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ABSTRACT

R&D, Socio-Economic Conditions and Regional Innovation in the United States*

This paper looks at the genesis of innovation in the United States from a territorial perspective. The analysis aims to disentangle the impact of local R&D expenditure from other contextual conditions supportive of the process of innovation. Particular emphasis is devoted to the role of socio-economic factors and systems of innovation conditions (‘social filter’ conditions) and to their impact on the returns of R&D expenditure in different territorial contexts. The empirical analysis is based on a Regional Knowledge Production Function approach, leading to an empirical model estimated by means of panel data analysis for the period between 1994 and 2007 at the US Bureau of Economic Analysis (BEA)-Economic Area level. The results unveil the complexity of the territorial dynamics of innovation of the US. Local R&D investments are important predictors for regional innovative performance and their impact is highly localized. However, social filter conditions are fundamental for the productivity of innovation efforts.

JEL Classification: O32, O33, R11 and R12
Keywords: innovation, R&D, socioeconomic conditions, systems of innovation and united states

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1. Introduction

The geography of innovation in the USA – the world's leading innovation system – shows significant spatial heterogeneity across States and metropolitan areas (OECD 2011). Interregional differences in innovative performance are substantially more pronounced than the variation in terms of employment growth and wages (Porter 2003). In addition, the US geography of innovation is constantly evolving over time. The country's innovation landscape has been reshuffled in recent decades: States in the Northwest and Southwest have substantially increased their share of total US patenting, whereas the traditional innovation hubs of the Northeast and Midwest have seen their share fall from 73 percent in 1963 to 51 percent in 1999 (Johnson and Brown 2004: 241). This 'regional inversion' occurred in the context of long-term structural change in the traditional manufacturing centers and the emergence of new industries (Storper and Walker 1989; Lanaspa-Santolaria et al. 2002). Generally, the more innovative US regions are located along the country's Eastern and Western coasts, as well as in the Great Lakes region. Less innovative regions are situated in the Midwest and South (Usai 2011). However, it is crucial to bear in mind that innovation in the US is a predominantly urban phenomenon (Carlino et al. 2007). Approximately 95% of the inventions for which US organizations filed patent applications in 1990-2004 were generated in MSAs, with the ten most innovative cities accounting for around 42% of total patenting in this period (Breschi and Lenzi 2012: 3).

Regarding the factors that may explain differences in local innovative performance in the US, a large number of authors have highlighted the connection between local investments in R&D and patent output in the US (Jaffe 1989; Acs et al. 1992; Anselin et al. 1997). Increases in local R&D investments are generally found to be associated with rises in local innovative output. Yet, local R&D efforts alone are by no means a sufficient explanation of regional-level innovative performance: In their analyses of the determinants of local patent output, Carlino and Hunt (2007, 2009) report that R&D investments have only marginal effects at the local level. At the European Union level an extensive literature has shed light on the role of geographical, social and institutional conditions as important explanations for the geographical heterogeneity of R&D investments' productivity. Both the qualitative literature on Regional Systems of Innovation[1] (Lundvall et al. 2009) and the quantitative works on 'social filters' (Rodríguez-Pose and Crescenzi 2008; Crescenzi and Rodriguez-Pose 2011) and 'intangible assets' (Foddi and Usai, 2013) have identified a set of highly localized contextual factors that shape the innovation process. Institutional conditions, human capital quantity and quality, demographic and social factors, social capital and cultural characteristics have been shown to make the relationship between innovative efforts and the generation of economically valuable knowledge far from linear in different ways in the European context. By contrast, evidence for the US is less forthcoming although some initial comparative work seems to suggest that similar processes may be in place on both sides of the Atlantic (Crescenzi et al. 2007; Fagerberg et al. 2011).

[1] Originally defined by Freeman (1987) as 'the network of institutions in the public and private sectors whose activities and interactions initiate, import, modify and diffuse new technologies', innovation systems are now viewed broadly as including social institutions, education and communications infrastructures and the norms and rules that regulate economic and social interaction (Lundvall et al. 2009).

This paper aims to shed new light on the US geography of innovation by looking at its territorial determinants using an integrated approach that combines insights from different streams of literature on the genesis of innovation. In particular, we develop the traditional linear approach which directly links R&D efforts to innovative output in order to account simultaneously for spatial/geographical processes of knowledge circulation and for localized socio-institutional factors in a Knowledge Production Function framework in an integrated framework (Crescenzi and Rodriguez-Pose 2011 and 2012a). The empirical analysis is based on a tailor-made panel database for the US Bureau of Economic Analysis (BEA) Economic Areas (EAs). The advantages of this approach are twofold. First, the use of panel data makes it possible to specify fixed effects regression models that fully control for all time-invariant unobservable characteristics of the regions. Second, the selection of BEA-EAs as spatial units of analysis allows us to focus on functionally defined regions that cover the entire surface of the US, overcoming the limitations of both arbitrary institutional borders (e.g. when US States are used) and uneven spatial coverage (e.g. with Metropolitan Statistical Areas).

The empirical results confirm the localized impact of R&D investments in the US functional Economic Areas. However, even if the impact of R&D expenditure tends to remain confined within the functional borders of the regions with limited inter-regional spillover effects, social filter conditions also exert a strong influence on innovative performance. It is not one single socio-economic factor in isolation that matters for innovation: it is the combination of a set of local features – human capital, young people, favorable sectoral structure – that facilitates the genesis of local innovation. The relevance of these factors emerges only when they are assessed in an integrated framework able to capture their synergies and interactions.

The article is organized into sections as follows. Section 2 presents the conceptual framework, which informs the ensuing quantitative analysis. Section 3 describes the model and data sources. Section 4 gives results of the quantitative analysis while section 5 provides brief conclusions and policy lessons. Details of variables and diagnostics are given in Technical Appendices A and B.

2. The territorial dynamics of innovation in the US: evolving frameworks of understanding.

A large body of scholarly literature has tended to identify local R&D investments as the key driver for innovative performance at the local level in the US (e.g. Jaffe 1989; Acs et al. 1992; Anselin et al. 1997). Additional research focusing on the geography of the knowledge flows generated by these innovative efforts underscores that the generation of innovative outputs in the US appears to occur in relatively self-contained areas, which rely on their own R&D inputs. Due to the relatively large size of US regions, spillovers are considered more likely to occur within rather than between regions (Usai, 2011). A large number of studies have found evidence of a strong spatial boundedness of knowledge spillovers in the US (Jaffe 1989; Varga 2000; Acs 2002; Sonn and Storper 2008; Li 2009; Singh and Marx 2011). Since large distances between innovative centers seem to limit the exposure of US regions to inter-regional flows, an efficient use of local inputs to innovation appears crucial. The maximization of the intra-regional knowledge circulation is facilitated by the relatively high factor mobility in the US , which allows US innovation hotspots to fully exploit the potential of local innovative efforts and simultaneously promotes the agglomeration of research activities (Crescenzi et al. 2007).

