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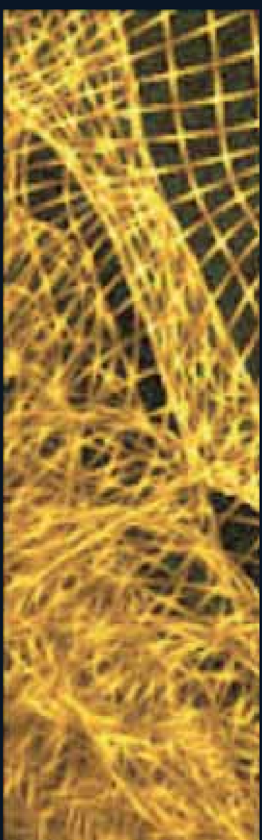

Do clusters generate greater innovation and growth?

An analysis of European regions

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Do clusters generate greater innovation and growth? An analysis of European regions

Abstract

The analysis of clusters has attracted considerable interest over the last few decades. The articulation of clusters into complex networks and systems of innovation – generally known as regional innovation systems – has, in particular, been associated with the delivery of greater innovation and growth. However, despite the growing economic and policy relevance of clusters, little systematic research has been conducted into their association with other factors promoting innovation and economic growth. This paper addresses this issue by looking at the relationship between innovation and economic growth in 152 regions of Europe during the period between 1995 and 2006. Using an econometric model with a static and a dynamic dimension, the results of the analysis highlight that: a) regional growth through innovation in Europe is fundamentally connected to the presence of an adequate socioeconomic environment and, in particular, to the existence of a well-trained and educated pool of workers; b) the presence of clusters matters for regional growth, but only in combination with a good 'social filter', and this association wanes in time; c) more traditional R&D variables have a weak initial connection to economic development, but this connection increases over time and, is, once again, contingent on the existence of adequate socioeconomic conditions.

Keywords: Clusters, regional innovation systems, innovation, regional economic growth, socioeconomic conditions, regions, European Union.

1. Introduction

One of the traditional advantages associated with clusters of firms has been their capacity to engender greater innovation and to transform this innovation into economic growth (Porter 2000). Groups of firms working in the same or in closely related sectors are deemed to generate agglomeration economies and knowledge spillovers. These spillovers, in turn, are at the root of self-reinforcing processes of innovation and growth (Capello 1999). Physical proximity among firms is considered to facilitate the emergence of interaction and the formation of interpersonal and firm networks leading to the genesis of complex collective learning mechanisms (Melachroinos and Spence 2001; Storper and Venables, 2004). Knowledge spillovers and collective learning mechanisms thus help transform mere clusters of firms into 'neo-Marshallian industrial districts' (Becattini 1987), 'new industrial spaces' (Scott 1988), 'innovative milieux' (Aydalot 1986), 'learning regions' (Morgan 1997), or 'regional innovation systems' (Cooke et al. 1997; Cooke and Morgan 1998), where firms and the territories they are located in – together with their intrinsic social and structural characteristics and interactions – are put at the centre of the innovation process and of the generation of economic growth. Hence, local social structures, interaction, and collective learning processes within clusters are viewed as making firms located in close physical proximity more innovative and more dynamic than isolated firms (Baptista and Swann 1998).

The link between clusters of firms, innovation, and economic growth has generally been based on a large number of case studies where the learning processes of firms in dense institutional environments are documented. However, as Martin and Sunley (2003, 22) acknowledge – possibly because of the constant resort to what can be considered as favourable cases – the positive connection between the presence of clusters and innovation and economic growth is far from well documented. There are relatively few studies that address the link between clusters, innovation and growth from a comparative perspective and even fewer that try to venture into quantitative analyses of a large number of territories, in order to assess whether the positive relationship between clusters, innovation and growth found in specific cases stands the scrutiny of including not only successful clusters, but also areas a priori less prone to the emergence of collective learning process.

This paper tries to address this gap in the literature by studying the interaction of the presence of clusters with other factors deemed to promote innovation – such as investment in R&D, patent applications or the presence of 'innovation prone' socioeconomic environments – and economic growth across 152 regions located in fifteen European Union (EU) countries over the period 1995-2006. Using pooled cross-section regressions, the model intends to capture both the static and the dynamic connection between a series of innovation promoting factors grouped into three different composite variables or 'innovation filters' – the 'R&D filter', the 'social filter' and the 'clusterisation index' – specially designed in order to proxy the complex interaction among growth enhancing innovation variables.

In order to achieve this aim, the paper is structured into five main sections. After this introduction, the analytical framework of the study is framed in the theoretical literature, paying special attention to the analysis of clusters and regional innovation systems. The third section is devoted to the question of how to operationalise the key factors emerging from the theoretical section. The fourth section presents the model and the results of both the static and dynamic analyses of the connection between different groups of innovation generating factors and economic growth in Europe. The main conclusions of the analysis are presented in the final section.

