Nonlinearities in regional growth: A nonparametric approach*

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February 2013

Abstract

This paper analyzes the determinants of regional economic growth in the European Union. The nonparametric approach adopted allows us not only to uncover their relevance but also to determine whether or not they exert a linear influence. We obtain evidence of a nonlinear relationship between regional growth and its determinants, especially population growth, R&D activities and the level of infrastructures. Threshold effects, mainly affecting human capital and geographic factors, are also found.

Keywords: Regional growth; nonparametric methods; variable selection; nonlinearities.

JEL codes: C14; C20; O18; R11.

*The authors acknowledge financial support from Ministerio de Ciencia e Innovación (ECO2009-09332 and ECO2009-13675 projects), Ministerio de Educación (Grant AP2008-03561) and the Regional Government of Aragón (ADETRE Research Group).

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1 Introduction

Since the mid-1950s, there has been a widespread interest in identifying the drivers of economic growth, both from a theoretical and an empirical point of view (Aghion and Durlauf, 2005; Aghion and Howitt, 2009). Although the first theoretical model was formulated within the neoclassical paradigm (Solow, 1956; Swan, 1956), growth theory took an important leap forward when growth was made endogenous (Romer, 1986; Lucas, 1988). On the empirical side, a great variety of methods have been applied to test the implications of these theoretical models or to analyze the relevant variables for growth: cross sectional regressions (Mankiw et al., 1992), time series methods (Jones, 1995), panel data models (Islam, 1995) and, more recently, model averaging techniques (Fernández et al., 2001).

Theoretical models of regional growth have experienced a parallel evolution to the mainstream of growth economics since the neoclassical contribution of Borts and Stein (1964) and led to the emergence of the *"new economics of urban and regional growth"* (Glaeser, 2000), clearly influenced by the endogenous growth theory. Nevertheless, empirical analyses of the determinants of regional economic growth are more limited than those available at country level, see Crespo-Cuaresma et al. (2011, 2012) and the references therein.

Following the work of Durlauf and Johnson (1995) and Liu and Stengos (1999), recent studies are questioning the linearity assumption in the empirical specifications of growth regressions. Moreover, the new growth theory predicts a nonlinear relationship between growth and some of its determinants (Masanjala and Papageorgiou, 2004; Fiaschi and Lavezzi, 2007; Tan, 2008). Against this background, the use of semiparametric and nonparametric methods is becoming increasingly popular in growth empirics due to their flexibility (Durlauf et al., 2001; Maasoumi et al., 2007).

In line with the recent trend in country-level analyses, several studies have tried to uncover nonlinear relationships between regional growth and its determinants. Funke and Niebuhr (2005) find the presence of threshold effects of human capital on growth in West Germany. Although mainly interested in convergence and spatial issues, Basile and Gress (2005) and Basile (2008), using semiparametric methods, conclude that initial per capita income and schooling have a nonlinear effect on growth for the European regions. Also within this framework, and with an emphasis on the role played by entrepreneurship, Fotopoulos (2012) finds that there is an income range where growth rates increase with initial income per capita. However, this author is not able to obtain evidence of nonlinear effects for human capital nor for entrepreneurship.

The nonlinearities considered in this paper refer to processes that, according to the multiple steady-state type of models (Azariadis and Drazen, 1990; Galor and Weil, 2000), imply different parameters across regions in growth regressions. We try to contribute to this literature in several ways. First, to the best of our knowledge, this is the first work that analyzes nonlinearities in regional growth through the exclusive use of nonparametric estimation methods. Second, the set of potential growth determinants considered is much wider than that used in previous related studies. Third, we make more effort to distinguish between nonlinearities that imply different effects of growth determinants across regions and those that imply the presence of threshold effects.

Before proceeding with the analysis, it is worth noting that the perspective adopted in this paper is intended to be theoretically-oriented. The reason is that our interest is to determine not only which variables are relevant in explaining growth but also to reveal which of them have a nonlinear relationship with it. We hope our results may motivate and guide future regional growth models.

The rest of the paper is structured as follows. Section 2 presents the data and variables considered while Section 3 explains the nonparametric methods applied in the empirical analysis. An assessment of the relevant regional growth determinants and their possible nonlinear influence is carried out in Section 4. Finally, Section 5 concludes.

2 Data and variables

Regional growth theory evolved in parallel to the mainstream of growth economics after the development of the neoclassical model in Borts and Stein (1964). Since there are several recent surveys and handbooks on this issue[1], we do not describe the existing literature in depth.

Trying to make a selection and a focused attempt to highlight general theoretical trends, it can be stated that the *"new economics of urban and regional growth"* (Glaeser, 2000) was clearly influenced by the endogenous theory where knowledge (Romer, 1986) and human capital (Lucas, 1988) accumulation and R&D activities (Romer, 1990) were explicitly modelled as determinants of long-run growth. Furthermore, the advent of the *"new economic geography"* (Krugman, 1991) also emphasized the role of agglomeration forces and spillovers, while there is also an interest in the link between different types of infrastructures and long-run growth (Easterly and Rebelo, 1993). As pointed out in

[1]See Capello (2009), Capello and Nijkamp (2009), Roberts and Setterfield (2010), Harris (2011) and Basile and Usai (2012), among others.

Basile and Usai (2012), and in line with the main aim of this paper, linear regression analyses are of limited use when looking for evidence to discriminate between these different theoretical approaches.

Against this background, we are interested in studying the relevance of these alternative theories and the possible existence of underlying nonlinear effects. The analysis has been carried out with data compiled by Crespo-Cuaresma and Feldkircher (2012) for 255 European NUTS-2 regions during the period 1995 to 2005[2]. The dependent variable is the average growth rate of regional real GDP per capita. When possible, empirical proxies for growth determinants are taken at the beginning of the period and have been grouped according to their nature and related theory.

Our baseline specification corresponds to neoclassical growth models that emphasize the role of capital accumulation, population growth, productivity and (exogenous) technology. Therefore, the related variables we consider are the initial real GDP per capita (GDPCAP), the population growth rate (GPOP), and the shares of total gross value added of the mining, manufacturing and energy sectors (SHCE) and of gross fixed-capital formation (SHGFCF). In line with a human capital-augmented version of this type of models (Mankiw et al., 1992), the ratio of persons involved in lifelong learning activities over the total number of employed persons (SHLLL) and the share of highly educated (according to the ISCED classification) people in the working-age population (SHSH) have also been included.

Endogenous growth theories give a prominent role to R&D activities and their innovation results. They have been proxied in the empirical analysis by the human resources devoted to science and technology (HRSTCORE), the total number of patents (PATENT) and the number of patents in information and communication technologies (PATENTICT) per thousand inhabitants. The share of patents in biotechnology (PATENTSHBIO) and in high technology (PATENTSHHT) over the total have also been included in a second specification ('R&D/Innovation').