The importance of the differences in the productivity of local innovative efforts has also been examined in the context of the 'regional inversion' of the geographical pattern of US patenting activity over the past decades (Lanaspa-Santolaria et al. 2002). Varga et al. (2005), for example, find that the emergence of new innovation hubs in the US West and South and the simultaneous loss of relative importance of traditional manufacturing areas in the Northeast and Midwest cannot be attributed to changes in the spatial distribution of local inputs to R&D. Conversely they posit that US regions may differ with respect to their capability to combine local knowledge resources more or less efficiently. Identifying a stronger impact of university research on patenting in Southern states, these authors argue that region-specific institutional factors could shape regional differences in technological knowledge production. Support for this view also comes from studies pinpointing that US states (Thomas et al. 2011), as well as MSAs (Varga 2000), differ considerably in terms of R&D efficiency, conceptualized as the ratio of R&D outputs to R&D expenditure. In addition, Koo and Kim (2009) provide evidence suggesting that the impact of local R&D investments on regional growth varies across US states, while Ceh and Gatrell (2006) do not find evidence of a large-scale shift in the spatial distribution of R&D efforts between 1963 and 1998. This has often led to the conclusion that the spatial pattern of invention in the US is "more complex than initially thought" (Ceh and Gatrell 2006: 548).

Consequently, considering R&D investment in isolation fails to make full justice to the complexity of the territorial dynamics of knowledge production across US regions. A crucial component that seems to be missing in most research is certainly the role of institutions supporting the process of innovation. Even if the notion of the regional system of innovation[2] (RSI) is more established in the European context (Cooke et al. 1997; Edquist 1997), the incipient evidence provided by a large number of qualitative and quantitative studies sheds light on the importance of institutional aspects in the territorial dynamics of innovation in the US.

In terms of qualitative evidence, Saxenian's (1994) landmark study comparing the innovative clusters of California's Silicon Valley and Massachusetts' Route 128 highlighted significant differences in the set of rules shaping innovation processes in the two contexts: the rules governing relations between innovative actors as well as the overall conditions for entrepreneurs varied significantly between the two clusters. Moore and Davis (2004) also emphasized the importance of continuous interactive learning in the rise of Silicon Valley, while Bathelt (2001) put the accent on the role played by institutional factors in the economic recovery of Route 128 from the mid-1990s onwards. Even if the Silicon Valley has monopolized the attention of both the conceptual and empirical literature (e.g. Kenney 2000; Lecuyer 2005; Adams 2011), dramatically influencing innovation policies (Leslie and

[2] The RSI approach emphasizes the great variety of participants involved in the innovative process. The organisations with which firms interact "to gain, develop and exchange various kinds of knowledge" (Edquist 1997: 1) include other enterprises but also government bodies, research institutes, universities, banks, etc. (Edquist 1997).

Kargon 1996; Leslie 2001; Hospers et al. 2009; Malecki 2011), a variety of other cases of success based on completely different models and institutional settings suggest that there are no universally replicable institutional models. Mayer (2011), for example, examined the institutional underpinnings of the innovative success of second-tier regions in the US , discovering that large firms acted as entrepreneurial seedbeds in cities like Boise, Kansas City, and Portland, in part compensating for the absence of a world-class university. Youtie and Shapira's (2008) contribution, by contrast, explicitly focused on examples of university-led development in a number of innovation hubs in the Sunbelt. Hence, 'innovative' places in the US differ considerably with regard to their institutional set-up and in terms of their development trajectory.

A number of quantitative studies seem to point in a similar direction. Mukherji and Silberman (2011a) used shift-share analysis to examine differences in patent output of US states between 1997 and 2007, focusing on states' ability to take advantage of new opportunities in rapidly growing technologies. They found that four states (California, Oregon, Washington, Massachusetts) displayed rates of patent growth that exceeded the expected level based on the national average patenting growth and the growth rates of the technologies in which these four states are specialized. This was interpreted as a sign of "strong innovation structures" in these states (Mukherji and Silberman 2011a: 425).

When examining the determinants of the creation of new knowledge in nanotechnology at the regional level, Zucker et al. (2007) found that the cumulative flow of non-nanotechnological knowledge between different knowledge-producing organizations in a given region had a significant positive effect on local nanotechnology patenting. These results, in accordance with the emphasis the innovation systems literature places on interactive learning process across organizational boundaries (Edquist, 1997), are interpreted as evidence that the regional production of knowledge in that field is embedded in the institutional and social context of the region. Koo and Kim (2009) also provided evidence that social capital – measured by the number of regional business associations – increases a region's capacity to translate R&D efforts into economic growth. The link between regional social capital and entrepreneurship has also attracted the attention of scholars examining the determinants of differential innovative performance of U.S regions. The presence of dealmakers providing active regional stewardship boosts local start-up rates and regional innovation (Feldman and Zoller 2012), with local entrepreneurship being also a major determinant of MSAs' ability to absorb external knowledge (Mukherji and Silberman 2011b).

This converging evidence on the influence of a variety of 'intangible' socio-institutional and geographical/spatial factors on the productivity of local R&D activities and on the circulation and absorption of the corresponding knowledge flows calls for a wider analytical framework able to assess the impact of all these factors in an integrated fashion.

3. Conceptual framework and empirical model for territorial analysis

The analysis of the different strands of literature paints a complex portrait of the factors which determine the territorial dynamics of innovation in the USA. In order to integrate this wide array of factors affecting innovation, we propose a conceptual framework able to explain the *dynamics* of each region's innovation system, including its *territorial* *components*, as well as capable of bringing to the fore the *interactions* between its component parts.

We explore the factors behind these innovation geographies using a modified regional knowledge production function. This approach extends the 'traditional' framework à la Griliches (Griliches 1979 and 1986) and Jaffe (1986) in order to account for the role of territorial characteristics and spatial processes discussed in the previous section (Audretsch and Feldman 1996; Crescenzi et al. 2007; O hUallachain and Leslie 2007; Ponds et al. 2010). In this way, we are able to take into consideration both systems of innovation conditions, as well as other internal and external factors.

The empirical model we use in order to assess the territorial dynamics of innovation from a more encompassing perspective adopts the following form:

$$y_{i,t} = \alpha_i + \tau_t + \beta R\&D_{i,t} + \gamma WR\&D_{i,t} + \delta SF_{i,t} + \zeta WSF_{i,t} + \vartheta x_{i,t} + \varepsilon_{i,t} \quad (1)$$

where:

y	represents Regional Patent intensity;
R&D	is the share of R&D Expenditure in regional GDP;
SF	is the social filter index;
WR&D and WSF	are spatial lags of R&D and SF respectively with appropriate Spatial Weights;
x	is a set of additional structural features/determinants of innovation of region *i*;
ε	is an idiosyncratic error;

and where α and τ are Economic Area-specific fixed effects and year dummies respectively and i represents the Economic Area and t time.