2. From clusters to innovation and growth

Clusters or “the geographic concentrations of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions” (Porter 2008, 213) have been at the centre of much of the literature aiming to understand and describe the link between innovation and economic growth. This literature has tended to highlight the importance of the presence of agglomerations of firms, organizations, and institutional actors, located in close geographical proximity and interlocked in intricate systems of cooperation, competition, and knowledge diffusion, for the genesis and the spreading out of innovation and, subsequently, economic growth. This literature – often grouped under the label of ‘regional systems of innovation’ literature – traditionally combines two main fields of theory: the innovation systems strand, on the one hand, and insights from regional science, on the other (Doloreux and Parto 2005, 134-5). The ‘regional systems of innovation’ framework is fundamentally grounded on the innovation systems theory developed in the 1980s by evolutionary theorists (cf. Iammarino 2005). This theory is based on the idea that economic performance is not only the result of individual firms’ efforts, but also of a series of other factors, external to the firm, that create an environment that is more or less prone to innovation and economic growth (Dosi 1988). Whether any particular territory is capable of becoming more innovative and, as a result, more dynamic, depends on the presence of a complex system of “inter-organisation networks, financial and legal institutions, technical agencies and research infrastructures, education and training systems, governance structures, innovation policies, etc” (Iammarino 2005, 499). This implies not only the co-location of firms and related industries, but also a degree of specialization combined with a certain level of scope or breadth across a range of industries included in the cluster and a minimum scale or critical mass of firms (Spencer et al. 2010, 702). The capacity of any territory to innovate and grow is considered to be closely dependent on the presence of these regional or local systems of innovation.

Regional science complements the regional innovation systems approach by bringing the specificities of the regional scale to the fore. By taking into account “the internal and dynamics regularities of territorially embedded socio-economic structures”

(Iammarino 2005, 501), regional science allows to determine to what extent specific regions are genuine ‘loci of innovation’ (Doloreux and Parto 2005, 135). This is achieved by focusing on two aspects: first, physical proximity among economic actors as a driver of innovation and, second, the idiosyncratic and innovation enhancing characteristics of a region.

Physical proximity is often regarded as the key aspect making some regions genuine ‘loci of innovation’. The basic reasoning is that innovation travels with difficulty and suffers from strong distance decay effects. Indeed, most analyses looking at the geographical diffusion of knowledge spillovers have highlighted that these knowledge effects are barely felt beyond the boundaries of the functional metropolitan region, in the case of the US (Anselin et al. 1997; Varga 2000; Sonn and Storper 2008) or surpass, in the case of Europe, the distance that can be reasonably covered by a person by car or public transport in a day – circa 200 kms (Moreno et al. 2005; Crescenzi et al. 2007; Rodríguez-Pose and Crescenzi 2008). Hence, innovation benefits from the proximity of the different actors involved in the generation, diffusion and absorption of knowledge and contributes, in turn, to the emergence of clusters. Economic actors clustered in close geographical proximity tend to innovate more and to benefit more from knowledge spillovers than those working in remote locations. Clusterisation also enables firms to exchange knowledge and information fast and increases the chance for an innovative firm to find partners and early-adopters of a new technology (Moore and McKenna 1999). From this perspective, the ‘clusterisation’ of firms working in the same sector or even “competing in the same industry or collaborating across related industries tends to trigger processes that create not only general dynamism and flexibility but also learning and innovation” (Doloreux and Parto 2005, 137). ‘Clusterisation’ is more effective, however, when it involves other actors in the innovation process beyond firms. That is, when universities, R&D research centres and other public and private institutions create ‘dense’ environments of socioeconomic actors, weaving complex networks of interaction that become the channels through which knowledge is disseminated and transformed into economically viable activity. Once again, clusters work best for innovation and economic growth when they are not just mere collocations of firms in similar or related sectors, but when they become regional systems of innovation.

Some research strands have also stressed that the best way to generate and absorb innovation is through a mixture of local ‘buzz’ and ‘global pipelines’ (Bathelt et al. 2004; Wolfe and Gertler, 2004). While local ‘buzz’ represents the quintessential elements of physical proximity, encompassing face-to-face contacts and other forms of human interaction in dense environments (Storper and Venables, 2004), ‘global pipelines’ channel knowledge through cognitive, social and institutional mechanisms, overcoming physical distance (Bathelt et al., 2004).

Physical proximity alone, however, does not suffice to generate innovation and growth. Other characteristics are at play in order to transform regions into truly functioning innovation systems. It is commonly accepted that regions with a similar institutional framework and organisation “may show different abilities to accommodate innovation” (Iammarino 2005, 503). Factors such as ‘social capability’ and ‘technological congruence’ (Abramovitz 1986; Fagerberg 1987 and 1994) contribute to determine to what extent any given region or territory is ‘innovation prone’ or ‘innovation averse’ (Rodríguez-Pose 1999). ‘Social capability’ refers to the capacity of a region to shape its institutional framework in order to support the emergence of what is known as the ‘socio-institutional environment’ or the ‘innovation-supportive culture’ (Doloreux and Parto 2005, 135) required for the generation of innovation. Local socio-institutional environments that favour entrepreneurship are, for example, more likely to generate systems which will be innovation enhancing than those environments that do not. ‘Technological congruence’ refers to the idea of technological frontier (Abramovitz 1990), i.e. the proximity of a region to develop cutting-edge knowledge and thus to make the most from new investment in the promotion of innovation. A region’s technological congruence depends, in turn, on characteristics, such as the presence of a specialized labour market or of developed ‘local learning processes’ integrating company networks (Doloreux and Parto 2005, 135).

The presence of a good ‘social capability’ and strong ‘technological congruence’ contributes to bridge the gap between the supply side of innovation – mainly the institutional sources of knowledge creation – and the demand side, featured by the productive systems that develop and apply such knowledge (Braczyk et al. 1998). Innovation thus becomes a territorially-embedded process (Rodríguez-Pose and

Crescenzi 2008, 54). In one way or another, this notion of 'territorial embeddedness' has been present in all approaches highlighting the importance of clusters for innovation and growth, articulating concepts such as 'innovative milieus' (Camagni 1995), 'learning regions' (Morgan 1997), 'industrial districts' (Becattini 1987), and, not least, that of 'regional innovation systems'. True territorial embeddedness is, however, considered to be "feasible only at regional level" (Cooke 2006, 6). Indeed, the regional dimension allows the different actors involved in the process of knowledge-sharing and exchange to get to know each other, to work together, and to trust each other. All these aspects make the region "the best geographical scale for an innovation-based learning economy" (Doloreux and Parto 2005, 136).

