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Cognitive Capital and Islands of Innovation: The Lucas Growth Model from a Regional Perspective

*Andrea Caragliu**
*Peter Nijkamp***

* Politecnico di Milano, Italy;
** VU University Amsterdam, and Tinbergen Institute, The Netherlands.

COGNITIVE CAPITAL AND ISLANDS OF INNOVATION:

THE LUCAS GROWTH MODEL FROM A REGIONAL PERSPECTIVE

Andrea Caragliu [†, *] - Peter Nijkamp [‡]

† Politecnico di Milano
Building Environment Science and Technology
Piazza Leonardo 32
20133 Milano (MI) - Italy
* Corresponding author

‡ Faculty of Economics and Business Administration
Department of Spatial Economics
VU University Amsterdam
De Boelelaan 1105
1081 HV Amsterdam
The Netherlands

Abstract

Knowledge triggers regional growth. Evidence suggests that skilled labour force concentrates in islands of innovation, determining an advantage for innovative regions and a challenge for lagging ones.

We address the role of knowledge in shaping effective markets for skilled labour. Estimates are based on the Lucas (1988) model, with EVS and EUROSTAT data. The externality driving growth in the model is cognitive capital.

Empirical tests show that a higher endowment of cognitive capital generates increasing returns to knowledge, favouring the emergence of islands of innovation; regions with a high endowment of cognitive capital attract knowledge spillovers from neighbours.

JEL classification codes: C21, E24, R11
Keywords: human capital, cognitive capital, knowledge spillovers, islands of innovation.

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1. Introduction

At any institutional level, from the European Union to regional governments, policymakers aim at reducing spatial disparities by focusing on factor endowments (EU 1999).[1] In particular, educational attainments seem to be of strategic importance. In a knowledge intensive economy human capital is a major driver of regional performance; hence, small differences in human capital endowments may induce large long-run differences in economic performance.

Despite the broadly recognized relevance of spatial imbalances, there is a growing evidence of disparities across the European space in terms of human capital endowment. Not only labour flows from peripheral to core regions, but also regional human capital tends to concentrate in a few, high-performance regions in the Pentagon area. This process is linked to the emergence of so called "islands of innovation" (FAST 1992, Cooke et al. 2000) or, in other words, spatial singularities where innovative activities tend to concentrate, and can be measured in different ways. In qualitative studies, such as Bagchi-Sen and Lawton-Smith (2008), the reasons of this Marshallian concentration of innovative firms in spatial clusters are analyzed from a perspective analogous to the present paper. In order to identify possible time trends in the concentration of skilled labour force in Europe, Figure 1 shows a time series of (modified versions of) the Krugman Specialization Index[2] and the Fractionalization Index;[3] the former is calculated as the sum of the absolute differences in human capital intensity between each NUTS region and the average EU27 level, the latter as one minus the Herfindahl index of educated labour force. We measure regional human capital as the regional labour force (in European NUTS1 regions[4]) with ISCED 5 and 6 education.[5]

Figure 1. Krugman Specialization Index and Fractionalization Index of human capital in European NUTS1 regions, 1999-2006.

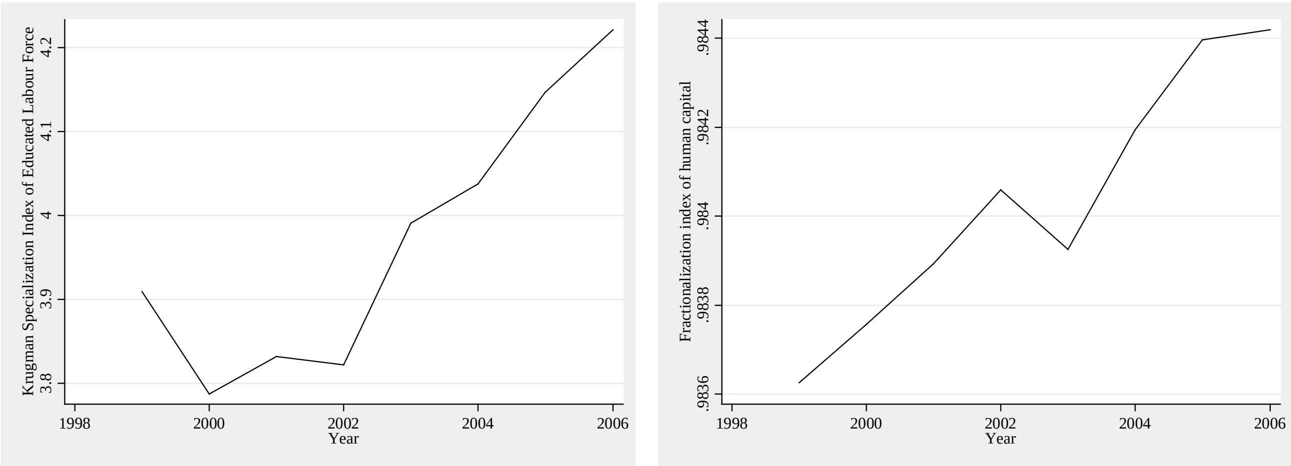

Figure 1a. Krugman Specialization Index for educated labor force, NUTS1 regions
Source: EUROSTAT, 1999-2006 data, own calculations

Figure 1b. Fractionalization index for educated labour force, NUTS1 regions
Source: EUROSTAT, 1999-2006 data, own calculations

[1] The EU (1999) sets "*three fundamental goals of European policy are achieved equally in all the regions of the EU: Economic and social cohesion; the conservation and management of natural resources and the cultural heritage; a more balanced competitiveness of the European territory*".

[2] Here the index is calculated as in Midelfart-Knarvik and Overman (2002). Our modified version does not cover sectoral issues; therefore, it does not satisfy all original index' properties, including assuming a maximum value of 2.

[3] Atlas Mira (1964).

[4] The sample comprises all EU27 NUTS1 regions, except Bulgarian regions, for which data on human capital attainments prior to 2006 are not available. The NUTS1 level of aggregation is chosen, as Germany and the UK only release data at this level.

[5] "*The International Standard Classification of Education (ISCED) was designed by UNESCO in the early 1970's to serve 'as an instrument suitable for assembling, compiling and presenting statistics of education both within individual countries and internationally'. It was approved by the International Conference on Education (Geneva, 1975), and was subsequently endorsed by UNESCO's General Conference when it adopted the Revised Recommendation concerning the International Standardization of Educational Statistics at its twentieth session (Paris, 1978)*" (from unesco.org).

With these two indices as background information, we aim to analyze two relevant issues on European regional human capital:

1. To identify the difference between the human capital endowment of each region *i* and all other regions by taking the absolute values of the difference between their shares of human capital-rich labour force, summed over all regions;
2. To measure the probability that two randomly selected individuals from a population have different levels of education.

Both graphs (see Figure 1) show an upward trend: this implies generally both a growing regional concentration of educated labour force in fewer *islands of innovation* (FAST 1992) as well as a growing probability for individuals within each region to meet people with different levels of education. Therefore, time series show both an increase in cross-regional as well as intraregional differentials of human capital-rich labour force.

Formal education tends to play an important role in regional growth performance, but represents just part of the story. Whilst conventional wisdom takes for granted that accumulation of human capital and formal cooperation lead to higher productivity, reality is more complex. For example, Xerox at first made the same mistake.[6] In the 1980s Xerox launched a new programme to monitor how its employees of the *tech rep* (copier repair technicians in the company's jargon) department worked, instead of merely submitting questionnaires to collect their feedback. The anthropologist in charge of this task discovered that tech rep employees did not only use their official repairing instructions manual; they also exchanged information during social activities which, in principle, were deemed to reduce productivity, instead of raising it. In particular, they exchanged technical knowledge in front of coffee machines, thus transferring knowledge outside formal business processes and official organization charts. Moreover, their conversations were much more fruitful as individual knowledge and education were mutually reinforcing and cumulative.