We assemble a panel dataset for the 179 US BEA Economic Areas (see Technical Appendix A for details) covering the thirteen year period from 1994 to 2007. The choice of empirical variables included in the model is set out below:

Vector	Variable	Internal Factors	External Factors
Innovation input	**R&D**	Local Investment in R&D (Only private R&D is available)	Investment in R&D in neighboring areas

Social Filter	**Social filter index**	Structural characteristics that would make a region more 'innovation prone', including: • Human Capital • Sectoral composition of the economy • Use of resources (unemployment) • Demographics	Same characteristics in neighboring areas
Additional controls (X)	**Specialization**	Krugman index	
	Relative wealth	GDP per capita	
	Agglomeration economies	Population Density	
	Infrastructure endowment	Kilometers (Kms) of motorways	
	Mobility of people	Migration rate	
	Fixed effects	Economic Area-specific fixed effect + Time Dummies	

Patent intensity - Regional patent applications per capita is the dependent variable and is used as a proxy for the innovative performance of the local economy. Our data stem from OECD Pat Stat and are based on data from the Patent Cooperation Treaty (PCT). PCT patents can be considered as 'worldwide patent applications' (OECD 2009), capturing patents of high economic value and minimizing potential distortions due to heterogeneous patenting behaviors in different sectors/localities (Jaffe and Lerner 2004)

R&D expenditure – Endogenous growth theories highlight the importance of human capital and knowledge in advancing the technological frontier. Subsequent productivity gains drive long-term growth rates (Romer, 1990). In practice, national governments have tended to operationalize endogenous growth ideas by seeking to raise overall levels of human capital and ideas production.

The percentage of regional GDP devoted to R&D has, therefore, been normally used as the basic measure of economic input employed to generate innovation in each region and is also frequently considered in the literature as a proxy for the local capability to 'absorb' innovation produced elsewhere (Cohen and Levinthal 1990; Maurseth and Verspagen 2002). In our framework R&D expenditure is a proxy for "the allocation of resources to research and other information-generating activities in response to perceived profit opportunities"

(Grossman and Helpman 1991: 6) in order to capture the existence of a localized system of incentives (in the public and the private sector) towards intentional innovative activities.

The lack of sub-state level data for R&D expenditure – given that there is no available information on public R&D efforts – has been addressed by relying upon Standard & Poor's Compustat North American firm-level data. The proxy was calculated by adding up the R&D expenditure of private firms located in each Economic Area. Although a rather rough approximation to the overall R&D expenditure in each area, this is the only measure available and similar proxies have been commonly used in the literature on the innovative activities in the USA at sub-state level (e.g. Feldman 1994). These data can thus be considered as a general proxy for (private) R&D dynamisms at the Economic-area level and not as an exact measurement of R&D investments: the estimated coefficients should be interpreted accordingly.

Social filter – Section 2 highlighted the importance of social and institutional factors in shaping the character of innovation systems and the productivity of innovative efforts. As capturing institutional factors in a single indicator is notoriously difficult, we resort to the concept of the 'social filter' (Rodríguez-Pose 1999; Rodríguez-Pose and Crescenzi 2008) as a way of encompassing some of the features which may facilitate the emergence of efficient innovation systems quantitatively. Data availability constraints make it extremely difficult to operationalize the features of actual regional innovation systems and the comparability between Economic Areas at different stages of their technological cycle is also limited by the use of highly context-specific indicators. Consequently, the social filter has to be proxied by means of a set of variables available for different Economic Areas in a consistent and comparable fashion. The social filter – rather than trying to capture the idiosyncratic relational characteristics of individual regions' innovation systems – looks at the structural pre-conditions for their 'successful' development. It is clear from studies of the EU itself, as well as comparative US-EU analyses, that local social and institutional conditions play an important role in determining regions' abilities to make the best use of knowledge spillovers from other regions, as well as indigenous knowledge creation (Crescenzi et al. 2007; Crescenzi and Rodriguez-Pose 2008; Foddi and Usai 2013).

The social filter includes three major domains: educational achievement (Crescenzi 2005; Malecki 1997; Marrocu et al. 2013), productive employment of human resources (Gordon 2001), and demographic structure (Rodríguez-Pose 1999). These three domains, when assessed simultaneously, generate a unique socioeconomic 'profile' which facilitates or limits the innovative capacity of each region. The key idea here is that one component in isolation – say human capital – is not per se sufficient to support innovation. In the absence of an adequate productive structure or of markets capable of assimilating talent, human resources may not count for much in order to spur innovation. A good endowment of human capital may simply lead to greater outmigration and brain-drain. Conversely, where the clustering of human capital is associated to demographic dynamism (presence of young people) and a dynamic labor market (low unemployment) the development of a virtuous circle of human capital retention and accumulation is more likely to take place.

The first domain of the social filter – educational achievement – corresponds to the human capital accumulation in any given region. Several authors have reported evidence of the pivotal role played by the availability of skilled labor in US regions (Carlino and Hunt 2007, 2009; Fallah and Partridge 2012; Usai 2011). Carlino and Hunt (2009) calculate that a one per cent rise of the adult population holding a college degree increases local innovative output by approximately one per cent.

The second domain, the structure of productive resources, is measured by the percentage of the labor force employed in agriculture and the rate of unemployment. We would expect both to have a negative association with innovation. In the USA's mature urban system, agriculture takes a declining share of economic activity; unemployment is also highest in 'struggling' regions. The unemployment rate reflects a lack of local labor demand and may also indicate a poor endowment of human resources (Gordon 2001).

As far as the third domain of the social filter is concerned, it appears plausible to assume that a relatively young population (aged between 15 and 24) encourages innovation: new entrants to the labor force are likely to 'update' and constantly renew the existing stock of knowledge and skills.

We fit the social filter both as a set of individual variables and as a 'social filter index', constructed through Principal Component Analysis (PCA). The social filter index provides us with a multidimensional profile of 'innovation prone' areas. The PCA output is shown in Tables B-1 and B-2 in Technical Appendix B. The first principal component alone is able to account for around 36 percent of total variance (Table B-1). Scores are computed from the standardized value of the original variables by using the coefficients listed under 'Comp1' in Table B-2, generating the social filter index. Because the Filter has positive weightings on components expected to be negative on innovation (unemployment and agricultural employment) and vice versa (share of young population and educational endowment), all scores for the individual variables are weighted by -1 to make the index a proxy for innovation prone-ness.

Spillovers – Geographical approaches show how agglomeration supports innovative activity, via localized knowledge spillovers (e.g. Jaffe, Tratjenberg and Henderson 1993; Malmberg et al. 1996; Audretsch and Feldman 1996; Acs et al. 2002; Carlino et al. 2007). As neither agglomeration, nor innovation can be measured directly, density and patenting are typically used as proxies. Alternatively, various kinds of distance weights can be used to model local agglomerations and spillovers to other areas.

In order to assess how geography and location affect innovation, the model also includes – in addition to the variables related to the 'internal' characteristics of each territory – variables representing the potential spatial-effects from neighboring regions. These variables are introduced in the model as the innovative success of an area depends both on its internal conditions and on those of neighboring interconnected regions. The spatially lagged R&D

variable captures the 'aggregate' impact of innovative activities pursued in the neighborhood. Innovative activities pursued in neighboring regions may exert a positive impact on local innovative performance, via inter-regional knowledge exchange channels and complementarities that make localized knowledge flows possible. We use a combination of first order contiguity weights and inverse-distance weights to capture localized and far-ranging knowledge spillovers respectively. Weighted measures of both R&D intensity and the social filter are generated.

