the empirical model. Although this variable only takes eight discrete values, its use may be preferable to that of alternatives based on information regarding the number of patents. These alternatives have been questioned in the literature because an invention does not imply the commercialization of a new product and, as a consequence, the information reflected by patents only accounts for a small share of total innovation (Charlot, Crescenzi, and Musolesi, 2015).

The effects that knowledge inputs and innovation exert on growth should be analyzed taking into consideration the role played by geography and socio-economic conditions as territorial-enabling factors (Crescenzi and Rodríguez-Pose, 2011). That is to say, innovative efforts are influenced by a variety of local features, thus contributing differentially to regional growth performance. In particular, a greater accessibility increases regional propensity to acquire new knowledge and ideas, so a measure of a region's rail and road potential accessibility over total area (INFRASTR) has been included in the empirical model[10]. Upper-level occupations tend to be skill intensive and, hence, more likely to create incentives for knowledge and innovation generation (Duranton and Puga, 2000). Functional specialization in high-skilled blue-collar occupations (ISCO codes 7 and 8) has been reflected through their share over total employment in a region (FUNCTIONAL). The ability that regions have to translate knowledge into useful innovations is related to business initiative (Braunerhjelm et al., 2010). Given that the measurement of entrepreneurship is problematic at the European level, this variable has been proxied using the share of self-employment over total labour force, excluding wholesale retail sectors (SELFEMPL). A trustworthy economic environment promotes cooperation between economic agents (Leite, Silva, and Afonso, 2014), fostering the circulation and acquisition of knowledge and innovation. Thus, the share of people trusting each other in a region (TRUST) has been included as a measure of the cooperative propensity and collective actions. The spatial dimension of the NUTS2 regions that make up our sample has been incorporated using the geographical coordinates provided by Eurostat.

Regional economic dynamism has also been controlled for in the empirical analysis. The employment growth rate (EMPLOYMENT) has been included to try to disentangle whether it is what determines GDP growth or whether, on the contrary, growth depends on productivity increases. Knowledge spillovers can take the form of traded goods or foreign direct investments (Rama, 2008). The latter represent a channel through which technology transfers take place and allow host regions to integrate more easily into global value chains (Carlsson, 2006). Therefore, inward foreign direct investment flows

(FDI) to a region have been considered to reflect its attractiveness and the relevance of trade. Finally, the location quotient of employment in knowledge intensive services (KIS) proxies the labour market specialization in this creative and highly dynamic sector that promotes growth even if it presents low levels of R&D expenditures (European Commission, 2012). This shows that regions with a weak formal knowledge base can also achieve innovation performance and growth (Capello and Lenzi, 2013a; 2013b).

Econometric Issues

There are several estimation issues that should be taken into account for the implementation of the empirical analysis outlined in the present paper and the interpretation of the results obtained from it. The first issue has to do with a drawback of nonparametric estimation methods: the "curse-of-dimensionality" problem. It consists of the difficulty in detecting the structure of high-dimensional data sets without making an excessive number of a priori assumptions. Even so, this limitation has to be confronted against the alternative of using a misspecified parametric model (Henderson and Parmeter, 2015). This dimensionality problem will be mitigated considering different specifications where knowledge inputs and the share of innovative firms will be analyzed both separately and in conjunction with the socio-economic factors, on the one hand, and the variables reflecting economic dynamisms, on the other. The reason is that a regression including all variables simultaneously would be based on fewer observations than those required to obtain reliable results.

Related to the "curse-of-dimensionality", and in line with the "theory-uncertainty" problem of empirical growth studies (Brock and Durlauf, 2001), our framework does not include some variables that have been found to explain growth in European regions[11] (see, among others, Crespo-Cuaresma, Doppelhofer, and Feldkircher, 2014). Although an ideal approach to deal with this issue would have been to estimate a panel fixed-effects type model, data availability precludes us from this possibility. Instead of controlling for regional unobserved heterogeneity, one way to mitigate this problem is to include country fixed-effects. The latter will account for unobserved country-specific characteristics that could affect economic growth. A preliminary analysis[12] shows that a factor variable reflecting a country-level indicator is not statistically significant. Moreover, its corresponding bandwidth parameter is almost zero. This result - that tends to be the norm in empirical studies - implies that each country is separated into their own individual samples, making the entire growth process different for each of them. That is to say, the sample is split in such a way that only the observations of a country are used to obtain the estimates of its regions. Given these findings, and as an alternative way to control for country effects in our cross-sectional framework, we have carried out the analysis considering the continuous variables as deviations from their corresponding sample country mean[13] (Sterlacchini, 2008; Sanso-Navarro and Vera-Cabello, 2015). Nonetheless, it is worth noting that differencing in nonparametric and parametric settings is not necessarily undertaken in the same way (Su and Lu, 2013).

Another reason for being cautious when interpreting our results is that it is difficult to identify causal relationships in empirical growth studies due to the inherent and unavoidable endogeneity (Durlauf, 2009; Bazzi and Clemens, 2013). As reflected in Table A1, our explanatory variables refer to or have been averaged over periods preceding those over which average GDP growth rates have been calculated. According to Crescenzi and Rodríguez-Pose (2011), this should lessen concerns about potential endogeneity problems. Nevertheless, it cannot be ruled out that some residual element remains, precluding us from making strong causal statements. Actually, R&D expenditures may introduce a certain degree of endogeneity because they may be both a cause and an effect of economic performance (Capello and Lenzi, 2014). For this reason, a robustness check to control for this possibility will be implemented using the nonparametric instrumental variable (IV) approach proposed by Henderson, Papageorgiou, and Parmeter (2013).

As pointed out by Capello and Lenzi (2014), the presence of R&D expenditures as a share of GDP together with the share of innovative firms in the same regression may be troublesome. R&D captures both commercialized and non-commercialized knowledge and, hence, may be reflecting innovative efforts made by firms. The correlation matrices reported in Tables A2 and A3 allow us to conclude that the regressors that have been considered in our empirical framework are not highly correlated and, even within each group of variables, capture different influences.

5 RESULTS

Regressor Relevance and Nonlinearities

Our empirical analysis begins with the calculation of the bandwidths for a local-constant kernel regression using the least-squares cross-validation selection rule. Repeated evaluations have been carried out using a multistart process of the search algorithm to ensure that the obtained smoothing parameters correspond to a global minimum of the criterion function. It can be stated from the comparison of the bandwidths shown in Table 1 with the descriptive statistics in Table A3 that, for most of the variables considered, the smoothing parameters are less than twice the sample standard deviation. The main exception is the proxy for the informal knowledge embedded in human capital. The level of infrastructures is smoothed out from the regression when average annual GDP growth is calculated for the years 2005-2007. Similarly, inward FDI flows as a percentage of GDP are not found to be relevant in explaining regional growth when measured over 2005-2012. The bandwidth parameter for R&D expenditures also exceeds its upper bound in this case. Nevertheless, we should be cautious when interpreting bandwidths near these arbitrary limits because a variable that is irrelevant in terms of smoothing the conditional mean function is not necessarily statistically insignificant.

[Insert Table 1 here]

Table 1 also reports formal significance tests - Racine, Hart, and Li (2006) for the discrete variable and Gu, Li, and Liu (2007) for the continuous ones - and their wild bootstrap p-values. These statistics widely confirm the conclusions drawn from the least-squares cross-validation bandwidths. Despite this, the final decision regarding the relevance of the variables in explaining growth in EU regions will be based on the significance tests. The share of innovative firms is not statistically significant when variables affecting regional economic dynamism are included in the estimation. The latter are especially relevant when growth is analyzed in the period 2005-2007. Socio-economic factors are more relevant for explaining real output growth over the longer sample period that, furthermore, covers years of economic difficulties. In particular, the influence of regional accessibility and cooperative propensity on the acquisition and circulation of knowledge and innovation seems to be less affected by the business cycle. More importantly, the strongest evidence of a significant effect of knowledge inputs and innovation on growth is found when the former are jointly considered with socio-economic variables. This result corroborates the role of these territorial-enabling factors as promoters of favorable systems of innovation.

Having identified the relevant regional growth determinants, the next step in our analysis is to determine which of them exert a nonlinear influence. As explained in the methodological section, this is related to the magnitude of the bandwidth calculated by the least-squares cross-validation selection rule for the local-linear kernel estimator. These smoothing parameters are shown in the upper panel of Table 2, where it can be observed that most of them are lower than twice their sample standard deviation. These results suggest that not only knowledge inputs and innovation exert a nonlinear influence on growth in European regions, but also socio-economic factors and, to a lesser extent, variables that reflect economic dynamism. The only exception corresponds to the case where informal knowledge embedded in human capital and the location quotient of employment in KIS sectors are jointly considered to explain average annual growth during the period 2005-2012. Nevertheless, the coefficients of determination reported in the lower panel of Table 2 show that this specification achieves the lowest explanatory power.

