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Abstract

The United States and European Union differ significantly in terms of their innovative capacity: the former have been able to gain and maintain world leadership in innovation and technology while the latter continues to lag. Notwithstanding the magnitude of this innovation gap and the political emphasis placed upon it on both sides of the Atlantic, very little systematic comparative analysis has been carried out on its causes. The empirical literature has emphasised the structural differences between the two continents in the quantity and quality of the major 'inputs' to innovation: R&D investments and human capital. The very different spatial organisation of innovative activities in the EU and the US – as suggested by a variety of contributions in the field of economic geography – could also influence innovative output. This paper analyses and compares a wide set of territorial processes that influence innovation in Europe and the United States. The higher mobility of capital, population, and knowledge in the US not only promotes the agglomeration of research activity in specific areas of the country but also enables a variety of territorial mechanisms to fully exploit local innovative activities and (informational) synergies. In the European Union, in contrast, imperfect market integration, and institutional and cultural barriers across the continent prevent innovative agents from maximising the benefits from external economies and localised interactions, but compensatory forms of geographical process may be emerging in concert with further European integration.

Keywords: Innovation, Research and development, Regions, Spillovers, Agglomeration, Systems of innovation, European Union, United States

JEL classification: R11, R12, O32, O33

1. Introduction

In 2000, the Conclusions of the presidency of the Lisbon European Council established the goal of making the European Union the "most competitive and dynamic knowledge-based economy in the world." In so doing, they explicitly acknowledged the gap separating the EU from the present world leader – the USA – and announced their intention to catch up within a ten-year period. A year earlier, the President of the United States had set the goal of "maintaining world leadership in science, mathematics, and engineering" (NTSC 1999). Nowadays, more than half a decade later, US leadership is still undisputed and – as highlighted by the International R&D scoreboard published by the UK Department of Trade and Industry in October 2006 – the transatlantic technology gap has widened.

Though there are limitations of the available proxies for innovative output, all standard indicators reveal a significant disadvantage in the innovative capacity of the European Union. When considering scientific activity, such as the number of scientific publications and citations weighted by population (as reported in Dosi et al. 2005 using OECD data), the output gap between the EU-15 and the US is immediately apparent, with 4.64 publications per thousand inhabitants in the US vs. 3.6 in the EU-15 in the 1997-2001 period. This gap is even wider when the impact of such scientific production is assessed in terms of article citations (39.75 per thousand inhabitants in the US against 23.03 in the EU-15) or shares in the top 1% most cited publications (0.09 top 1% publications per thousand inhabitants in the US against 0.04 in the EU-15). When considering technological output, the United States shows the best innovative performance, as measured by its share of the total triadic patent families[1] (36.4% in 2003 against the 30.3% of the EU). When triadic patent families are weighted by population, US patent intensity is 47% higher than for the EU-15 and almost double that of the EU-25 (our calculations based on OECD 2006).

In spite of the magnitude of this innovation gap and the political emphasis attached to it on both sides of the Atlantic, very little systematic comparative analysis has been pursued on its causes.

[1] "A patent is a member of the triadic patent families if and only if it has been applied for and filed at the European Patent Office (EPO), at the Japanese Patent Office (JPO) and if it has been granted by the US Patent and Trademark Office (USPTO)" (Eurostat 2006: 6). Patent families are supposed to improve international comparability by suppressing the home advantage.

Existing analyses have mainly addressed the differences between the two continents in terms of the major 'inputs' to innovation, such as R&D investments, the level of human capital accumulation, the structure of the educational system and the capacity to generate and retain top-level scientists. Other analyses emphasise the ways that organisational and institutional settings shape the use of such innovative inputs. Thus, unequal inputs to the process of innovation, together with different systems of innovation, form the core of existing explanations of the innovation output-gap.

Even though these factors account for a large part of differential innovative performance, it stands to reason that their spatial organisation may also play a role. The spatial organisation of the sources of innovation determines levels of localised economies of scale and localised knowledge externalities, and may in this way affect the level of innovative output. Studies of the geography of innovation have indeed emphasised agglomeration of innovation inputs, proximity effects, and knowledge spillovers. Much less attention has been devoted to the dynamic process through which agglomeration and specialization are constructed and reconstructed over time, through the spatial mobility and matching of innovative factors. This process, or flow, gives rise to specific levels and types of proximity and spillovers.

This paper aims to fill the gap by focusing on the 'process geography of innovation' in the EU and the USA. These two areas of the world are characterised by a different historical geography of innovation systems (where the public and private actors have been created and how they have been coordinated over distance). Behind such histories, we argue, there are different contemporary institutions, rules and incentives governing the creation and geographical mobility and combination of such inputs to innovation. In order to analyse the geographical processes underlying innovation, this paper builds a model, which considers these geographical processes in conjunction with the factors evaluated in standard models. The analysis shows that the higher mobility of capital, population, and knowledge in the economically- and culturally-integrated US market enables combinations of factors that respond rapidly to shifts of the technological frontier, and allow full exploitation of local innovative activities and (informational) synergies. In the European Union, by contrast, imperfect market integration, and institutional and cultural barriers across the continent produce a spatial configuration both less dynamic and less coherent at the local level.

2. Structural determinants of the innovation gap: a review

The innovation output gap between Europe and the USA is most frequently attributed to differences in inputs to innovation production. The quantity and quality of inputs, as well as the broader 'innovative infrastructure' in the two contexts – by reflecting their cultural, institutional, and economic diversity – are indeed substantially greater in the United States.

First, the total amount of the resources devoted to innovative activities varies significantly. In 2004, 1.9% of GDP was spent on Research and Development in the EU-25 (1.95% in the EU-15) (Eurostat 2006a) compared to 2.6% of GDP (NSF 2006) for the US. Furthermore, the nature of such expenditure differs considerably. On the one hand, as Dosi et al. (2005) point out, "the usual claim concerning the higher amount of publicly funded R&D in the EU as compared to the US is simply groundless"(p.12): government financed R&D expenditure as a percentage of GDP was 0.66% in the EU-25 against 0.70% in the US (in 2003 and 2004 respectively). However, a large percentage of this US public expenditure is for R&D carried out by private firms, about double the corresponding figure in the EU. American private firms not only benefit from a larger share of public funds than their EU counterparts, they also devote a higher proportion of their internal resources to R&D. Industry-financed R&D expenditure is about 1.9% of GDP in the US (NSF 2006), but only around 1% of GDP in the EU (Eurostat 2006a).

Second, the gap in human resources devoted to R&D is large and significant: "in 2003, the number of researchers (in full-time equivalents) per thousand of the labour force amounted to only 5.4 in the EU against 10.1 in Japan and 9.0 in the US. This EU deficit is mainly located in the business sector" (European Commission 2005: 6). Furthermore the advantage of the US in this area is not only 'quantitative' but also 'qualitative', as the US attracts and retains a large proportion of high impact researchers: of the top 1,222 most cited individuals in 14 scientific fields, 66% live and work in the US, while only 20% are from the sum of the EU countries (Batty 2003).

This situation in the research sector reflects a more general trend in human-capital accumulation, which, in turn, is the result of different structures and levels of investment in the educational system. In 2004, only 34.1% of all 20 year olds were enrolled in higher education in the EU-25 (and 33.4 in the Euro zone), in comparison to 46.2% in the US (European Commission 2005b). Furthermore, public and private investment in education is significantly higher in the US than in the EU: in 2003 the expenditure per student in Higher Education – adding public and private expenditure – was just 39.3% that of the US in the EU-25 and 41.1% in the Euro zone[2] (Eurostat data). The combination of higher US investment in higher education with existing gaps in R&D investment and in the capacity to generate, attract, and retain top scientists is reflected in a growing gap in the standing and influence between American and European universities. According to the ranking produced by the Shanghai University, among the top 20 universities in the world 17 are in the US and 2 in the UE (both in the UK) [3] (Institute for Higher Education, Shanghai Jiao Tong University 2006).

The two Continents also show marked differences in the institutions and policies governing the invention, development, and adoption of new technologies. "The foundations of the US 'national system of innovation' were largely put in place during 1945-1950 (when) demobilization for peace was replaced by Cold War rearmament" (Mowery 1998: 640). In contrast, despite the recent and rapid formal institutional-building efforts at EU level, there is yet no analogous Europe-wide system in place, i.e. which could complement and integrate existing national systems in the way the US institutions do (Borrás 2004; Gregersen and Johnson 1997; Stein 2004). While the US's integrated (though decentralized) system was forged by the implementation of consistent innovation policies with large-scale federally-funded projects largely benefiting private firms and basic research, the European innovation system still suffers from fragmented, small-scale projects and highly bureaucratic government policies. As a result, the US national innovation system seems oriented towards technological 'shifting' rather than 'deepening': radical innovations are more easily achieved in the US,

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[2] € 8,049.5 in the EU-25 and € 8,422.6 in the Euro Zone vs. € 20,487 in the US, measured in PPS, based on full-time equivalents.

[3] When the ranking is extended to the top 100 universities we find that 57 are in the USA and 35 in the EU (of which 11 in the UK). The ranking of the top 500 universities in the world is based upon a variety of performance indicators (see http://ed.sjtu.edu.cn/rank/2005/ARWU%202005.pdf for further details).

because it is capable of rapidly reallocating resources in line with the requirements of new technological paradigms (Ergas 1987). The 'shifting' capacity of the US system is supported by the way its research universities develop complex interactions with the world of business. Furthermore the antitrust and intellectual property regulatory frameworks seem to offer a fertile environment for the marketing of new technologies[4] (Hart 2004). Conversely, EU firms, on average, have weaker entrepreneurial culture and greater resistance to organizational change (Delmas 2002). Major constraints also arise from barriers to the access to venture capital (a major source of funds for US innovation) and European labour market rules, which frequently lead to mismatches between staffing patterns and the true demand for skills, since they slow down recomposition of staff in response to technology and market shifts.