The third model considered in the empirical analysis ('Infrastructures') will also reflect the influence that different types of infrastructures can exert on growth through agglomeration forces and knowledge spillovers. The level of infrastructures is measured by the airport (AIRPORTDENS), road (ROADDENS) and rail (RAILDENS) densities; the connectivity (in hours) of the capital to commercial airports by car (CONNECTAIR); the proportion of firms with their own website (INTF); and a typology of the level of household (TELH) and business (TELF) telecommunications access and

[2] Further details to those presented in this subsection can be found in the material available at http://onlinelibrary.wiley.com/doi/10.1002/jae.2277/suppinfo.

uptake.

Basile and Gress (2005) and Basile (2008) admit that there is a trade-off between the identification of nonlinearities and the estimation of spatial parameters. For this reason, and because we are more interested in the former, socio-geographic variables have also been considered as an attempt to proxy for further spatial aspects. More specifically, in a fourth specification ('Socio-geographic'), we have included the sum of all weighted hazard values (HAZARD), the distance to the capital (DISCAP) and the settlement structure (SETTL). Dummies for coastal (REGCOAST), border (REGBORDER) and 'objective 1' (REGOBJ1) regions and an indicator of whether the region contains the capital (CAPITAL) have also been considered.

3 Nonparametric kernel regression methods

To a great extent, the empirical analysis carried out in Section 4 follows the approach proposed by Henderson et al. (2012a) which, at the same time, is based on the work of Hall et al. (2007). These authors exploited the fact that the relevance and nonlinear influence of the explanatory variables in nonparametric kernel regressions are uncovered by their corresponding bandwidth parameters when those are determined using a least-squares cross-validation selection method[3].

A nonparametric specification of a growth regression is:

$$g_i = m\left(x_i\right) + u_i; \quad i = 1, \ldots, n \tag{1}$$

where g_i is real output growth for region i, x_i is a vector of q variables related to growth, u_i is a zero mean additive error and n the number of regions. $m(\cdot)$ is the (smooth) unknown function for the conditional mean:

$$m(x) = E[g_i|x_i = x] \tag{2}$$

The flexibility of nonparametric estimation methods derives from the fact that it is not necessary to make any assumption about the functional form for the conditional mean or the distribution of the error term. One alternative for estimating the conditional mean function is by locally averaging the growth rates of the regions that are similar in terms of the values taken by their determinants. This method is known as

[3] An excellent textbook treatment of nonparametric econometric techniques can be found in Li and Racine (2007).

the local-constant kernel estimator:

$$\hat{m}\left(x\right)=\sum_{i=1}^{n}g_{i}w_{i} \tag{3}$$

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

$$w_{i}=\frac{K(\frac{x_{i}-x}{h})}{\sum\limits_{j=1}^{n}K(\frac{x_{j}-x}{h})} \tag{4}$$

with

$$K(\frac{x_{i}-x}{h})=k(\frac{x_{i1}-x_{1}}{h_{1}})\cdot\ldots\cdot k(\frac{x_{iq}-x_{q}}{h_{q}}) \tag{5}$$

and $h(\cdot)$ being a kernel function.

The amount of information used to obtain the local average is controlled by the bandwidths $h=(h_{1},...,h_{q})$. A data-driven method for selecting these smoothing parameters is least-squares cross-validation, which consists of choosing h to minimize

$$CV_{LC}(h)=\frac{1}{n}\sum_{i=1}^{n}(g_{i}-\hat{m}_{-i}(x_{i}))^{2}M(x_{i});\quad 0\leq M(\cdot)\leq 1 \tag{6}$$

where $\hat{m}_{-i}(x_{i})$ is the leave-one-out estimator of the conditional mean function:

$$\hat{m}_{-i}(x_{i})=\sum_{l\neq i}^{n}\frac{g_{l}K(\frac{x_{i}-x_{l}}{h})}{\sum\limits_{l\neq i}^{n}K(\frac{x_{i}-x_{l}}{h})} \tag{7}$$

and $M(\cdot)$ is an arbitrary weighting function.

Least-squares cross-validation bandwidth selection, in conjunction with the local-constant kernel estimation, is capable of automatically reducing the dimension of the problem when some of the regressors are irrelevant. The irrelevant variables will be smoothed out as $k(\frac{x_{is}-x_{s}}{h_{s}})\rightarrow k(0)$ when $h_{s}\rightarrow\infty$.

The local-constant kernel estimator can also be obtained as

$$\hat{a}=\arg\min_{a}\sum_{i=1}^{n}(g_{i}-a)^{2}K(\frac{x_{i}-x}{h}) \tag{8}$$

and, hence, uses a constant to approximate g in the neighbourhood of x.

Another alternative for estimating the conditional mean function is to use a local-linear kernel regression method. This provides an estimator for $m^{(1)}(x) = \frac{\partial m(x)}{\partial x}$ based on the following problem:

$$\min_{a,b} \sum_{i=1}^{n} (g_i - a - (x_i - x)'b)^2 K(\frac{x_i - x}{h}) \tag{9}$$

It has been demonstrated (Li and Racine, 2007) that the solutions $\hat{a} = a(x)$ and $\hat{b} = b(x)$ are consistent estimators of $m(x)$ and $m^{(1)}(x)$, respectively. Due to its analogy to local least-squares, the local-linear estimation method nests the least-squares estimator as a special case for sufficiently large values of h_s; $s = 1, ..., q$.

The least-squares cross-validation approach for bandwidth selection in the local-linear framework consists of choosing h to minimize

$$CV_{LL}(h) = \frac{1}{n} \sum_{i=1}^{n} (g_i - \hat{m}_{-i,LL}(x_i))^2 M(x_i); \quad 0 \leq M(\cdot) \leq 1 \tag{10}$$

As before, $\hat{m}_{-i,LL}(x_i)$ denotes the leave-one-out local-linear estimator and $M(\cdot)$ is an arbitrary weighting function.

What is important for the main aim of this paper is that the least-squares cross-validation criterion for the local-linear estimation method has the ability to select a large value of h_s when the conditional mean function is linear in x_s. If not, it will select small values of the bandwidth parameter for regressors that have a nonlinear relationship with growth.

The kernel function used in the empirical analysis is the Gaussian one:

$$k(v) = \frac{1}{\sqrt{2\pi}} e^{-\frac{v^2}{2}} (-\infty < v < \infty) \tag{11}$$

For this reason, we consider that a continuous variable enters the conditional mean in an irrelevant fashion (local-constant regression) or linearly (local-linear) if its corresponding bandwidth parameter is more than two times its sample standard deviation. Finally, it is worth noting that, when necessary, the version of the estimation methods applied are those that allow us to handle both continuous and discrete variables in x_i (Li and Racine, 2003).