[**Insert Table 2 here**]

In order to verify the suitability of our empirical framework, we have implemented the test for correct parametric specification proposed by Hsiao, Li, and Racine (2007). Alternative linear and nonlinear parametric specifications have been tested against the estimated nonparametric model. In particular, we have considered a standard OLS model (HLR1), a quadratic specification (HLR2) and a specification that considers R&D expenditures and the share of innovative firms interacted with five dummies that correspond to the territorial innovation patterns identified by Capello and Lenzi (2013a) (HLR3). This last specification has been used by Capello and Lenzi (2014) to try to better understand the spatial heterogeneity in the response of GDP growth to formal knowledge and innovation. Although there is one specification without evidence against the parametric models, the test statistics that have been calculated allow us to conclude that the adoption of a nonparametric approach seems to be more suitable in the present context. This is especially true when growth is measured from 2005 to 2012. Therefore, it can be stated that a nonparametric model will more likely lead us to consistent parameter estimates and correct inferences when growth is analyzed over longer time horizons.

Nonparametric kernel estimators assume that the observations are independent, so they do not explicitly account for the presence of spatial dependence. In order to analyze the extent to which these methods and the empirical specifications considered in our analysis capture this feature of European regional data, the global Moran's I test has been calculated for the residuals of the local-linear kernel regressions. This has been done using two k-nearest neighbors matrices[14] and an inverse-distance weights matrix that ensures that all regions have, at least, one neighbor. The null hypothesis of the absence of spatial autocorrelation can only be rejected at the 5 percent significance level in two cases. This can be interpreted as confirmatory evidence that kernel regressions are able to control for the spatial dependence when explanatory variables are close not only in the variable space but also in the geographical space, as is the case in our data.

The specification with the highest explanatory power corresponds to the analysis of European regional growth in the period 2005-2012 using knowledge inputs, innovation and socio-economic factors as regressors. In this case, least-squares cross-validation bandwidths for the local-linear estimator suggest that these variables have a nonlinear influence on growth and, as a consequence, a nonparametric model is preferred to both linear and nonlinear parametric alternatives. In addition, the evidence of residual spatial autocorrelation is weak. For these reasons, we will base the analysis of the partial effects carried out in the next subsection on this specification which may be of interest from a policy-making point of view with sustained growth and resilience to economic difficulties as its main goals.

Partial Effects: Heterogeneity and Spatial Association

In a multivariate parametric setting, partial slopes are commonly obtained by selecting an explanatory variable and holding the remaining ones at specific values. Proceeding in this way, some links between the variables might be obscured. As an alternative to parametric models, kernel regressions can be used to obtain partial effects of a covariate at a given point. That is, the marginal effect of a covariate for each observation is calculated at the observed values of all the covariates for this same observation. For a continuous variable, they are calculated as the derivative of the conditional mean in

Equation (2) at $\mathbf{x}$. For discrete variables, partial effects are obtained as the difference between the conditional mean evaluated at one value for the regressor minus the value of the regressor, holding everything else constant.

[Insert Table 3 here]

Local-linear kernel regression estimates can be examined through the mean and quantiles of the partial effects, their bootstrap standard errors and the percentages that are positive/negative. These results, shown in Table 3, suggest that partial effects display an important variation, which can be interpreted as evidence of heterogeneous effects of these variables on growth in EU regions (Capello and Lenzi, 2014). Knowledge inputs and innovation performance have an average positive influence on growth. Among them, R&D expenditures have the highest percentage of positive and statistically significant gradients, followed by the variable that proxies for capabilities embedded in human capital. Average partial effects for the level of infrastructures and the share of high-level blue-collar occupations are negative. These variables also have a higher percentage of negative and significative gradients. Therefore, regions with a lower-skilled workforce tend to experience lower growth rates. As suggested by Capello and Lenzi (2013b), the counterintuitive sign of the partial effects for accessibility may be reflecting congestion effects. By contrast, the self-employment rate and, especially, the proxy for social capital tend to exert a positive influence on growth. This implies that a more entrepreneurial, cooperative and trustworthy economic environment promotes knowledge and innovation and, as a consequence, enhances regional growth potential. In accordance with the results reported in Table 2, the estimated partial effects of labour market specialization in KIS sectors are positive and display a low level of variability.

The robustness of previous results to the potential endogeneity of R&D expenditures has been assessed using the nonparametric instrumental variable estimation of

Henderson, Papageorgiou, and Parmeter (2013). These authors extend the procedure developed by Su and Ullah (2008) - similar in spirit to two-stage least-squares in a parametric framework - to handle discrete regressors and put forward a new method to select appropriate instruments. Although the regressors that are smoothed out of a local-constant nonparametric estimation do not explain the left-hand side variable, Henderson, Papageorgiou, and Parmeter (2013) suggest that they may be related to the potential endogenous variable. If the latter is the case, these excluded regressors will be valid instruments, which can be checked using their least-squares cross-validation bandwidths for the same estimation framework.

In a first stage, a local-constant estimation of the potential endogenous variable (R&D expenditures) on the rest of the regressors has been carried out. The variables considered as instruments are those that have been shown not to explain our variable of interest (regional growth) in the period 2005-2012: employment growth rate and inward FDI flows (see Table 2). In a second stage, a local-linear kernel regression has been estimated excluding the instruments and adding the residuals from the first stage as an explanatory variable. Least-squares cross-validation smoothing parameters for both stages are reported in Table B1. The bandwidths for the local-constant estimation show that the self-employment rate is the only regressor that is smoothed out in the first stage. More interestingly, the bandwidths for the variables used as instruments do not exceed their upper bounds. It can also be observed that only the local-constant residuals are smoothed out in the second-stage estimation. This finding leads us to affirm that the potential endogeneity of R&D expenditures is not a concern in our context. This assertion is confirmed by the partial effects from the second-stage local-linear estimation shown in Table B2 which, in general terms, are similar to those obtained without adopting an instrumental variable approach (see Table 3).

[Insert Figure 1 here]

Hitherto, the information analyzed mainly refers to four points of the partial effects distribution. Henderson, Papageorgiou, and Parmeter (2012) propose using a visual alternative consisting of representing 2-dimensional figures that, for a given variable, plot the estimated gradients against themselves together with their upper and lower confidence bands. The idea of these 45^o plots is to discern both the heterogeneity of the estimated partial effects and their statistical significance. These graphs are shown in Figure 1 for the statistically significant partial effects of the eight relevant regressors in our empirical framework. This figure supports the heterogeneous character of the influence that these variables have on growth across EU regions. Knowledge inputs and innovation tend to display positive partial effects. These graphs also highlight the growth-enhancing role of socio-economic factors, especially the self-employment rate and social capital.

[Insert Figure 2 here]

The results from the local-linear kernel regression can be further analyzed through the spatial distribution of the estimated partial effects. This has been done by generating cluster maps with the local indicator of spatial association (LISA; Anselin, 1995) using a four-neighbors weights matrix. These maps are shown in Figure 2 for the variables where spatial patterns have been found[15]. The first row displays LISA cluster maps for knowledge inputs and innovation and the second row shows the maps for selected socio-economic variables.

There is a significant "high-high" cluster of spatial correlation in the partial effects of the share of innovative firms and infrastructures in German regions that belong to the ESBA and the ASA territorial innovation patterns. These regions are not only more intensive in knowledge and innovation and have higher levels of accessibility but they also obtain greater growth benefits from all of them. On the contrary, the less entrepreneurial character of German regions is reflected in the "low-low" cluster of the partial effects of the self-employment rate. A "low-low" cluster of spatial association is also found in the gradients of innovation in UK regions that belong to the STAA. This result may be related to the higher preconditions for knowledge and innovation acquisition of the regions that form this innovation pattern. There is a "high-high" cluster of partial effects of the share of high-skilled blue-collar occupations over total employment in Polish regions belonging to the SCDA, showing the benefits that they obtain from external knowledge. Conversely, there are two "low-low" clusters of the gradients of functional specialization in German (ESBA and ASA) and Swedish (STAA) regions with large capability potentials.

The positive influence of informal knowledge on growth across European regions is corroborated by the "high-high" clusters of the partial effects of human capital capabilities formed by regions from all territorial innovation patterns except IIA. The latter is characterized by knowledge and innovation variables with below EU average values. Nonetheless, its entrepreneurial character is reflected by the "high-high" clusters of the gradients of the self-employment rate which are made up of regions from Bulgaria and Spain that belong to the IIA. Finally, the "high-high" cluster of the partial effects of R&D expenditures in Polish regions of the SCDA and IIA innovation patterns suggests the necessity to increase the formal knowledge base also in regions with a narrower knowledge and innovation profile.

Threshold Effects

In order to obtain further insights on the heterogeneity of local-linear partial effects, their kernel density functions have been compared after splitting the sample according to the median of a given variable. In particular, a formal comparison has been carried out through the test of equal density functions proposed by Li, Maasoumi, and Racine (2009). Rejection of the null hypothesis of equality implies the existence of interactions between the variables. The test statistics obtained, along with their bootstrap p-values, are reported in Table 4. Each row corresponds to the variable that generates the threshold effects, that is, the variable that takes values above or below the European sample median. Each column refers to the variable that experiences the threshold effect and, thus, for which the densities of the gradients are compared. Although they are not relevant for explaining growth in the period 2005-2012, variables related to regional economic dynamism have also been considered to potentially generate threshold effects.