All these factors directly influence innovative performance. But in addition to this, they also lead to different patterns of spatial organisation of innovation in each Continent. As we will argue in the next section, these territorial dynamics further differentiate the rate and direction of innovation in the US and the EU.

3. Geography and innovative performance in the EU and the US

The spatial distribution of innovative output in both Europe and in the United States, as proxied by patents, exhibits a strong tendency towards disproportionate concentration in a few locations: "during the 1990s, 92 percent of all patents were granted to residents of metropolitan areas, although these areas account for only about three-quarters of the US population, and for about 20 percent of land area of the continental United States" (Carlino et at. 2001: 1). In the EU, patenting is 'highly concentrated' as well (Eurostat 2006b). The cumulative percentage of total patents recorded by the 100 most innovative EU-15 regions and US MSAs (Figure 1) is similar in the two continents and in both contexts the twenty most innovative regions account for around 70% of total patents.

[4] Though the effects of the 1982 patenting system reform are debated (see Jaffe and Lerner 2004).

[Insert Fig.1 approximately here]

The literature on the geographical determinants of innovation in the two Continents has focused on the role of agglomeration and the density of economic interactions as the key catalysers of innovation. Agglomeration and density are indeed relevant forces behind a variety of economic processes. As illustrated by Ciccone and Hall (1996), average labour productivity is significantly greater where employment density is higher. In line with this approach, different studies have found that agglomeration increases innovative output even after controlling for differences in human capital, high-tech industry structure and R&D university infrastructure, both in the US (Sedgley and Elmslie 2004; Carlino et al. 2004) and in some EU countries (e.g. Andersson et al. 2005, for the case of Sweden). As Ciccone (2002) points out, the "agglomeration effects in European countries (France, Germany, Italy, Spain, and the UK) are only slightly lower than in the US and do not vary significantly across countries" (p.214). Agglomeration influences economic outputs and innovative performance through a mix of different sources of Marshallian agglomeration economies (labour market interactions, linkages between intermediate and final good suppliers, knowledge spillovers) that is present in each place[5]. Following Duranton and Puga (2003), the forces behind agglomeration economies can be broken down into 'sharing' (e.g. sharing of indivisible facilities, gains from variety of input suppliers), 'matching', and 'learning' mechanisms. The creation, accumulation, and diffusion of knowledge also rely upon different types of coordination enabled by face-to-face contacts (Storper and Venables 2004). Close proximity thus becomes a condition for the dissemination of information, which would otherwise be impossible or too expensive to codify (Charlot and Duranton 2006).

From an empirical perspective, it is however difficult to isolate the learning, matching, and sharing components of agglomeration. Empirical analysts have thus had to rely upon indirect (output) measurements of learning and proximity – notably the geography of patenting – as a means to

[5] Duranton and Puga (2003) use as an example a model "in which agglomeration facilitates the matching between firms and inputs. These inputs may be labelled workers, intermediates, or ideas. Depending on the label chosen, a matching model of urban agglomeration economies could be presented as a formalisation of either one of Marshall's three basic sources of agglomeration economies even though it only captures a single mechanism" (p.2)

distinguish informational spillovers from the other ‘Marshallian forces’ (Fujita and Thisse 2002). Along these lines, research has established a connection between density and patenting, where density is a proxy for agglomeration and patenting for learning.

Yet a simple dense/not dense dichotomy does not adequately capture the potential complexity of the geography of matching and learning processes. Knowledge matching and learning are logical outcomes of the many ways in which agents move, signal, and match to other agents. This means not just ‘being’ in established patterns of proximity to other agents, but also the dynamic process by which such densities and proximities are achieved, and how they adjust over time. Such adjustments refer to the types of agents (who they are and what they bring to the innovation process), in relation to changing technologies, markets and types of knowledge required to innovate. We call these ‘flow’ dimensions of the problem the ‘process geography of innovation’ and view its analysis as a complement to what the literature has to say on levels of density, proximity, and innovation.

Let us now consider these geographical processes and their socio-institutional underpinnings in greater detail. First of all, rather than thinking of agglomerations one by one, it is helpful to consider their interrelations and connections to other places. Even similarly ‘dense’ economic fabrics may be exposed to external knowledge flows to different degrees, with different levels of knowledge spillovers from neighbouring areas. Even if the use of tacit and highly specialised knowledge is maximised in the ‘core’ of dense agglomerations, some of that knowledge travels more widely (Anselin et al. 1997; Ács 2002; Varga 2000; Sonn and Storper 2003, for the US, and Greunz 2003; Bottazzi and Peri 2003; Moreno et al. 2005; Rodríguez-Pose and Crescenzi 2006, for the EU case). This means that core regions may potentially benefit from proximity to other innovative neighbourhoods, such that they form a wider network structure through which knowledge flows are transmitted. Inter-agglomeration knowledge flows are different in the two Continents. The higher average population density of the EU with major metropolitan areas relatively closer together than in the United States (where instead metropolitan areas are farther away from one another) may allow a stronger Continent-wide circulation of knowledge, and possibly limit the distance decay of useful knowledge.

In addition, an agglomeration is not merely a stock of resources; it has a dynamic, consisting of the flow of resources into and out of it (a 'churn' or turnover). Migration flows contribute to the creation of new knowledge at the local level, by 'increasing' the density of the local skill pool and changing its quality, in terms of the variety of skills and cultures it may contain (De Blasio 2005; Ottaviano and Peri 2006). In the most innovative places, we expect migration to update the matching of knowledge, skills and competencies in line with the evolution of the technological frontier. On the contrary, where agglomerations are less often re-composed through migration, innovative agents may benefit from proximity relationships but find it more difficult to dynamically match existing agents to new knowledge producers. Migration trends are crucially influenced by the costs of mobility – in turn affected by issues such as culture, identity, or social and personal links – and by institutional incentives to labour mobility, which are very different in the US and Europe. The degree of (domestic) labour mobility is substantially higher in the United States than in the EU, as extensively documented by Puhani (2001),Vandamme (2000), and Zimmermann (1995 and 2005) for the EU[6] and by Peri (2005) in a comparative perspective, and there are considerable differences in foreign in-migration as well.

Third, these forces that influence the composition and recomposition of clusters and agglomerations may affect the nature and level of innovation through the types of knowledge they match. If they generate increasing specialisation, then they will likely foster MAR (Marshall-Arrow-Romer) externalities within the same industry; if, on the other hand, they promote diversity, they allow local actors to benefit from knowledge base complementarities and across-industry exchange of ideas (Jacobian externalities). The empirical literature suggests that both MAR (Glaeser et al. 1992; Henderson 1999) and Jacobian externalities (Andersson et al. 2005; Carlino et al. 2001; Feldman and

[6] Zimmermann (2005) points out that the EU shows "a split labour market that is characterized by high levels of unemployment for low-skilled people and a simultaneous shortage of skilled workers. This lack of flexible high-skilled workers and the aging process has created the image of an immobile labour force and the eurosklerosis phenomenon (thus preventing) the best allocation of resources and hence economic efficiency" (p.448).

Audretsch 1999) may play an important role in fostering innovation, but they do so in different sectors, Henderson et al. (1995) find that Jacobs-type externalities prevail in high-tech and MAR in capital goods industries. Duranton and Puga (2001) suggest that agglomeration economies play roles in innovation at different phases of the product life cycle: firms develop new products in diversified creative urban contexts, subsequently relocating to specialised cities in the mass production phase in order to exploit cost advantages. Where the broader historical, institutional, and political forces inhibit mobility, they could prevent the cluster from adjusting in such a way that the most efficient combination of the two types of external economies is maintained, thus hampering innovative productivity. This could be the case of Europe, where incomplete economic integration, 'national' redundancies, and duplications in economic structures may have lead to a suboptimal pattern of specialisation.

Finally, the process geography of innovation is deeply rooted in a complex institutional process that shapes the capacities and attitudes of the population toward innovation, and distribute these populations in geographical space. These capacities and attitudes can be captured empirically as the 'social filters' of the local population, i.e. characteristics of people that either favour or deter the development of successful regional innovation systems (Rodríguez-Pose, 1999: 82).

4. The model

Our empirical analysis is based on the Knowledge Production Function (KPF), formalised by Griliches (1979, 1986) and Jaffe (1986). However, rather than focusing our attention upon the firm as unit of observation, we adopt a geographical unit (NUTS regions for the EU and MSAs for the US) similar to that of Audretsch (2003), Audretsch and Feldman (1996), Feldman (1994), Fritsch (2002), and Varga (1998). Though our research questions differ from the existing literature in that we focus upon the 'process geography of innovation' in the two Continents, our use of the knowledge production function is very similar to them. All this literature, including the present study, is constrained by the limited availability of comparable data at the sub-national level for the US and the EU. Still, it allows us to account for the role of technological externalities and other geographical dimensions of innovation in the two areas.