The role of the key drivers for the process of innovation and of their spatial organization is assessed after controlling for the geography of other key economic variables influencing regional innovative performance. These measures include:

Degree of Specialization (Krugman index) – Following Midelfart-Knarvik et al. (2002) the Krugman specialization index (K) is used to measure the specialization of local employment. Different patterns of specialization are assumed to give rise to different types of knowledge flows at the territorial level. A high degree of specialization facilitates the exchange of specialized, industry-specific knowledge: knowledge exchange and synergies are maximized firms in the same industry (Marshall-Arrow-Romer (MAR) knowledge flows). Conversely, Jacobian-type knowledge flows are associated with a diversified economic fabric, which is often found in large cities. Jacobs (1969) argues that the most valuable sources of knowledge that a firm may benefit from lie outside its own industry. This view suggests that a diverse industrial structure allows for cross-industry knowledge flows which induce recombinant innovations. Of course, MAR and Jacobian knowledge flows are not mutually exclusive (Beaudry and Schiffauerova 2009). As Storper and Manville (2006) have underlined, large cities may be specialized in at least one sector, while simultaneously displaying a diverse range of further industries.

Level of GDP per capita – As customary in the literature on the determinants of regional growth performance, the initial level of GDP per capita is introduced in the model in order to account for the region's initial wealth. It is also used as a proxy for the distance from the technological frontier as has been the case in the technological catch-up literature (e.g. Fargerberg 1994).

Agglomeration – The geographical concentration of economic activity has an impact on innovation (Duranton and Puga 2003; Charlot and Duranton 2004), which needs to be controlled for in order to single out the differential impact of other 'knowledge' assets such as R&D intensity and the social filter conditions. Highly valuable knowledge tends to be considered as geographically 'sticky' (Von Hippel 1994; Morgan 2004) and face-to-face (F2F) contact constitutes an economically efficient means for its transmission. Encompassing verbal, physical, non-intentional and intentional as well as contextual elements, F2F allows for the communication of complex, contextual messages and minimizes free-rider problems by promoting the development of trust (Storper and Venables 2004). The dependency on F2F may thus induce innovative actors to locate close to each other, which in turn may lead to the emergence of geographical clusters of high innovative performance: F2F contacts can be interpreted as a pivotal factor underlying the spatial clustering of innovative activities (Leamer and Storper 2001) and their intensity is strongly influenced by close geographical proximity and spatial density. From this perspective, population density is a useful – though rather rudimentary – proxy for these factors.

Existing stock of transport infrastructure endowment – Transport infrastructure may affect innovative performance through a variety of mechanisms also associated to its influence on the spatial organization of innovative activities. "Technological catch-up is facilitated by intensive trade relationships and, therefore, spatially connective infrastructure is a necessary condition not only for trade between places, but also for the transfer of technology and knowledge diffusion" (Crescenzi and Rodriguez-Pose, 2012b, p.492). Following the line of reasoning developed above, a good endowment of transport infrastructure is essential to support spatial interactions between individuals and to promote the development and evolution of 'dense' innovation clusters. In order to capture the direct impact of transport infrastructure on innovation, the stock of transport infrastructure is proxied by total motorways in region standardized by regional population (Canning and Pedroni 2004). See Technical Appendix A for further detail.

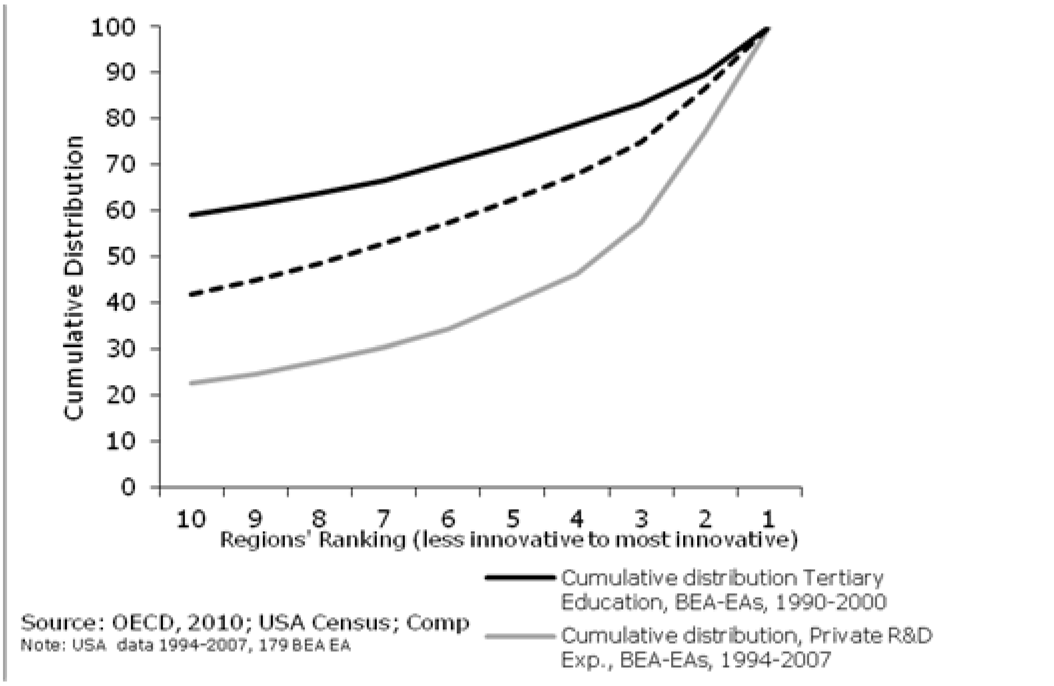
Migration – The degree of internal labor mobility is reflected by the regional rate of migration. A positive rate of migration (i.e., net inflow of people from other regions) is a proxy for the capacity of the region to benefit from external human capital and knowledge (Ottaviano and Peri 2005). In addition, mobile individuals flowing into the regional economy bring new non-redundant knowledge, fostering local innovative capabilities and reinforcing outward networking. The existence of a positive impact of mobility on innovation is supported by studies on Canada (Partridge and Furtan 2008), New Zealand (Mare' et al. 2011) and Europe (Miguélez and Moreno 2010).

4. Empirical Results

4.1 The US geography of innovation and its drivers

By displaying some simple descriptive statistics about the geography of innovative output at the territorial level and its determinants, we uncover a number of relevant features of the US Innovation System (Figure 1). In Figure 1 we look at the cumulative distribution of patenting, R&D investments and tertiary education across space in the USA from 1994 to 2007, focusing on the top 10 Economic Areas in terms of these three dimensions. The graph should be read from right to left. The slope of the curve shows the degree of spatial clustering: the steeper the line, the greater the degree of clustering. Spatial 'shares' can then be read as points on the line. Figure 1 shows that the five US regions with the highest shares of patent applications together represent 35% of all US patenting and contain 25% of all individuals with higher education, as well as 60% of total private R&D Expenditure.

Figure 1 –Cumulative Distribution of Patent Applications, R&D Investments and Human Capital in the top 10 BEA-Economic Areas.



In terms of population-weighted patent counts, the three leading Economic Areas are San Jose-San Francisco-Oakland (Northern California), San Diego-Carlsbad-San Marcos (Southern California) and Appleton-Oshkosh-Neenah (Wisconsin). As a general rule, the more innovative regions in the US are located on the Western and Eastern seaboards, with a smaller hub in the Great Lakes area (Michigan, Wisconsin). Less innovative areas are located in the Midwest and the South, with the exception of Houston-Baytown-Huntsville (Texas) and Denver-Aurora-Boulder (Colorado).