The concentration of educated and innovative labour force calls for a solid conceptual and empirical analysis. The discrepancy between policy objectives and actual achievements is due to several complex reasons. In this paper we argue that a severe misspecification of the problem may be due to ignoring the role of the so-called cognitive capital in specifying the correct production function underlying the economic analysis. We will argue that by including informal cooperation patterns among workers and firms as well as the economic value of cooperating, thus adding significantly to our understanding of the emergence of "islands of innovation". Moreover, by using modern spatial econometric techniques we will verify the long-run impact of each of the variables considered, therefore identifying possible spillover effects of human capital and cooperation networks in regional innovative labour forces.

2. Human capital and economic growth

2.1 The traditional approach

Since the seminal work of Becker (1964) and Mincer (1974), many publications have been devoted to disentangling the complex relationship between schooling and economic performance. In view of endogenous elements in this dynamic relationship, it is not easy to identify unambiguously cause-effect patterns in a long-run analysis. The literature on the role of education in explaining long-run growth started from the striking fact that neoclassical predictions on the relatively fast convergence of countries towards their steady-state growth rates showed disappointing results in real life. The 1960s were a decade of exceptionally fast growth in most western countries, and several LDCs tried to achieve a rapid development pace by means of accumulating physical factors. However, this did not suffice to achieve their goals, and economists found a likely reason for this failure in the relatively low endowment of education and skills in the LDCs' labour forces.

[6] We refer here to Brown and Grey (2007).

Becker (1964) and Mincer (1974) have summarized at length the rich literature on this topic produced in the 1960s and 1970s, with a clear exposition of some possible ways in which human capital in a broad sense may cause an increase in the long-run growth rates of countries (although being a-spatial in nature, most of the conclusions of these works can be applied to regions as well).

There are numerous studies that arrive at similar findings. A comprehensive review of recent versions of such studies is given by Krueger and Lindahl (2001). Their study offers a theoretical bridge between "Mincerian" (i.e. studies at the micro level with the general aim of identifying monetary returns from an additional year of schooling) and human capital-based growth regressions, where a society's aggregate level of education is shown to be positively correlated with the countries' growth rates. Among the most recent and comprehensive studies of the first type, Ashenfelter et al. (1999) construct a comprehensive meta-analysis of micro returns and find that OLS returns to schooling average 0.066, whereas the IV estimates yield an average return of 0.093 per year, on a sample of 96 estimates and 27 studies.[7] However, the most frequently cited study on the role of human capital in long-run growth is instead Mankiw et al. (1992), where a bridge between traditional neoclassical growth models à la Solow and Swan (Solow 1956, 1957; Swan 1956) and endogenous growth models is given, through the mechanism of human capital.

Correlations between education and economic performance are traditionally explained on the basis of the theory of human capital (Becker 1993; Mincer 1974). This theory posits that as individuals commit more time to the accumulation of skills, they become more productive in the workplace. Mincer's famous wage equation reads as follows:

$$\ln W_i = \beta_0 + \beta_1 S_i + \beta_2 X_i + \beta_3 X_i^2 + \varepsilon_i \,, \qquad (1)$$

where $\ln W_i$ is the natural base log of the wage for the i^th^ individual; S_i is a measure of schooling; X_i is a measure of experience; X_i^2 is experience squared; and ε_i is a disturbance term. The idea behind this literature is that the labour force becomes more productive as the level of formal education increases. Although this model offers a consistent improvement in our understanding of how labour markets work, this early literature was not capable of fully explaining what the classical Solow (1956) model left unexplained.

More recently, it has also been recognized that formal education may exhibit increasing returns when moving to the aggregate level: not only does more education make people more productive per se, but also increasing returns enter because of the mutually more productive interaction of higher educated people (Booth and Coles 2007; Trostel 2004).

While neoclassical economics dealt with human capital and growth mainly by means of micro-founded mathematical models, regional economists tended to study the role of education in regional competitiveness primarily on the basis of a more qualitative case study approach. Using internally coherent analytical frameworks, it was argued that a systematic investment in enhancing the educational and knowledge basis of regions would lead to an increase in the long-run performance of regional systems. Clearly, regions may be hampered by socio-cultural isolation and geographical distance frictions. Following Capello (2007), we classify the main analytical approaches on the role of education in regional development by their underlying treatment of distance (or proximity) (see Table 1). This systematic survey table prompts the issue of knowledge spillovers to adjacent regions.

Table 1. Theories on the role of human capital in regional development

Definition of distance	*Physical*	*Relational*	*Institutional*
Knowledge theory	*Knowledge spillovers*	*Milieu innovateur*	*Learning region*

[7] The choice of the proper estimation technique for individual Mincerian regressions is a highly debated issue. As personal ability is believed to influence the level of schooling of an individual, this generates endogeneity in these regressions. As personal ability is non-observable, Instrumental Variables (IV) are used to infer the individual's set of skills, frequently using his/her parents' level of schooling as a valid instrument. By their nature, nevertheless, IV regressions yield slightly higher estimation results than a simple OLS.

The Knowledge Spillover (henceforth KS)[8] theory studies the role of physical proximity (as a proxy for more complex underlying distance variables) in explaining knowledge transfer processes among agents and regions (see Döring and Schnellenbach 2006). If knowledge were a truly public good, and space did not matter, we should observe a spatially-even distribution of knowledge indicators. Real data, on the contrary, show that knowledge and innovation are highly concentrated economic facts, which, according to the KS theory, may be due to the tendency of economic agents to access physically close knowledge, because of lower transaction and transport costs, shorter distance in terms of tacit and social knowledge, and local social or network capital. Operationally, KS have been analysed in three main ways:

- tracking patent citations, following the seminal study by Jaffe et al. (1993);
- following career paths of 'star scientists', on the assumption that consistent knowledge is embedded in people, who bring it to new work places when they relocate (see, for example, Maier et al. 2007);
- testing knowledge production functions in spatial econometrics models, where the coefficient of the lagged dependent variable, which usually is a measure of knowledge output, represents an assessment of the extent to which knowledge flows over space (see, for instance, Fischer and Varga 2003).

2.2 The modern approach

Physical distance cannot account for all regional variations in human capital growth-enhancing effects. Moreover, in the long run education levels tend to grow steadily over all advanced regions, although it ought to be recognized that innovation and economic performance still display wide differentials. These have been mainly accounted for by means of two, territorially-oriented and spatially-bounded, definitions of proximity: relational[9] and institutional proximity. The first definition of distance mainly characterizes the "innovative milieu" theory; the second one characterizes the learning region approach (see also Hassink 2005).

According to both theories, regional knowledge is the basis for a region's socio-economic performance. The local relational aspect of the mechanism of formation of increasing returns is the focal point of the *milieu innovateur* approach. This was developed by the GREMI group[10]; it focuses mainly on the construction of knowledge through cooperative learning processes, enabled and fostered by spatial proximity (which enters the theoretical foundations of the *milieu* literature as a form of 'atmosphere' effects), network relations (where long-distance relationships can be as effective as face-to-face contacts in a selected set of top-notch, knowledge-intensive relationships), socio-cultural interaction, and creativity. The role of the local *milieu* is to make things happen: abstract geographical space becomes real 'territory', i.e. a relational space where functional and hierarchical, economic and social interactions take place and are embedded in active geographical space. The *milieu* works as a 'cognitive engine' fostering innovation, by reducing uncertainty and information asymmetries, fostering interactions among agents, and, finally, socially sanctioning free riding, thereby reducing its likelihood of occurrence.[11]

[8] See, for example, Acs et al. (1994), who studied the capability of firms to exploit knowledge spillovers; Audretsch and Feldman (1996) and Feldman and Audretsch (1999), who critically reviewed the stylization of scientifically diversified and specialized spillovers; and Anselin et al. (1997), who identified the maximum distance threshold, equal to 50 miles, beyond which spillover effects from Metropolitan Statistical Areas (or MSAs) fade away. Finally, we refer to de Groot et al. (2001), who critically reviewed the literature on KS.