[Insert Table 4 here]

Focusing on the highest numbers of rejections, it can be stated that the variables more prone to induce threshold effects are the share of innovative firms and the location quotient of employment in KIS sectors. Thresholds especially affect the gradients of socio-economic territorial enabling factors, implying that they have a different relationship with growth depending on the innovative attitude and the level of creativity of a region. Meanwhile, informal knowledge, self-employment and employment growth do not induce differences in the distribution of the estimated partial effects. High-skilled blue-collar occupations and self-employment rates are found to be the ones more affected by this type of nonlinearity and, hence, their growth-enhancing potential is widely influenced by local conditions.

Figure 3 shows the density functions of the estimated gradients for the knowledge and innovation-related variables where equality has been rejected. These graphs show that less innovative regions have a higher density of partial effects around zero for the share of firms introducing product and/or process innovations. However, these kernel densities reflect that less innovative regions may be as successful as more innovative ones in translating innovation into growth (Capello and Lenzi, 2014). Regions with lower innovation performance also display higher partial effects for R&D expenditures.

Furthermore, R&D exerts a higher positive influence on growth in regions that devote a lower share of their GDP to these expenditures. In line with the results obtained in the previous subsection, these findings recommend not disregarding formal knowledge in less knowledge and innovation intensive regions.

[**Insert Figure 3 here**]

The values obtained for Li, Maasoumi, and Racine (2009)'s test statistic allow us to conclude that socio-economic factors do not induce threshold effects on knowledge inputs. By contrast, regions with potential accessibility and social capital levels above the EU median have higher estimated partial effects for the share of innovative firms. Higher accessibility and cooperative attitudes promote the acquisition and circulation of new ideas and, as a consequence, improve regional economic performance. These results show that the most innovative regions (ESBA and ASA territorial innovation patterns) have the highest levels of accessibility and outperform the others in terms of propensity to network (Capello and Lenzi, 2013a). Knowledge inputs - especially capabilities embedded in human capital - exert a more positive influence on growth in regions with higher inward FDI flows. This finding reinforces the idea that regional growth potential can be enhanced through the exploitation of informal knowledge capabilities and knowledge spillovers from other regions. A lower specialization in KIS sectors implies higher growth benefits derived from human capital capabilities. Therefore, less creative regions should exploit their internal preconditions to translate external knowledge into innovation.

[**Insert Figure 4 here**]

Finally, a comparison has been carried out between the kernel densities of partial effects for socio-economic variables (those more affected by thresholds) depending on whether or not innovative performance and the location quotient of employment in KIS sectors (those more prone to induce this type of nonlinearity) are above or below the EU sample median. The results obtained from this comparison are shown in Figure 4. It can be concluded from the graphs in the upper panel that regions with innovation below EU median levels obtain higher growth benefits from functional specialization, entrepreneurial activity and, to a lesser extent, social capital. This reflects that upper-level occupations, entrepreneurship and collective learning are potential assets for less innovative regions. Kernel densities plotted in the lower panel show that regions with a less developed KIS sector tend to display higher gradients for functional specialization, suggesting a relationship of substitutability between a high-skilled labour force and creativity.

6 COUNTERFACTUAL POLICY ANALYSIS

There is a wide consensus that European innovation policies should move from a generic to a selective strategy because, as shown in the previous section, an increase in innovative efforts will not produce the same effect in all regions. The design of innovation-based development policies also needs to take socio-economic factors into account because the ability of regions to translate knowledge and innovation into economic growth is enhanced when local socio-economic sources of competitive disadvantage are effectively addressed (Crescenzi and Rodríguez-Pose, 2011). That is to say, local endowments need to be reinforced in order to guarantee the greatest return from policies based on R&D.

As noted before, the misspecification of the relationship between the variables in an empirical model may lead to inconsistent parameter estimates, incorrect inferences and, as a consequence, misleading policy prescriptions. Therefore, nonlinearities should not only be detected but also taken into consideration when exploring policy options. Cohen-Cole, Durlauf, and Rondina (2012) developed a method to determine optimal policies in the presence of nonlinearities. The present paper will follow the extension of this methodology proposed by Henderson, Papageorgiou, and Parmeter (2013), consisting of implementing a bootstrap within a nonparametric regression context.

Policy outcomes are compared over a model space $\mathbf{M} = \{m_1, m_2, ..., m_5\}$, made up of a local-constant and a local-linear kernel regressions with knowledge inputs and the share of innovative firms as explanatory variables; the same two estimations adding socio-economic variables as regressors; and the nonparametric instrumental variable estimation used as a robustness check for the potential endogeneity of R&D expenditures. Given that the continuous variables have been expressed as deviations from their sample means, we will consider five policy alternatives ranging from an increase of two standard deviations to a decrease of an equal amount. For the discrete variable reflecting regional innovative performance, the five policy choices will range from an increase of two categories to a decrease of the same order of magnitude. Whatever the type of variable, the policy space can be denoted as $\mathbf{P} = \{p_1, p_2, ..., p_5\}$. The expected value of a generic loss function $\mathrm{l}(\cdot)$ from implementing a policy in region i can be expressed as:

$$\mathrm{El}_i = \mathrm{E}\{\mathrm{l}[g_i, p(i), \boldsymbol{\vartheta}_i] | p(i), m, \mathbf{x}_i\}, \tag{4}$$

where g_i is the growth rate in region i when policy $p \in \mathbf{P}$ is implemented under model $m \in \mathbf{M}$. The characteristics of the region that may affect the calculation of the expected loss are included in $\boldsymbol{\vartheta}_i$.

The expected value in Equation (4) is calculated from a loss distribution generated by the following bootstrap procedure:

1. For a given model $A \in \mathbf{M}$, obtain the residuals $\hat{u}_i = y_i - \hat{\mathrm{m}}_A(\mathbf{x}_i)$ $(i = 1, ..., n)$ and

construct a two-point wild bootstrap error:

$$\begin{cases} u_i^* = \left(\frac{1-\sqrt{5}}{2}\right)\hat{u}_i, & \text{with probability } r = \frac{1-\sqrt{5}}{2\sqrt{5}}; \\ u_i^* = \left(\frac{1+\sqrt{5}}{2}\right)\hat{u}_i, & \text{with probability } (1-r). \end{cases}$$

2. Create $y_i^* = \hat{\mathrm{m}}_A(\mathbf{x}_i) + u_i^*$ $(i = 1, ..., n)$ and the resulting bootstrap sample $\{y_i^*, \mathbf{x}_i\}_{i=1}^n$.

3. Obtain the expected growth for each policy counterfactually using $\{y_i^*, \mathbf{x}_i\}_{i=1}^n$ and modifying x_{iq} successively.

4. For each region and policy, calculate the loss as $\mathrm{l}(g_i) = (-1/1-\sigma)(\lambda + g_i)^{(1-\sigma)}$.

5. Repeat steps (1-4) a large number (B) of times[16].

Taking into account the expected losses calculated for each policy and model, two criteria have been applied to establish the best policy alternative. The first of them is known as the "minimax" criterion and consists of choosing the policy that minimizes the expected loss under the least favorable model. An alternative "minimin" criterion will select the policy that, under some state of nature and for a given region, delivers the minimum loss (highest growth):

$$\begin{aligned} \text{minimax} &: \quad \min_{p\in\mathbf{P}} \max_{m\in\mathbf{M}} \mathrm{El}_i. \\ \text{minimin} &: \quad \min_{p\in\mathbf{P}} \min_{m\in\mathbf{M}} \mathrm{El}_i. \end{aligned}$$

Figure 5 shows maps that display the regions where, for a given variable related to knowledge and innovation, the "minimax" (upper row) and "minimin" (lower row) criteria consider it optimal to implement a moderate (light grey) or high (dark grey) increase. Broadly speaking, these maps support smart innovation policies intended to increase regional innovative capacity and knowledge production and use (Camagni and Capello, 2013). It can also be observed in this figure that the shaded regions generally coincide for both criteria. Therefore, we will focus on the description of the results obtained under the "minimin" criterion because it is directly related to the promotion of regional growth.

Although with some degree of heterogeneity, increasing R&D expenditures will enhance growth in most European regions. Innovation-oriented policies seem to be optimal in regions in the periphery and western Europe. Apart from being an argument for the implementation of targeted innovation policies, these results endorse that there are regions lacking a strong knowledge base that may be highly responsive to innovations (Capello and Lenzi, 2013b). The promotion of human capital capabilities seems to be a better policy alternative in central Europe and the northern regions of Spain and Italy. Either of these two policies will result in higher growth in the United Kingdom and the south of Norway and Sweden.

[**Insert Figures 5 and 6 here**]

The shift in European innovation strategy from an exclusive focus on R&D to a broader set of dimensions has been advocated by Charlot, Crescenzi, and Musolesi (2015). Therefore, the Cohesion Policy should also take social and institutional factors into account in the new programming period 2014-2020. Figure 6 shows the counterfactual policy analysis for the socio-economic variables in our empirical framework. These maps support the policy funding shift from infrastructure provision to innovation-related actions and the promotion of entrepreneurship (McCann and Ortega-Argilés, 2013). Although higher functional specialization may lead to higher growth in some regions, policies intended to increase the level of social capital will have a more widespread benefit across Europe. This result may be interpreted as a need to improve the quality of the institutions that, in the end, will lead to higher growth.