There has certainly been no shortage of high quality research dealing with the implications of clusters for innovation and economic growth (Cheshire and Malecki, 2004). Among this research, qualitative case-study analyses abound. Most of these studies have focused on a handful of cases, including a limited number of well-known technology clusters, such as Cambridge (e.g. Keeble, 1999), or of industrial clusters in the Third Italy or Baden-Württemberg. Other research has stepped away from these traditional cases and wandered into apparently less fertile ground. Cumbers et al. (2003) analysis of SMEs in the Aberdeen oil complex represents one such example. However, while many of these analyses provide deep insights into the internal and external relationships that may – or may not – make clusters hotbeds of innovation and growth, there is always the uncertainty of whether we have been simply observing the lushest trees, while, at the same time, overlooking the overall condition of the forest. More systematic analyses, trying to map out clusters across Europe have been few and far between. Crouch et al. (2001), in perhaps the most ambitious attempt to date, have mapped local production systems across France, Germany, Italy, and the United Kingdom, however the analysis has been confined to national borders, generally avoiding dynamic quantitative analysis. This noticeable absence of robust quantitative evidence is without doubt the result of problems with measuring the intricate interactions, the institutional linkages and the complexity of the collective learning processes happening within clusters, learning regions or regional innovation systems. But this absence of more systematic analysis flies in the face of recent improvements in databases measuring clusters and of the importance clusters have acquired in policy circles. The belief that clusters, in general, and regional systems of innovation, in particular, are key drivers of innovation and growth has become widespread among academics and policy-makers alike. The diffusion of the cluster concept by leading management academics such as Michael Porter and the impulse that research on regional innovation systems has witnessed in recent years have lead to the extensive implementation of cluster policies as a means to achieve economic dynamism.

Yet the perception of clusters as the fundamental drivers of innovation and growth is challenged by more traditional theoretical strands dealing with the genesis and diffusion of innovation. One of these strands is the linear model of innovation, which is based on the basic premise that innovation and growth are driven by greater investment in research and development (R&D) (MacLaurin 1953). The greater the investment in R&D, the greater the output, and the greater the economic growth. Linear models of innovation and growth have thus fundamentally focused on the role of two parameters: the level of expenditure in R&D of a country (or a region), as the key input, and the number of patent applications, as the main output. In particular, "R&D investment becomes [even] more essential when industries move closer to their technological frontier" (Aghion 2006, 2). Other factors, such as the protection of intellectual property rights, also matter for innovation. However, beyond these basic factors, most other parameters are considered either not to count for the genesis of innovation, or to play a mere supporting role.

The linear model neglects, however, another key aspect of the innovation process: 'the context' in which it occurs or, as mentioned earlier, its territorial-embeddedness (Rodríguez-Pose and Crescenzi 2008, 54). From a linear model perspective, innovation is seen as a static process, not influenced by the dynamics and the quality of the different interactions between the actors at play. Yet, from a different perspective, the context in which the interaction among economic actors takes place is fundamental in determining whether innovation will occur or not, or whether it will be assimilated by economic actors or not. This is what Rodríguez-Pose (1999) has called the 'social filters', or the unique combination of "innovative and conservative (…) elements that favour or deter the development of successful regional innovation systems" (Rodríguez-Pose 1999, 82) in any given territory. These elements are neither the networks, nor the institutions which permit the formation of regional innovation systems, but the substrata which encourage the creation and success of these local networks and institutions. They include, among others, the level of education and skills in the population, the level of use of human resources, the demographic dynamism, risk-taking, and the sectoral specialization. The unique combination of these factors in any particular space makes any territory either 'innovation prone' or 'innovation averse' (Rodríguez-Pose 1999).

However, despite these contrasting, and not always complementary, approaches, relatively little effort has been made in order to discriminate between them and to identify which approach has a greater sway over the generation and diffusion of innovation and economic growth. Do clusters have a greater influence over innovation than investment in R&D? Is the role of education greater than that of R&D and the presence of regional systems of innovation in generating economic growth? The interaction among these factors has also been underexplored. Does the presence of a favourable social filter reinforce the potentially positive effects of the presence of clusters on innovation and growth? And how does it interact with R&D? These are questions which have been overlooked or, at most, addressed tangentially by the literature studying innovation and economic growth and which have been mainly examined in case studies. This paper tries to cover this gap in the literature by looking at the interaction between R&D, social conditions and the presence of clusters and regional innovation systems across the regions of the enlarged EU for the period between 1995 and 2006, from both a static and dynamic perspective.

3. From theory to practice

3.1. Operationalising the model

That the questions presented in the previous section have been somewhat neglected can be largely put down to the difficulties in defining – and, consequently, operationalising – most of the concepts involved in this type of analysis. In particular, the concept of what a regional system of innovation is far from straightforward. The most commonly accepted definition of a regional innovation system is that by Cooke et al. (1998, 13), who define a regional innovation systems as "a production structure embedded in an institutional structure in which firms and other organizations are systematically engaged in interactive learning". The interaction between the production and the institutional structure generates territorially-embedded networks which determine the genesis, import capacity, diffusion and assimilation of knowledge within any given cluster (Howells 1999; Evangelista et al. 2002). These networks generate, in turn, a governance and a business structure within the cluster (Braczyk et al. 1998). The governance dimension involves the "soft infrastructure of enterprise innovation support" (Cooke 2006, 6), such as "public policy, institutions, and knowledge infrastructure" (*ibid*). The business dimension includes the "industrial base: [..] the type of firms, the level of R&D investment, the level of linkages" (*ibid*, p. 7).