[9] See, for example, Aydalot (1986); Aydalot and Keeble (1988); Bellet et al (1993); Camagni (1991, 1995); Camagni and Maillat (2006); Ratti et al. (1997).

[10] The GREMI (Groupe de Recherche Européen sur les Milieux Innovateurs) was created by Philippe Aydalot in 1984 and focused its research on the determinants of the spatial concentration of small firms.

[11] Camagni (1991, 2004); Bellet et al. (1993); Rallet and Torre (1995); Cappellin (2003).

A different approach has formed the base of the learning region theory.[12] In this case, it is mainly the institutional distance that forms the basis of evolutionary economic growth analyses. The 'learning region' approach addresses local actors and their interactions which belong to a system of homogeneous socio-economic and institutional conditions. Although this has often been applied to regional development analyses, it is essentially an a-spatial approach: it has in fact been applied to different spatial aggregations related to nations or regions. Its main contribution is, therefore, the stress put on the role of knowledge for the socio-economic success of a spatial unit. The spatial component enters the analysis only through spatial networks. In a mainly qualitative approach, increasing returns are triggered by the interactions among economic agents in this ideal knowledge economy.[13] This process tends to prompt the rise of "islands of innovation".

All these theories share some common elements, which form the root of the analysis presented here. All regional theories underline the role of synergies among actors, and in particular the characteristic of the formation of increasing returns to knowledge use in trust-oriented networks. Labour markets thus benefit from a capital of stable business-oriented relationships, that may enhance the emergence of increasing transaction by reducing costs and completing contracts. Therefore, these theories may work as tools to interpret and explain both the formation and the evolution of European islands of innovation.

In the next section, we will outline a model based on Lucas' endogenous growth theory, including knowledge factors. This model is inspired by the above mentioned cognitive approaches.

3. Cognitive capital: all wine in new bottles?

The recent emergence of neuroscience as a discipline merging research from medical science, psychology, anthropology and natural sciences aims at shedding more light on the complex mechanism governing the way the human mind perceives the surrounding environment. This may also represent a crucial step forward in research in economic science. Identifying what reality means is a difficult challenge, let alone understanding how human beings translate reality into perception. Finally, finding an operational measure of such phenomena is even more challenging.

The idea behind this paper is that formal education does not suffice per se to generate increasing returns in regional growth. While more educated workers are also on average more productive, the network of such workers may benefit by an increased wealth of cognitive characteristics, which we label as "cognitive capital". An open and interactive regional economy may then be regarded as a cognitive complex with a high economic synergy. In fact, such externalities in the form of synergies among individuals arise when cooperation becomes not only feasible, but also inexpensive; and this in turn happens when trust, sense of belonging, the existence of long–lasting business relations characterize networks of actors. This argument is strongly linked to the *milieu innovateur* literature, according to which spatially bounded territories would benefit from the existence of such a wealth of relations (as explained in Subection 2.2). This set of relations has been labeled "Relational capital". For the sake of clarity we provide first a concise definition of relational capital (D1):

D1. Relational capital is the *economic value of stable, long-run business networks.*

This definition encompasses the set of economic characteristics, in terms of reduced transaction, information procurement and contract enforcement costs, associated with the existence of localized networks of long-run and stable business relations.

However, even this rich concept alone does not fully explain interregional differences in terms of knowledge exploitation. Empirical evidence shows that a significant share of growth differentials is yet to be explained. In order to reduce our ignorance of growth processes we use the concept of cognitive capital.

[12] See Lundvall (1992); Lundvall and Johnson (1994); Morgan (1997).
[13] The literature on the "innovative milieu" and the learning region is critically summarized in Capello (2007).

Although this label has already been used in previous studies,[14] we will offer here a more solid economic basis for this concept. From a neuroscience perspective, the concept of cognitive capital resorts on the notion of *cognitive functions.* Cognitive functions are "*concerned with those human faculties such as memory, attention, perception, problem solving and mental imagery that are central to cognitive capacity and adaptive capability in adult life*" (Bynner. and Wadsworth 2007). The set of actors' perceptions of the surrounding environment comprises the actor's cognitive map. When the focus moves to more aggregate and complex systems such as regions, aggregate cognitive maps comprise so many objects that it becomes difficult to synthetically represent them. In fact, "t*he basic problem is that the mappings we are trying to learn are usually multidimensional, possibly involving several dimensions in a complex, nonlinear relation. We only have a finite, often very small, data sample of real experiences from which to learn this mapping*" (Denzau and North 1995). This is the point of departure for a new, regional concept of cognitive capital. In order to better understand the economic side of the concept of cognitive capital defined in the neuroscience field, the object of our analysis needs to be focused on a subset of individual perceptions- or elements in the cognitive map- i.e., on the perception of the importance of relational capital.

If we would assume a world of imperfect information and incomplete contracts, repeated interaction where trust is missing may become cumbersome and inefficient. Completing contracts may require a lengthy and detailed list of rules to obey and subsequent punishment for infringing them. In the people's mind, a belief on the possible behaviour of the counterpart of any economic interaction determines the agents' actions not less than other, more objective economic facts (such as market conditions, current exchange rates, the availability of a high-quality labour force, etc.). If those beliefs concern possible infringements of formal contracts, more time and resources will be devoted to writing down complex formulae to avoid free riding behaviour of actors. However, this behaviour may not necessarily become reality, since economic interactions may be fostered by a capital of trust among individuals. The higher the level of trust among actors, the higher the ease with which economic interactions can take place, the lower transaction costs among them, the stronger the sense of belonging to the same social environment; in other words, the stronger the inclination to cooperate.

People's beliefs about the importance of trust–oriented business relations leads to our definition of cognitive capital (D2):

D2. Cognitive capital is a collective asset in which the *economic value of a joint ownership of a high stock of relational capital is perceived of high importance.*

In Section 5 we will provide more details on the way we measure this concept in an empirical analysis.

4. A model for cognitive capital and spatial knowledge spillovers

This section will show how an endogenous growth model with a cognitive capital externality can generate increasing returns to physical production factors. Here, we follow the approach advocated by Lucas (1988). As Rebelo (1991) points out, endogenous growth models obtain long-run growth with a factor that can perpetually accumulate, while never falling into decreasing returns. In the original Lucas (1988) model, this mechanism is the average human capital in a society or area: people enjoy positive spillovers from fellow members of the same social group, thus becoming more productive themselves. In our version of the model, the mechanism that produces increasing returns is the presence of a higher cognitive capital.

At the individual level, the production function in the original Lucas model exhibits constant returns to scale, so that technological progress is assumed to be exogenous, as in Solow (1957). To avoid this trap in our growth analysis, we assume that people benefit from positive externalities from cognitive capital. In an environment that is endowed with fluent interpersonal relationships, where people trust each other, tolerance for diversity enhances creativity, and governance of cultural and natural institutions is able to properly manage public endowments, people are expected

[14] See for example Henry (2004).

to gain more than proportionally in productivity. This is in line with the concept of islands of innovation.

Lucas's model incorporates the agents' choice on how much time to devote to schooling and to working. The economy is made up of N(h) workers with skill level h; therefore, $N = \int_0^{\infty} N(h)dh$. Each worker faces the choice of how much of his/her non-leisure time to devote to work, u(h), while the rest, 1-u(h), is devoted to schooling (the activity that allows the worker to accumulate human capital). Aggregate human capital in the model is defined as $h_a = \int_0^{\infty} hN(h)dh / \int_0^{\infty} N(h)dh$.