[**Insert Tables 5 and 6 here**]

The results obtained from the policy analysis have been related to the territorial innovation patterns identified by Capello and Lenzi (2013a) in Tables 5 and 6 for knowledge and innovation and socio-economic variables, respectively. For a given criterion, these tables show the number and percentage of regions in each group for which a policy is optimal. Reinforcing previous results, Table 5 shows that increasing R&D expenditures is optimal in the great majority of regions (85 percent). Innovation patterns formed by regions with higher levels of knowledge and innovation will also benefit from increases in their human capital capabilities, further improving their territorial preconditions for knowledge creation. By contrast, regions with narrower knowledge and innovation profiles will obtain the highest growth benefits from innovation-related policies. Therefore, these regions should rely less on external knowledge and imitation activities and increase their endogenous innovation potential.

Finally, the results reported in Table 6 suggest that policies oriented to upgrading socio-economic factors will have a less widespread growth-enhancing influence than knowledge and innovation-related policies. The variables whose increases display a higher number of positive effects on growth are the self-employment rate and social capital. It can also be stated that the advantages from improving these territorial-enabling factors are mainly experienced by regions with smaller knowledge bases and lower innovation intensities. This entails that lagging regions will especially benefit from a trustworthy and entrepreneurial economic environment.

7 CONCLUDING REMARKS

This paper has applied nonparametric methods to introduce the possible presence of nonlinearities into the study of the link between knowledge, innovation and growth in European NUTS2 regions. The strongest evidence of a significant relationship between these variables is found when they are jointly considered with socio-economic conditions. Therefore, the influence of knowledge and innovation on regional growth should be studied in conjunction with their local territorial-enabling factors. The empirical analysis carried out has mainly focused on the years 2005-2012 because this period may be of more interest from the point of view of a policy-maker whose goals are to achieve sustained growth and regional resilience to economic difficulties.

Our results provide evidence that knowledge, innovation and socio-economic factors have a nonlinear relationship with growth and, hence, a nonparametric approach will lead to more consistent parameter estimates and correct inferences. We find there is an important variation (heterogeneity) in the estimated partial effects of these variables (Capello and Lenzi, 2014). More importantly, it has been shown, for the first time in the related literature, that these partial effects can be further analyzed by detecting clusters of spatial association. Those identified in the present paper have been related to the territorial innovation patterns identified by Capello and Lenzi (2013a). In addition, kernel densities of these estimated gradients have been compared to find interactions between the variables in the form of threshold effects. We show that less innovative regions may be as successful as more innovative ones in translating innovation into growth. Moreover, regional growth potential can be enhanced through the exploitation of informal knowledge capabilities and knowledge spillovers from other regions.

The evidence obtained regarding heterogeneous partial effects of knowledge, innovation and socio-economic variables and their nonlinear relationship with growth has been taken into account when implementing a counterfactual analysis for optimal policy design. This exercise reveals that increasing R&D expenditures is optimal in most regions, regardless of their territorial innovation pattern. On the one hand, regions with higher levels of knowledge and innovation will also benefit from further improvements in their human capital capabilities. On the other, regions with narrower knowledge and innovation profiles should also increase their endogenous innovation potential. This finding supports smart specialization policies that make innovation a priority beyond research hubs. Policies oriented towards upgrading socio-economic factors will have a less widespread growth-enhancing effect than knowledge- and innovation-related policies. Nonetheless, regions with smaller knowledge bases and lower innovation intensities will especially benefit from a trustworthy and entrepreneurial economic environment.

Notes

[1] At this point, it is worth noting that knowledge and innovation are different concepts. According to the "Schumpeterian distinction", while it is invention that creates new ideas and formal knowledge, it is their commercial exploitation that leads to innovation.

[2] Regulation 1301/2013 of the European Parliament defines smart specialization strategies (RIS3) as the *"national or regional innovation strategies which set priorities in order to build competitive advantage by developing and matching research and innovation own strengths to business needs in order to address emerging opportunities and market developments in a coherent manner, while avoiding duplication and fragmentation of efforts".*

[3] See Li and Racine (2007) and Henderson and Parmeter (2015) for a textbook treatment of nonparametric techniques.

[4] Only Capello and Lenzi (2013b) have provided some cursory evidence that the impact of innovation on growth is characterized by the presence of nonlinearities in the form of threshold effects. In a study on the relationship between growth and knowledge and human capital endowments in EU regions, Sterlacchini (2008) shows that R&D activities have to reach a minimum level to foster economic growth.

[5] To the best of our knowledge, these results have only been exploited by Sanso-Navarro and Vera-Cabello (2015).

[6] This implies that nonparametric methods are not only robust to functional form but also have the ability to remove irrelevant variables. Therefore, it can be stated that these techniques allow us to deal with both specification and variable uncertainty.

[7] Using the principal-component factor method, the percentage of variance explained is 0.55 and the magnitude of the rotated factor loadings (varimax and Kaiser normalized matrix) is 0.74.

[8] Danish regions have not been included in our sample due to data limitations in the European Labour Force Survey.

[9] See also Capello and Lenzi (2013a, 2013b, 2014).

[10] We also considered the introduction of population density as a proxy for local knowledge spillovers due to agglomeration economies. Nonetheless, this variable has not been included due to its high correlation with the level of infrastructures. Unreported results are available from the authors upon request.

[11] Rather than trying to find robust regional growth determinants, we are more interested in uncovering the possible presence of nonlinearities in the knowledge-innovation-growth relationship. Furthermore, Breinlich, Ottaviano, and Temple (2014) have pointed out that the use of regional data may be much less vulnerable to omitted variables.

[12] Unreported results are available from the authors upon request.

[13] For this reason, countries that make up a NUTS2 region - Cyprus, Estonia, Lithuania, Luxembourg, Latvia and Malta - have not been included in our sample.

[14] The presence of islands in our sample does not allow us to use contiguity matrices because unconnected observations would have been dropped in the calculation of global Moran's I test statistics.

[15] For the sake of clarity, LISA maps for social capital the labor market specialization in KIS are not included because no significant clusters in the estimated effects for these variables have been detected. Unreported results are available from the authors upon request.

[16] Following Henderson, Papageorgiou, and Parmeter (2013), we have set $\lambda = 15$, $\sigma = 2$ and $B = 99$.

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TABLE 1: LSCV Bandwidths and Significance Tests

	Growth 2005-2007			Growth 2005-2012		
	(1)	(2)	(3)	(4)	(5)	(6)
R&D	0.06	0.06	0.54	0.15	3.55*	0.65
	[1.67]	[1.79]	[0.16]	[1.71]	[-1.69]	[-1.41]
	(.01)	(.01)	(.06)	(.01)	(.08)	(.28)
CAPABILITIES	2.18E+07*	0.26	7.20E+06*	1.47*	2.41*	0.70
	[-1.80]	[-0.96]	[-1.20]	[-0.66]	[-1.65]	[-1.64]
	(.14)	(.05)	(.12)	(.10)	(.04)	(.09)
INNOV	0.05	0.22	0.47	0.52	0.34	0.39
	[356.17]	[421.22]	[115.01]	[12.41]	[79.59]	[76.63]
	(.02)	(.00)	(.78)	(.05)	(.00)	(.17)
INFRASTR		282.03*			28.93	
		[-1.10]			[-1.55]	
		(.10)			(.07)	
FUNCTIONAL		7.74			3.45	
		[-0.77]			[0.29]	
		(.04)			(.00)	
SELFEMPL		4.95			1.40	
		[-0.99]			[1.30]	
		(.07)			(.01)	
TRUST		14.66			3.15	
		[-1.06]			[1.90]	
		(.14)			(.00)	
EMPLOYMENT			0.68			0.71

TABLE 2: LSCV Bandwidths and Diagnostic Test Statistics

	Growth 2005-2007			Growth 2005-2012		
	(1)	(2)	(3)	(4)	(5)	(6)
R&D	0.19	0.53	1.55	0.28	0.70	—
CAPABILITIES	—	0.52	—	—	0.30	1.46*
INNOV	0.16	0.50	—	0.40	0.58	—
INFRASTR		—			30.83	
FUNCTIONAL		2.89			2.97	
SELFEMPL		1.89			2.68	
TRUST		—			5.50	
EMPLOYMENT			1.34			—
FDI			0.87			—
KIS			0.04			0.43*
R^2	.49	.69	.82	.34	.87	.10
HLR1	0.29 (.37)	-0.19 (.34)	2.50 (.02)	2.18 (.00)	2.08 (.02)	-0.65 (.04)
HLR2	0.43 (.26)	-0.22 (.43)	2.46 (.01)	2.98 (.00)	1.59 (.03)	-0.80 (.07)
HLR3	0.90 (.05)	-0.66 (.46)	1.86 (.04)	0.03 (.08)	1.24 (.02)	-0.65 (.04)
I(k=4)	-0.05 (.14)	-0.05 (.13)	-0.01 (.41)	-0.03 (.26)	-0.08 (.03)	-0.03 (.29)
I(k=8)	-0.04 (.08)	-0.02 (.23)	-0.01 (.44)	-0.02 (.25)	-0.03 (.20)	0.00 (.46)
I(min_dist)	-0.02 (.04)	-0.01 (.31)	0.00 (.35)	-0.01 (.19)	0.00 (.38)	-0.01 (.16)