Private R&D spending patterns are in marked contrast to the spatial distribution of patenting (in line with similar evidence for Europe – Crescenzi et al. 2007 – but also China and India, Crescenzi et al. 2012): R&D is significantly more clustered than patenting and the concentration of R&D activities is more marked than in Europe or China and India, reflecting the existence of large, self-sustaining clusters such as the Boston-Route 128 corridor and Silicon Valley. The San Jose-San Francisco-Oakland is the top Economic Area both in terms of patenting and R&D, while two other regions (Seattle-Tacoma-Olympia and Rochester-Batavia-Seneca Falls) are also in the top ten regions for both R&D and patenting. In total thirteen regions are both in the top 20 Economic Areas for R&D and for patenting. This confirms that R&D expenditure is an important predictor of patent intensity in the US, however, a number of other localized factors influence the translation of R&D activities into patentable output.

Unlike R&D spending, human capital is considerably less concentrated than patenting. Washington-Baltimore-Northern Virginia is the economic area with the highest share of graduates, but does feature in the top twenty patenting regions. This is largely explained by DC's large community of graduates working in politics and public policy rather than sciences or high-tech manufacturing. Austin-Round Rock, by contrast, is a well-known US tech cluster with a large university, explaining its presence high up patents, R&D and human capital rankings.

Table C.1 in Appendix C includes the correlation matrix for these indicators and other territorial factors discussed above whose role will be systematically explored in the regression analysis.

4.2 Panel data regression analysis

We fit the panel data with the model specified in equation (1), which we run as a two-way fixed effects regression.[3] All regressions presented in the paper include Economic-Area (regional level) fixed effects and time dummies (two-way fixed effect). The fixed effect controls for all time-invariant unobservable characteristics of the regions (including institutional characteristics) while the time dummies control for all unobserved time-varying factors influencing all Economic Areas simultaneously (e.g. Macro-economic shocks).[4]

By introducing the 'spatially lagged' variables WR&D and WSF, we take into consideration the interactions between neighboring regions, minimizing any effect on the residuals. The presence of spatial autocorrelation in the residual has been also tested by means of the Moran's I Test that rejected this hypothesis.[5] Results also use robust standard errors clustered on economic areas. We minimize the potential endogeneity of the right-hand side variables by fitting these as one-period lags. In addition, as a robustness check, we re-estimate all regressions by means of GMM-diff estimators confirming the results presented in the main tables (see robustness checks section).

Finally, because of different accounting units we express all explanatory variables as a percentage of the respective GDP or population. As this is exploratory analysis, our interest lies mainly on the sign and significance of coefficients, rather than the size of specific point estimates.

[INSERT TABLE 1 HERE]

Table 1 gives the main results for the estimation of the model presented above. Regressions (1) through (3) explore components of the innovation system derived from a 'linear' approach to innovation, regressing patenting rates on R&D expenditure and various spatial

[3] Breusch-Pagan tests suggest fixed effects estimation is preferred due to the high significance of the individual effects.

[4] The Fixed Effect approach makes it impossible/redundant to include in the specification other time invariant characteristics (including state-level dummies). In other to control for state-level time-varying characteristics we included state-specific time trends (e.g. to control for state-level changes in policy conditions). This inclusion left the results qualitatively unchanged.

[5] The absence of spatial correlation is confirmed by conducting Moran's I test for each year. The results of these tests are not significant for the majority of the years.

lags of science spending. Regressions (4) through (8) introduce the spatial filter and spatially weighted variants. Regressions (9) to (11) bring in the wider structural factors.

Overall, results indicate a stable geography of innovation organized around large, specialized spatial clusters.

Regressions (1) – (3) display a consistently strong connection between regional R&D expenditure and patenting activity – a relationship that holds throughout the specifications. Greater investment in R&D seems to yield a higher degree of innovation, regardless of the number and types of variables included.

By contrast, the results suggest the absence of R&D spillovers. There are no significant effects of R&D spillovers in any specification (Table 1). This reflects wider analysis that knowledge spillovers within US regions exhibit considerable distance decay, tending to die out within the economic area in which ideas are generated (e.g. Acs et al. 2002). Other empirical analyses have shown that knowledge spillovers are highly localized, generally in a radius of approximately 80 to 120km from their origin (Anselin et al., 1997; Varga, 2000), although the exact range remains subject to debate. Analyzing patent citations, Belenzon and Schankerman (2010) find that spillovers attenuate rapidly with distance up to approximately 240km from their origin and are constant thereafter. Mukherji and Silberman (2011b) calculate that being within 80km increases the likelihood of a knowledge flow by 215% compared to the average likelihood of two inventors in the US citing each other. Similarly, based on the analysis of the connection between clustering of R&D labs and R&D productivity, Carlino et al. (2011) conclude that spillovers in the US context may be operating at different scales: at very small scales (roughly half a kilometer) and at a scale that approximately corresponds to MSAs. Given the relatively large geographical size of most US regions, the diffusion of technological knowledge across regions appears to be weaker in the US than in Europe (Usai 2011).

The strong evidence showing that the high returns to R&D investment, as well as spillovers in the US largely occur at the MSA-level confirms research suggesting that US regions rely mostly on their own innovative efforts and the maximization of internal spillovers rather than on proximity to other innovative areas. These results concur with those of Singh and Marx (2011), who find that the likelihood for intra-MSA knowledge flows is 126 per cent higher than for flows across metropolitan boundaries. Agrawal et al. (2008) conclude that co-location in the same MSA increases the likelihood of knowledge flows (measured by patent citations) between two inventors by 24 per cent relative to two non-co-located inventors, whereas a 1000-mile increase in distance is associated with a two percentage point reduction in the probability of a knowledge flow.

Socio-economic factors – as proxied by the social-filter index – exhibit a robust positive influence on innovation. Regressions (4) through (7) indicate that the social filter is significant on patenting at 1%, a relationship that persists in further specifications. The social filter spillovers display, in contrast, a mixed effect: inverse distance weights are positive significant, while first order contiguity weights are negative significant, and become progressively less important as wider structural factors are introduced. Overall, it can be said that while the social filter conditions in any given BEA-Economic Area are crucial for innovation, regions do not generally benefit from the presence of adequate social filters in neighboring regions. The socio-economic preconditions for innovation need to be generated locally, as there is no possibility of free-riding on those of neighboring areas. Indeed, being surrounded by areas with good social filters may be detrimental for innovation (Table 1, regressions 7, 8 and 9), unless an adequate social filter is already in place locally.

Regressions (9) through (11) bring in wider structural factors. These confirm what is already apparent from regressions (1) to (3): that traditional agglomeration factors play important roles in explaining the geography of innovation. Population density and GDP per capita are both strongly positive on patenting. Interacting R&D spending with population density (regression 11) helps explore the relative role of linear and structural factors: the interaction term and population density are both significant, while R&D spending becomes insignificant. This suggests that the joint effect of agglomeration is driven by structural factors. These results are in line with theoretical contributions highlighting the importance of 'local buzz' (Storper and Venables, 2004) and confirm the evidence on the impact of agglomeration economies on regional innovative output (Lobo and Strumsky 2007; Usai 2011). They further support results by Carlino and Hunt (2009: 2) who find that doubling the employment density of an MSA increases patenting per capita by 22 percentage points. In accordance with literature suggesting that face-to-face contacts are most important for innovative activities in new technologies (Duranton and Puga, 2001; Storper and Venables, 2004), Orlando and Verba (2005) show that incremental innovations in mature technologies prevail in less populated areas in the US.