Lucas (1988) assumes that some of the positive effects of human capital accumulation are not taken into consideration by individual agents when deciding how much time to allocate to schooling (hence they face a real, positive, externality). The stock of human capital is accumulated obeying the following law of motion:

$$\dot{h}_t = h_t \delta (1 - u_t), \; u_t > 0, \tag{2}$$

whilst preferences over consumption are described by a Constant Elasticity of Substitution (CES) function of the usual form:

$$U_0 = \int_0^{\infty} \frac{c_t^{1-\sigma} - 1}{1-\sigma} e^{-(\rho - \lambda)} dt, \tag{3}$$

where *σ-1* measures the intertemporal elasticity of substitution, and *ρ* is a discount rate. In the Lucas model, labour productivity is raised not only by individual human capital but also as a result of the increase in the aggregate level of human capital. Mathematically, this boils down to solving the model from an individual (household) and a (benevolent) social planner perspective. Whilst individuals do not take into account the positive externalities arising for the society in which they live, and stemming from their individual choices of the level h_i they accumulate, the social planner does do this, thus preventing the society as a whole from underinvesting in the education of individuals.

Analogously, when facing their time allocations, agents do not take into account the possible positive spillovers from their collective behaviour. Aggregate cognitive mechanisms, in the form of improved mutual understanding (e.g. district economies), thick and dense social networks (relational capital), wise management of collective goods that prevents spoiling natural resources, and the efficient transfer of R&D results, all combine as a cognitive catalyst that optimizes the combination of physical factors and generates increasing returns (see also Bathelt and Gluckler 2003; Steiner and Ploder 2008). Therefore, it is not just aggregate human capital that determines the generation of increasing returns to individual education, but also the regional endowment of cognitive capital. This last point represents a crucial assumption in our paper and will be fully explained in the subsequent section.

The share of time (1-u) devoted to schooling in the model is not simply the result of the sum of individual time devoted to individual learning; a common mutual understanding, social networks, mutual trust, and sense of belonging generate collective learning, which is higher than the sum of knowledge obtained by the sum of individual time devoted to learning. Knowledge externalities arise as a result of an additional investment in the accumulation of these soft forms of capital.

The model for the individuals in this economy is:[15]

$$y_{r,t} = Ak_{i,r,t}^{\alpha} (uh_{i,r,t})^{1-\alpha}, \tag{4}$$

while our aggregate economy is described by the following equation:

$$y_{r,t} = Ak_{r,t}^{\alpha} (uh_{r,t})^{1-\alpha} cc_{r,t}^{\eta}, \tag{5}$$

where *0<α<1*; and *A*, *k*, *u* and *h* are defined, respectively, as the technology parameter, the stock of capital (which we estimate with the perpetual inventory method[16]), the share of time

[15] The details of the model can be found in Lucas (1988); Barro and Sala-i-Martín (1995) explain in details the model.

devoted to working, and the stock of human capital (i.e. education) of an individual (or in a region); here cc is a measure of cognitive capital. The crucial assumption of the empirical component of our paper is that individuals create collective (i.e., regional) cognitive capital when investing in their own education. Formally, we may rewrite the definition of the Lucas model externality as follows:

$$cc_{r,t} = \int_0^\infty h_{i,t} N(h) dh / \int_0^\infty N(h) dh \qquad (6)$$

Eq. (6) states that the average aggregate level of human capital in the economy creates ultimately the level of cognitive capital. The previous model will now be tested empirically. Section 5 describes the data we used to estimate equations (4) and (5) and explains the empirics of our measure of cognitive capital externality.

5. Data set and analysis

We built a comprehensive data set on European regions by combining EUROSTAT data for the quantitative variables in the Lucas model and EVS data for the cognitive elements of regional knowledge systems. All data cover a cross section on the year 2000: this choice is due to the availability of EVS data for that year.[17] Table 2 shows the main sources of our data set. The top section of the table shows the main variables used to test the Lucas model in an individual setting (see eq. 4); the central part of the table shows data for the aggregate setting test (eq. 5); and finally, the bottom part of the table shows the cognitive capital measures.

Table 2. The data set

Data description	*Source*
Household real income	EVS
Household education level	EVS
Household stock of capital/savings	EVS
Share of time devoted to work activities	EVS
Regional GDP in constant 2000 prices	EUROSTAT
Regional investments (yielding the capital stock with the perpetual inventory method)	EUROSTAT
Regional human capital: share of human resources in Science and Technology	EUROSTAT
Collective action capability	EVS
Cooperation capability	EVS
R&D receptivity	EUROSTAT
Governance of land resources (share of arable land in 2000)	EUROSTAT
Agglomeration economies (population density in 2000)	EUROSTAT

The individual household test was carried out on 16,929 observations in the EVS data set, which are those in the EU27 for which we have answers to all four questions related to the Lucas model (Table 3). The *uh* component, which represents a crucial departure of the Lucas model from similar endogenous growth models, can be aggregated at the regional level (by calculating regional averages of the household levels). This should thus reflect a double mechanism: the *u* variable should capture both the work incentives (given by the local wage structure, public incentives to work activities, etc.), as well as the social propensity to work (which tends to be spatially and socially clustered due to cultural factors; see, for example, Hofstede 2001[18]).

Figure 2 maps the regional average levels of the uh variable, which does indeed show consistent spatial patterns, with peripheral countries (Spain, Greece, Italy, Bulgaria and the Baltic countries) presenting the highest combination of time devoted to work activities times the skills accumulated with private education.

[16] The assumptions include a depreciation rate equal to 2.5 per cent, while the starting point of the capital stock time series is 1998.

[17] A fourth wave of the EVS is currently being collected, but results have not yet been disclosed.

[18] Geert Hofstede's model entails a classification of cultural differences along 5 dimensions, namely Power distance, Individualism, Masculinity, Uncertainty avoidance, Long-term orientation.

Table 3. EVS questions chosen to test the Lucas model at the individual household level

Variable	*EVS id*	*Question*
Household real income	Q110 (v320)	Here is a scale of incomes and we would like to know in what group your household is, counting all wages, salaries, pensions and other income that comes in. Just give the letter of the group your household falls into, after taxes and other deductions. (1 to 10 scale)
Household education level	Q94 (v304)	What is the highest level you have reached in your education? (1 to 8 scale)
Household stock of capital/savings	Q110a (o49)	Socio-economic status of the respondent (1 to 4 scale)[19]
Share of time devoted to work (u)	Own calculation	Obtained as 1-Q93(v303[20])/80
Units of effective labour	Own calculation	Obtained as u*Q94(v304)

Figure 2. Average regional units of effective labour in 2000

The innovative feature in the present study is our attempt to measure relational and cognitive capital variables. As the set of soft regional production factors is extremely complex both to understand and to represent, we believe a rational classification to be useful as a starting point. We choose the conceptual framework described in Camagni (2008). Within this framework we stress the role of cognitive elements in the qualitative domain of the territorial capital definition. We identify for each of the cognitive capital elements an indicator which is able to proxy the underlying economic mechanism. As these measures capture radically different economic facts, we will next employ a Principal Components Analysis. As one of the elements, viz. social capital, in our cognitive capital definition is rather complex and highly debated, we used one of the most cited and convincing studies on the topic (Putnam 2000) in order to identify the four major axes along which social capital can be measured: community organizational life, engagement in public affairs, community volunteerism and informal sociability.[21]

[19] This is essentially a proxy for the extent of household savings, based on the assumption that the socio-economic status of the respondent crucially depends on his/her wealth.

[20] Question Q93 (v303) is: "At what age did you (or will you) complete your full time education, either at school or at an institution of higher education? Please exclude apprenticeships"; 80 years is the assumed life expectancy at birth for all EU citizens.

[21] See Putnam (2000), p. 291.