Note: Reported results correspond to local-linear kernel regressions. For a given variable, * indicates that the

TABLE 3: Estimated Partial Effects

	Mean	Q1	Q2	Q3	Positive	Negative
R&D	0.22	0.02	0.15	0.29	0.79	0.21
	(0.09)	(0.08)	(0.06)	(0.06)	[.44]	[.08]
CAPABILITIES	0.08	-0.18	0.14	0.42	0.60	0.40
	(0.22)	(0.31)	(0.12)	(0.25)	[.32]	[.17]
INNOV	4.07E-03	-0.06	-8.56E-08	0.05	0.46	0.50
	(8.58E-03)	(0.05)	(0.01)	(0.03)	[.22]	[.19]
INFRASTR	-0.01	-0.01	-0.01	-2.26E-03	0.19	0.81
	(1.50E-03)	(2.97E-03)	(0.01)	(3.84E-03)	[.09]	[.58]
FUNCTIONAL	-0.01	-0.05	-3.33E-03	0.02	0.46	0.54
	(0.01)	(0.03)	(0.02)	(0.03)	[.18]	[.27]
SELFEMPL	0.02	-0.02	0.03	0.07	0.66	0.34
	(0.03)	(0.03)	(0.02)	(0.04)	[.32]	[.16]
TRUST	0.02	0.01	0.03	0.04	0.82	0.18
	(4.34E-03)	(0.01)	(5.00E-03)	(0.01)	[.60]	[.09]
KIS	0.77	0.68	0.75	0.83	1.00	0.00
	(0.39)	(0.40)	(0.40)	(0.39)	[.36]	[.00]

Note: For the relevant regional growth determinants during 2005-2012, reported partial effects are the estimated derivatives from a local-linear kernel regression using the bandwidths in Table 2. Bootstrap standard errors (399 replications) in parentheses. Percentage of gradients that are significant in brackets.

TABLE 4: Threshold Analysis

	R&D	CAPABILITIES	INNOV	INFRASTR	FUNCTIONAL	SELFEMPL	TRUST
R&D	-11.17	4.77	-3.06	-17.71	-0.48	12.18	0.03
	(.01)	(.21)	(.66)	(.58)	(.02)	(.00)	(.26)
CAPABILITIES	-14.03	-1.37	-1.78	-18.34	-3.61	1.65	-1.51
	(.34)	(.20)	(.44)	(.68)	(.66)	(.31)	(.33)
INNOV	-4.82	0.07	2.36	-12.04	1.19	7.83	-3.66
	(.00)	(.13)	(.00)	(.00)	(.00)	(.00)	(.02)
INFRASTR	14.59	-4.01	3.27	9.66	-3.70	3.49	-4.55
	(.77)	(.70)	(.00)	(.65)	(.28)	(.04)	(.08)
FUNCTIONAL	20.46	4.00	0.34	7.47	-0.88	-1.38	4.17
	(.29)	(.79)	(.80)	(.78)	(.01)	(.00)	(.41)
SELFEMPL	-14.19	0.27	4.34	-1.52	4.20	1.47	5.92
	(.80)	(.37)	(.77)	(.90)	(.45)	(.47)	(.12)
TRUST	-12.58	3.58	3.30	-17.73	0.45	4.38	2.29
	(.10)	(.10)	(.06)	(.60)	(.00)	(.12)	(.23)
EMPLOYMENT	-12.35	1.65	1.23	-11.20	8.51	-1.06	3.74
	(.37)	(.78)	(.91)	(.54)	(.59)	(.98)	(.30)
FDI	19.04	1.27	2.81	14.71	-3.39	-3.39	3.71
	(.08)	(.02)	(.00)	(.06)	(.68)	(.37)	(.42)
KIS	19.63	4.39	-0.35	18.95	9.36	5.44	9.24

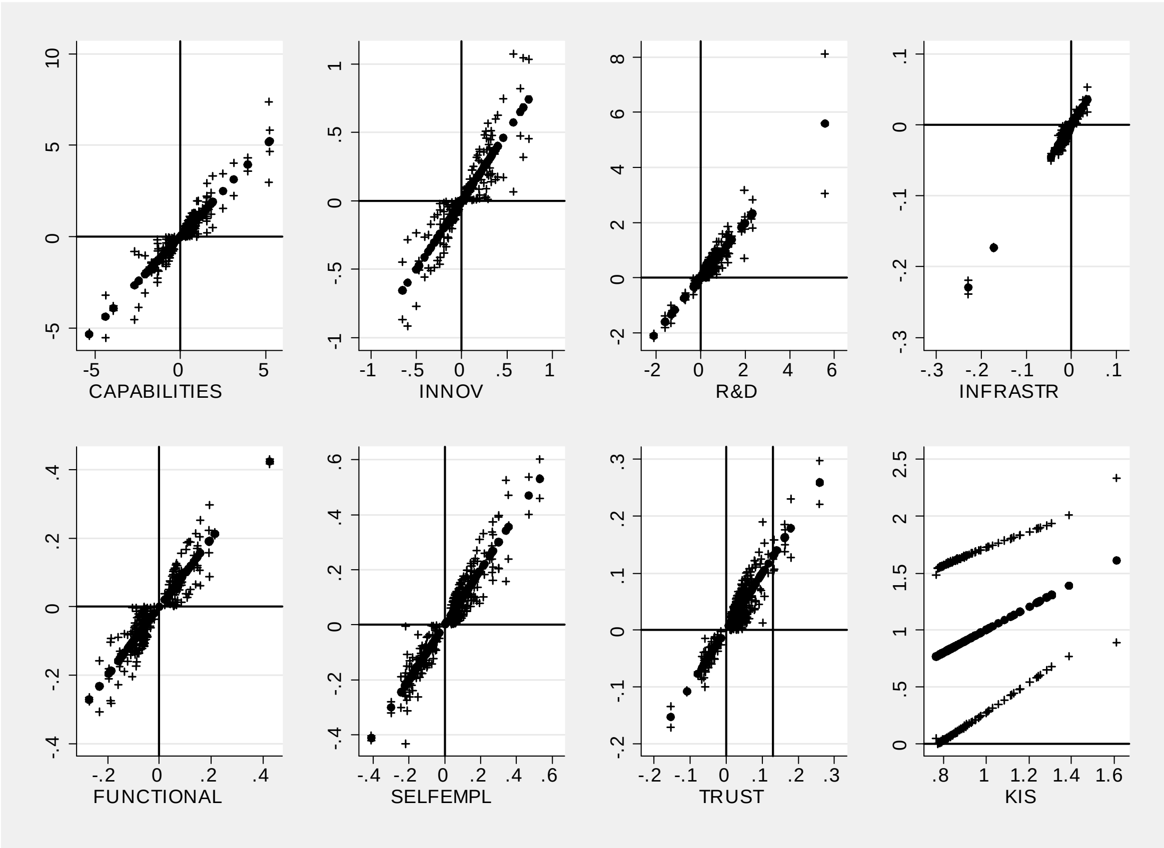
TABLE 5: Counterfactual Policy Analysis. Knowledge and Innovation

	minimax						minimin					
Variable: R&D	IIA	SCDA	STAA	ASA	ESBA	Total	IIA	SCDA	STAA	ASA	ESBA	Total
Increase	33	60	45	30	12	180	31	82	55	34	12	214
	[.92]	[.70]	[.69]	[.65]	[.63]	[.71]	[.86]	[.96]	[.85]	[.74]	[.64]	[.85]
No change	1	5	4	2	0	12	1	3	4	7	2	17
	[.03]	[.06]	[.06]	[.04]	[.00]	[.05]	[.03]	[.03]	[.06]	[.15]	[.10]	[.07]
Decrease	2	21	16	14	7	60	4	1	6	5	5	21
	[.05]	[.24]	[.25]	[.31]	[.37]	[.24]	[.11]	[.01]	[.09]	[.11]	[.26]	[.08]
Total	36	86	65	46	19	252	36	86	65	46	19	252
	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]
Variable: CAPABILITIES	IIA	SCDA	STAA	ASA	ESBA	Total	IIA	SCDA	STAA	ASA	ESBA	Total
Increase	12	42	50	31	12	147	8	21	42	38	11	120
	[.33]	[.49]	[.77]	[.67]	[.63]	[.58]	[.22]	[.24]	[.64]	[.83]	[.58]	[.48]
No change	2	2	1	4	0	9	3	10	4	5	4	26
	[.06]	[.02]	[.01]	[.09]	[.00]	[.03]	[.08]	[.12]	[.06]	[.11]	[.21]	[.10]
Decrease	22	42	14	11	7	96	25	55	19	3	4	106
	[.61]	[.49]	[.22]	[.24]	[.37]	[.39]	[.70]	[.64]	[.30]	[.06]	[.21]	[.42]
Total	36	86	65	46	19	252	36	86	65	46	19	252
	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]
Variable: INNOV	IIA	SCDA	STAA	ASA	ESBA	Total	IIA	SCDA	STAA	ASA	ESBA	Total