The Krugman index is weakly significant or insignificant. Net inter-BEA migration is not robust to the introduction of subsequent controls for local economic conditions, reflecting the relative stability of the country's innovation geography. Labor mobility is certainly an important component of the mechanisms underpinning the territorial dynamics of innovation in the US However, what seems to matter more for innovation is intra-Economic Areas mobility in particular as far as inter-firm mobility is concerned. Analyzing patent citation patterns in the US semiconductor industry, Almeida and Kogut (1999) show that localized knowledge flows occur only in regions with high internal mobility of inventors across companies.

[INSERT TABLE 2 HERE]

Table 2 further explores the dynamics of the social filter by analyzing its constituent components separately. For this purpose regressions 8, 9 and 10 (Table 1) are re-estimated by replacing the social filter index with its constituent variables. The new regressions confirm the robustness of previous results as all explanatory variables show the same sign and significance as in the specification with the social filter index. However, what clearly emerges is the capability of the social filter index to draw a multidimensional profile of 'innovation prone' areas where all factors are assessed jointly. Conversely, its individual components – when assessed in isolation – are not necessarily good predictors for innovative performance. In particular, only human capital is positively and significantly associated with innovation, in line with existing literature on the impact of human capital on regional growth and innovation in the US (Fallah and Partridge, 2012; Rupasingha et al. 2002; Yamarik 2006 and 2011; Hoyman and Faricy 2009).

Conversely and in contrast to theoretical expectations, unemployment and agricultural labor force seem to be positively associated with innovation. Ceh and Gatrell (2006) find that total unemployment is positively correlated with R&D in expenditure in US states in 1990. They argue that increases in R&D expenditure may have occurred particularly in states undergoing a process of industrial restructuring associated with rises in unemployment (and possibly higher shares of agricultural employment). Following a similar line of argument Lee, Florida, and Acs (2004) suggest that unemployment has a positive impact on entrepreneurship.

As far as the third domain of the social filter is concerned, a relatively young population seems to have no statistically significant correlation with innovation. While theory and evidence of other countries suggest that new entrants to the labor force are likely to renew and 'update' the existing stock of knowledge and skills, the econometric results of Hunt and Gauthier-Loiselle (2010) underline that a higher average age is conducive to innovation in US states. These results are explained as a sign of the significance of "management or other skills complementary to innovation" (Hunt and Gauthier-Loiselle 2010: 44), confirming the potential ambiguity of the impact of this indicator when taken in isolation.

Robustness Checks

In order to control for the impact of the potential endogeneity of our explanatory variables, we follow Martin et al. 2011 and re-estimate all regressions by instrumenting the first-differenced equation with second-order lagged levels of the endogenous variables (Difference GMM). These additional results are presented in Tables 3 and 4.

[INSERT TABLES 3 and 4 HERE]

The test statistics for all specifications are presented in the lower section of each table and confirm the robustness of the results discussed below. The Arellano-Bond serial correlation test for the first differences of the residual always rejects the hypothesis of no first-order serial correlation, while it fails to reject at higher orders as desired (no residual serial correlation). In addition the Hansen statistics is used to test overidentifying restrictions: the results of the Hansen test coincide with the Sargan test for 'non-robust' GMM. If non-sphericity is suspected as in the case of our robust GMM estimations, the Sargan test would be inconsistent and the Hansen test is to be preferred (Roodman, 2006). The Hansen test confirms the validity of selected instruments in all specifications.

The results reported in tables 3 and 4 are organised in the same way as in Tables 1 and 2. however, in this case, the use of instruments makes it possible to better account for the potential impact of endogeneity on the estimated coefficients. These additional results confirm the robustness of the estimations presented in the paper.

5. Conclusions

The empirical results presented in this paper confirm the relevance of a territorial perspective for the understanding of the process of innovation in the US. The concentration of R&D activities is an important predictor of innovative performance at the local level. However, our results stress that localized socio-economic factors together with other geographical characteristics (and agglomeration economies, in particular) play an equally important role.

What can policy-makers learn from the geographical approach developed in the paper? Compared to Europe, spatial equity considerations figure less prominently in the US political debate (Hewings et al., 2009). The distribution of federal funds for academic research has traditionally been designed as a peer-reviewed merit-based competition (Brooks, 1996) and is hence concentrated in those areas where a large share of the most successful scientists operates (Wu, 2010). EPSCoR, a program started in 1980 with the objective of counterbalancing this concentration through special assistance to a number of eligible states, has been found to have a relatively small effect on the participating states' share of total federal spending on basic research (Wu, 2010). Despite a resurgence of US policy-makers' interest in the cluster concept (Porter, 1990) and place-based development policies (Dabson, 2011), the budget for federal development programs with a spatial component is still very small compared to the funds allocated – for example – to the EU cohesion policy (Erickson and Pool, 2011). Hence, the spatial dimension of federal innovation policies remains limited in the US context.

Conversely, a number of recent contributions show that state-level policies can influence knowledge flow patterns and innovation territorial dynamics. For example, non-compete laws, which limit employees' freedom to move to a competitor within the same state for a specific time period, have been shown to affect the link between intra-regional labor mobility and patent output (Almeida and Kogut 1999). Exploiting the reversal of non-compete legislation in Michigan as a natural experiment, Marx et al. (2007) show that the shift to a more rigid non-compete policy reduced internal labor mobility. For the same case, Belenzon and Schankerman (2010) and Singh and Marx (2011) find that the enforcement of non-compete agreements reduced localized spillovers within the state.

While measures based on spatial equity considerations seem to play a relatively marginal role, the example of Michigan shows that subnational policies may – even in the case of legislation that is not directly related to innovation policy – significantly contribute to interregional disparities in innovative performance. A better understanding of the geographical processes underlying the creation of knowledge is therefore crucial for the design of policies that aim to maximize the efficiency of national innovation efforts while minimizing their potentially distortive effects.