The modified Cobb-Douglass knowledge production function (KPF) takes the form:

$$I_i = AK_i^{\beta} RD_i^{\gamma} SpillRD_i^{\delta} C_i^{\zeta} SpillC_i^{\eta} \qquad (1)$$

Where I is level of innovative output of region *i*, A is constant, K is the initial stock of knowledge available in the region *i*, RD is the knowledge created in the region or 'regional technological activity', SpillRD is a vector of neighbouring regions' innovative efforts which may spill over into and contribute to the local production of innovative output, C is a vector of local economic and socio-institutional characteristics, SpillC is a vector of broader socio-institutional characteristics in neighbouring regions.

The choice of the proxies for the arguments in function (1) is determined according to the following matrix:

	Endogenous factors	**Spillovers**
Initial patent intensity	Initial patent applications	
R&D	Investment in R&D in the region	Investment in R&D in neighbouring regions
Agglomeration economies	Total regional of state GDP/ Population density	
Specialisation of the local economy	Krugman index	
Human capital mobility	Migration	
Social filter	Structural characteristics that would make a region more 'innovation prone', including: 1. Education 2. Life-long learning 3. Sectoral composition 4. Use of resources (unemployment) 5. Demographics	Similar conditions in neighbouring regions
National effects	National dummies (in the case of Europe) and Geographical dummies (for the US)	

By developing this framework, equation 1 allows us to specify the following empirical model:

$$\frac{1}{T}\ln\left(\frac{Pa_{i,t}}{Pa_{i,t-T}}\right) = \alpha + \beta\ln(Pa_{i,t-T}) + \gamma RD_{i,t-T} + \delta SpillRD_{i,t-T} + \zeta_1 SocFilter_{i,t-T} + \zeta_2 Mig_{i,t-T} +$$

$$+\zeta_3 KrugmanIndex_{i.t-T} + \zeta_4 Agglom_{i,t-T} + \eta SpillSocFilter_{i,t-T} + \theta D + \varepsilon_i \qquad (2)$$

where:

$\frac{1}{T}\ln\left(\frac{Pa_{i,t}}{Pa_{i,t-T}}\right)$	is the logarithmic transformation of the ratio of patent applications in region *i* at the two extremes of the period of analysis (t-T,t);
α	is a constant;
$\ln(Pa_{i,t-T})$	is the log of the initial level of patent applications per million inhabitants at the beginning of the period of analysis (t-T);
RD_{t-T}	represents expenditure in R&D as a % of GDP in region *i* at time (t-T);
$SocFilter_{i,t-T}$	is a proxy for the socio-economic conditions of region *i*, representing its 'social filter';
$Mig_{i,t-T}$	denotes the migration balance of region *i* at time (t-T);
$KrugmanIndex_{i.t-t}$	represents the level of specialisation of local employment of region *i* at time (t-T);
$Agglom_{i,t-T}$	is either (the natural log of) population density or regional percentage of national GDP of region *i* at time (t-T) as proxies for agglomeration economies;
Spill	indicates the presence of these factors in neighbouring regions;
D	denotes a set of national/geographical dummy variables;
ε	is the error term.

Patent growth rate – Patent statistics provide a measure of innovative output (OECD 2006). Their strength is to provide comparable information on inventions across a broad range of technological sectors. However, patent indicators suffer from a number of limitations in their ability to proxy innovation, and hence must be interpreted with care. Such limitations include the heterogeneous value or degree of novelty of patented products or processes; the different propensity to patent across countries and sectors; and the non-patentability of many inventions or the better cost-effectiveness of other protection methods (e.g. secrecy) (OECD 2001; Sedgley and Elmslie 2004). Moreover, for the United States, even ostensibly minor changes in the organisation of patenting institutions, by altering the structure of incentives of all participants in the patenting process (applicants, patent office employees, potential imitators), have produced a substantial inflation in the number of patent applications without any underlying 'real' change in inventive performance (Jaffe and Lerner 2004). Despite all these caveats, Ács and Audretsch (1989) show that regression analyses based on patent counts deliver results highly comparable with those based on more direct measures of innovation.

Initial level of patents per million inhabitants – The initial level of utility[7] patents granted/applied for[8] in the region is a proxy for the existing technological capacity of the area and its distance from the technological frontier. This variable also controls for the differential overall propensity to patent, which reflects different initial sectoral specialisation patterns.

R&D expenditure – is the investment in R&D as a percentage of GDP (R&D intensity). The value of R&D intensity expresses the relative innovative effort of a region. It is the main input in the knowledge production function.

Spillovers – In the knowledge production function, inter-territorial spillovers contribute to the creation of new local knowledge. For this purpose, we have developed a measure of the 'innovative activities' (in terms of R&D expenditure) that can be 'reached' from each region at a 'cost' which increases with

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[7] The majority of patents issued by the USPTO are utility (i.e. invention) patents. Other types of patents and patent documents issued by USPTO, but not included in this report, are plant patents, design patents, statutory invention registration documents, and defensive publications. While in 1999 the number of utility patents granted reached 153,493, just 14,732 design patents, 448 reissue, and 421 plant patents were awarded. Our data do not include these other categories.

[8] The USPTO provides data at the sub-state level on utility patents granted from 1990 - 1999 with a first-named inventor who resided in the United States. For the EU, instead, patents are organized by EUROSTAT according to the application years rather than the grant years. However, the US patent data at the national level show that the numbers of patent applications and patents granted are highly correlated over time (0.94 for the period 1989-2002) and across geographical units (0.98 for 1990).

distance. Consequently, for each region the R&D expenditure recorded in neighbouring regions is weighted by the inverse of their bilateral distances.

The proxy $Spillx_i$ for spillovers from variable x_i flowing into region i is calculated as:

$$Spillx_i = \sum_j x_j \frac{\frac{1}{d_{ij}}}{\sum_j \frac{1}{d_{ij}}} = \frac{\sum_j x_j d_{ij}}{\sum_j d_{ij}} \qquad (3)$$

where x_i is the variable under analysis, d_{ij} is the average trip-length (in minutes)/distance between region i and j.

For the EU the measure of distance is based on the travel time calculated by the IRPUD (2000) for the computation of peripherality indicators and made available by the European Commission[9]. We chose road distance, rather than straight line distance, as, in particular on a smaller scale, it provides a more realistic representation of the real 'cost' of interaction and contacts across space. However for the US, this kind of distance measure is not available and we rely straight line distance[10].

Krugman Index – Following Midelfart-Knarvik et al. (2002) we call the index K the Krugman specialisation index, used to measure the specialisation of local employment by calculating:

a) for each region, the share of industry k in that region's total employment: $v_i^k(t)$;

b) the share of the same industry in the employment of all other regions: $\bar{v}_i^k(t)$; and

c) the absolute values of the difference between these shares, summed over all industries:

$$K_i(t) = \sum_k abs(v_i^k(t) - \bar{v}_i^k(t)) \text{ with } v_i^k(t) = \sum_{j \neq i} x_i^k(t) / \sum_k \sum_{j \neq i} x_i^k(t) \qquad (4)$$

The index takes the value zero if region i has an industrial structure identical to the rest of the EU/US regions, and takes the maximum value of two if it has no industries in common with the rest of the EU/US. For the US, the Krugman Index has been calculated on the basis of the industry classification

[9] As the time distance-matrix is calculated either at the NUTS1 or at the NUTS2 level, in order to make it coherent with our data which combine different NUTS levels we relied on the NUTS distance matrix using the NUTS 2 regions with the highest population density in order to represent the corresponding NUTS1 level for Belgium, Germany, and the UK.

[10] Data on distances between MSAs are calculated on the assumption that a 1 degree difference in latitude is constant regardless of the latitude being examined. This assumption is not problematic for smaller countries, but for a large country like the US, it results in a substantial underestimation of the distance between Southern cities and an overestimation of that between Northern cities.

system developed for the 1990 census[11] which consists of 235 categories for employed persons, classified into 13 major industry groups. For the EU, we rely on the Branch Accounts ESA95 data for employment in NUTS1 and 2 regions, which are based on a 17-branch classification of economic activities (NACE Rev. 1.1 A17) available from 1995 onwards.

Social Filter – The literature suggests three principal aspects of the 'social filter' of a region: educational achievements (Lundvall 1992; Malecki 1997), productive employment of human resources, and demographic structure (Fagerberg et al. 1997; Rodríguez-Pose 1999). A set of variables proxies for each domain (given data availability at the regional level and comparability between the EU and the US). Educational attainment is measured by the percentage of population and labour force having completed tertiary education. Participation in lifelong learning programmes is used as a measure for the accumulation of skills at the local level for the EU, while for the US we use the number of people who completed 'some college (or associate) level education but no degree' and the number of people with 'bachelor's, graduate or professional degrees'[12].

For the second area (structure of productive resources), the percentage of the labour force employed in agriculture was available for both the EU and the US. Long-term unemployment is only available for the EU, thus requiring us to use the US unemployment rate (rather than its long term component). These two variables are used because of the traditionally low productivity of agricultural employment in relationship to that of other sectors, and because agricultural employment, in particular in some peripheral regions of the EU but also in some southern states of the US, is in reality synonymous to 'hidden unemployment'[13]. The rate of unemployment (and in the case of the EU especially its long-term component) is an indicator of the rigidity of the labour market and of the presence of individuals whose possibilities of being involved in productive work are hampered by

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[11] The 1990 census classification was developed from the 1987 Standard Industrial Classification (SIC) Manual published by the Office of Management and Budget Executive Office of the President.

[12] The first category includes people whose highest level of schooling is an associate degree (for example: AA, AS) or some college credit, but no degree. The second group includes those whose highest level of schooling is a bachelor's degree (for example: BA, AB, BS), a master's degree (for example: MA, MS, MEng, MEd, MSW, MBA) or a professional degree (for example: MD, DDS, DVM, LLB, JD) (US Census Bureau).