TABLE 6: Counterfactual Policy Analysis. Socio-Economic Factors

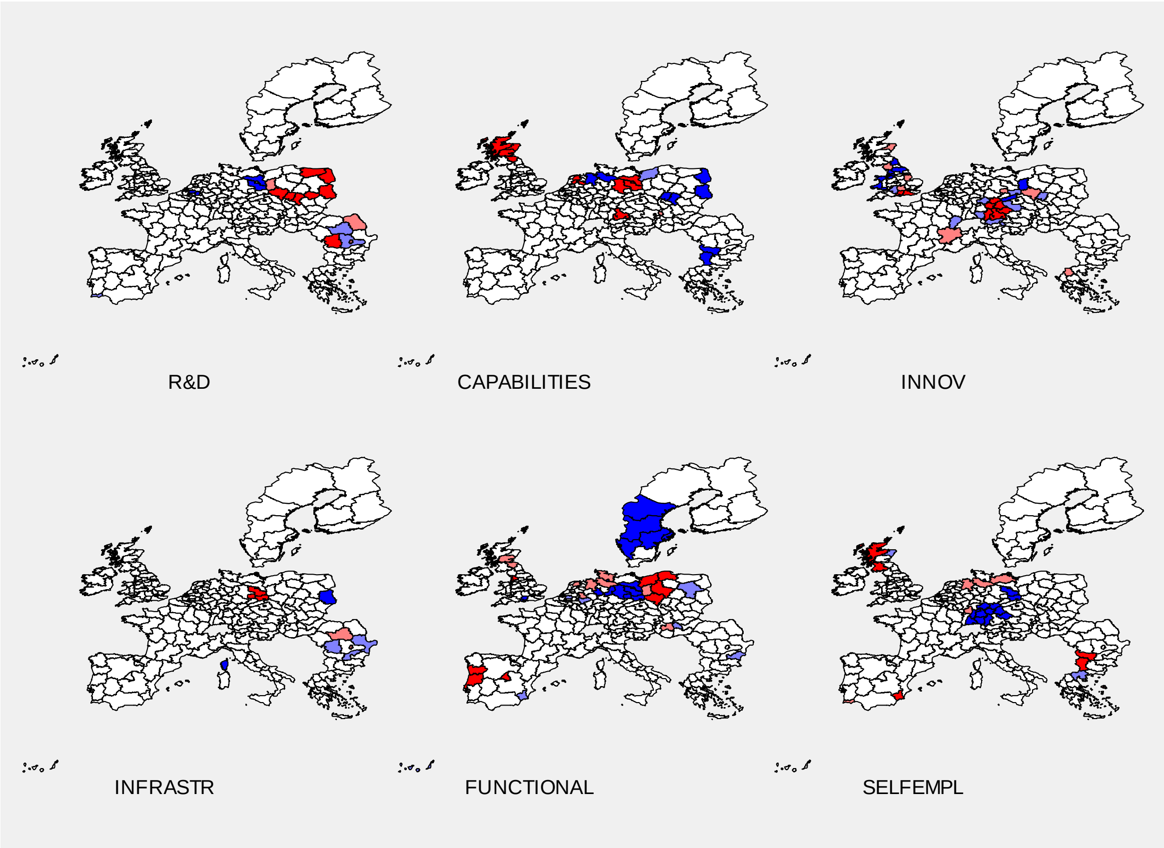
	minimax						minimin					
Variable: INFRASTR	IIA	SCDA	STAA	ASA	ESBA	Total	IIA	SCDA	STAA	ASA	ESBA	Total
Increase	2	11	12	11	2	38	0	5	3	8	1	17
	[.06]	[.13]	[.18]	[.24]	[.10]	[.15]	[.00]	[.06]	[.05]	[.17]	[.05]	[.07]
No change	3	7	8	9	5	32	16	38	24	32	8	118
	[.08]	[.08]	[.12]	[.20]	[.26]	[.13]	[.44]	[.44]	[.37]	[.70]	[.42]	[.47]
Decrease	31	68	45	26	12	182	20	43	38	6	10	117
	[.86]	[.79]	[.70]	[.56]	[.64]	[.72]	[.56]	[.50]	[.58]	[.13]	[.53]	[.46]
Total	36	86	65	46	19	252	36	86	65	46	19	252
	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]
Variable: FUNCTIONAL	IIA	SCDA	STAA	ASA	ESBA	Total	IIA	SCDA	STAA	ASA	ESBA	Total
Increase	29	53	41	19	6	148	13	30	20	4	6	73
	[.81]	[.62]	[.63]	[.41]	[.32]	[.59]	[.36]	[.35]	[.31]	[.09]	[.32]	[.29]
No change	4	6	7	6	6	29	15	38	23	31	9	116
	[.11]	[.07]	[.11]	[.13]	[.32]	[.12]	[.42]	[.44]	[.35]	[.67]	[.47]	[.46]
Decrease	3	27	17	21	7	75	8	18	22	11	4	63
	[.08]	[.31]	[.26]	[.46]	[.36]	[.29]	[.22]	[.21]	[.34]	[.24]	[.21]	[.25]
Total	36	86	65	46	19	252	36	86	65	46	19	252
	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]
Variable: SELFEMPL	IIA	SCDA	STAA	ASA	ESBA	Total	IIA	SCDA	STAA	ASA	ESBA	Total
Increase	16	39	36	15	3	109	18	38	33	9	4	102
	[.44]	[.45]	[.55]	[.33]	[.16]	[.43]	[.50]	[.44]	[.51]	[.20]	[.21]	[.40]
No change	4	8	8	5	3	28	17	43	23	30	8	121
	[.11]	[.09]	[.12]	[.11]	[.16]	[.11]	[.47]	[.50]	[.35]	[.65]	[.42]	[.48]

FIGURE 1: 45^o Plots of Estimated Partial Effects



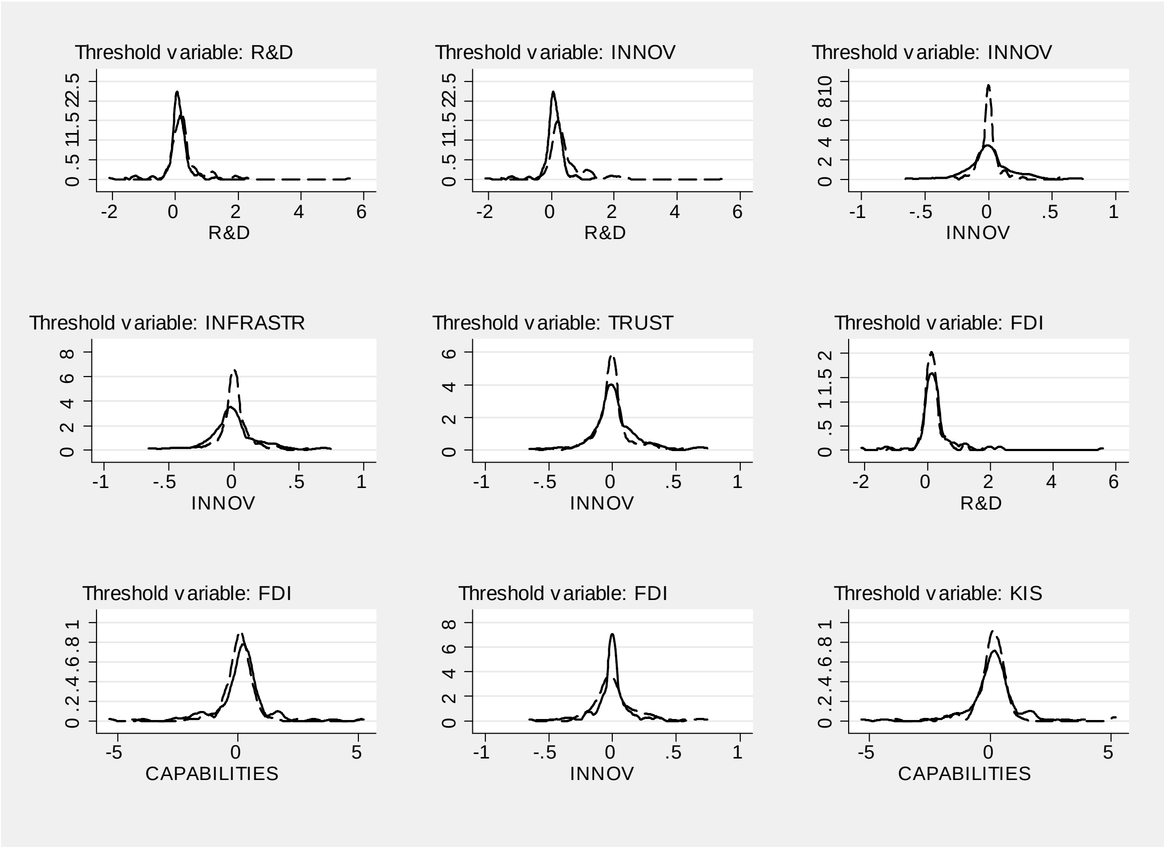
Note: These plots display the statistically significant estimated partial effects ($\pm 1.96 \cdot$ SEs) for the relevant growth determinants during 2005-2012.