Table 1 - USA, Genesis of Innovation in BEA-Economic Areas: social filter index, 1995-2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Depended Variable: Patents per capita											
Regional R&D Expenditure	0.277**	0.279**	0.276**	0.278**	0.275**	0.274**	0.279**	0.259**	0.244**	0.233**	0.0739
	(0.125)	(0.125)	(0.125)	(0.125)	(0.124)	(0.123)	(0.124)	(0.109)	(0.104)	(0.0972)	(0.165)
Spatially Weighted R&D (Inverse Dist)		-0.185		-0.206		-0.0571	-0.188	-0.136	0.0429	0.0458	0.114
		(0.194)		(0.192)		(0.183)	(0.198)	(0.185)	(0.170)	(0.170)	(0.197)
Spatially Weighted R&D (First Order Contig.)			0.0489		0.0454						
			(0.0911)		(0.0886)						
Social Filter				0.00582***	0.00566***	0.00624***	0.00822***	0.00627**	0.00738***	0.00642**	0.00668***
				(0.00216)	(0.00214)	(0.00218)	(0.00265)	(0.00249)	(0.00252)	(0.00248)	(0.00256)
Spatially Weighted Social Filter (Inverse Dist.)						0.0384**					
						(0.0164)					
Spatially Weighted Social Filter (First Order Contiguity)							-0.0119*	-0.00891	-0.00587	-0.00433	-0.00513
							(0.00690)	(0.00649)	(0.00588)	(0.00573)	(0.00604)
Krugman index								-0.0868*		-0.0253	-0.0373
								(0.0488)		(0.0442)	(0.0428)
Road Density								4.31e-05*		3.29e-05	3.20e-05
								(2.60e-05)		(2.28e-05)	(2.19e-05)
Population Density									0.000589	0.000466	0.000359
									(0.000359)	(0.000366)	(0.000287)
Net Domestic Migration									-1.50e-07	-8.07e-08	-2.40e-08
									(1.01e-07)	(7.94e-08)	(8.10e-08)
GDP Per Capita									5.77e-06***	5.30e-06***	4.95e-06***
									(1.93e-06)	(1.85e-06)	(1.55e-06)
Inter.Term Exp.R&D*Pop.Density											0.000790
											(0.000758)
Constant	0.0217***	0.0267***	0.0189*	0.0260***	0.0179*	0.0165*	0.0266***	0.00743	-0.159**	-0.189*	-0.161**
	(0.00718)	(0.00782)	(0.00989)	(0.00772)	(0.00981)	(0.00952)	(0.00778)	(0.0800)	(0.0704)	(0.0960)	(0.0767)
Economic Area-level Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
Year Dummies	X	X	X	X	X	X	X	X	X	X	X
Observations	2,327	2,327	2,327	2,327	2,327	2,327	2,327	2,327	2,327	2,327	2,327
R-squared	0.252	0.253	0.253	0.256	0.256	0.261	0.260	0.296	0.312	0.330	0.340
Number of BEA-Econ.Areas	179	179	179	179	179	179	179	179	179	179	179
Moran's I Test on the Residuals for each year	Not Sign.	Not Sign.	Not Sign.	Not Sign.	Not Sign.	Not Sign.	Not Sign.	Not Sign.	Not Sign.	Not Sign.	Not Sign.

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2 - USA,BEA, Social Filter Component, 1995-2007

	(1)	(2)	(3)
Depended Variable: Patents per capita			
Regional R&D Expenditure	0.246**	0.239**	0.228**
	(0.103)	(0.100)	(0.0937)
Spatially Weighted R&D (Inverse Dist)	-0.0297	0.0858	0.0942
	(0.155)	(0.158)	(0.155)
Share of population aged 15 to 24	-0.140	-0.303	-0.217
	(0.392)	(0.406)	(0.395)
Share of People with Bachelor's degree and higher	2.090***	1.176*	1.277*
	(0.621)	(0.669)	(0.686)
Unemployment rate	0.150	0.291**	0.276*
	(0.132)	(0.145)	(0.147)
Share of agricultural employment in total employment	0.0127*	0.0126*	0.00913
	(0.00720)	(0.00723)	(0.00689)
Spatially Weighted Social Filter (First Order Contiguity)	-0.00922	-0.00847	-0.00697
	(0.00658)	(0.00609)	(0.00600)
Krugman index	-0.0447		-0.00521
	(0.0451)		(0.0430)
Road Density	4.20e-05*		3.36e-05
	(2.39e-05)		(2.20e-05)
Population Density		0.000505	0.000395
		(0.000362)	(0.000370)
Net Domestic Migration		-1.51e-07	-8.11e-08
		(9.27e-08)	(7.36e-08)
GDP Per Capita		5.07e-06**	4.54e-06**
		(2.09e-06)	(2.03e-06)
Constant	-0.422**	-0.334**	-0.416**
	(0.175)	(0.133)	(0.169)
Economic Area-level Fixed Effects	X	X	X
Year Dummies	X	X	X
Observations	2,327	2,327	2,327
R-squared	0.319	0.322	0.341
Number of BEA-Econ.Areas	179	179	179
Moran's I Test on the Residuals for each year	Not Sign.	Not Sign.	Not Sign.

Table 3 - Robustness Check - GMM Analysis - USA,BEA, Social Filter Index, 1995-2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VARIABLES											
Regional R&D Expenditure	0.276	0.307*	0.278*	0.353**	0.293*	0.312**	0.331**	0.284**	0.215*	0.208*	0.171
	(0.174)	(0.172)	(0.166)	(0.174)	(0.160)	(0.154)	(0.163)	(0.143)	(0.114)	(0.112)	(0.162)
Spatially Weighted R&D (Inverse Dist)		0.167		-0.0214		0.122	0.00480	0.228	0.433*	0.462**	0.342
		(0.258)		(0.265)		(0.229)	(0.263)	(0.257)	(0.228)	(0.234)	(0.219)
Spatially Weighted R&D (First Order Contig.)			0.0587		0.186						
			(0.169)		(0.160)						
Social Filter				0.0203***	0.0255***	0.0186***	0.0224***	0.0166***	0.0166***	0.0144***	0.0138***
				(0.00601)	(0.00752)	(0.00559)	(0.00697)	(0.00576)	(0.00556)	(0.00503)	(0.00499)
Spatially Weighted Social Filter (Inverse Dist.)						0.0414***					
						(0.0158)					
Spat. Weigh. Social Filter (First Order Cont.)							-0.0144	-0.00623	-0.0130	-0.00951	-0.00734
							(0.0104)	(0.00805)	(0.00945)	(0.00847)	(0.00849)
Krugman index								-0.118**		-0.0668	-0.0744
								(0.0500)		(0.0467)	(0.0508)
Road Density								9.65e-05***		6.04e-05**	6.14e-05*
								(3.04e-05)		(2.72e-05)	(3.19e-05)
Population Density									0.000515	0.000393	0.000342
									(0.000383)	(0.000385)	(0.000291)
Net Domestic Migration									-1.59e-07	-6.38e-08	-2.58e-08
									(1.02e-07)	(8.35e-08)	(7.09e-08)
GDP Per Capita									7.45e-06***	5.97e-06***	5.76e-06***
									(2.07e-06)	(1.99e-06)	(2.00e-06)
Inter.Term Exp.R&D*Pop.Density											0.000217
											(0.000643)
Observations	2,148	2,148	2,148	2,148	2,148	2,148	2,148	2,148	2,148	2,148	2,148
Number of BEA-Economic Areas	179	179	179	179	179	179	179	179	179	179	179
Year Dummies	X	X	X	X	X	X	X	X	X	X	X
Hansen J statistic	120.6	162.9	165.5	172.3	169.6	171.6	165.2	170.5	154.1	191.2	696.7
p value of Hansen statistic	3.37e-05	0.0266	0.0193	0.878	0.905	1.000	1.000	1	1	1	0.00107