Most of these networks, institutions and dimensions are idiosyncratic and dependent on the context on which every cluster is placed. As the characteristics of each region and locality are unique, operationalising clusters in a quantitative manner is virtually impossible (Iammarino 2005). It is often the case that regions with, on paper, very similar socio-institutional structures diverge (often wildly) in terms of their innovative capacity. These differences underline that "there is no single model that is able to generalize the dynamics of successful regional innovation systems" (Doloreux and Parto 2005: 138) and question whether the regional innovation framework can be really applied beyond the identification of 'stylized regional innovation systems' (Iammarino 2005), that is, purely theoretical concepts with no clear equivalent on the ground.

Despite these gargantuan difficulties, some authors have embarked on the heroic task of trying to identify clusters and/or design cluster policies in Europe on a large scale. This is, for example, the case of the pioneering work of Jacobsson et al. (2006), who, using functional analysis, aim to identify and measure the different functions of a cluster and the different steps in its creation. In a more systematic way, the European Commission has used the INNOVA initiative to gather best practices from European clusters and to promote them (EC 2006). But it is possibly the European Cluster Observatory (ECO) the organisation, which has made the greatest effort in order to systematically identify, measure and map clusters in Europe. Their measures – not exempt, as any such measure, of controversy – are used in this paper in order to assess clusterisation across the regions of Europe.

Operationalising other constituents of innovation and growth, such as R&D and, in particular, 'social filters' is also not devoid of controversy. But the indicators behind the construction of this type of variables tend to generate, by and large, greater consensus.

3.2. Identifying the variables

Bearing in mind the caveats presented above, in this section we now define the variables included in the analysis. In order to do this we follow previous empirical work and, in particular, the work of Rodríguez-Pose and Crescenzi (2008), who resorted to a series of parameters to measure 'social filters' across the regions of Europe.

The dependent variable is perhaps the most straightforward and widely accepted of all the variables included in the analysis: the growth of the logarithm of the regional GDP per capita. The explanatory variables deserve, by contrast, much greater attention.

Following the three key strands presented in the theoretical section (linear model, 'context', and clusters and regional systems of innovation), in order to analyse the link between (regional) economic growth and the factors that generate innovation in Europe's regions we resort to three basic explanatory variables, which we call the three filters. These are the 'R&D' filter, the 'social' filter and the 'clusterisation' filter.

R&D Filter – The 'R&D filter' is directly derived from the basic principle of the linear model of innovation. We create a composite index using the two basic input and output variables of this approach. The former is represented by the regional expenditure in R&D as a percentage of GDP, whereas the latter is depicted by the number of patent applications per million inhabitants in any given region. Despite the controversy surrounding patent applications as a measure of innovation outputs – not all sectors patent in the same way, not all patents lead to true innovation and not all patents lead to short term economic returns – the inclusion in the analysis of the number of patent applications responds to its value as a proxy for the capacity of a region to absorb and generate knowledge and its correlation with regional economic growth. *R&D expenditure* and *patent application* are given equal weight in the resulting 'R&D filter' index. As could be expected, the higher the R&D expenditure and the higher the patent applications per capita, the higher the value of the R&D filter.

Social Filter – The concept of 'social filter' aims at building a composite index reflecting the socio-economic conditions that make a region innovation prone or innovation averse. This filter reflects the 'territorially-embedded' character of innovation as often presented in regional innovation systems approaches. Multiple aspects can play a role in the emergence of innovation. Among these we highlight: (a) local market rigidities, (b) demographic aspects, (c) education, skills, and human capital, and (d) the scientific base of the region.[1]

The 'social filter' variable used in this paper is based on that of Rodríguez-Pose and Crescenzi (2008), including some additional variables, in order to reproduce better the socioeconomic setting in which innovation and growth take place. The first aspect covered – that of market rigidities – refers to the local use of resources. The variables covered by this domain include long term unemployment (*long term unemployment*) as a means of measuring the degree of rigidity in the local labour market and, at the same time, as a potential indication of the share of the active population with inadequate or insufficient skills. The second variable is agricultural employment (*agricultural employment*), used as a proxy to partially measure levels of 'hidden unemployment', especially prevalent in some of the new members of the EU. These two parameters are also indirectly linked with the productivity level of the labour force. The last variable in this domain is the level of corporate tax rate (*corporate tax rate*). The rationale for the inclusion of this variable is based on the complaints often raised by entrepreneurs and other economic actors. A high level of corporate taxation is said to diminish the investment capacity of firms (especially in R&D) and to be a disincentive for location in certain regions.

[1] Another aspect is local institutions, which are, however, hard to measure at the regional level for the whole of Europe.

The second aspect covered by the 'social filter' relates to the demographic characteristics of a region. It is assumed that the total population of a region (*total population*) may have an impact on its innovative capacity and thus on its growth potential. Indeed, in regions with large populations, the presence of a large market pool will make it easier for a company to find workers with the right skills and knowledge. Moreover, a larger population may be at the source of both greater diversification (Jacobs type) and specialization (Marshall-Arrows-Romer type) externalities. The influence of the number of people living in a region on innovation and growth is complemented by the average age of the population (*% of young*). The impact of this variable on economic growth is difficult to predict theoretically. On the one hand, a young population is often associated with less risk aversion and greater openness to innovation. On the other, if a large percentage of the young is still studying or in full-time training, their immediate impact on economic growth is bound to be limited.