[13] Unemployment is 'hidden' in the fabric of very small farmholdings in many EU peripheral areas and in many Southern states of the US (Demissie 1990; Caselli and Coleman 2001). In both these contexts agricultural workers show low levels of formal education, scarce mobility, and tend to be aged.

inadequate skills (Gordon 2001). Demographic structure is indicated by the percentage of population aged between 15 and 24, with the substantive goal of identifying dynamic demographic trends. Young people contribute towards the renewal of the local society, which should influence the collective attitude towards innovation and social change in general.

We deal with the problems of multicollinearity, which prevent the simultaneous inclusion of all these variables in our model, by means of principal component analysis (PCA). PCA allows us to merge the variables discussed above into an individual indicator that preserves as much as possible of the variability of the source data. The output of the PCA is shown in Tables B-1 and B-2 in the Appendix for both the US and the EU. The eigenanalysis of the correlation matrix shows that the first principal component alone is able to account for around 39% and 34% of the total variance for the EU and US case, respectively, with an eigenvalue significantly larger than 1 in both cases (Table B-1).

The first principal component scores are computed from the standardised value of the original variables by using the coefficients listed under PC1 in Table B-2. These coefficients assign a large weight to the educational achievements of the population in both Continents; this is a major component of the 'social filter' part of our model. In the EU, educational achievement, employed people and, to a lesser extent, the participation in life-long learning programmes complete the index with a positive weight. Both in the EU and the US a positive weight is also assigned to the percentage of young people, but it is significantly more important in the US. A negative weight is assigned, in both contexts, to the rate of unemployment (US) and to its long term component (EU). The percentage of agricultural labour has a negative influence in the EU, while in the US, it has a small but positive influence.

Agglomeration and economies of scale- The degree of agglomeration of the local economy is proxied by the log of population density, as customary in the literature. In addition, the presence of regional economies of scale is proxied by the relative concentration of economic activities (regional percentage of national GDP).

Migration – The degree of internal (EU[14] and US) labour mobility is reflected by the regional rate of migration (i.e. the increase or decrease of the population due to migration flows as a percentage of the initial population). A positive rate of migration (i.e. an inflow of people from other regions) is a proxy for the capacity of the region to attract new workers, thus increasing the size of its labour pool and its 'diversity' in terms of skills and cultural background.

5. Results of the analysis

5.1 Estimation issues and data availability

We estimate the model by means of heteroskedasticity-consistent OLS (Ordinary Least Square) regressions. The effect of spatial autocorrelation (i.e. the lack of independence among the error terms of neighbouring observations) is minimized by including a set of national dummy variables for the EU case and a set of geographical dummies for the US, accounting for the 'national fixed effect'. Furthermore, by introducing spatially lagged variables in our analysis, we explicitly consider the interactions between neighbouring regions and thus minimize their effect on the residuals. Another concern is endogeneity, which we address by incorporating the value of the explanatory variables into the model as a mean over the period (t-T-5) – (t-T), while the average growth rate of patents was calculated over the period from t-T to t. In addition, in order to resolve the problem of different accounting units, explanatory variables are expressed, for each region, as a percentage of the respective GDP or population.

For the USA, the model was estimated for 1990-1999, the period for which patent data are available at the sub-state level from the US Patent Office. The analysis is based upon 266 MSA/CMSAs[15] covering all continental US States (and the District of Columbia), while MSAs in Alaska, Hawaii, or in

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[14] Migration data are provided by Eurostat in the 'Migration Statistics' collection. However there are no data for Spain and Greece. Consequently, in order to obtain a consistent measure across the various countries included in the analysis, we calculate this variable from demographic statistics. "Data on net migration can be retrieved as the population change plus deaths minus births. The net migration data retrieved in this way also includes external migration" (Puhani 2001: 9). The net migration was standardised by the average population, obtaining the net migration rate. Consequently, while for the EU it is impossible to distinguish between national, intra-EU and extra-EU migration flows for the US domestic in-migration and out-migration data consist of moves where both the origins and destinations are within the United States.

[15] The MSA/CMSA list is based on *Metropolitan Areas and Components, 1993, with FIPS Codes*, published by the Office of Management and Budget (1993).

other non mainland territories of the US are excluded from the analysis. The lack of sub-state level data for R&D expenditure was addressed by relying upon Standard & Poor's Compustat[16] North American firm-level data which provide a proxy for private R&D expenditure in 145 MSAs out of the total of 266. The proxy was calculated by summing up firms' R&D expenditure in each MSA. Though rough, this is the only measure available and similar proxies have been commonly used in the literature on the MSA innovative activities (e.g. Feldman 1994). All other US variables are based on US-Census data included in the *USA Counties 1998 CD-Rom*.

For the EU, the model is run for 1990-2002. Lack of data led to the exclusion of the new member states of the Union. This is actually fortuitous, because the new, central and eastern European member states have much lower development levels than the EU-15 and are less economically integrated with them. Because of data constraints, but also for reasons of homogeneity and coherence in terms of relevant institutional level, the analysis uses NUTS1 regions for Germany and Belgium and NUTS2 for all other countries (Austria, France, Greece, Italy, Spain and Portugal). Countries without equivalent sub-national regions (Denmark, Ireland, Luxembourg) were excluded *a priori* from the analysis[17]. In addition, regional data on R&D expenditure are not available in the Eurostat databank for Sweden. The entire dataset of the EU is based on EUROSTAT Regio data. Table A-1 in the appendix provides a detailed definition of the variables included in the analysis for both the US and the EU.

5.2 Results

The results for model (2) are presented in Tables 1 and 2 for the US and Table 3 for the EU. Table 1 includes the R&D expenditure variable which is available for only 145 MSAs. However, the regions for which R&D data are available are not a random sample of the total 266 MSAs: on the contrary, when

[16] Standard & Poor's Compustat North America is a database of financial, statistical, and market information covering publicly traded companies in the U.S. and Canada. It provides more than 340 annual and 120 quarterly income statements, balance sheets, flows of funds and supplemental data items on more than 10,000 active and 9,700 inactive companies.

[17] As far as specific regions are concerned, no data are available for the French Départments d'Outre-Mer (Fr9). Trentino-Alto Adige (IT31) has no correspondent in the NUTS2003 classification. Due to the nature of the analysis, the islands (PT2 Açores, PT3 Madeira, FR9 Départements d'Outre-mer, ES7 Canarias) and Ceuta y Melilla (ES 63) were not considered, as time-distance information, necessary for the computation of spatially lagged variables, is not available.

this variable is introduced, the less economically successful and less innovative regions[18] (i.e. those where it is less likely to find firms included in S&P database on which we rely for our R&D data) are excluded from the sample. Consequently, in order to account for the sample bias[19], in Table 2 we exclude R&D expenditure, and estimate the model for all 266 observations. As will be highlighted when commenting on the specific results, the sample selection bias affects only some of the results reported in Table 1.

[Insert Tables 1, 2, and 3]

In regressions 1-2 of Table 1 (US) and Table 3 (EU) the initial level of patents, the measure for local innovative efforts, the proxy for knowledge spillovers, and the social filter variable are successively introduced. In regressions 3-7 the individual components of the social filter are included separately in order to discriminate among them. From regression 8 onwards the variables relative to the territorial organisation of the local economy (migration, agglomeration, and specialisation) are introduced sequentially. Table 2 follows the same order but without controlling for R&D expenditure and knowledge spillovers.

The Adj-R^2 confirms the overall goodness-of-fit of all the regressions presented and in all cases F-statistics probability lets us reject the null hypothesis that all regression coefficients are zero. VIF tests were conducted for the variables included in all the specifications of the model excluding the presence of multicollinearity. There was no spatial autocorrelation in the residuals detected using the Moran's I test (Cliff and Ord 1972).

These results offer a number of insights into the territorial dimension of knowledge production in the EU and the US. One of the key similarities in the geography of regional innovation of the US and Europe is the presence of territorial convergence in the regional distribution of innovative outputs over the last few years. The coefficient on the initial level of patenting activity is in both cases negative and

[18] The 145 MSAs for which R&D data are available account for 89,9% of the GDP generated in all 266 MSAs and show an average of 225.19 patents per million inhabitant against 176.83 for the whole sample.

[19] Beeson, DeJong, and Troesken (2001) discuss the 'sample selection bias' introduced when choosing cities as unit of analysis rather then county-level data: only places that experienced successful growth in the past are considered in this way. The use of standard metropolitan statistical areas minimises this first bias. However, in order to keep the bias at the minimum, we not only report the results for the most innovative subsample of MSAs, but also for all MSAs in the Continental US.

significant (Tables 1, 2 and 3). This suggests that adequate conditions for the generation of patents – e.g. the emergence or re-location of innovative firms, the changing balance between positive and negative externalities arising from agglomeration at different stages of product life cycles, and changes in the competitive advantage of some locations in response to changes in technological paradigms – have spread to formerly peripheral areas, making the regional distribution of innovative output more evenly spread. This generalised trend towards the dispersion of innovative activities seems to be less accentuated in the United States than in the EU: when all the 266 MSAs are included in the analysis (thus also taking into account the less innovative MSAs), the convergence parameter is smaller and less significant in the US than in the EU.