FIGURE 2: LISA Maps of Estimated Partial Effects



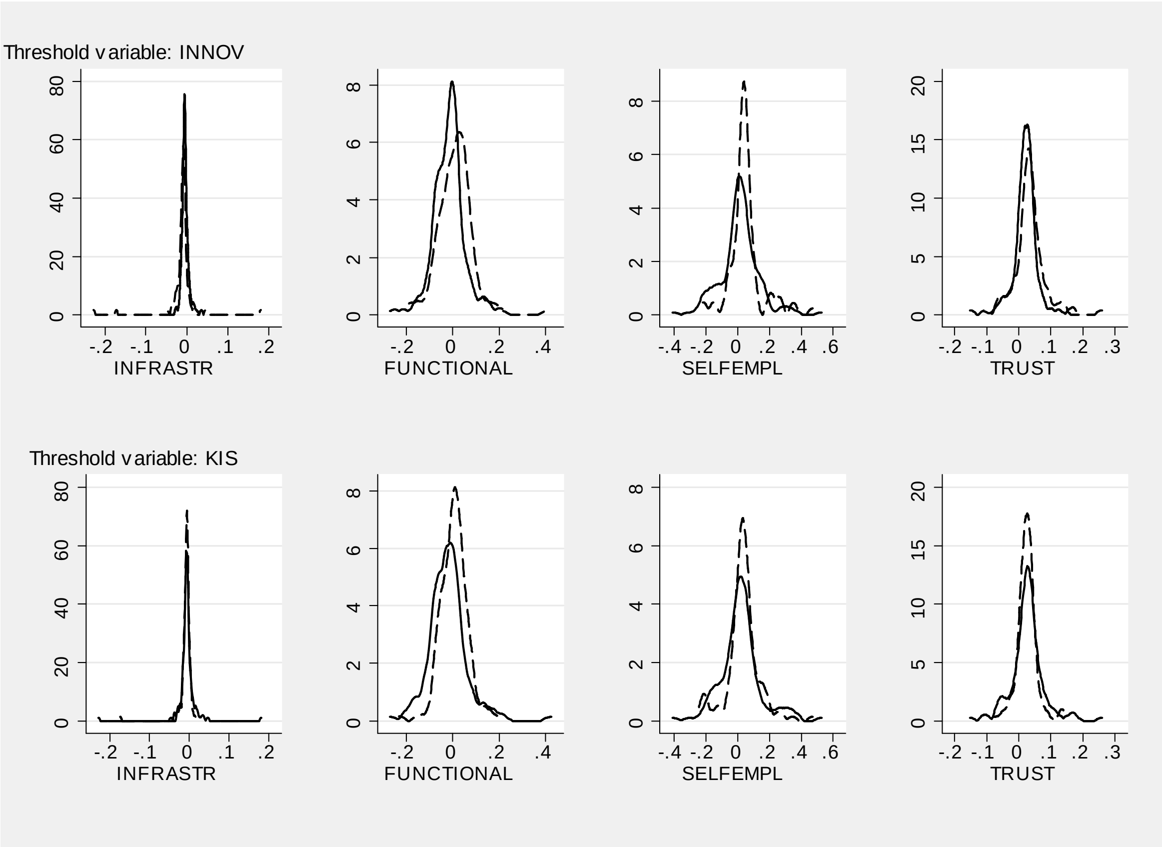
Note: LISA cluster maps of the estimated partial effects for selected regional growth determinants during 2005-2012. HH: red; LL: blue; HL: light red; LH: light blue.

FIGURE 3: Kernel Densities of Estimated Partial Effects. Knowledge and Innovation



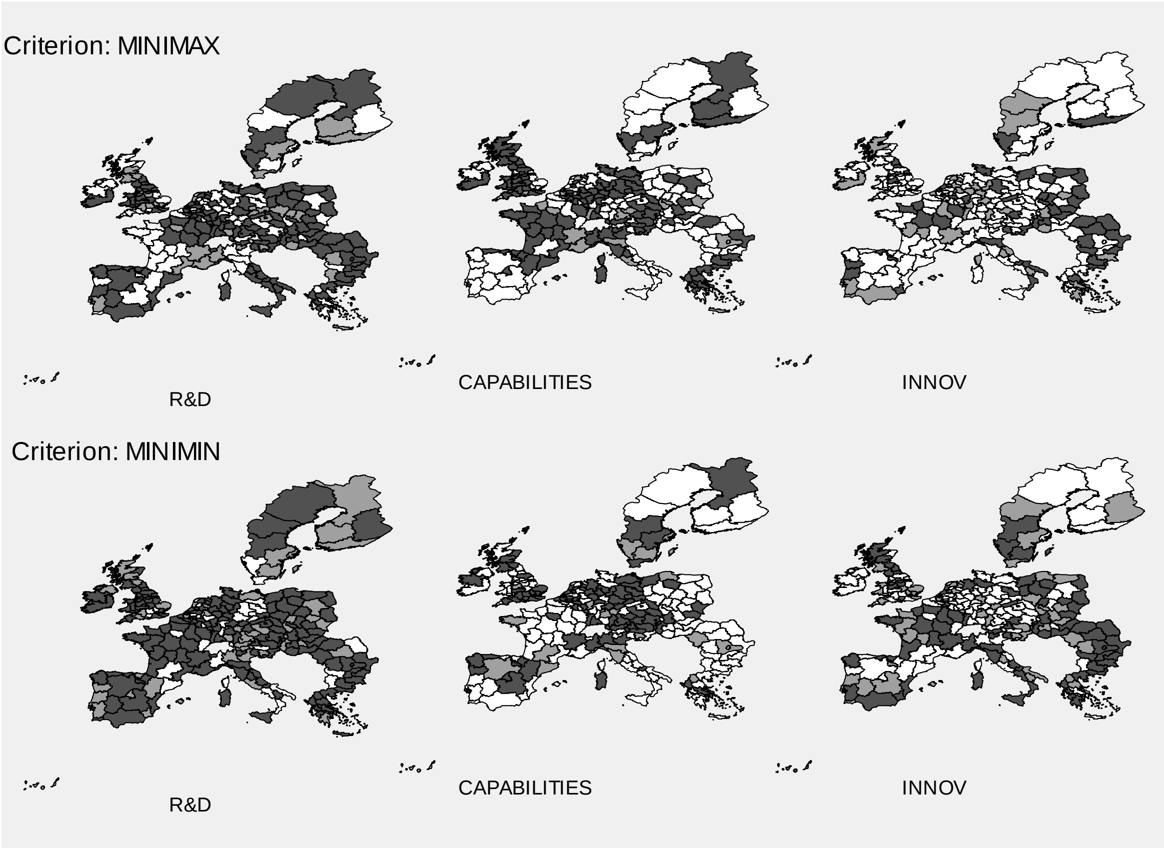
Note: Threshold effects depend on whether a variable takes values above (solid) or below (dashed) the sample median (see Table A2).

FIGURE 4: Kernel Densities of Estimated Partial Effects. Socio-Economic Factors



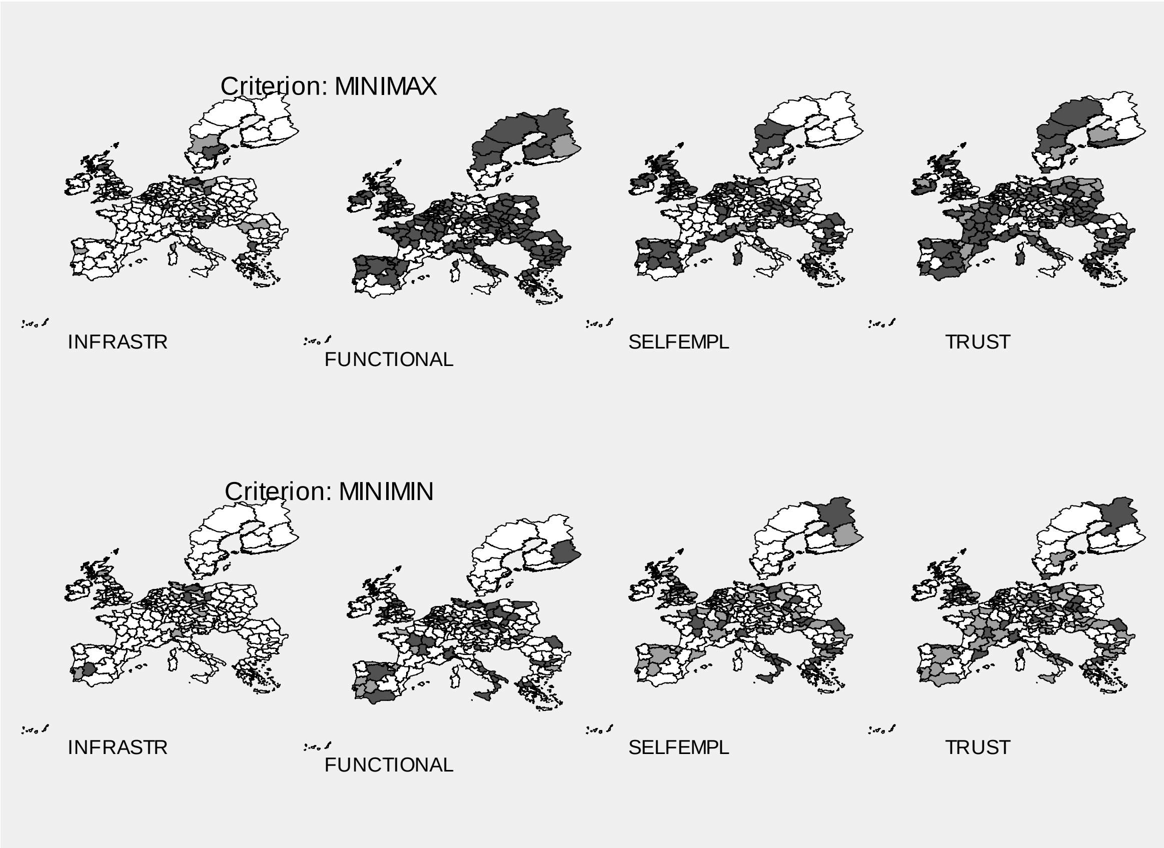
Note: Threshold effects depend on whether a variable takes values above (solid) or below (dashed) the sample median (see Table A2).