The third domain refers to the education and skills level of the population. Education is widely regarded as a key source for innovation and economic growth. Two variables are included in this domain: the share of the population with a higher education degree (*education population*) and the percentage of adults participating in lifelong learning activities (*lifelong learning*).

The final domain in our 'social filter' index reflects the importance of the presence of scientists in the innovation process. The variable included is the share of employed in science and technology (*hr in science & techno*), as a proxy for the human resources devoted directly to the generation of new knowledge. A strong scientific community in a region can be considered as a competitive advantage for innovation and growth. This aspect was not included in Rodríguez-Pose and Crescenzi's (2008) operationalisation of 'social filter'.

Principal Components Analysis (PCA) is used in order to create the resulting composite variable 'social filter'. The advantage of resorting to PCA is that it can be used as a means for identifying patterns in data and of merging "a set of variables [...] into an individual indicator able to preserve as much as possible of the variability of the initial information" (Rodríguez-Pose and Crescenzi 2008, 57). The results of amalgamating all the variables included in the 'social filter' into one composite variable by means of PCA are presented in Table A1a in Annex 2. The first principal component – used as our 'social filter' variable – accounts for 38% of the total variance. The contribution of individual variables to the composite variable 'social filter' has the expected sign: high long-term unemployment, agricultural employment, corporate tax rates or young populations lower the social filter index; big populations, high educational achievement and life-long learning levels in the population and a good endowment of researchers in science and technology increase the social filter index.

Clusterisation Index – The third and final filter represents an approximation – given the complexity of the task – at capturing the 'clusterisation' effects which are, according to the literature on clusters and regional innovation systems, believed to be directly behind the economic dynamism of a region. The logic for including this index is based on the importance of proximity in the generation of innovation as explained in the theoretical section of the paper. The variables included try to measure the propensity of firms to cluster – or concentrate geographically – in similar or related industries. As mentioned earlier, such dynamics are expected to create important internal flows of knowledge and a strong potential to innovate.

The three variables used in this 'clusterisation index' stem from data collected by the European Cluster Observatory (ECO). The ECO has identified clusters in the 27 members states of the EU, sorting them by region and assessing them through a detailed methodology[2]. Using different criteria, the ECO develops a series of regional indices. The index of cluster specialisation (*specialisation*) exploits employment data in order to create a specialisation quotient representing the employment intensity of a given regional cluster sector compared to the employment intensity in general for this region (please see Annex 1 for the exact formula). The *Focus* index captures the share of a region's total employment represented by a specific cluster. If this share is large, this means that the 'clusterisation' effects for that sector in this region are strong (see Annex 1 for the exact formula). The last variable included in this index intends to

[2] The detailed methodology is available directly on the website: www.clusterobservatory.eu. Only clusters with at least 1000 workers are taken into consideration in order to "prevent the appearance of very small insignificant clusters" (Cluster Observatory website in Methodology: Evaluation of regional cluster strength).

control for the diversification of clusters in a region (*diversification*), i.e. the presence of economic cluster activities in different industries. If a region is characterized by the existence of several clusters in various sectors (even if these clusters are relatively small in comparison to those in regions with only one large cluster), it can expect to benefit from diversification or Jacobs-type externalities, likely to foster greater innovation and growth.

As in the previous filter, the three variables are combined into a composite one using PCA (Table A2a in Annex 2). The first principal component, used as the 'clusterisation filter variable', accounts for 49% of the total variance. Greater specialisation, focus, and diversification of clusters in a region result in a higher clusterisation index.

3.3. Data and geographical coverage

The analysis covers 152 regions in fifteen EU Member States for the period 1995-2006.[3] The economic analysis is conducted at NUTS2[4] regional level for most of the countries – Austria, Czech Republic, Finland, France, Italy, Hungary, Poland, Portugal, Slovakia and Spain. NUTS1 regions have been used for Belgium, Germany, Greece, the Netherlands and the United Kingdom, both for reasons of data constraints and as a need to reflect – at least in the case of decentralised countries – similar tiers of government and levels of decision making capacity.[5]

The data used in the paper stem from two main sources: the European Statistical Office (Eurostat) and the European Cluster Observatory. Eurostat data are mainly used for the variables included in the 'R&D' and 'Social filter' and for the dependent variable. European Cluster Observatory data are used in the construction of the 'Clusterisation filter'. Missing data were estimated using trends. All data are gathered

[3] Bulgaria, Cyprus, Denmark, Estonia, Ireland, Latvia, Lithuania, Luxembourg, Malta, Romania, Slovenia and Sweden were excluded because of lack of sufficient and/or reliable regional data on R&D expenditure.
[4] Nomenclature of Territorial Unit for Statistics as defined by the European Commission on http://ec.europa.eu/comm/eurostat/ramon/nuts/home_regions_en.html.
[5] In addition, some specific regions have been excluded because of lack of data. This is the case of all the French Overseas Departments and Territories, and of the regions of the Åland islands (Finland), Açores and Madeira (Portugal) and the African enclaves of Ceuta and Melilla (Spain)

at the regional level, with the exception of the corporate tax rate, which is national. It is also worth noting that the European Cluster Observatory bases its data on what it calls a 'reference year' (corresponding to the year of the most recent available data). This 'reference year' differs for each country. This implies taking the assumption that the Clusterisation Index of a region is homogenous over the period of analysis.

The names, definitions and sources of the fourteen variables included in the analysis are presented in Table 1.