In the US the relatively higher stability of the geography of the innovative output is associated with a positive and statistically significant impact (Table 1 Regression 1) of local innovative activities on innovative output: the higher the level of local R&D expenditure, the higher the patent growth rate at the local level. The production of knowledge and innovation are more localised in the US than in Europe, as implied also by the lack of evidence of inter-MSA spillovers: the spatially-weighted average of neighbouring MSAs' R&D expenditure does not exert any statistically significant influence upon patent growth rate. In the EU the opposite territorial dynamic occurs. Local innovation productivity is not directly related to the level of R&D expenditure or at least, the relationship seems to hold only in the short run. When patent growth over the 1990-2002 time span is regressed on initial R&D expenditure the coefficient is not significant (Table 3 Regression 1) but, when the shorter period 1995-2002 is considered, the coefficient is positive and significant (Table 3 Regression A). Instead, the positive and significant coefficient of the spatially-weighted average of neighbouring region R&D expenditure (Table 3 Regression 1) shows that the long-run growth rate of innovative activities in the EU is shaped more by exposure to interregional knowledge spillovers.

Three potential factors may lie behind the differences between the US and Europe in the impact of innovative inputs on innovative outputs: the distance between innovative centres, the composition of R&D investments, and labour mobility. Large innovative areas tend to be physically closer in Europe than in the US. In addition, empirical analyses of the diffusion of spillovers have highlighted the presence of very strong distance decay effects in the US – knowledge spillovers, in general, do not spread beyond a 80 to 110 kms radius from the MSA where they are generated (Varga 2000; Ács 2002) – whereas in Europe the geographical diffusion of spillovers is felt in a radius of 200 to 300 kms from the point of origin (Bottazzi and Peri 2003; Moreno et al. 2005; Rodríguez-Pose and Crescenzi 2006). Greater proximity and lower distance decay suggest a greater potential for European regions to rely on innovative inputs in neighbouring areas as a source of innovation. Greater distance and stronger distance decay effects are, in contrast, likely to lead to the creation of self-contained innovative areas in the US, which necessarily have to rely on their own innovative inputs rather than on spillovers from other MSAs.

R&D inputs in the US tend also to be more specialised and better targeted than in Europe. A legacy of efforts by virtually every European nation-state to have a presence in a large number of areas of knowledge has resulted in duplications and redundancies in R&D that European integration has, so far, failed to overcome (Gambardella and Malerba 1999: 9; Mariani 2002). The existence of a much more integrated market in the US has favoured the formation of a more specialised geographical innovation structure.

Last but not least, difference in labour mobility between the two Continents may also leave an important imprint on their respective geographies of innovation. In the US, high levels of mobility allow better ongoing matching of innovative actors in space; consequently, they interact more strongly on a local basis, relying less on spillovers from other MSAs than in Europe. The weaker convergence parameter in the USA is an outcome not only of the stronger impact of local R&D expenditure, but also because of the higher and more variable productivity of such expenditure, thanks to the better spatial matching obtained through higher factor mobility. In contrast, weaker intra-regional synergies force European innovators to rely upon neighbouring regions' innovative efforts (extra-regional spillovers). The more stable EU population distribution – with a lower degree of internal mobility – produces a more inter-regionally integrated and 'redistributive' innovation system, which depends for its functioning on inter-regional communication and ‘distance’ learning. Matching at the local level is severely hampered by low levels of mobility[20].

While the spatial diffusion of knowledge exhibits different territorial dynamics in the EU and the US, empirical evidence suggests that, in both contexts, the endogenous socio-economic factors, which enable the translation of both endogenously produced and exogenous knowledge into innovative output, are quite similar. Both in the US and in Europe the social filter variables show positive and significant signs (Table 1 Regression 2; Table 3 Regression 2). The existence of a set of local socio-economic factors may be a pre-condition for the establishment of a successful regional system of innovation and seems to play an important role in explaining differential innovative performance in the regions of the EU and in US MSAs. In addition, in both contexts, the local economy is not strongly affected by the socio-economic conditions of neighbouring areas: the spatially weighted average of the socio-economic conditions of neighbouring regions is not significant for either the US or the EU (Table 1 Regression 2 and Table 3 Regression 2, respectively). However this evidence needs to be placed in the context of the different geographical processes in the two Continents. The fact that neighbouring regions’ social filter conditions have no impact on local innovative performance is consistent with the more ‘localistic’ and ‘self-sufficient’ nature of the US process geography of innovation. In the European Union the similarly localised impact of the social filter conditions is at odds with the less localistic, inter-regional communications deemed necessary to enable knowledge matching. This suggests a potential inconsistency in the EU system of innovation, where social filter conditions are unable to extend their benefit over distance thus reinforcing the need for long-distance knowledge flows as a way of compensating the consequences of low factor mobility.

When the individual components of the social filter are assessed separately, the significant and positive effect of higher education is apparent in both contexts (Regressions 3 and 4 in Tables 1 and

[20] When assessing this phenomenon it must, however, be borne in mind that the unit of analysis in the case of the EU are NUTS regions i.e. territorial units for the production of regional statistics for the European Union whose definition mainly serves administrative purposes. As a consequence, NUTS regions might not always approximate the functional borders of the regional economy. Conversely, US MSAs are closer to the concept of ‘functional urban regions’ (Cheshire and Hay, 1989) and likely to be more ‘self-contained’ in terms of economic interactions. Consequently, part of the difference between the empirical evidence recorded in the two cases may be due to the different nature of the spatial unit of analysis.

2). More specifically, from the inspection of Table 1, the key resource for the US regions seems to be the population holding bachelors, postgraduate, or professional degrees. The percentage of people holding only some ‘college level education’, without a full degree, is insignificant. However, this result in the case of the US may be partially due to the sample selection bias discussed above: when the whole sample of MSAs is considered (Table 2 Regressions 2 and 3) both education variables are significant. This implies that for the most innovative MSAs, where the majority of the R&D expenditure is concentrated, the true differential competitive factor seems to be a higher level of specialised skills while, in the overall sample of the MSAs, more generic skills may also play a role in improving local innovative performance. In the EU context, where slightly different indicators are available, the educational achievements of the population (Table 3 Regression 4) exert a positive and significant influence on innovative output (while those of employed people only are not significant – Table 3 Regression). An additional factor that seems to foster innovation in both the EU and the US is the presence of a favourable demographic structure: the regions where the incidence of young adults is higher tend to produce more innovation (Tables 1 and 3 Regression 5). Only in the US does a higher rate of unemployment seem to discourage the production of innovation (Table 1 Regression 6 and Table 2 Regression 5), while in the EU this effect is not statistically significant. The percentage of the labour force concentrated in agriculture is not significant in either context. From this we conclude that the productive use of human resources is less important than the quality of such resources.

The final part of the empirical analysis takes up the territorial organisation of the factors of production: migration flows and the density of human interactions, on the one hand, and the agglomeration and specialisation of economic activities, on the other. In US MSAs the rate of net domestic migration exercises a positive and significant effect on patent growth rates (Table 1 Regression 8; Table 2 Regression 7). By contrast, the innovative productivity of the EU regions is unable to benefit from this kind of flow due to lower mobility of European workers: as Peri (2005) points out, not only does the US receive a much larger flow of immigrants (in absolute and relative terms) from the rest of the world than the EU, but “the US also complements these large inflows of immigrants with a very high internal mobility of its citizens" (p.22). Our results underscore how these different features of the labour market impact upon the innovative performance of the two Continents (echoing the results of Ottaviano and Peri 2006). US MSAs benefit from the inflows of skilled labour that result in higher productivity and innovation, but innovation also acts as a magnet for skilled individuals that would, in turn, contribute to further innovation. A virtuous circle of innovation and migration is thus generated in the US. In Europe, due to the greater cultural and institutional barriers to mobility, this virtuous circle is not replicated.

Looking at the role of agglomeration effects, Table 1 suggests that in American MSAs neither population density (Regression 9), nor the percentage of total US personal income (Regression 10) have a significant effect. However, when the sample selection bias discussed before is accounted for, by considering the whole 266 MSA sample, 'population density' shows a positive and significant sign (Table 2 Regression 8) – and its significance increases when assessed together with migration rate[21] (Table 2 Regression 11) – while 'regional % of national GDP' remains insignificant in either case. In the EU context the opposite is true: population density is not significant (Table 3 Regression 9) while 'regional % of national GDP' is positive and significant both alone and after controlling for population density (Table 3 Regression 10 and 11 respectively). It appears that in the US, the density of human contacts is important for innovative productivity since it enables the maximisation of intra-regional spillovers. As previously discussed, these exchanges prevail over inter-regional knowledge flows. Conversely, the agglomeration of economic activities, a proxy which emphasizes the 'scale' side of agglomeration economies, is not a differential source of competitive advantage for US MSAs: the optimal scale of production is easily achieved by the US MSAs, which are larger on average than their European counterparts. Consequently the 'scale component' of agglomeration economies does not emerge as a differential innovative factor (i.e. in addition to the density of human interactions/localised knowledge spillovers).

[21] This is consistent with the notion that because mobility is higher in the US, innovation systems have more local matching and learning and hence are more 'local' than in Europe, where long distance communication is necessary in order to match relatively immobile agents.

In the EU, local interaction density does not seem to stimulate innovation productivity. The positive effect of population density on human interaction – predicted by the theory of agglomeration and observed empirically in the US case – seems to be offset, in the EU, by a broader set of territorial forces. Population density, in a context of low labour mobility as in the EU, may encourage the pooling and stratification of inadequate skills while US agglomerations are usually newer and, in absolute terms, less densely populated. Competitive advantage for the EU regions is instead promoted by the relative concentration of wealth which, as seen above, proxies the 'scale' side of agglomeration economies.