4 Regional growth determinants: relevance and nonlinear effects

4.1 Relevance: parametric vs. nonparametric approaches

Mainly for comparison purposes, the empirical analysis begins with the estimation of a standard parametric OLS regression for the four different specifications, made up of variables taken from the leading regional growth theories.

As noted in Section 2, the first of these specifications corresponds to our baseline model that includes regional growth determinants related to a human capital-augmented version of the neoclassical model. Results are reported in the first column of Table 1. In line with the theoretical predictions, the estimated parameters suggest that the GDP per capita at the beginning of the period has a negative effect on growth while population growth and the share of highly educated working-age population promote growth. The other three variables included in the baseline specification (lifelong learning activities, the shares of total gross value added of the mining, manufacturing and energy sectors and of gross fixed-capital formation) are not statistically significant, despite having the correct sign.

[Insert Table 1 here]

As can be observed in the other three colums of Table 1, only initial GDP per capita and educational level at the beginning of the period are statistically significant in the four specifications considered and, hence, robust drivers of growth. Four out of the seven neoclassical growth determinants are significant in the specification that also includes socio-geographic variables where, apart from those in the baseline model, the initial share of the primary sector also seems to promote growth. This specification is the one in which the highest explanatory power is achieved.

When variables related to R&D activities and innovation results are added to the baseline model, it is found that the total number of patents and the number of patents in information and communication technologies per thousand inhabitants have a significant effect on growth. However, the negative sign of the former is counterintuitive and there is no gain in terms of explanatory power with respect to the baseline model. The introduction of variables related to the level of infrastructures leads us to conclude that only those related to air transport have a positive effect on growth. Finally, the results reported in the fourth column of Table 1 suggest that the only socio-geographic variable that is related to regional growth is that of housing the country's capital city.

The results described above contrast sharply with those obtained from the application of a nonparametric approach. Bandwidths calculated with a least-squares cross-validation selection rule for the local-constant kernel regression estimation method are reported in Table 2. The bandwidth parameters corresponding to the baseline specification are similar to those in Henderson et al. (2012a) at country level. Lifelong learning activities is the only irrelevant neoclassical growth determinant. Nevertheless, this proxy for human capital is always significant in the other three specifications. The shares of the mining, manufacturing and energy sectors and of gross fixed-capital formation of total gross value added are significant in the four specifications when local-constant nonparametric kernel regression methods are applied. Population growth is related to regional growth in all cases except when the variables reflecting socio-geographic factors are added to the baseline model.

[Insert Table 2 here]

Going into the details of each specification, it can be seen that the variables reflecting R&D activities and their innovation results that are significant are the more general ones (human resources devoted to science and technology and the total number of patents). Infrastructures other than those related to airports significantly influence growth. This result confirms those obtained by Del Bo et al. (2010) and Del Bo and Florio (2012) who find that transport and telecommunication infrastructures play an important role in promoting regional growth in the European Union. Finally, it can be observed that none of the socio-geographic variables are smoothed out. This finding emphasizes once again the role played by space and geography in explaining regional growth.

To sum up, while standard parametric OLS estimation leads us to conclude that the main drivers of regional growth are the variables related to convergence, human capital, innovation results and aerial infrastructures, a wider set of variables and, hence, theories become relevant when adopting a more flexible nonparametric approach. This is especially true for variables related to infrastructures and socio-geographic factors.

4.2 A nonparametric assessment of nonlinearities

Having identified, using nonparametric methods, 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 section devoted to the methodology, this is related to the magnitude of the bandwidth parameter calculated by using a least-squares cross-validation rule for the local-linear kernel regression. The results obtained are reported in Table 3.

The magnitude of the bandwidths for the baseline model in the first column suggests that the only neoclassical variable that exerts a linear influence on growth is gross fixed-capital formation. This finding is common to the four specifications considered. It can also be observed that the only neoclassical variable that has a robust nonlinear relationship with growth across specifications is population growth. Including additional growth determinants taken from the other theories not only increases the explanatory power but also mitigates the nonlinear effects of neoclassical variables. Nonlinear effects are especially relevant for the empirical proxies of R&D, innovation results and the level of infrastructures. As is shown in the last column of Table 3, continuous socio-geographic variables (weighted hazards and distance to the capital) seem to have a linear relationship with growth. This result will be qualified later.

[**Insert Table 3 here**]

The statistics reported in the lower panel of Table 3 point to the convenience of adopting a nonparametric approach. First, the coefficients of determination are considerably higher than those corresponding to the standard parametric OLS estimation shown in Table 1. For the nonparametric approach, the highest explanatory power is achieved with the specification that includes variables measuring the level of infrastructures. Second, the test of Hsiao et al. (2007) favours the use of a nonparametric estimation for all the specifications.

The influence of the relevant and continuous growth determinants has been further analyzed through the estimated sign of the partial effect (gradient) from the local-linear kernel regression method using the bandwidths in Table 3. Relevant quartiles for the neoclassical growth variables in the four specifications considered are shown in Table 4. The results obtained are robust as there are no big differences across specifications for any of the variables. It should be noted that the partial effects that will be analyzed hereafter are those estimated for the specification with the variables measuring the level of infrastructures. The reason is that the highest coefficient of determination is achieved with this specification and all of the variables in the baseline model are relevant.

The estimated partial effects provide further evidence of the presence of a convergence process across European regions as they have a negative sign for initial GDP per capita and a positive one for the initial share of total gross value added of the mining, manufacturing and energy sectors, when statistically significant. The levels of investment and human capital are also found to be positively related to growth. In line with the results in Table 3, the interquartile range of the estimated partial effects for population growth suggests that the relationship of this variable with growth is highly nonlinear.

[**Insert Table 4 here**]

Following Henderson et al. (2012b), results from the (multivariate) nonlinear kernel regressions are better represented using 45° plots. This graphical instrument consists of a representation of the estimated partial effects for a given variable against themselves, allowing us to distinguish where the bulk of the effects lie. Their main advantage is that they do not require fixing the remaining variables at a specific value. Significant estimated gradients at a 95% significance level along with their bootstrap confidence bands (399 replications) for the determinants in our baseline specification are displayed in Figure 1. The conclusions drawn are in line with those in Table 4. That is, gradients for the initial GDP per capita tend to be negative while those for the primary sector, capital investment and human capital are mainly positive. In addition, and confirming previous results, nonlinearities are evident for population growth.