Insert Table 1 around here

4. The model and empirical analysis

4.1. The model

The econometric model used in the empirical analysis adopts the following form:

$$\Delta \ln GDPpc_{i,(t+1)-t} = \alpha + \beta_1 \ln GDPpc_{i,t-1} + \beta_2\ RDFilter_{i,t} + \beta_3\ SocFilter_{i,t} + \beta_4\ ClusterIndex_{i,t} + \beta_5\ ND + \varepsilon \quad (1)$$

Where:

$\Delta \ln GDPpc_{i,(t+1)-t}$	is the growth of GDP per capita in region i during the period of analysis;
α	is a constant;
$\ln GDPpc_{i,t-1}$	represents the natural logarithm of GDP per capita in region i at the beginning of the period of analysis;
$RDFilter_{i,t}$	denotes the R&D filter conditions in region i and time t;
$SocFilter_{i,t}$	represents the social filter conditions in region i and time t;
$ClusterIndex_{i,t}$	denotes the degree of clusterisation in region i and time t;
ND	are a series of national dummies;

ε is the error term.

The specific characteristics of the data included in the 'Clusterisation index' – the use of a 'reference year' by the European Cluster Observatory – constrain us to estimating the model by means of heteroskedasticity-consistent pooled OLS (Ordinary Least Square) regressions. This method has the advantage of allowing us to present both a static and – by resorting to annual lags – a dynamic image of the association between the different indices included as independent variables and regional economic growth. All the estimates carried out are based on a robust variance matrix estimator which is valid in the presence of heteroskedasticity or serial correlation (Wooldridge 2006). VIF tests have been conducted for all the variables in the model, with no multicollinearity having been detected. In order to account for unobserved national fixed effects, a set of national dummies (variable *ND*) is included in the model.

The main aim of the analysis is to examine the association between the composite variables representing the competing explanations of the factors behind innovation presented in the theoretical section – clusters and regional innovation systems, the local socioeconomic conditions or social filter, and traditional investment in R&D and patent applications – and economic growth. The analysis is conducted in three steps. First, a static picture is presented in Table 2. In this table the results of running fourteen different regressions are reported. These regressions aim to capture both the aggregate connection between each composite variable representing the different approaches to the analysis of innovation or filters (regression 1), as well as the individual correlation of between each individual variable included in each of the three filter variables (regressions 2 to 9 for the *Social Filter,* regressions 10 and 11 for the *R&D Filter* and regressions 12 to 14 for the *Clusterisation Index*), on the one hand, and economic growth in the regions of Europe, on the other. The three composite filter variables – R&D filter, social filter and clusterisation index – have been standardised in order to make it possible to compare their effects on regional growth. The standard errors are presented (in italic) under the value of the coefficient. In each regression, tests have been conducted in order to account for the good specification and goodness of fit of the model.

Second, the dynamic dimension of the relationship is reported in Table 3. This table includes seven pooled HC-OLS regressions, with the dynamic effect achieved by regressing regional per capita growth on the initial GDP per capita and lagged filters, where the number of lags is $n \in [1;6]$. While this econometric approach enables us to give a global picture of the dynamics of the model, it has the drawback of reducing the number of observations after each lag. In any case, even after six annual lags, the number of observations (n=796) remains relatively large. As in the case of the static analysis, the potential presence of spatial serial correlation is controlled for. No multicollinearity is detected in the model.

Third, and in order to better assess how the association between the different filters may affect innovation and growth, the dynamic analysis is rerun substituting each of the dependent variables of interest in model (1) – R&D filter, Social filter, and Clusterisation index – by their pairwise interaction.

4.2. Static analysis

The first fact that can be underlined in the static analysis is the goodness of fit of the model (Table 2). A very high proportion of the variance in regional growth is explained, implying that the combination of the more traditional variables of innovation, with the social filter and its components and the different indicators aimed at identifying the presence of clusters have a powerful association with regional economic growth.

Most variables are significant and tend to remain so despite the introduction of different controls. This is the case of the initial GDP per capita of a region, which is positively and robustly associated with regional economic growth in all fourteen regressions (Table 2). When the three composite filter variables are considered together, the social filter and the clusterisation index have a positive and significant relationship to economic growth, but the R&D filter variable is not significant (Table 2, Regression 1). This, in principle, represents a confirmation of the views of those strands of research which have highlighted importance of both the presence of clusters and complex regional innovation systems and the presence of the basic socioeconomic conditions on which these networks and systems can be constructed for economic growth. Indeed successive regressions (Regressions 2 to 9) reveal the close interaction between the presence of clusters and of favourable socioeconomic conditions. When the composite social filter variable is excluded from the analysis, the coefficient of the clusterisation index becomes generally insignificant (Regressions 2, 3, 4, 5, 6 and 8, Table 2). This also points to the fact that the association of clusters with regional economic growth is closely related to the presence of a good level of education in the population (Regression 7), with an emphasis on life-long learning (Regression 8) and, essentially, with the existence of a good pool of researchers (Regression 9). The presence of a relatively 'high-tech' labour force thus seems to play a major role in the settlement of innovation-enhancing socio-economic conditions and, more globally, in the economic growth of a region. This may be a confirmation of some of the basic characteristics associated with regional innovation systems. In these complex systems the presence of a pool of researchers surrounded by a highly educated workforce will naturally tend to form a community where innovation is generated, diffused and absorbed in the workplace. This is, in essence, the 'local learning process', as defined by Doloreux and Parto (2005). If companies in a region are, in addition, geographically clustered, this is likely to increase intra-regional knowledge flows between high-tech workers and educated people. Therefore, clusterisation, on the one hand, and the presence of a high density of researchers and of a well educated labour force, on the other, will reinforce each other in the generation of innovation and growth. The greater the density of clusters in any given region, the easier the knowledge flow between innovative firms and the rest of the production fabric, facilitating the diffusion and absorption of knowledge. This renders the impact of clusters significant to economic growth. The absence of these conditions, in contrast, makes clusters almost irrelevant for growth.