Next, we merge the definition of the main social capital axes with the variables described above in the Camagni (2008) setting (collective goods, transfer of R&D results, governance of land and cultural resources, district economies). The data set on which we base our PCA is built with one single question for each of the four Putnam domains, along with EUROSTAT data on the other territorial capital variables. EVS data cover all 'soft elements' domains. Each EVS question we used has a specific aim and scale: to test for the effect of high levels of soft forms of capital on economic performance, and calculate the percentage of the main answers for each question in each region. Table 4 summarizes the questions we chose and the respective scales. The PCA technique allows us to decompose the variance in our data set into a subset of variables which capture as much of the original variance as possible, without imposing a pre-determined structure on the statistic summarizing the data. In other words, PCA represents the internal structure of an (n-dimensional) data set with a lower-dimensional picture, projecting the original data on a hyperplane of smaller dimensions.

Table 4. Selected questions in the EVS dataset

Domain	Question	Scale
Community organizational life	How often is time spent in clubs and voluntary associations?	1 every week 2 once or twice a month 3 a few times a year 4 not at all
Engagement in public affairs	Participation in any social activity	0-1
Community volunteerism	Voluntary work in any community activity	0-1
Informal sociability	Agree that "Most people can be trusted"	1 trust them completely 2 trust them a little 3 neither trust nor distrust them 4 do not trust them very much 5 do not trust them at all

The indicator of cognitive capital is obtained by running a PCA for the above questions, along with the EUROSTAT data which were described in Table 2. The first component explains 37 per cent of the total variance; this is a satisfactory result, given the markedly different aspects that our indicators capture within the territorial capital theoretical framework. The vector scores high in all cognitive characteristics underlying our sample (frequency of club meetings, engagement in public affairs, trust and a measure of cognitive receptivity, i.e. the spatial lags of patent applications to the EPO. Therefore, we call this vector "cognitive capital".[22] Cognitive capital as we measure it is characterized by a synergic interaction with human capital in the production of regional GDP. This provides an indirect proof of the relationship formally described in eq. (6.). Graphically, this is also evident by plotting on a three-dimensional diagram (Figure 3) our measure of cognitive capital (x-axis), the measure of units of effective labour (y-axis) and the dependent variable in eq. (5), i.e. labour productivity (z-axis). Productivity depends positively both on cognitive as well as on human capital, and the interaction mechanism between the two identifies a relation of complementarity;[23] analytically, this implies the existence of a concave function mapping from the human and cognitive capital plane on the productivity vector. In terms of the main topic of this paper, we may view this interaction as the synergy arising from more educated individuals in regional labour force when cooperating. As individuals increase their own education level, labour markets as a whole benefit from more productive interactions. This is exactly the mechanism underlying the emergence of islands of innovation.

[22] The PCA technique should ideally be performed on a complete data set (each gap in a single vector causing a missing value in the final scores). We filled in the missing value for each single vector on which we performed the PCA with the closest (in time or space) data. When data were missing, reasonable substitutes were chosen, according to spatial or time proximity. For example, we substituted the value of the patent applications to the EPO in Lincolnshire, UK (NUTS2 code: UKF3) with that of the neighbouring counties of Leicestershire, Rutland and Northamptonshire (whose NUTS2 code is UKF2). We preferred temporally- to spatially-close observations when both were available.

[23] All variables are in logs in the graph.

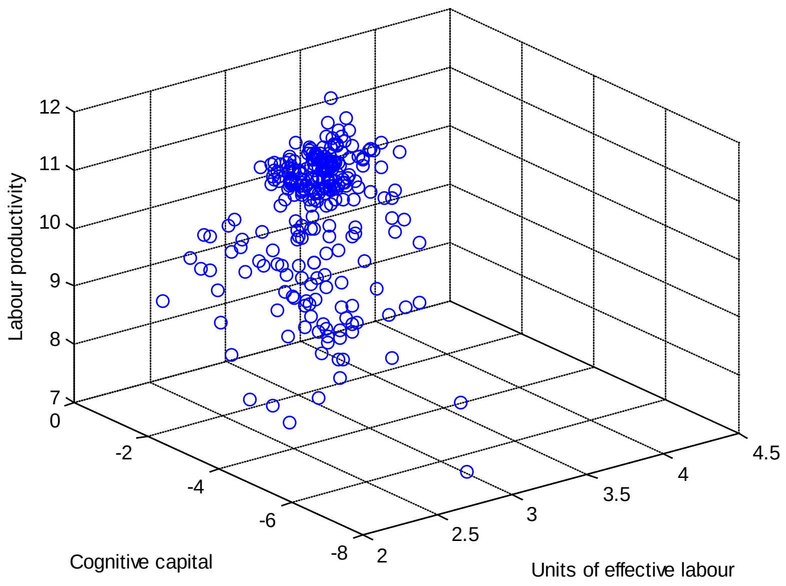

Figure 3. Synergies between human and cognitive capital

6. Empirical model results

The aim of this Section is to assess the relative contribution of highly skilled labour to the formation of regional wealth. The Lucas (1988) model offers an insightful tool to understand the mechanism through which individual and aggregate productivity increases as regional societies enjoy higher levels of education. However, its use has been so far rather to theoretically show the relative importance of human capital in long run growth, rather than as an empirical instrument. Here we argue that the model is actually capable of a good explanatory power of European growth patterns. This Section comprises three basic sets of empirical tests. In Section 6.1 we show the results of testing the micro-level version of the Lucas model – an individual production function based on the level of education of the individual worker. In Section 6.3 we extend the analysis to a linear growth model where individual levels of education are aggregated and identify the notion of cognitive capital. Spatial patterns in our data are evaluated in Section 6.3, with the use of the Le Sage and Pace Spatial Durbin (henceforth, SDM) and Spatial Error (henceforth, SEM) models.[24]

6.1 Micro regressions

In our operational experimentation, testing the cognitive capital-augmented Lucas model calls for the use of log-linearized equations (4) and (5). In the first case we get:

$$\ln(y_{i,r,t}) = \ln(A_{r,t}) + \alpha \ln(k_{i,r,t}) + (1-\alpha)\ln(uh_{i,r,t}) \qquad (7)$$

Equation (7) can be tested with OLS, provided that classical assumptions are respected. It says that individuals become more productive as their capital labour ratio increases, but also as their optimal choice of schooling leads to a higher individual productivity (the uh term in fact is the product of the time devoted to working times the individual level of education).

Table 5 shows the results of this empirical test. In this first case, only OLS estimates have been carried out (spatial estimates are not feasible, due to the simultaneous presence of more than one individual in each single point in space). We used a wide sample of micro-data, i.e. the 16,929 observations on those individuals who answered the EVS questions needed to build the data set and live in one of the 261 NUTS2 regions in our European sample. The individual capital stock is proxied by the individual level of savings as calculated in the EVS survey.

Table 5 shows that the Lucas model is not only an interesting normative tool, suggesting that human capital is conducive to growth. It also offers a simple, yet powerful and elegant, tool for regional analysis. In our sample of individual EU citizens, savings are positively associated with household income, and so are the units of effective labour. Thus not only do longer working hours

[24] See Le Sage and Pace (2009), chapter 4.

lead to a higher income, but also their interaction with the level of education of European citizens is conducive to higher income levels. All coefficients yield meaningful and highly significant estimates. A first building block is laid down to explain the first step in our reasoning: from an individual perspective, more education increases the individual productivity level.