[**Insert Figure 1 here**]

The same analysis as above has been carried out with the remaining continuous and significant growth determinants. The relevant quantiles and 45^o plots for the estimated gradients are found in Table 5 and Figure 2, respectively. Nonlinearities for the variables related to R&D and innovation are more evident for the total number of patents per thousand inhabitants. Only the upper quartile for the gradients of the human resources devoted to science and technology is significant and has a positive sign. Road and rail densities are related to growth in a nonlinear way, but only the significant gradients for the relevant quartiles have a negative sign. Although this finding can be interpreted as evidence of inefficiencies in infrastructure provision, it is much more reasonable to think that it is a result of the convergence process. Furthermore, this analysis confirms the negative and linear relationship of the connectivity to commercial airports by car with growth.

[Insert Table 5 and Figure 2 here]

The quartiles for the estimated gradients and their corresponding 45^o plots for the relevant and continuous socio-geographic variables contrast with the bandwidths shown in Table 3. Both the lower and upper quartiles for the sum of all weighted hazard values and the distance to the capital are significant but of different signs[4]. These results lead us to suspect that some type of nonlinearity other than those captured by the cross-validation bandwidth selection rule for the local-linear estimation is present. These findings are also reflected in the two 45^o plots in the lower part of Figure 2 and, as will be seen in the following subsection, are related to the existence of threshold effects.

4.3 Uncovering threshold effects

The different conclusions about the relationship between socio-geographic variables and growth drawn from the local-linear cross-validation bandwidths and the 45^o plots lead us to look for a specific type of nonlinearities, namely, threshold effects. This has been done by comparing the density functions of the partial effects for each growth determinant depending on whether or not the value of a given threshold variable is above its sample median. The comparison has been carried out by applying the density equality test proposed by Li et al. (2009) that is also based on the least-squares cross-validation bandwidth selection. The null hypothesis is that of equal density functions.

[Insert Table 6 here]

The test statistics obtained, along with their corresponding bootstrap p-values (399 replications), are shown in Table 6. Each row displays the results for the variable that generates the threshold effects, that is, the variable that takes values above or below its sample median. Each column refers to the variable that experiences the threshold effect and, hence, for which the densities of the gradients are compared. Focusing on the strongest rejections, it can be stated that the variables for which a higher number of rejections are found are initial GDP per capita and R&D activities, followed by human capital. On the contrary, the geographical variables are least prone to induce threshold effects. In addition, the variables that are more affected by this type of nonlinearity are initial GDP per capita, the share of highly educated working-age population and

[4]Existing studies have already established that natural disasters affect economic growth, but not always negatively (Loayza et al., 2012).

the geographical variables. These findings are in line with the 45^o plots in Figures 1 and 2 and, more importantly, with the conclusions drawn by Basile and Gress (2005) and Basile (2008). However, our results also suggest R&D activities as generating, and geographical factors as experiencing, threshold effects.

[Insert Figures 3 and 4 here]

Taking these results into account, a comparison of the estimated kernel density functions for the gradients of the variables mainly affected by threshold effects depending on whether initial GDP per capita and the share of highly-educated working-age population are above or below their sample medians is shown in Figures 3 and 4, respectively. It can be observed that positive gradients for initial GDP per capita tend to be obtained when both threshold variables are in their upper regimes (above their sample medians). When this is the case, the positive effect of human capital also tends to be greater. Finally, the estimated density functions also suggest that the adverse effects induced by the geographic variables are aggravated when both threshold variables are below their sample medians.

5 Concluding remarks

Nonparametric methods have been applied in this paper to jointly deal with variable selection and nonlinearities (model uncertainty) in regional growth regressions. This approach leads us to conclude that a wider set of variables and, hence, theories is able to explain regional growth processes in comparison with standard parametric methods. In line with existing results at country level, we obtain evidence of nonlinear relationships between regional growth and some of its determinants. They are especially relevant for population growth, R&D activities and the level of infrastructures. Threshold effects, mainly affecting human capital and geographic factors, are also found.

From a theoretical point of view, it is worth noting that these conclusions may motivate and guide future regional growth models. Moreover, and from an empirical point of view, the extension of the methodology applied to consider the complete distribution of growth rates and to allow for spatial dependence would surely enrich the analysis. These are promising avenues of research.

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Tables and Figures

Table1. Regional growth determinants. Standard OLS regression.

Variable	Baseline	R&D / Innovation		Infrastructures		Socio-geographic	
GDPCAP	-0.02***		-0.02***		-0.02***		-0.02***
	(1.78E-03)		(2.09E-03)		(3.59E-03)		(2.00E-03)
GPOP	0.23*		0.20		0.20		0.27**
	(0.14)		(0.14)		(0.14)		(0.12)
SHCE	0.01		0.02		0.02		0.03**
	(0.01)		(0.02)		(0.01)		(0.01)
SHGFCF	0.01		0.01		0.01		0.01
	(0.01)		(0.01)		(0.01)		(0.01)
SHLLL	2.01E-03		-2.75E-03		0.01		0.01
	(0.01)		(0.01)		(0.02)		(0.01)
SHSH	0.07***		0.07***		0.06***		0.05***
	(0.01)		(0.01)		(0.01)		(0.01)
		HRSTCORE	-5.39E-06	AIRPORTDENS	5.14**	CAPITAL	0.02***
			(0.01)		(2.14)		(2.25E-03)
		PATENTICT	0.08*	CONNECTAIR	-0.01***	DISTCAP	-6.54E-07
			(0.04)		(1.56E-03)		(3.93E-06)
		PATENTSHBIO	0.02	INTF	2.63E-03	HAZARD	-4.13E-06
			(0.02)		(0.01)		(2.13E-05)
		PATENTSHHT	-1.22E-03	RAILDENS	3.34E-03	REGBOARDER	4.39E-04
			(0.01)		(0.02)		(1.27E-03)
		PATENT	-0.03*	ROADDENS	-0.01	REGCOAST	-3.85E-04
			(0.02)		(0.01)		(1.31E-03)
				TELF	-1.03E-03	REGOBJ1	2.30E-03
					(8.36E-04)		(2.01E-03)
				TELH	-5.31E-04	SETTL	-2.07E-04
					(9.30E-04)		(1.41E-03)
Intercept	0.21***		0.19***		0.22***		0.19***
	(0.02)		(0.02)		(0.03)		(0.02)
Adjusted R^2	0.41		0.41		0.45		0.59
Observations	255		255		255		255

Note: Standard errors in parentheses. ***, ** and * denote statistically significant at the 1, 5 and 10% level, respectively.

Table 2. Least-squares cross-validation bandwidths for the local-constant kernel estimator.