Absolute size of clusters. There is a vigorous debate in the literature over whether agglomeration economies can be fully captured by measures of relative concentration, or whether the absolute size of clusters is more relevant to understanding the effects of geographical concentration on productivity (see Duranton and Puga, 2000, for a review). Some recent literature places increasing emphasis on the absolute size of clusters as the basis for calculating the level of specialization, arguing that this level is systematically underestimated for larger metropolitan areas when relative levels of concentration are used (Drennan and Lobo 2007). We address this issue by proxying the absolute economic size of each MSA/region by its total population, total employment, and total GDP. We then calculate an interaction term between the degree of specialisation of the regional economy (Krugman Index) and its absolute size (proxied as specified above). The results are reported in, Table 4 – for the 145 MSAs for which R&D data are available, Table 5 – for the full US sample (266 MSAs) and Table 6 – for the EU.

[Insert Tables 4, 5, and 6]

All proxies for the absolute size of the MSAs/Regions show a positive and significant effect both in the US (but only when all the 266 MSAs are considered, Table 5) and in the EU (Table 6). Thus, larger clusters are able to produce more innovation both in Europe and the US The interaction term between absolute size and specialisation is negative and significant in the US (when the full sample is considered, Table 5) while it is not significant for the EU regions (Table 6). When the interaction term between absolute size and specialisation is introduced:

$$\frac{1}{T}\ln\left(\frac{Pa_{i,t}}{Pa_{i,t-T}}\right) = \alpha + \beta_1 \ln(Pa_{i,t-T}) + \beta_2 \text{KrugmanIndex} + \beta_3 \text{RD} + \beta_4 \text{SocFilter} + \beta_5 \text{Size} + \beta_6 \text{KrumanIndex} * \text{Size} + \varepsilon \quad (5)$$

from which, when considering the partial effect of absolute size on patent growth rate (holding all other variables fixed) one obtains:

$$\frac{\Delta\left(\frac{1}{T}\ln\left(\frac{Pa_{i,t}}{Pa_{i,t-T}}\right)\right)}{\Delta \text{Size}} = \beta_5 + \beta_6 \text{KrugmanIndex} \quad (6)$$

this implies, with $\beta_6<0$, that *ceteris paribus* the more a cluster is 'specialised' (high Krugman index score), the more an increase in its absolute size reduces its productivity in terms of new patents. This can be interpreted as showing that in the US the absolute size of clusters exerts a positive impact on innovation, but such impact is reduced when large absolute size is coupled to high specialisation. Specialisation is not inherently negative for innovative performance (Krugman index not significant) but larger clusters need to be 'specialised in more than one sector' in order to fully exploit the benefit from their absolute economic size. In the EU, the absolute size of clusters always exerts a positive influence on innovative performance and the degree of specialisation has always a negative impact (Krugman Index negative and significant). However, there is no significant (negative or positive) interaction between the two terms. Thus, ceteris paribus, an increase in the size of a cluster improves its innovative performance whatever its degree of specialisation and, symmetrically, more specialisation would lead to less innovation whatever the absolute economic size of the region.

These results reconfirm the 'national' bias of the EU process of innovation. In Europe low economic integration and factor mobility make specialisation a handicap for innovative performance. In contrast, in the integrated US context, only very large clusters in highly specialised local economies seem to suffer from reduced capacity to exploit knowledge-base complementarities. Special care is called for in the interpreting the results on the significance of the coefficients, as one does not have to test separately the significance of β_5 and β_6 but rather the joint hypothesis H_o:$\beta_5=0$, $\beta_6=0$ (Wooldridge

2003). To test this joint hypothesis, we implement the Wald Coefficient Test whose results, in the case of the US 266 MSAs, permit to reject H_o at the 1 percent level, allowing to conclude that the estimated coefficients are significant in both cases. Additionally, the Wald Test is not affected by the intrinsically lower orthogonality of the two variables.

This picture is further enriched when accounting for the influence on innovative performance of the degree of specialisation of the local economy in the two Continents. In the United States, the proxy for the degree of specialisation of the local economy (the Krugman Index) is not statistically significant (Table 1 Regressions 11 and 12). In the European case (Table 3 Regression A), in contrast, more specialised regions seem to be persistently disadvantaged in their capability to produce innovation. Specialisation is not a constraint for the process of innovation of US regions, where there seems to be mix of MAR and Jacobs externalities, more so than in the EU. In the US context, the higher labour mobility and the relatively less constrained (by political, institutional, and cultural factors) location choices of firms and individuals allow each innovative actor to select the most advantageous location according to its own technological or organisational needs (e.g. according to the current stage of the life-cycle of their product, as in Audretsch, 2003 and Duranton and Puga, 2005). In this context the geography of innovative actors effectively accommodates the possibility, offered by each region, to benefit from either sectoral specialisation or diversity. By virtue of this mechanism, specialisation ceases to be an obstacle for the production of innovation since internal factor mobility will allow specialised areas to attract agents able to benefit from MAR externalities while pushing the other agents towards more diversified areas. Furthermore the larger economic size of US agglomerations may also allow them to benefit from a certain degree of knowledge-base complementarities even in relatively more specialised contexts. This dynamism of the ongoing process of re-organisation of US economic activities in response to changing sectoral location advantages is confirmed by the evidence produced by Desmet and Fafchamps (2005) for county-level employment. They find both de-concentration of non-service employment and clustering of service jobs in high aggregate employment agglomerations: location patterns in certain sectors may be changing in response to shifts in the pattern of localised externalities. However, the de-concentration of manufacturing has benefited counties 20 to 70 km away from large agglomerations, while service activities have clustered in large agglomerations within a 20 km radius. This particular spatial scope of concentration/de-concentration dynamics seems to suggest the existence of fundamentally intra-MSA adjustments, along the lines of the 'localistic' view of the US process geography. As the EU and USA show different rates of adjustment, through mobility of labour and capital, they generate different underlying patterns of specialization (even if the overall levels are similar). This clarifies the meaning of the observed negative impact of specialisation on the innovative performance of the EU. It suggests that for the USA, it is not so much the level of specialisation that matters, as the ability to adjust the content of local factors to the changing needs of innovation.

Ciccone (2002) suggests that the degree of agglomeration of the local economy is not substantially different in the two Continents. Our results indicate that the comparative analysis of the processual aspects of the production of new knowledge cannot be 'reduced' to the level of agglomeration. On the contrary, the analysis of agglomeration economies needs to be pursued in conjunction with other relevant territorial processes, in the context of the overall geographical dynamic of the economy and its factor markets.

6. Conclusions

Our empirical analysis of the geography of innovation in the US and Europe reveals that knowledge production in both Continents is governed by different geographical processes. In the US the generation of innovation usually occurs in self-contained geographical areas that rely on their own R&D inputs, on favourable local socio-economic environments, and on the training and attraction of highly skilled individuals. In Europe the process is much more linked not just to having an adequate local socio-economic context, but to proximity to other innovative areas and to the capacity to assimilate and transform inter-regional knowledge spillovers into innovation. Human capital mobility, in contrast to the US case, does not play a role. Specialization is also negatively associated with the genesis of innovation in Europe, where agglomeration is a better driver of innovation. Hence, while Europe relies on Jacobian externalities for innovation, US MSAs can count on both MAR and Jacobian externalities. It can then be inferred that the dynamic reorganisation of European innovation resources is severely limited by the EU's lower levels of factor mobility and integration than in the US.

It would nonetheless be premature from this analysis to generate anything like firm policy conclusions. At first glance, it would be tempting to echo many other analyses in calling for an 'Americanization' of European process geography: greater factor mobility, bigger and more specialised agglomerations, more integration. The analysis pursued here, however, also sees some signs of a distinctly European pathway to integration: given these lower levels of mobility, and an historically more dispersed and less specialised urban system, and the persistence of national institutions and cultures, it may be that Europe is developing functional equivalents for American mobility and specialisation, in the form of greater inter-metropolitan knowledge exchange and cooperation. Certainly, the advances in the European transport system (high speed rail, cheap flights) are bringing metropolitan areas closer together than ever before, as are heightened levels of intra-firm, inter-firm, and inter-governmental cooperation. The question is whether, at some point, these represent viable functional alternatives to the American process geography, i.e. capable of helping Europe overcome the innovation gap. In any event, the present analysis suggests that, in both Continents, the process geography of innovation, as well as its basic geographical foundations, are essential elements in considering the innovation system of any economic area.