Table 5. Estimation results for eq. (6)

Dependent variable: log of household income	*OLS*
Stock of capital/savings	0.47***
	(0.011)
Units of effective labour	0.24***
	(0.009)
Constant term	0.42***
	(0.016)
R^2	*0.19*
Adjusted R^2	*0.19*
Number of obervations	*16,929*

: Significant at 90% confidence level. **: Significant at 95 confidence % level. *: Significant at 99% confidence level. P-values in parentheses.*

Regarding the assumption that regional economies in our dataset are supposed to be in equilibrium, this implies an individual maximization problem that identifies the best possible combination of time devoted to schooling. Solving this maximization problem, individuals do not take into account a crucial (and positive) externalities generated as their education increases. In fact, societies benefit more than proportionally from the aggregate wealth of education generated from agents. Assuming that individuals generate cognitive capital when increasing their own level of education (see eq. 6), we may now test our framework at the aggregate level by estimating a modified version of the Lucas model.

6.2 Regional growth regressions

The Lucas model is now solved from a (benevolent) social planner perspective. In this case, Lucas assumes that a rational planner takes into account the positive externalities arising from individuals being more educated, and thus more productive. By doing so, he/she solves the problem of underinvestment in education because individuals do not take into account the positive spillovers from their own private education. Then, by log-linearizing eq. (5), we obtain:

$$\ln(y_{r,t}) = \ln(A_{r,t}) + \alpha \ln(k_{r,t}) + (1-\alpha)\ln(uh_{r,t}) + \eta \ln(cc_{r,t}) \tag{8}$$

This double solution can also be interpreted from a regional perspective. Not only do societies become more productive as average education levels increase but it is also plausible that social interactions become more fruitful in more indirect, albeit not less powerful, ways. Cognitive proximity is fostered by the accumulation of human capital. People with higher education levels are also facilitated in their mutual understanding, in shaping a more fruitful set of interpersonal relationships, which in turn become more productive. Education levels are positively and strongly correlated with non material forms of capital, such as social and relational capital. A higher level of education for a society as a whole reduces the costs associated with investing in human relations and networks; this refers essentially to the “weak ties” in Granovetter’s definition.[25] Higher levels of education are also associated with higher levels of trust among citizens, which in turn fosters personal relations and enhances the capability of persons to interact in an economically fruitful way. To see how trust and human capital measures are highly correlated, it suffices to represent some measure of these two variables on a map or a plot.[26]

[25] Granovetter (1973, 1985) deals with the role of “weak” (i.e. low intensity, and relatively impersonal) relationships in generating economically fruitful interactions. From Polanyi’s work the concept of “embeddedness” is then further developed to explain how interpersonal relationships are rooted in social networks, which generate trust among economic agents in a framework which differs from that of the traditional neoclassical rational agent.

[26] This is done in Appendix A, Figures 6-8.

Cognitive proximity is not always automatically conducive to growth. Too much cognitive proximity can also result in social losses, such as reduced access to external information.[27] However, it seems consistent to state that cognitive capital is expected, on average, to foster the effectiveness of hard and structural soft production factors in growth processes.

We will now test this statement within the Lucas (1988) model framework, to assess whether cognitive capital may represent an additional source of increasing returns in a neoclassical, micro-founded model, thus bridging regional development and neoclassical growth approaches to economic dynamics. To do so we again estimate the model on a cross section of 261 NUTS2 regions, where, along with traditional (measurable) production factors, we evaluate the role of cognitive capital. Instead of aggregating EVS data for the former variables, we use EUROSTAT data, thus proving the capability of EVS data to measure the underlying dynamic processes at the individual level. In this second set of estimates, we assume that the regional economies lie on their balanced growth path, or, in other words, they lie on or around their steady state growth path; this may be a plausible assumption, given the long time span before the year on which we test our assumptions. This implies that u, i.e. the share of time individuals in each region devote to work, is constant over space.[28] As such, we ignore the 'u' term in our estimates, as it then enters the definition of the constant term. Data, therefore, comprise the log of per capita GDP in the year 2000 Euros, the log of the capital stock, the log of the share of human resources in Science and Technology, and, finally, our measure of cognitive capital. Table 6 shows the OLS estimates for the aggregate (society) level model.[29]

Table 6. Estimation results for eq. (7.)

Dependent variable:log of per capita GDP	*OLS*
Stock of capital	0.40***
	(0.029)
Units of effective labour	0.30**
	(0.134)
Cognitive capital	0.16***
	(0.025)
Constant term	3.95***
	(0.04)
R^2	*0.64*
Adjusted R^2	*0.63*
Number of observations	*249*

All coefficients turn out to be positively and significantly associated with regional GDP levels. While the magnitude of the coefficients is similar to the estimates we obtain by estimating the simple household-level model, cognitive capital adds consistent increasing returns. Its estimated elasticity equals 0.16, which implies that, ceteris paribus, investing an extra euro in accumulating cognitive capital increases the level of per capita GDP by 16 eurocents in European regions. From our empirical estimates we can conclude that the role of human capital in economic performance is enhanced when a high level of cognitive capital is available in society. Individual endowment would then not suffice to contribute to economic growth in the absence of structural characteristics that lubricate the economy's mechanisms and a society's interactions. The estimates for R^2 are also much higher, thus providing evidence of a much better fit of the model with the inclusion of the cognitive capital variable. These findings once more form an underpinning of the relevance of islands of innovation. Furthermore, inn these spatial singularities, endowed with educated and

[27] See, for example, Boschma (2005) for a theoretical perspective; similar arguments are summarized in Putnam (2000) from a social capital perspective.

[28] For a thorough analysis of the mathematical properties of the Lucas (1988) model, we refer to Piras (1997). Piras kindly provided us with a printed version of his paper upon request.

[29] Analogous results in terms of signs and significance are also obtained by regressing regional averages of the individual EVS questions. The corresponding table is shown in Appendix B.

creative labour forces, the endowment of cognitive capital causes economic interactions to be more productive.

6.3 Spatial econometric growth regressions

As several variables may be strongly correlated across space, in particular the output measure, we have to test for spatial autocorrelation patterns. The local Moran's I statistic for the log of regional per capita GDP equals 0.4441, significant at the 0.001 level. Next, running a Wald test for spatial autocorrelation in the residuals of the linear regression model,[30] we obtain a chi-square statistic equal to 262.5, which should be compared with the threshold level of 6.635 for a 99% significance level.[31] Therefore, the null hypothesis of no spatial autocorrelation of the residuals of the linear model is rejected at any conventional level.

We then test for the best spatial regime to obtain unbiased coefficient estimates. We adopt a general to specific strategy: we start by testing the most general spatial Durbin model, which takes on the unrestricted form $y = \rho Wy + x\beta + Wx\gamma + \varepsilon$ and encompasses the spatial lag and spatial error models as special cases (the spatial lag model obeying the restriction $\gamma = 0$, and the spatial error model the COMFAC restriction $\rho\beta + \gamma = 0$).[32] Estimation results are shown in Table 7. Columns (1) and (2) show the results of estimating the main spatial model, respectively, with and without the constant term (the second case to account for some possible patterns of nonlinearity in the DGP).

Table 7 shows that while significance and signs of the main regression coefficients are retained, magnitudes vary with respect to the original linear model (Table 6). In particular, all main coefficients in the model have a lower estimated parameter value; however, this must be confronted with the direct and indirect effects of each variable. This is done with the use of maximum likelihood estimation routines as suggested in LeSage and Pace (2009). Along with the estimation of the usual spatial model parameters, in fact, this routine evaluates partial derivates of the spatial model in order to infer direct, indirect and overall impacts of each variable in the model. Thus, each variable impact can be decomposed into a direct (i.e., simultaneous) impact on the dependent variable, a medium range impact, due to the spatial interaction between the direct impact and the stimulus given to neighbouring regions, and finally a total effect, as the sum of the two impacts above, which may be read as a long run, "equilibrium" impact.