Variable	Baseline	R&D / Innovation		Infrastructures		Socio-geographic	
GDPCAP	0.22		0.36		0.38		0.24
GPOP	0.00		0.00		0.00		38610.63*
SHCE	0.05		0.06		0.03		0.06
SHGFCF	0.05		0.05		0.06		0.07
SHLLL	400520.46*		0.03		0.01		0.08
SHSH	0.02		0.07		0.03		0.01
		HRSTCORE	0.03	AIRPORTDENS	2573.97*	CAPITAL	0.00
		PATENTICT	262162.01*	CONNECTAIR	0.45	DISTCAP	168.40
		PATENTSHBIO	380193.84*	INTF	375614.54*	HAZARD	20.02
		PATENTSHHT	0.20*	RAILDENS	0.03	REGBOARDER	0.49
		PATENT	0.06	ROADDENS	0.05	REGCOAST	0.36
				TELF	0.58	REGOBJ1	0.50
				TELH	0.70	SETTL	0.25

Note: * Denotes that the variable is smoothed out of the regression.

Table 3. Least-squares cross-validation bandwidths for the local-linear kernel estimator.

Variable	Baseline	R&D / Innovation		Infrastructures		Socio-geographic	
GDPCAP	0.36		0.38		37237.37*		248534.07*
GPOP	0.00		0.01		0.01		—
SHCE	0.06		47280.18*		0.04		4149.45*
SHGFCF	113471.95*		124187.28*		40702.89*		14269.49*
SHLLL	—		0.03		9757.53*		0.04
SHSH	0.05		0.05		5823.55*		0.09
		HRSTCORE	0.07	AIRPORTDENS	—	CAPITAL	0.00
		PATENTICT	—	CONNECTAIR	260555.77*	DISTCAP	302026219.01*
		PATENTSHBIO	—	INTF	—	HAZARD	64.26*
		PATENTSHHT	—	RAILDENS	0.10	REGBOARDER	0.50
		PATENT	0.11	ROADDENS	0.14	REGCOAST	0.06
				TELF	0.17	REGOBJ1	0.03
				TELH	0.24	SETTL	0.12
R^2	0.74		0.83		0.96		0.90
HLR test	5.75		4.73		2.74		4.66
p-value	0.00		0.00		2.50E-05		0.00

Note: HLR is the specification test of Hsiao et al. (2007). * Denotes that the variable enters the regression linearly.

Table 4. Partial effects for regional growth determinants. Baseline specification.

	Baseline					R&D / Innovation				
	Mean	Q1	Q2	Q3	IQ range	Mean	Q1	Q2	Q3	IQ range
GDPCAP	-0.01	-0.02	-0.01	-0.01	0.01	-0.01	-0.02	-0.02	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)		(4.65E-03)	(2.50E-03)	(3.45E-03)	(4.83E-03)	
GPOP	0.01	-0.28	0.09	0.50	0.78	0.11	-0.07	0.21	0.42	0.49
	(0.24)	(0.25)	(0.26)	(0.28)		(0.22)	(0.25)	(0.33)	(0.18)	
SHCE	-2.98E-03	-0.02	-2.72E-03	0.02	0.04	0.03	-5.35E-03	0.03	0.06	0.07
	(0.03)	(0.02)	(0.02)	(0.03)		(0.02)	(0.02)	(0.02)	(0.02)	
SHGFCF	0.03	3.74E-03	0.03	0.06	0.06	0.03	-0.01	0.03	0.05	0.06
	(0.02)	(0.04)	(0.03)	(0.02)		(0.01)	(0.01)	(0.03)	(0.02)	
SHLLL	—	—	—	—	—	-0.02	-0.05	-0.01	0.02	0.07
	—	—	—	—		(0.07)	(0.06)	(0.09)	(0.08)	
SHSH	0.10	0.07	0.08	0.11	0.04	0.09	0.04	0.09	0.14	0.10
	(0.03)	(0.01)	(0.01)	(0.03)		(0.04)	(0.07)	(0.04)	(0.03)	
	Infrastructures					Socio-geographic				
	Mean	Q1	Q2	Q3	IQ range	Mean	Q1	Q2	Q3	IQ range
GDPCAP	-0.01	-0.02	-0.01	-3.19E-03	-0.02	-0.01	-0.02	-0.01	-5.24E-03	-0.01
	(3.14E-03)	(3.48E-03)	(2.08E-03)	(3.73E-03)		(1.87E-03)	(2.26E-03)	(2.93E-03)	(2.41E-03)	
GPOP	-0.08	-0.54	-0.16	0.37	0.91	—	—	—	—	—
	(0.16)	(0.16)	(0.28)	(0.30)		—	—	—	—	
SHCE	0.04	-2.24E-04	0.04	0.07	0.07	0.03	-0.01	0.02	0.04	0.05
	(0.01)	(0.02)	(0.02)	(0.02)		(0.02)	(0.01)	(0.02)	(0.02)	
SHGFCF	0.03	4.76E-04	0.03	0.07	0.07	0.03	-1.59E-04	0.03	0.06	0.06
	(0.02)	(0.01)	(0.01)	(0.02)		(0.02)	(0.01)	(0.01)	(0.01)	
SHLLL	-0.01	-0.02	0.02	0.07	0.09	0.03	-3.64E-03	0.02	0.05	0.05
	(0.02)	(0.02)	(0.01)	(0.01)		(0.02)	(0.02)	(0.01)	(0.03)	
SHSH	0.07	0.02	0.06	0.09	0.07	0.05	0.03	0.04	0.06	0.03
	(0.02)	(0.02)	(0.02)	(0.02)		(0.02)	(0.01)	(0.02)	(0.02)	

Note: Partial effects from local-linear nonparametric regressions. Bootstrap standard errors in parentheses (399 replications).

Table 5. Partial effects for continuous and relevant regional growth determinants.

	Mean	Q1	Q2	Q3	IQ range
R&D / Innovation					
HRSTCORE	-3.46E-03	-0.05	-0.01	0.04	0.09
	(0.02)	(0.04)	(0.01)	(0.02)	
PATENT	-0.04	-0.07	-0.02	0.03	0.10
	(0.01)	(0.02)	(3.31E-03)	(0.01)	
Infrastructures					
CONNECTAIR	-4.87E-03	-0.01	-5.01E-03	-2.08E-03	7.92E-03
	(1.85E-03)	(1.33E-03)	(1.70E-03)	(1.34E-03)	
RAILDENS	-0.03	-0.13	-0.04	0.01	0.04
	(4.49E-03)	(0.02)	(0.01)	(0.02)	
ROADDENS	-0.01	-0.03	-0.01	0.01	0.04
	(0.02)	(0.02)	(0.01)	(0.02)	
Socio-geographic					
DISTCAP	-9.95E-06	-1.18E-05	-5.23E-06	8.37E-06	2.02E-05
	(3.98E-06)	(3.97E-06)	(3.07E-06)	(3.47E-06)	
HAZARD	-1.93E-05	-9.84E-05	-2.01E-05	1.67E-06	1.00E-04
	(2.17E-05)	(4.85E-05)	(3.21E-05)	(2.67E-05)	

Note: Partial effects from local-linear nonparametric regressions. Bootstrap standard errors in parentheses (399 replications).