FIGURE 5: Counterfactual Policy Analysis. Knowledge and Innovation



Note: Shaded regions represent those for which the optimal policy alternative is to implement a moderate (light) or a high (dark) increase.

FIGURE 6: Counterfactual Policy Analysis. Socio-Economic Factors



Note: Shaded regions represent those for which the optimal policy alternative is to implement a moderate (light) or a high (dark) increase.

TABLE A1: Variable Description and Data Sources

Variable	Description	Years	Source
GROWTH	Real gross domestic product (GDP). Average annual growth rate	2005-2007	Cambridge Econometrics
		2005-2012	
Knowledge and innovation			
R&D	R&D expenditures as a percentage of GDP	Average	EUROSTAT
		2000-2002	
CAPABILITIES	Knowledge embedded in human capital. Proxy for the human resources devoted to	Average	European Labour Force Survey
	science and technology (ISCO codes 13 and 31)	1997-2001	
INNOV	Share of firms introducing product and/or process innovations. Ranked values.	2002-2004	ESPON
	1: 0-16.31%; 2: 16.32-23.53%; 3: 23.54-28.72%; 4: 28.73-33.97%; 5: 33.98-40.04%		
	6: 40.05-47.53%; 7: 47.54-59.06%; 8: 59.07-87.10%		
Socio-economic factors			
INFRASTR	Rail and road potential accessibility over total area. Proxy for infrastructure endowment	2001	ESPON
FUNCTIONAL	Share of high-skilled blue-collar occupations (ISCO codes 7 and 8) over total	Average	European Labour Force Survey
	employment. Proxy for high-level functional specialization	1997-2001	
SELFEMPL	Share of self-employment over total labor force (excluding wholesale retail sectors)	Average	European Labour Force Survey

TABLE A2: Descriptive Statistics, Raw Data

	Mean	SD	Min.	Max.	Correlation matrix 1	2	3	4	5	6	7	8	9	10	11	12
1 GROWTH0507	2.34	3.99	-6.82	13.09	1											
2 GROWTH0512	0.35	1.82	-3.14	5.83	.81***	1										
3 R&D	1.39	1.23	0.07	8.85	-.29***	-.13**	1									
4 CAPABILITIES	-2.29E-10	1.00	-3.46	2.75	-.33***	-.03	.36***	1								
5 INNOV	4.42	1.87	1	8	-.48***	-.33**	.55***	.34***	1							
6 INFRASTR	36.60	64.63	0.01	562.89	-.35***	-.21***	.25***	.18***	.42***	1						
7 FUNCTIONAL	24.03	6.40	7.86	39.50	.11*	-.00	-.36***	-.01	-.20***	-.36***	1					
8 SELFEMPL	12.44	6.46	3.45	38.08	.20***	-.05	-.34***	-.46***	-.34***	-.18***	.02	1				
9 TRUST	30.43	15.08	0	82.35	-.17***	-.12**	.34***	.30***	.35***	.12*	-.28***	-.29***	1			
10 EMPLOYMENT	-1.66	2.87	-11.65	6.87	.15**	.10	-.20***	-.14**	-.21***	-.24***	.27***	.26***	-.10	1		
11 FDI	2.12	4.76	0	41.81	.21***	.16**	-.20***	.03	-.26***	-.15**	.26***	-.05	-.15**	.15**	1	
12 KIS	0.96	0.17	0.51	1.97	.03	.14**	.23***	.22***	.16**	.27***	-.35***	-.25***	.15**	-.12*	.10	1

Note: ***, ** and * denote statistically significant at the 1, 5 and 10 percent significance level, respectively.

TABLE A3: Descriptive Statistics, Variables as Deviations from Country Means

					Correlation matrix											
	Mean	SD	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12
1 GROWTH0507	-5.60E-10	1.24	-4.54	9.30	1											
2 GROWTH0512	4.24E-10	0.72	-2.91	4.64	.70***	1										
3 R&D	-5.67E-10	0.99	-2.43	6.57	.22***	.20***	1									
4 CAPABILITIES	2.28E-10	0.48	-3.17	2.14	-.08	-.02	.17***	1								
5 INNOV	4.42	1.87	1	8	.02	.08	.17***	.17***	1							
6 INFRASTR	-7.06E-08	50.28	-86.40	416.83	-.01	-.04	.01	.01	.04	1						
7 FUNCTIONAL	2.85E-09	4.34	-18.01	12.86	-.03	-.11*	-.23***	-.10*	.05	-.25***	1					
8 SELFEMPL	-7.86E-09	3.56	-16.96	13.71	.02	-.08	-.07	-.10*	-.16***	.03	-.32***	1				
9 TRUST	1.40E-03	8.21	-23.31	33.41	.08	.17***	-.02	.08	.02	-.07	-.06	.03	1			
10 EMPLOYMENT	-7.14E-04	2.33	-10.95	9.57	-.02	-.01	-.02	-.17***	-.08	-.16**	.07	.02	.01	1		
11 FDI	6.35E-04	3.61	-10.84	26.67	-.08	-.08	-.04	-.19***	-.01	-.01	.09	-.15**	.01	.04	1	
12 KIS	-6.35E-04	0.16	-0.33	0.92	.10	.22***	.23***	.20***	.12*	.28***	-.55***	-.28***	.16***	-.14**	.07	1

Note: ***, ** and * denote statistically significant at the 1, 5 and 10 percent significance level, respectively.

TABLE B1: LSCV Bandwidths, IV Estimation

	First stage (Local-constant)	Second stage (Local-linear)
R&D	—	0.56
CAPABILITIES	0.14	0.30
INNOV	0.94	0.43
INFRASTR	96.90	32.28
FUNCTIONAL	2.64	3.04
SELFEMPL	11.74*	3.07
TRUST	2.13	5.30
EMPLOYMENT	0.92	—
FDI	0.30	—
$\widehat{u}$	—	0.64*
R^2	.90	.95

Note: For a given variable, * indicates that the bandwidth is higher than twice its sample standard deviation (see Table A3). $\widehat{u}$ denotes the residuals from the local-constant estimation in the first stage.

TABLE B2: Estimated Partial Effects, IV Estimation

	Mean	Q1	Q2	Q3	Positive	Negative
R&D	0.27	-0.06	0.14	0.47	0.68	0.32
	(0.14)	(0.09)	(0.04)	(0.18)	[.47]	[.16]
CAPABILITIES	0.07	-0.28	0.13	0.46	0.58	0.42
	(0.36)	(0.09)	(0.11)	(0.08)	[.38]	[.23]
INNOV	4.02E-04	-0.08	0.00	0.07	0.47	0.49
	(1.91E-05)	(0.02)	(0.00)	(0.06)	[.30]	[.30]
INFRASTR	-0.01	-0.01	-4.43E-03	5.59E-04	0.26	0.73
	(5.42E-03)	(3.14E-03)	(1.43E-03)	(2.04E-03)	[.14]	[.50]
FUNCTIONAL	-0.01	-0.05	-0.01	0.03	0.42	0.58
	(0.01)	(0.02)	(0.02)	(0.01)	[.26]	[.33]
SELFEMPL	0.03	-0.02	0.03	0.06	0.66	0.34
	(0.01)	(0.02)	(0.03)	(0.02)	[.47]	[.17]
TRUST	0.02	2.51E-03	0.02	0.04	0.77	0.23
	(5.53E-03)	(0.01)	(4.49E-03)	(0.01)	[.59]	[.14]

Note: Partial effects are the estimated derivatives from the second stage local-linear kernel regression using the bandwidths reported in Table B1. Bootstrap standard errors (399 replications) in parentheses. Percentage of gradients that are significant in brackets.