We can now interpret the results in Table 7 in light of these causal patterns. Whilst the accumulation of physical capital generates an overall positive long run effect on the production of regional wealth, the effects of accumulating human capital and its interaction with the labour force parameter is more difficult to understand. Whilst its linear impact is positive and significant, its indirect effect seems to be strongly negative, and the magnitude of such coefficient implies an overall negative impact in the mode. This result is compatible with the notion of regional competitiveness: competition on non material resources may cause the educated labour force to emigrate in the long run and cause a possible loss of productivity in the host country.

The sign of the cognitive capital parameter is positive over all decomposed classes of the total effect. This implies that not only accumulating cognitive capital in the home regions increases productivity levels of the local labour force; also, regions benefit from being located near to regions with similarly high levels of cognitive capital. This first set of spatial estimates, therefore, shows that regional labour markets enjoy positive spillovers from the local and general perception of the importance of cooperation networks.

Table 7. Estimation results for eq. (7.) , spatial Durbin model.

[30] In running this test and in the rest of this section, unless explicitly stated, we use a row-standardized first-order contiguity matrix.
[31] See Anselin (1988), pp. 103-104.
[32] See Roberts (2006).

Dep. variable:log of per capita GDP	*Spatial Durbin estimates* (1)	(2)
Stock of capital	0.20***	0.40***
	(0.000)	(0.000)
Units of effective labour	0.26***	1.10***
	(0.005)	(0.000)
Cognitive capital	0.06*	-0.09**
	(0.060)	(0.02)
Constant term	6.24***	-
	(0.000)	
Spatial autocorrelation coefficients		
ρ	0.53***	0.48***
	(0.000)	(0.000)
W*Stock of capital	-0.086*	-0.07
	(0.07)	(0.29)
W*Units of effective labour	-1.01***	-0.74***
	(0.000)	(0.000)
W*Cognitive capital	0.44***	0.18***
	(0.000)	(0.000)
Direct effects		
Stock of capital	0.20***	0.42***
	(0.000)	(0.000)
Units of effective labour	0.15	1.07***
	(0.11)	(0.000)
Cognitive capital	0.12***	-0.08
	(0.000)	(0.03)
Indirect effects		
Stock of capital	0.04	0.23***
	(0.59)	(0.005)
Units of effective labour	-1.77***	-0.39
	(0.000)	(0.16)
Cognitive capital	0.94***	0.25***
	(0.000)	(0.003)
Total effects		
Stock of capital	0.24***	0.65***
	(0.000)	(0.000)
Units of effective labour	-1.61***	0.69**
	(0.000)	(0.02)
Cognitive capital	1.05***	0.17**
	(0.000)	(0.04)
R^2	*0.70*	*0.57*
Adjusted R^2	*0.69*	*0.56*
Log likelihood	*-13.74*	*-95.78*
Number of observations	*261*	*261*

Our results were also tested on several consistency checks. Whilst the results in general do not suffer from consistent biases, we do find evidence of heteroskedasticity in the model. In particular, residuals of the Spatial Durbin model seem to be clustered by country (Figure 4). In that Figure, “sdm” indicates the spatial Durbin model; the continuous line represents actual observations on regional labour productivity in our sample, while the dashed line plots the value predicted with the sdm specification; regions are shown on the x-axis, in alphabetical order according to NUTS classification.

This result may be due either to real differences in levels of the variables measured (i.e., statistically different levels of human capital, GDP etc.) or to different procedures that national statistical institutes follow to collect basic data. Although EUROSTAT instructs national statistical institutes to meet standardized requirements, national statistical offices may actually partially deviate from such guidelines.[33] The second explanation seems to us quite plausible. Therefore, in order to correct from this possible source of misspecification we test again the spatial Durbin specification with the inclusion of 26 Country dummies (assuming Austria to be the base country). Results are shown in Table 8.

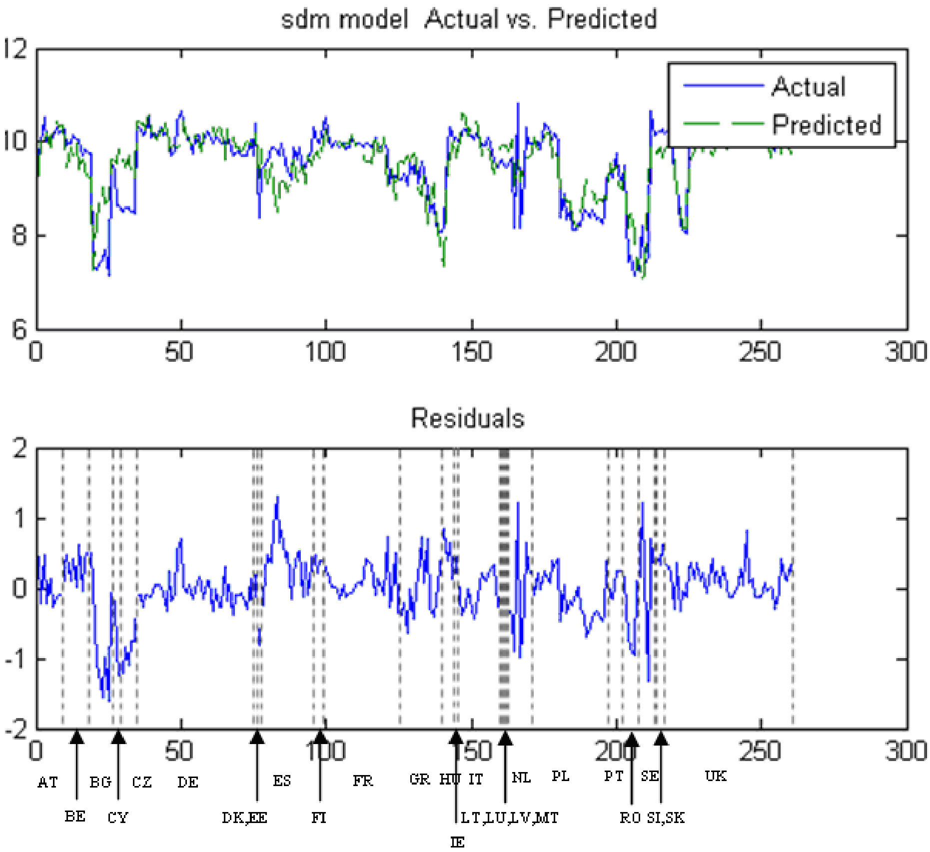

Figure 4. Residuals of the Spatial Durbin estimation of the Lucas model.

According to Table 8, 12 country dummies turn out to be significant, at least at a 5% significance level. Countries whose fixed effect is significant include Bulgaria, Czech Republic, Estonia, Hungary, Ireland, Lithuania, Luxembourg, Latvia, Poland, Romania, Slovenia and the Slovak Republic. The only western European countries which are present here are Ireland (which experienced extraordinary growth rates at the time our dataset was assembled) and Luxembourg. Interestingly enough, 10 out of 12 New Member States display significant departures from the predicted level of wealth within a spatial Lucas model. Moreover, countries whose fixed effect is significant are also those which display highest residuals in Figure 4.

A final refinement of our estimates implies the test of the best spatial regime in the model given the analyzed data sample. A likelihood ratio test carried out on the SDM model rejects the null of the spatial lag restriction at all conventional levels, while it strongly suggests the validity of the SEM (i.e., the COMFAC restriction cannot be rejected). Therefore, we decided to use an error specification for our estimates.

[33] Similar findings are described in Ertur et al. (2008).