Table 6. Threshold analysis of partial effects for continuous and relevant regional growth determinants.

	GDPCAP	GPOP	SHCE	SHGFCF	SHLLL	SHSH	HRSTCORE	PATENT	CONNECTAIR	RAILDENS	ROADDENS	DISTCAP	HAZARD
GDPCAP	7.80	4.34	2.70	8.19	2.44	9.53	1.97	2.40	4.26	4.13	2.77	27.96	22.85
	(0.00)	(0.00)	(0.47)	(0.00)	(0.00)	(0.00)	(0.71)	(0.00)	(0.00)	(0.00)	(0.17)	(0.00)	(0.00)
GPOP	7.08	7.31	3.41	6.30	1.38	3.65	2.56	-3.24	3.77	3.75	4.58	9.66	8.86
	(0.00)	(0.00)	(0.09)	(0.02)	(0.01)	(0.00)	(0.13)	(0.12)	(0.04)	(0.02)	(0.01)	(0.00)	(0.00)
SHCE	7.24	2.57	2.81	9.57	-1.83	5.89	7.59	4.60	-0.30	1.55	-0.39	5.08	1.12
	(0.00)	(0.03)	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.02)	(0.04)	(0.02)	(0.28)	(0.76)	(0.00)
SHGFCF	0.54	-0.21	3.39	-0.78	4.07	2.89	4.02	4.64	-1.45	0.42	0.89	4.36	6.72
	(0.35)	(0.42)	(0.23)	(0.44)	(0.04)	(0.00)	(0.00)	(0.01)	(0.32)	(0.26)	(0.04)	(0.00)	(0.16)
SHLLL	10.69	1.32	-1.63	5.72	1.18	13.50	8.25	7.05	3.15	3.80	8.01	14.98	3.09
	(0.00)	(0.03)	(0.33)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.37)	(0.00)	(0.00)	(0.00)	(0.02)
SHSH	10.72	-0.53	1.41	7.85	6.09	13.94	14.58	0.51	2.27	6.32	5.66	10.58	4.38
	(0.00)	(0.60)	(0.01)	(0.00)	(0.83)	(0.00)	(0.00)	(0.01)	(0.43)	(0.25)	(0.00)	(0.00)	(0.00)
HRSTCORE	7.75	0.38	3.13	5.79	0.08	8.40	9.00	1.91	2.09	2.36	6.36	12.19	2.96
	(0.00)	(0.25)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.36)	(0.07)	(0.00)	(0.00)	(0.00)
PATENT	10.87	1.79	0.09	11.74	5.59	13.57	2.58	3.53	4.46	3.91	5.15	31.20	27.53
	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)	(0.25)	(0.00)	(0.01)	(0.00)	(0.03)	(0.00)	(0.00)
CONNECTAIR	7.40	1.78	0.17	4.91	-6.16	9.09	-2.14	2.21	0.53	-3.50	2.15	17.04	2.14
	(0.00)	(0.10)	(0.04)	(0.00)	(0.37)	(0.00)	(0.26)	(0.01)	(0.03)	(0.20)	(0.00)	(0.00)	(0.00)
RAILDENS	2.34	0.88	-1.02	3.82	11.55	5.16	3.50	3.40	3.15	9.19	3.62	2.76	6.98
	(0.01)	(0.13)	(0.18)	(0.10)	(0.40)	(0.02)	(0.21)	(0.00)	(0.00)	(0.06)	(0.12)	(0.16)	(0.00)
ROADDENS	5.58	2.09	6.35	2.57	3.10	7.70	5.44	0.95	4.17	3.71	-1.03	8.48	4.98
	(0.00)	(0.02)	(0.02)	(0.16)	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)	(0.38)	(0.00)	(0.00)
DISTCAP	2.34	-0.22	1.47	-0.16	1.37	-0.73	8.37	6.92	3.02	0.92	1.64	4.89	5.25
	(0.01)	(0.74)	(0.63)	(0.22)	(0.38)	(0.50)	(0.00)	(0.50)	(0.00)	(0.21)	(0.10)	(0.00)	(0.00)
HAZARD	3.50	0.79	0.26	4.17	1.09	0.01	2.99	3.93	1.87	3.05	-1.42	11.00	1.64
	(0.00)	(0.25)	(0.02)	(0.08)	(0.75)	(0.12)	(0.37)	(0.56)	(0.04)	(0.01)	(0.82)	(0.00)	(0.01)

Note: Reported values correspond to the $\hat{T}_n$ test statistic for equality of distributions of Li et al. (2009). Bootstrap p-values in parentheses (399 replications).