Insert Table 2 around here

Factors such as the presence or absence of long-term unemployed, of greater or lower levels of agricultural employment, of a younger or older population, or the overall dimension of the region neither enhance, nor reduce the potential relationship between the presence of clusters and economic growth. In fact, they contribute to make it irrelevant (Table 2).

Extracting the social filter from the analysis renders the more traditional R&D variables of R&D expenditure and patent applications positive and significant (Regressions 2 through 9, Table 2), with the exception of when the R&D filter is considered in combination with corporate tax rate (Regression 4) and the regional human resources devoted to science and technology (Regression 9).

Turning to the individual variables included in each filter – while controlling for other filters – exposes other interesting associations. First, the decomposition of the R&D filter variable into its two components brings to the fore a significant and positive correlation between the number of patent applications and growth (regression 10) whereas, investment in R&D turns out as non significant (regression 11). The weak association between R&D expenditure and economic growth, at least in the short term, comes in support of the views which highlight the relative irrelevance of policies dominated by public investment in R&D in environments associated with inadequate or weak socioeconomic conditions and in the presence anaemic networks and systems to absorb it (Cooke 2001). However, the results regarding patent applications are in line with the linear approach to innovation.

The different regressions including individual social filter variables (Regressions 2 to 9) give a more detailed information about the socioeconomic conditions which may matter for innovation and growth in the regions of Europe. Among the socioeconomic variables that have a positive and significant association with economic growth, the educational parameters clearly stand out. Both coefficients of the level of education of the population and of a life-long learning dimension in the workforce are strongly positive and significant and of great importance for growth (Regressions 7 and 8). The human resources devoted to science and technology go in the same direction (Regression 9). By contrast, the level of long term unemployment, that of agricultural employment, the corporate tax rate and the percentage of young (Regressions 2 to 5) are negatively and significantly associated with regional economic growth. The demographic size of a region is completely dissociated from growth, once the R&D and clusterisation indices are included in the analysis (Regression 6, Table 2).

Finally, of the variables making up the clusterisation index, specialisation and focus are positively and significantly – albeit at the 10% level – correlated with regional economic growth (Regressions 12 and 13, Table 2), The coefficient of the variable representing the diversification of clusters is, however, not significant (Regression 14).

In brief, the static analysis exposes the very strong, positive and robust association between the social filter of a region and its economic growth. The strength of this relationship is significantly stronger than that of the other two filters with regional growth. The link between R&D and patents and growth, on the one hand, and the presence of clusters, combining both specialisation and diversity externalities, and growth, on the other, is contingent on their interplay with the presence or absence of adequate social filters. The R&D variable only becomes significant when the social filter is not taken into account, while the relevance of the existence of clusters in a region for economic growth only comes to the fore in areas with adequate social filters (Table 2). The capacity by economic actors to absorb innovation across European regions depends on the overall combination of social conditions and, more specifically, on the educational endowment of the population and on the existence of a 'high-tech literate' labour force. Clusters also matter, but their importance for growth is contingent on the presence of adequate social filters. Weak or rigid social filters – characterised by factors such as the prevalence of long term unemployment, low productivity employment and high levels of corporate taxation – may damage significantly the innovation potential of a region and render the association between clusters and economic growth irrelevant. Adequate social filters (i.e. those featured by well-educated populations, a high-tech labour force and limited market rigidities) combined with the capacity to transform R&D into patents quickly and to develop clusters both specialised and focused – in comparison to those in other regions – are at the base of the formation of innovative and economically dynamic regions.

4.3. Dynamic Analysis

The dynamic analysis in an up to seven year horizon is presented in Table 3. It adds a series of interesting nuances to the relationship between the key factors behind innovation and economic growth, outlined in the static approach. The most relevant finding is the enduring importance of an adequate social filter for regional economic growth in Europe. The social filter is the only composite variable to remain significant throughout the whole period of analysis, despite the fact that the strength of its relationship with regional economic growth wanes in time. The association of the social filter with the variation of regional economic growth in Europe is only half as strong when considering a six-year time lag as when no time lags are considered (Table 3).

Insert Table 3 around here

Another important finding is the contrasting trajectories of the relationship between the R&D filter, on the one hand, and the clusterisation index, on the other, and regional economic growth. As highlighted in the static analysis, the presence of a greater specialisation and focus in clusters in favourable socioeconomic environments is connected to higher growth in the short term. This positive relationship is, however, short-lived. The strength and the significance of the coefficient starts to wane quickly and becomes non significant beyond three years (Table 3). The R&D filter, by contrast, is insignificant in the first year considered, but becomes significant after one year. The strength of this association remains more or less intact during the remaining years. The importance of this association also increases over time, especially as the intensity of the connection between the social filter and regional economic growth starts to decline (Table 3). This may be a signal that, at least in the European case, the importance of clusters and innovation systems for regional economic growth may have been somewhat overstated. Conversely, hard R&D indicators may have a greater sway over short and medium-term economic performance than admitted by some recent strands of literature.