Table 8. Estimation results for eq. (7.), spatial Durbin model, with country fixed effects

Dependent variable:log of per capita GDP	*Spatial Durbin estimates* (1)
Stock of capital	0.10*** (0.000)
Units of effective labour	0.08 (0.25)
Cognitive capital	0.04** (0.03)
Constant term	8.29*** (0.000)
Spatial autocorrelation coefficients	
ρ	-0.05 (0.47)
W*Stock of capital	0.05 (0.23)
W*Units of effective labour	0.16 (0.34)
W*Cognitive capital	0.07 (0.18)
Direct effects	
Stock of capital	0.10*** (0.000)
Units of effective labour	0.08 (0.29)
Cognitive capital	0.04** (0.03)
Indirect effects	
Stock of capital	0.04 (0.22)
Units of effective labour	0.15 (0.37)
Cognitive capital	0.06 (0.22)
Total effects	
Stock of capital	0.15*** (0.001)
Units of effective labour	0.23 (0.22)
Cognitive capital	0.11** (0.05)
Country dummies	Yes
R^2	*0.95*
Adjusted R^2	*0.94*
Log likelihood	*167.97*
Number of obervations	*261*

The choice of the spatial error model also has an interesting econometric interpretation, compatible with the notion of contagion.[34] Within a human and cognitive capital framework, this implies that education and relational capital stocks in a region's labour force influence the neighbouring regions' levels as well, and that the opposite also applies. This contributes to the debate on the death of distance:[35] our analysis shows that both in geographical, as well as in cultural terms, distance is far from dead, and that initial physical, but also cognitive and cultural aspects of a location still matter and influence the final outcome of regional growth patterns. The results of estimating the SEM are shown in Table 9.

[34] See, for example, Anselin (2002).
[35] The classic reference on this issue is Cairncross (1997).

Table 9: Estimates results of eq. (7.), spatial Error Model.

Dependent variable:log of per capita GDP	*SEM estimates* (1)
Stock of capital	0.21*** (0.000)
Units of effective labour	0.17* (0.07)
Cognitive capital	0.13*** (0.000)
Constant term	6.69*** (0.000)
Spatial autocorrelation coefficient	
λ	0.60*** (0.000)
R^2	*0.79*
Adjusted R^2	*0.79*
Log likelihood	*-26.94*
Number of observations	*261*

It thus turns out that the main findings of this empirical section confirm our conceptual framework. Both an educated labour force as well as cognitive capital contribute to the formation of regional GDP. A high and significant degree of spatial autocorrelation of the residuals characterizes the dataset, which is accounted for by the lambda parameter in Table 9. About 80% of total regional GDP variance is explained in this cross section, with just three growth determinants.

7. Conclusions

In this paper we have combined two alternative approaches to the relation between education and economic performance, viz. the regional development and the neoclassical growth approach. Empirical estimates of the Lucas (1988) growth model in our study are based on the EVS data set; we show that the level of education exhibits increasing returns from a social perspective. The externality driving the formation of increasing returns is not the aggregate level of education but the region's endowment with cognitive capital. Thus societies benefit not only from a more educated labour force but also from their level of cognitive capital, which represents the aggregate perception of the relevance of cooperation behaviours.

The results are robust with respect to the choice of the estimation technique and the measure of human capital. Spatial issues in the data set are also taken into account, and unbiased estimates of the returns to human capital are obtained. This paper, therefore, contradicts the commonly held view that the Lucas (1988) model offers more a profound insight into the mechanisms of economic growth, rather than an effective policy instrument. We have demonstrated, instead, that the model fits the European data well and also highlights the crucial relevance of knowledge in modern regional economies. This has important implications islands of innovation and growth.

Long run trends of concentration of skilled labour force in spatial singularities have relevant policy implications. As collective learning takes place at the regional level (Storper 1995; Florida 1995; Malmberg and Maskell 2006), only those regions that succeed in retaining skilled labour force formed in their own schools as well as in attracting skilled labour force from outside will manage to sustain long-run development. A competition on the possession of skilled labour force, while already being evident from the data, will increasingly characterize European regions. The possible negative effects of outward skilled migration on sending countries' productivity levels, though increasingly on the policymaker's agenda, will have to be more carefully considered. The emergence of islands of innovation, while representing an opportunity of higher growth rates for regions endowed with such islands, will also offer a challenge to regions incapable of attracting innovative and creative labour force. If, therefore, the EU really aims at reducing spatial disparities, this issue should definitely be taken into account.

Regional labour markets for skilled personnel should consequently be shaped in order to maximize the returns to private education, and ease the transfer of knowledge across workers and the speed with which ideas cross-fertilize individuals. The attraction of skilled labour force, while increasing productivity levels per se, may also increase the regional labour markets stocks of cognitive capital, thus generating a self-fulfilling prophecy: labour markets with higher stocks of human and cognitive capital may be more attractive to skilled and cognitively rich labour, star scientists, top productivity innovators, in turn fostering the persistence of this situation over time.[36]

The importance of such competences is maximum. Econometric analysis suggests that human capital, in the form of formal education and training, enhances the productivity of individual workers, who are nevertheless incapable of fully reaping the positive effects of their own level of schooling, generating in the end a potential market failure. Aggregate (i.e.-labour market-wide) positive spillovers are found to be generated when a high stock of cognitive capital is present, i.e., when people perceive the economic value associated to stable, long run business networks.

This paper has also offered a contribution to the current regional growth debate by testing a micro-founded level, at both the individual and the regional level. The empirical evidence suggests both the relevance of skilled labour force for a region's development, but also the synergic mechanism arising from geographical proximity to regions with similarly high endowments of skilled labour force. In our study, the competition on human capital effects is modelled and tested in a spatial Durbin framework, whereas evidence on knowledge spillovers is mixed and depends on the chosen functional form.

Evidence is also found on the role of cognitive capital in catalyzing the formation of increasing returns to the efficiency of skilled labour force. The higher the endowment of cognitive capital both within and outside a region, the higher the level of per capita GDP produced. A high endowment of cognitive capital may reduce the dispersion of the positive effects of human capital, thus representing the best solution for regions lagging in the attraction of skilled labour force capability. However, non-material components imply long periods of accumulation; therefore, regional policymakers should take this into account and devise long run growth strategies, which may sometimes be at odd with short-run political cycles typically associated with short-run policy instruments.

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[36] Indeed, this situation has taken place in the academic world after WWII, when German scientific superiority in the chemical and physical field was gone forever due to the migration of most of the best scientists to the US, because of the political situation in their homeland. Germany never got the scientific edge again.

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Appendix A – Human capital and trust

Figure 5. Trust in EU regions
Source: EVS data, own calculations

Figure 6. Human capital in European regions
Source: EUROSTAT

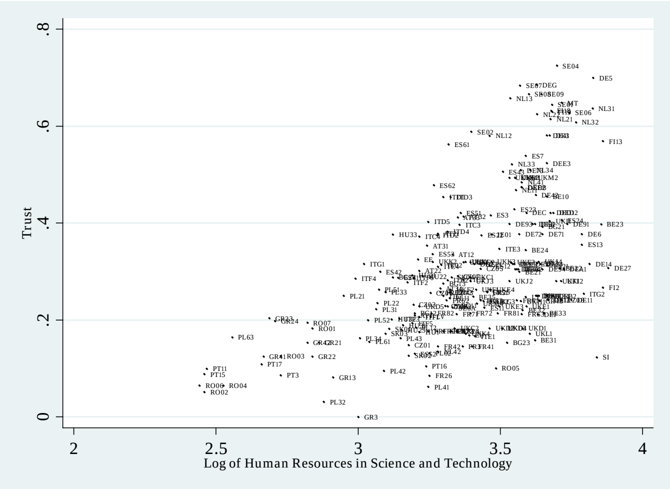

Figure 7. Human capital and trust

Appendix B – Estimates of the aggregate Lucas model with EVS data

Table 10. Estimation results for eq. (7) with regional averages of EVS data

Dependent variable: log of regional GDP	*OLS*
Stock of capital	0.06***
	(0.021)
Units of effective labour	1.31***
	(0.032)
Cognitive capital	0.019*
	(0.01)
Constant term	-0.225*
	(0.129)
R^2	*0.90*
Adjusted R^2	*0.90*
Number of obervations	*200*