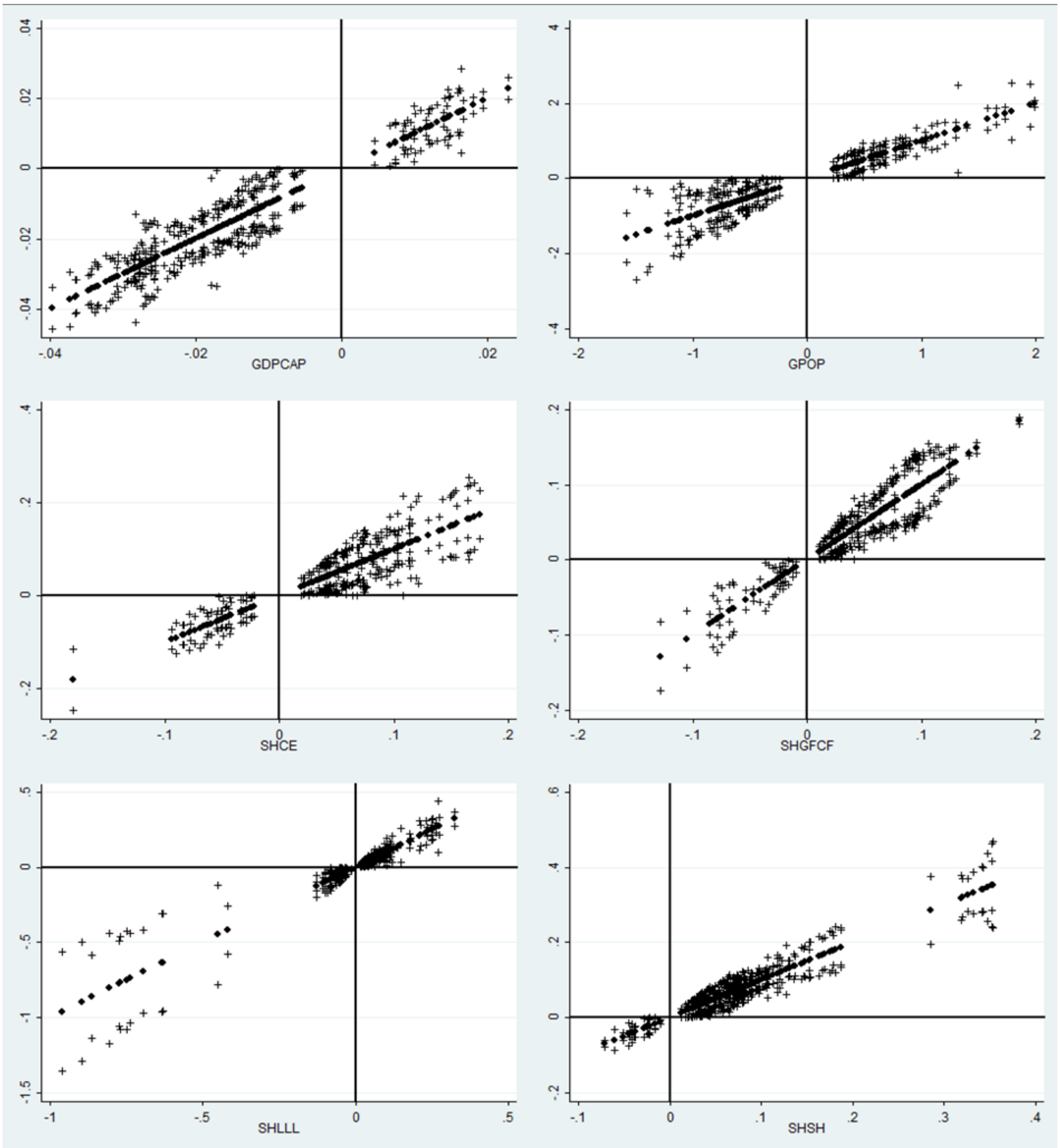

Figure 1: 45^o plot of the statistically significant (95% level) estimated gradients for regional growth determinants. Baseline specification.

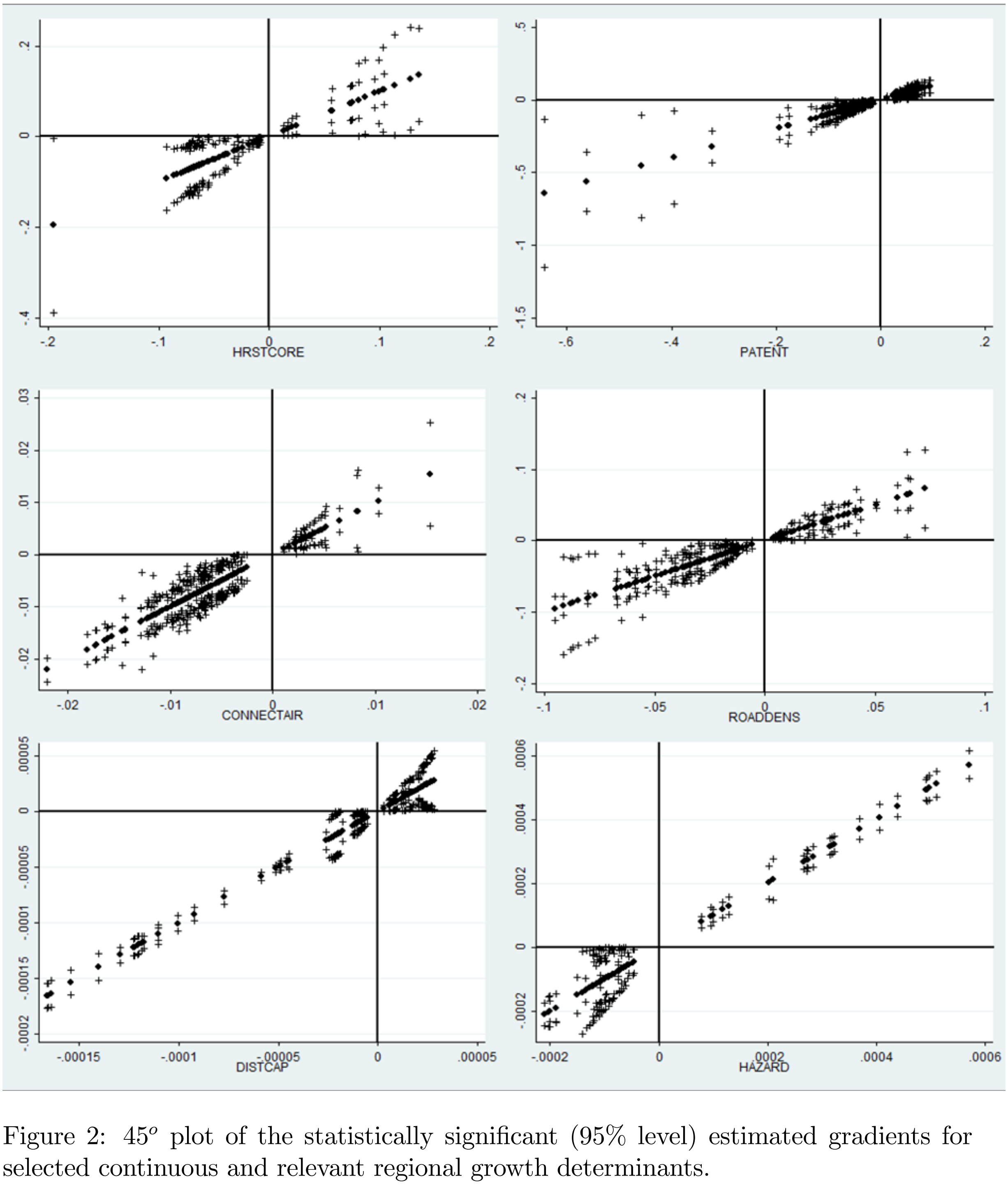

Figure 2: 45^o plot of the statistically significant (95% level) estimated gradients for selected continuous and relevant regional growth determinants.