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Fig.1 - Distribution of total patents across regions and MSAs

100 most innovative EU regions and US MSAs

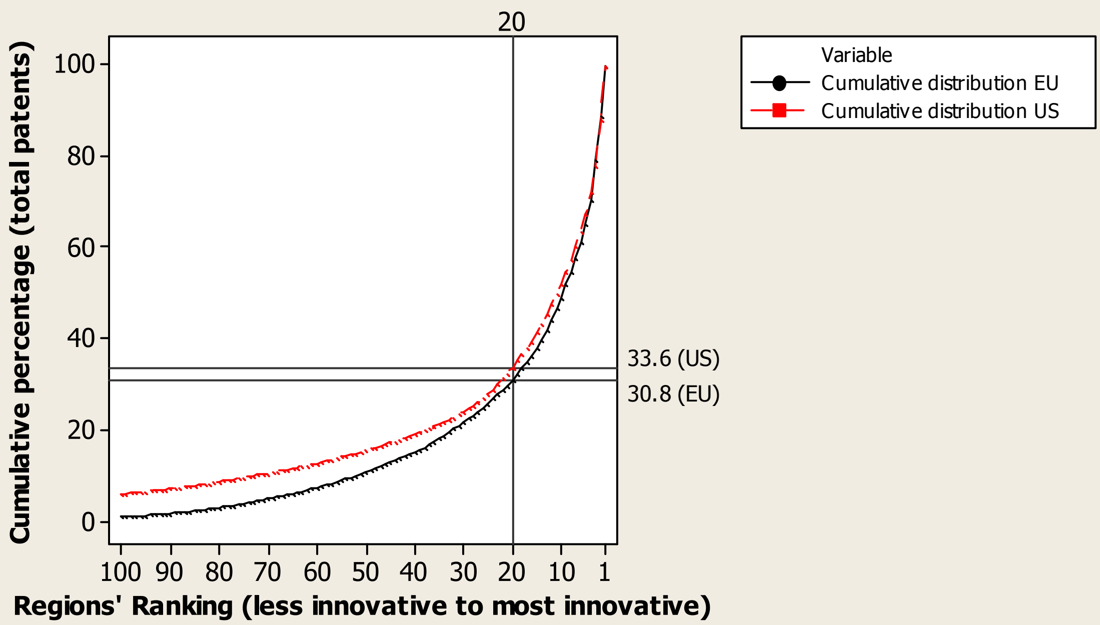

Table 1 - H-C OLS estimation of the empirical model. Annual Patent growth rate 1990-99, US MSAs with R&D (145 Obs.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	0.205***	0.220***	0.140***	0.162***	0.162***	0.267***	0.215***	0.200***	0.222***	0.214***	0.207***	0.162***
	(0.042)	*(0.045)*	*(0.041)*	*(0.057)*	*(0.043)*	*(0.046)*	*(0.046)*	*(0.038)*	*(0.043)*	*(0.034)*	*(0.034)*	*(0.051)*
Natural Log of patents per million inhab., 1990	-0.019**	-0.028***	-0.030***	-0.021***	-0.020**	-0.023***	-0.019**	-0.032***	-0.028***	-0.028***	-0.029***	-0.033***
	(0.008)	*(0.008)*	*(0.007)*	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*	*(0.007)*	*(0.007)*	*(0.007)*	*(0.007)*	*(0.007)*
Private R&D expense (% of regional personal income)	0.009*	0.011**	0.008	0.009*	0.010*	0.012**	0.008	0.014***	0.011**	0.012**	0.012**	0.013**
	(0.005)	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.006)*
Spat. Weigh. average of neighbouring regions' R&D	-0.029	-0.010	-0.002	-0.023	-0.033	-0.007	-0.031	0.020				0.012
	(0.035)	*(0.036)*	*(0.031)*	*(0.035)*	*(0.035)*	*(0.033)*	*(0.036)*	*(0.033)*				*(0.034)*
Social Filter		0.016***						0.017***	0.016***	0.016***	0.016***	0.018***
		(0.003)						*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Spat. Weigh. Average of neighbouring MSAs' Social Filter		-0.005										
		(0.022)										
% population with bachelor’s, graduate or professional degrees			0.446***									
			(0.090)									
% population with some college level education (no degree)				0.150								
				(0.107)								
% Population aged 15-24					0.316***							
					(0.104)							
Rate of unemployment						-0.010***						
						(0.004)						
% of agricultural labour force							-0.003					
							(0.003)					
Rate of NET DOMESTIC migration								0.003***				0.003*[illegible]
								(0.001)				*(0.001)*
Population density (Ln)									-0.002			0.009
									(0.005)			*(0.007)*
Total regional personal income as a percentage of total US										-0.002		-0.001
										(0.003)		*(0.003)*
Krugman Index											0.046	0.031
											(0.042)	*(0.046)*
Geographical Dummies (North-East, South, Great Lakes and Planes)	X	X	X	X	X	X	X	X	X	X	X	X
Observations	145	145	145	145	145	145	145	145	145	145	145	145
R-squared	0.12	0.24	0.26	0.13	0.16	0.19	0.13	0.32	0.24	0.24	0.24	0.32
F	3.59***	10.48***	12.17***	3.74***	4.17***	5.23***	3.24***	12.63***	11.96***	11.73***	12.81***	11.88***

Robust standard errors in parentheses - * significant at 10%; ** significant at 5%; *** significant at 1%

Table 2 - H-C OLS estimation of the empirical model. Annual Patent growth rate 1990-99, US MSAs with R&D (Full sample, 266 Obs.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	0.154***	0.073***	0.046	0.072**	0.230***	0.117***	0.162***	0.128***	0.155***	0.155***	0.120***	0.166***
	(0.025)	*(0.026)*	*(0.039)*	*(0.029)*	*(0.033)*	*(0.028)*	*(0.025)*	*(0.027)*	*(0.026)*	*(0.027)*	*(0.032)*	*(0.028)*
Natural Log of Patents per million inhab.	-0.019***	-0.017***	-0.010**	-0.007	-0.017***	-0.009*	-0.022***	-0.020***	-0.019***	-0.018***	-0.025***	-0.023***
	(0.005)	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.006)*	*(0.005)*
Social Filter	0.019***						0.017***	0.018***	0.018***	0.018***	0.016***	0.016***
	(0.003)						*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.002)*
Spat. Weigh. Average of neighbouring MSAs' Social Filter	-0.024											
	(0.025)											
% population with bachelor's, graduate or professional degrees		0.374***										
		(0.058)										
% population with some college level education (no degree)			0.219**									
			(0.094)									
% Population aged 15-24				0.194*								
				(0.100)								
Rate of unemployment					-0.012***							
					(0.002)							
% of agricultural labour force						-0.002						
						(0.002)						
Rate of NET DOMESTIC migration							0.002***				0.002***	0.002*
							(0.001)				*(0.001)*	*(0.000*
Population density (Ln)								0.007*			0.011**	0.000
								(0.004)			*(0.005)*	*(0.000*
Total regional personal income as a percentage of total US									0.003		0.003	0.003
									(0.003)		*(0.003)*	*(0.003)*
Krugman Index										-0.002	0.014	-0.0045
										(0.035)	*(0.712)*	*(0.037)*
Geographical Dummies (North-East, South, Great Lakes and Planes)	X	X	X	X	X	X	X	X	X	X	X	X
Observations	266	266	266	266	266	266	266	266	266	266	266	266
R-squared	0.17	0.15	0.05	0.05	0.14	0.04	0.21	0.17	0.17	0.16	0.23	0.2242
F	10.83***	10.82***	3.39***	2.23**	7.92***	1.84	11.14***	10.27***	10.43***	10.32***	7.91***	7.65***

Robust standard errors in parentheses - * significant at 10%; ** significant at 5%; *** significant at 1%

Table 3 - H-C OLS estimation of the empirical model. Annual Patent growth rate 1990-2002, EU Regions

	(1) 1990-2002	(2) 1990-2002	(3) 1990-2002	(4) 1990-2002	(5) 1990-2002	(6) 1990-2002	(7) 1990-2002	(8) 1990-2002	(9) 1990-2002	(10) 1990-2002	(11) 1990-2002	**A** **1995-2002**
Constant	0.060**	0.094***	0.050*	0.043	-0.010	0.064	0.069**	0.078***	0.108**	0.067**	0.086*	-0.388
	(0.026)	*(0.032)*	*(0.029)*	*(0.029)*	*(0.050)*	*(0.040)*	*(0.030)*	*(0.026)*	*(0.049)*	*(0.029)*	*(0.044)*	*(0.285)*
Natural Log of Patents per million inhab.	-0.021***	-0.025***	-0.022***	-0.023***	-0.021***	-0.021***	-0.023***	-0.029***	-0.024***	-0.025***	-0.029***	-0.055**
	(0.006)	*(0.007)*	*(0.006)*	*(0.006)*	*(0.006)*	*(0.007)*	*(0.008)*	*(0.008)*	*(0.007)*	*(0.007)*	*(0.008)*	*(0.021)*
R&D Expenditure (% Regional GDP)	0.960	0.712	0.556	0.233	1.245*	0.994	1.018	0.969	0.766	0.359	0.702	4.830**
	(0.691)	*(0.773)*	*(0.719)*	*(0.708)*	*(0.713)*	*(0.713)*	*(0.699)*	*(0.704)*	*(0.706)*	*(0.764)*	*(0.716)*	*(2.267)*
Spatially weighted average of neighbouring regions' R&D	8.311**	7.066*	8.218**	8.018**	8.830**	8.282**	8.433**	9.357**	7.782*	8.260**	9.305**	45.968*
	(3.884)	*(3.575)*	*(3.710)*	*(3.581)*	*(4.008)*	*(4.002)*	*(3.985)*	*(3.999)*	*(3.949)*	*(3.904)*	*(4.198)*	*(23.190)*
Social Filter		0.011*						0.010*	0.012	0.008	0.010	0.062
		(0.006)						*(0.006)*	*(0.007)*	*(0.006)*	*(0.007)*	*(0.055)*
Spatially weighted average of neighbouring regions' Social Filter		0.014										
		(0.037)										
% of employed persons with tertiary education			0.155									
			(0.112)									
% of total population with tertiary education				0.346**								
				(0.155)								
% of Population aged 15-24					0.362*							
					(0.204)							
Long Term Unemployment						-0.007						
						(0.047)						
% Agricultural Labor Force							-0.047					
							(0.101)					
Migration rate								0.009			0.009	
								(0.007)			*(0.007)*	
Population Density (Ln)									-0.004		-0.005	
									(0.005)		*(0.005)*	
Percentage Regional of National GDP										0.069*	0.087**	
										(0.038)	*(0.040)*	
Krugman Index of Specialisation (Employment in 16 NACE sectors)												-0.171*
												(0.099)
National Dummies	X	X	X	X	X	X	X	X	X	X	X	X
Observations	97	97	97	97	97	97	97	97	97	97	97	97
R-squared	0.43	0.45	0.44	0.45	0.45	0.43	0.43	0.46	0.46	0.46	0.47	0.21
F	6.11***	4.65***	5.26***	5.62***	6.27***	5.61***	5.26***	5.11***	5.71***	5.33***	5.58***	2.11**

Robust standard errors in parentheses - * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4 - H-C OLS estimation of the empirical model: interaction terms. Annual Patent growth rate 1990-99, US MSAs with R&D (145 Obs.)