AR(1) test statistic	-2.613	-2.679	-2.568	-2.789	-2.605	-2.730	-2.794	-3.363	-2.837	-3.142	-3.221
p value of AR(1) statistic	0.00896	0.00738	0.0102	0.00528	0.00919	0.00634	0.00520	0.000772	0.00455	0.00168	0.00128
AR(2) test statistic	0.523	0.492	0.520	0.332	0.344	0.358	0.349	-0.0346	0.432	0.203	0.128
p value of AR(2) statistic	0.601	0.623	0.603	0.740	0.731	0.720	0.727	0.972	0.666	0.839	0.898
Number of instruments	78	144	144	210	210	276	276	384	434	542	608

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4 - Robustness Check - GMM Analysis -USA,BEA, Social Filter Components, 1995-2007

VARIABLES	(1)	(2)	(3)
Regional R&D Expenditure	0.283*	0.250**	0.228*
	(0.150)	(0.124)	(0.123)
Spatially Weighted R&D (Inverse Dist)	0.246	0.269	0.332
	(0.245)	(0.213)	(0.220)
Share of population aged 15 to 24	-0.450	-1.082**	-0.739
	(0.452)	(0.436)	(0.479)
Share of People with Bachelor's degree and higher	3.296***	2.500***	2.104**
	(0.759)	(0.829)	(0.866)
Unemployment rate	-0.103	-0.0318	0.0467
	(0.194)	(0.215)	(0.205)
Share of agricultural employment in total employment	0.00936	0.0103	0.00475
	(0.00832)	(0.00912)	(0.00849)
Spatially Weighted Social Filter (First Order Contiguity)	-0.00385	-0.00562	-0.00519
	(0.00793)	(0.00992)	(0.00910)
Population Density		0.000324	0.000249
		(0.000382)	(0.000381)
Net Domestic Migration		-2.07e-07**	-9.65e-08
		(1.02e-07)	(7.71e-08)
GDP Per Capita		4.80e-06**	3.88e-06*
		(2.27e-06)	(2.29e-06)
Krugman index	-0.0908*		-0.0672
	(0.0508)		(0.0480)
Road Density	7.94e-05***		5.73e-05**
	(2.60e-05)		(2.55e-05)
Observations	2,148	2,148	2,148
Number of BEA-Economic Areas	179	179	179
Year Dummies	X	X	X
Hansen J statistic	162.0	173.8	10486
p value of Hansen statistic	1	1	0
AR(1) test statistic	-3.224	-2.837	-3.077
p value of AR(1) statistic	0.00126	0.00456	0.00209
AR(2) test statistic	-0.0629	0.400	0.164
p value of AR(2) statistic	0.950	0.689	0.870
Number of instruments	533	583	691
Number of instruments	533	583	691

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Appendix A: Definitions of the Variables and geographical units

Variable	Definition	Sources
Patenting indicator (Dependent Variable)		
PCT applications per capita (per 1000 persons)	Number of PCT applications (Count) / total population of the BEA - Economic Area (EA)	OECD.Stat
Innovation efforts		
Regional R&D Expenditure	Private R&D Expenditure in the BEA EA as a percentage of Total Personal Income of the BEA - Economic Area	Compustat from Standard & Poor's - Wharton Research Data Services (WRDS)
Social Filter		
Unemployment rate	Rate of unemployment at the BEA EA level.	US Bureau of Labor Statistics, Local Area Unemployment Statistics
Agricultural employment	Agricultural employment as a share of total employment at the BEA EA level.	USA Census Bureau Counties Data Files
Human Capital Accumulation (Tertiary Education)	People with Bachelor's degree and higher as a share of total BEA EA population (aged 25 and above)	USA Census Bureau Counties Data Files
Young people	People aged 15-24 as a share of total BEA EA population	USA Census Bureau Counties Data Files
Structure of the local economy		
Population density	Calculated as average population (units) in year t /surface of the BE EA (Sq-kms)	USA Census Bureau, USA Counties Data files/Bureau of Economic Analysis
Personal Income per capita	This is used as a proxy for GDP per capita (see note) as is calculated as Total Personal Income on the BEA EA /BEA EA population (units)	USA Census Bureau, USA Counties Data files/Bureau of Economic Analysis
Krugman Index	Economic Areas-level Krugman index calculated on the basis BEA-EA Employment in 10 major sectors	USA Census Bureau, USA Counties Data files/Bureau of Economic Analysis
Net Migration	Domestic Inter-EA net migratory in-flows per 1000 persons	USA Census Bureau, USA Counties Data files/Bureau of Economic Analysis
Road Density	Calculated as the length of highways (Kms) /surface of the Economic Area (Sq kms)	USA Bureau of Transport Statistics, National Transportation Atlas Database.

Spatial Unit of Analysis: BEA Economic Areas (EAs)

“BEA's economic areas define the relevant regional markets surrounding metropolitan or micropolitan statistical areas. They consist of one or more economic nodes - metropolitan or micropolitan statistical areas that serve as regional centers of economic activity - and the surrounding counties that are economically related to the nodes. The economic areas were redefined on November 17, 2004, and are based on commuting data from the 2000 decennial population census, on redefined statistical areas from OMB (February 2004), and on newspaper circulation data from the Audit Bureau of Circulations for 2001.”

http://www.bea.gov/regional/docs/econlist.cfm

Appendix B – Social Filter Index - PCA results

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

USA, BEA				
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.4628	0.380224	0.3657	0.3657
Comp2	1.08258	0.107053	0.2706	0.6363
Comp3	0.975522	0.49642	0.2439	0.8802
Comp4	0.479102	.	0.1198	1

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

USA, BEA					
Variable	Comp1*	Comp2	Comp3	Comp4	Unexplained
Young Population (15-24)	-0.1487	0.4121	0.8939	-0.095	0
Population with Tertiary Educ.	-0.727	-0.0067	-0.045	0.6852	0
Unemployment Rate	0.4163	-0.6588	0.4222	0.4631	0
Agricultural Employment	0.5254	0.6294	-0.1439	0.5542	0

*For the calculation of the social filter index the score for Comp1 has been pre-multiplied by -1 to match the interpretation of the index as a proxy for 'innovation prone-ness'

Appendix C – Correlation Matrix

Table C1 - Correlation Matrix

	Patents Per Capita	Regional R&D Expenditure	Spatially Weighted R&D (Inverse Dist)	Social Filter	Spatially Weighted Social Filter (First Order Contiguity)	Krugman index	Road Density	Population Density	Net Domestic Migration
Regional R&D Expenditure	0.6418								
Spatially Weighted R&D (Inverse Dist)	-0.0314	0.1026							
Social Filter	-0.4739	-0.2994	0.1137						
Spatially Weighted Social Filter (First Order Contiguity)	-0.0922	0.0428	0.0488	0.3197					
Krugman index	-0.3651	-0.4279	-0.0175	0.273	-0.0023				
Road Density	0.3401	0.3557	-0.1036	-0.3021	-0.0033	-0.6145			
Population Density	0.4254	0.4328	0.0491	-0.2607	-0.0641	-0.5277	0.2624		
Net Domestic Migration	-0.1873	-0.3036	-0.018	0.0331	-0.0093	0.2437	-0.1819	-0.3518	
GDP Per Capita	0.5225	0.3753	-0.0011	-0.5335	-0.3384	-0.2977	0.3672	0.3949	-0.1426