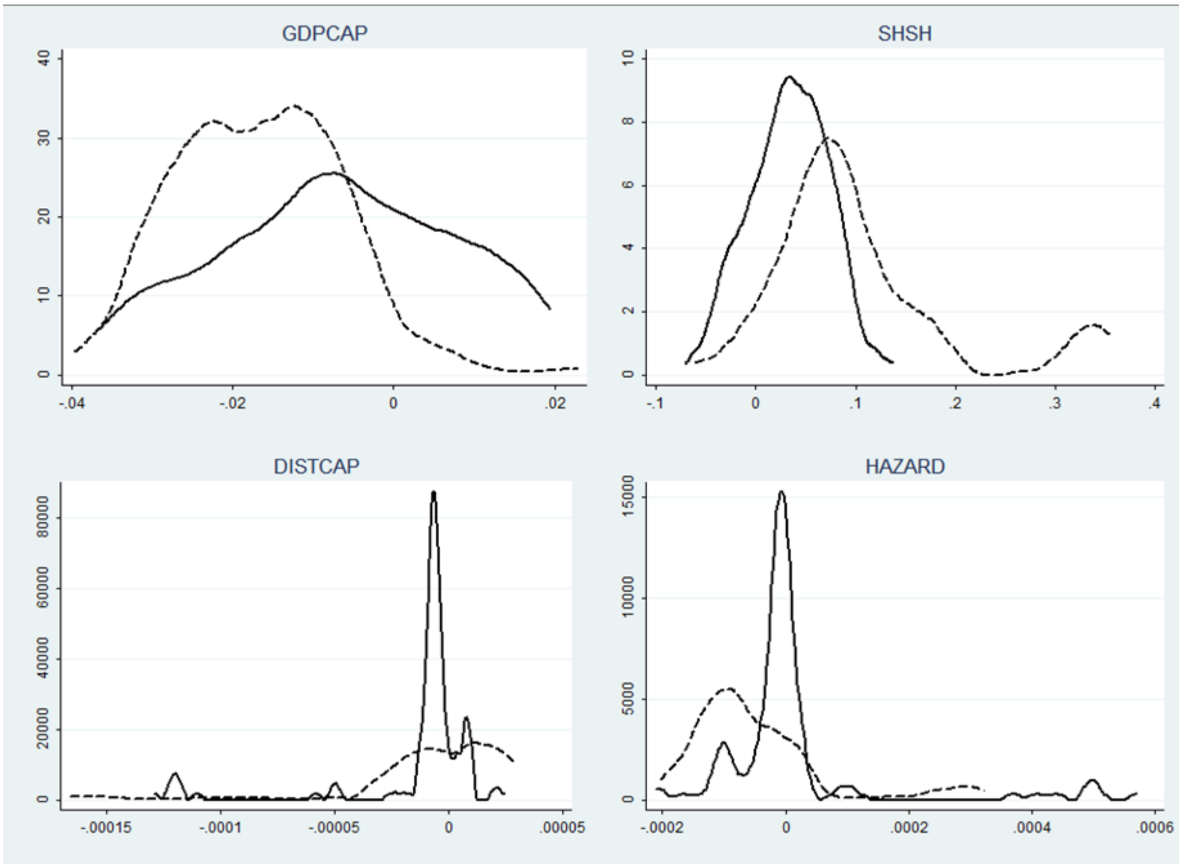

Figure 3: Partial effects for selected regional growth determinants. Kernel density estimation. Threshold variable: GDPCAP. Above (solid) and below (dashed) median.

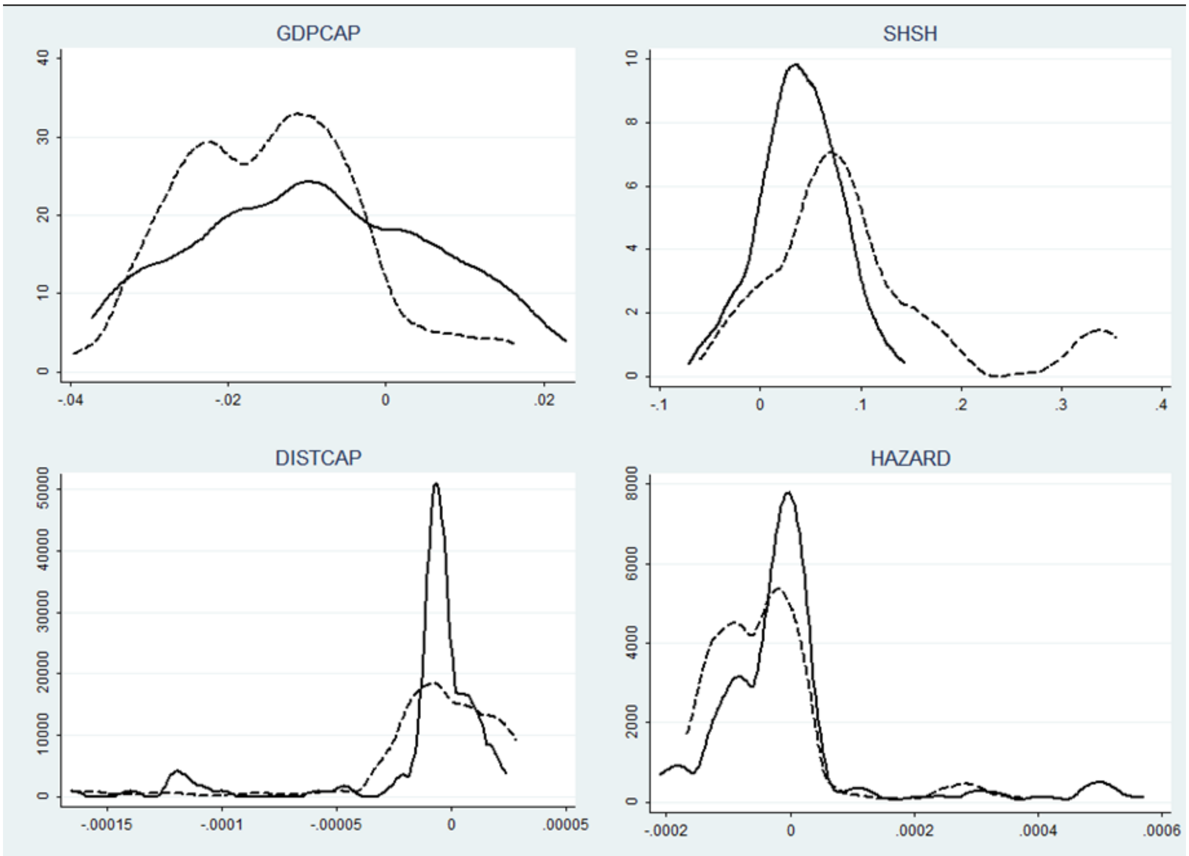

Figure 4: Partial effects for selected regional growth determinants. Kernel density estimation. Threshold variable: HRSTCORE. Above (solid) and below (dashed) median.