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.210***	0.145	0.200***	0.150	0.198**	0.150
	(0.077)	*(0.136)*	*(0.072)*	*(0.129)*	*(0.084)*	*(0.145)*
Natural Log of patents per million inhab.	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***
	(0.007)	*(0.007)*	*(0.007)*	*(0.007)*	*(0.007)*	*(0.008)*
Private R&D expense (% of total personal income)	0.012**	0.012**	0.012**	0.012**	0.012**	0.012**
	(0.005)	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.006)*
Social Filter CP 1	0.016***	0.015***	0.016***	0.015***	0.016***	0.015***
	(0.003)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Krugman Index	0.044	0.430	0.048	0.340	0.048	0.330
	(0.045)	*(0.590)*	*(0.045)*	*(0.559)*	*(0.045)*	*(0.620)*
Total Population (Ln)	-0.000	0.005				
	(0.005)	*(0.009)*				
Interaction term Krugman Index*Total Population		-0.030				
		(0.044)				
Total employment (Ln)			0.001	0.005		
			(0.005)	*(0.009)*		
Interaction term KrugmanIndex*Total Employment				-0.024		
				(0.044)		
Total Income (Ln)					0.001	0.004
					(0.005)	*(0.008)*
Interaction term KrugmanIndex*Total Income						-0.018
						(0.038)
Geographical Dummies (North-East, South, Great Lakes and Planes)	X	X	X	X	X	X
Observations	145	145	145	145	145	145
R-squared	0.24	0.24	0.24	0.24	0.24	0.24
F-stat	11.12***	10.31***	11.22***	10.31***	11.21***	10.30***

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

^ joinlty significant at 10%; ^^ significant at 5%; ^^^ significant at 1% (Wald test)

Table 5 - H-C OLS estimation of the empirical model: interaction terms. Annual Patent growth rate 1990-99, US MSAs (full sample)

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.039	-0.001	0.050	0.011	0.021	-0.026
	(0.047)	*(0.095)*	*(0.043)*	*(0.088)*	*(0.050)*	*(0.106)*
Natural Log of Patents per million inhab.	-0.025***	-0.026***	-0.026***	-0.026***	-0.026***	-0.026***
	(0.006)	*(0.006)*	*(0.006)*	*(0.006)*	*(0.006)*	*(0.006)*
Social Filter	0.017***	0.016***	0.016***	0.016***	0.016***	0.016***
	(0.003)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Krugman Index	0.028	0.255	0.028	0.245	0.027	0.288
	(0.041)	*(0.438)*	*(0.040)*	*(0.399)*	*(0.041)*	*(0.492)*
Rate of NET DOMESTIC migration	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*
Total Population (Ln)	0.010***	0.014** ^^^				
	(0.003)	*(0.007)*				
Interaction term Krugman Index*Total Population		-0.018^^^				
		(0.034)				
Total employment (Ln)			0.010***	0.014** ^^^		
			(0.003)	*(0.007)*		
Interaction term KrugmanIndex*Total Employment				-0.019^^^		
				(0.032)		
Total Income (Ln)					0.010***	0.013** ^^^
					(0.003)	*(0.006)*
Interaction term KrugmanIndex*Total Income						-0.017 ^^^
						(0.031)
Geographical Dummies (North-East, South, Great Lakes and Planes)	X	X	X	X	X	X
Observations	266	266	266	266	266	266
R-squared	0.24	0.24	0.24	0.24	0.24	0.24
F-Stat	8.61***	7.73***	8.58***	7.73***	8.48***	7.65***

Robust standard errors in parentheses
*significant at 10%; ** significant at 5%; *** significant at 1%
^ joinlty significant at 10%; ^^ significant at 5%; ^^^ significant at 1% (Wald test)

Table 6 - H-C OLS estimation of the empirical model: interaction terms. Annual Patent growth rate 1990-2002 and 1995-2002, EU Regions

	(1)	(2)	(3)	(4)
	1990-2002	1990-2002	1995-2002	1995-2002
Constant	-0.091	-0.026	0.001	-0.327
	(0.088)	*(0.065)*	*(0.572)*	*(0.411)*
Natural Log of Patents per million inhab.	-0.025***	-0.025***	-0.048**	-0.052**
	(0.007)	*(0.007)*	*(0.019)*	*(0.020)*
R&D Expenditure (% Regional GDP)	-0.105	-0.145	3.200	3.240
	(0.718)	*(0.752)*	*(2.149)*	*(2.082)*
Spatially weighted average of neighbouring regions' R&D	8.268**	8.008**	41.907*	44.060*
	(3.654)	*(3.687)*	*(22.461)*	*(22.918)*
Social Filter	0.008	0.008	0.017	-0.006
	(0.006)	*(0.006)*	*(0.055)*	*(0.068)*
Krugman Index °			-2.737	-1.235
			(2.110)	*(1.192)*
Total Population (Ln)	0.012**		-0.023	
	(0.006)		*(0.032)*	
Interaction term Krugman Index*Total Population°			0.187	
			(0.148)	
Total Income (Ln)		0.012**		-0.001
		(0.006)		*(0.027)*
Interaction term KrugmanIndex*Total Income°				0.114
				(0.117)
National Dummies	X	X	X	X
Observations	96	96	96	96
R-squared	0.48	0.48	0.26	0.26
F-stat	5.90***	5.57***	2.40***	2.36***

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%
^ joinlty significant at 10%; ^^ significant at 5%; ^^^ significant at 1% (Wald test)
° Data to calculate the Krugman index are available from 1995 only

Appendix A – Description of the variables

Table A-1 – Description of the variables, European Union

Variable	Definition
	Innovation
R&D	Expenditure on R&D (all sectors) as a % of GDP
	Social Filter
Life-Long Learning	Rate of involvement in Life-long learning - % of Adults (25-64 years) involved in education and training
Education Labour Force	% of employed persons with tertiary education (levels 5-6 ISCED 1997).
Education Population	% of total population with tertiary education (levels 5-6 ISCED 1997).
Agricultural Labour Force	Agricultural employment as % of total employment
Long Term Unemployment	People aged 15-24 as % of total population
Young People	Long term unemployed as % of total unemployment.
	Structure of the local economy
Migration rate	Net migration was calculated from population change plus deaths minus births and then standardised by the average population thus obtaining the net migration rate
Population density	Calculated as Average Population (units) in the base year/ Surface of the region (Sq Km)
% regional of national GDP	Total regional GDP as a percentage of national GDP
Krugman index of specialisation	The index is calculated as discussed in the text on the basis Regional employment data classified according to the “Classification of economic activities - NACE Rev. 1.1 A17” branches.

Table A-2 – Description of the variables, United States

Variable	Definition
	Innovation
R&D	Private expenditure on R&D as a % of GDP was calculated from Standard & Poor’s Compustat North America firm-level data
	Social Filter
Education: bachelor’s, graduate or professional degrees	Persons 25 years and over - some college or associate degree as a percentage of total population
Education: some college level education	Persons 25 years and over - bachelor's, graduate, or professional degree as a percentage total population
Agricultural Labour Force	Agricultural employment as % of total employment
Unemployment Rate	Rate of unemployment
Young People	People aged 15-24 as % of total population
	Structure of the local economy
Domestic migration	Rate of net domestic migration
Population density	Calculated as Average Population (units) in the base year/ Surface of the region (Sq Km)
% regional of national GDP	Total regional GDP as a percentage of national GDP
Krugman index of specialisation	The index is calculated on the basis of the 13 major industry groups reported by 1990 census classification and developed from the 1987 Standard Industrial Classification (SIC) Manual.

Appendix B – Results of the Principal Component Analysis

Table B-1 – Principal Component Analysis: Eigenanalysis of the Correlation Matrix

			EU			
Eigenvalue	2.7303	1.4878	1.1732	0.7642	0.5814	0.0135
Proportion	0.39	0.213	0.168	0.109	0.083	0.002
Cumulative	0.39	0.603	0.77	0.879	0.962	1
			US			
Eigenvalue	1.6979	1.0514	1.0306	0.9499	0.2702	
Proportion	0.34	0.21	0.206	0.19	0.054	
Cumulative	0.34	0.55	0.756	0.946	1	

Table B-2 - Principal Component Analysis: Principal Components' Coefficients

Variable	PC1	PC2
EU		
Education Population	0.513	-0.361
Education Employed People	0.497	-0.395
Life-Long Learning	0.253	0.413
Long Term Unemployment	-0.094	-0.201
Agricultural Labour Force	-0.46	-0.383
Young People	0.016	0.575
US		
People with any college level degree	0.413	0.491
People with Bachelor Degree	0.682	-0.105
Rate of unemployment	-0.203	0.856
Agricultural Labour Force	0.174	0.119
Young People	0.542	0.04