4.4. Dynamic analysis with interaction terms.

But how does the interplay between the three different filters affect economic growth? In order to get a more accurate picture of how the interaction between the factors behind innovation promote regional growth in Europe, the dynamic analysis is rerun substituting the independent variables representing each of the filters by their interactions – interaction between the R&D filter and the Social filter, between the

R&D filter and the Clusterisation index, and between the Social filter and the Clusterisation index. All regressions are run including the GDP per capita of the region and national dummies.

The results of this analysis, presented in Table 4, underline once again the importance of social conditions for the genesis of innovation and growth. The interaction between the Social filter and the R&D filter yields a positive and significant coefficient, which remains so over the period of analysis. Adequate social conditions – and, in particular, a good human capital endowment (Rodríguez-Pose and Crescenzi, 2008) – facilitate the transformation of R&D investment and patent applications into economic growth (Table 4). The interaction between the presence of clusters and a good R&D environment is, by contrast, not associated with higher levels of growth. Regions which benefit from high levels of investment in R&D and from a relative good endowment of clusters do not necessarily grow faster that regions lacking these characteristics, in the absence of adequate social filters which would help transform these factors into greater economic dynamism. Similarly, the interaction between the social filter and the presence of clusters is completely dissociated from the economic performance of the region (Table 4).

4. Conclusion

The objective of the paper has been to assess through the use of an econometric model with a static and a dynamic dimension the association between the different factors that promote innovation and economic growth across the regions of Europe. In particular, we have analysed the role that the presence of clusters within regions play in this relationship. The intention was to overcome the tendency by most of the literature on clusters to concentrate on the most favourable cases (Martin and Sunley, 2003), which was ultimately raising important questions about the role of clusters in the generation of innovation and economic growth. Are all clusters a source of innovation and growth? Or is it just those that happen to be located in the right environments, in the right sectors, and/or in places where adequate management is available and adequate support policies have been implemented? The paper has thus examined the role of clusters across regions in Europe, looking not just at the brightest trees in the forest – the Cambridges, Venetos, Jutlands or Württembergs of the cluster world – but also at the average and even the moribund trees – i.e. the clusters which happen to be located perhaps in the wrong environments, the wrong sectors and with inadequate management and policies. The size of employment in clusters relative to overall employment, the dominance of specific clusters, and cluster diversification were the three criteria used in order to measure the presence of clusters across regions in Europe. Two other composite indices or filters, covering 'hard' innovation indicators – the R&D filter – and the socioeconomic conditions on which innovation takes place – the Social filter – were included in the analysis in order to represent the other factor which can promote regional innovation and growth.

Three primary conclusions can be extracted from the analysis. First and foremost is the importance of having a favourable socioeconomic setting in order to foster innovation and growth. Much more than the presence or absence of clusters, having a good level of education, a strong endowment of skills in the population or a workforce with sufficient high tech skills is not just crucial in order to generate and absorb innovation, but also as a way of ultimately promoting greater economic growth. Having a good employment/unemployment balance is also equally important for innovation and economic growth. Fiscal incentives can also become useful in fostering innovation, if they help attract companies with a high innovative potential. These socioeconomic conditions weave a complex substratum that allows certain territories to become more innovation prone than others.

Second, regional clusters have a strong association with economic growth in the static model, especially when they help increase the knowledge flow in already highly integrated communities, among well endowed with firms, skilled workers, researchers and scientists. However they appear only as 'second-best factors' in relation to the social filter. This may be partly a result of the way the clusterisation effect is measured in the analysis. The method used may have introduced, as the European Cluster Observatory explains "a bias towards employment-intensive clusters" (ECO, website). Therefore, these data will need to be completed by other information – not yet available at the European level – such as "wage bill, productivity or value added [in order] to shift the balance in favour of capital- or knowledge-intensive cluster categories" (*ibid*). In any case, the results may also highlight that the association between the presence of clusters, innovation and economic development in the regions of Europe is a) contingent on the presence of adequate social filters that would help make the transition from a mere cluster of firms into a real regional system of innovation, and b) less relevant in time than the socioeconomic substrata on which the clusters are based. Clusters seem to matter when they become the hub for regional systems of innovation, but this tends to happen only when they are located in innovation prone environments with adequate social filters and even in this cases, their influence seems to be weaker than, for example, investment in R&D. Hence, the influence of clusters for economic growth may be lower than what many think. What really matters for economic growth is setting up in every territory the adequate conditions for innovation, including greater education and life-long learning opportunities, a better and more efficient use of human resources, a better matching of investment in training and innovation to local production fabric and more emphasis in science and technology.

The third conclusion is the limited short-term association between R&D investment and patent applications and economic development across the regions of Europe. However, the presence of adequate social conditions helps improve the returns on R&D investment and patents over time.

The research presented here probably sends a message of warning against the adoption of one-size-fits-all and even 'mesmeric' types of cluster policies for local economic development (Taylor, 2010). Policies aimed at fostering or encouraging the agglomeration of firms may, without paying attention to local conditions and potential, end up yielding lower results – if at all – than expected. Indeed the analysis points towards the need of addressing local social filter bottlenecks as a precondition for achieving greater returns in R&D and in cluster policies. However, neither all clusters have the same transactions costs and internal relations characteristics, nor the same technological regimes and knowledge features (Iammarino and McCann, 2006). This implies a need to make greater distinctions in policy-making among different types of clusters, as different clusters in different contexts may require different types of intervention (Gordon and McCann, 2000). In any case, while the analysis presented here provides a springboard for some potential practical policy implementations and recommendations, it also calls for further research, and in particular of research trying to better reproduce and capture the effects of different types of clusters.

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ANNEX

ANNEX 1- The exact formula of *Specialisation* and *Focus*

These formulas are directly extracted from the European Cluster Observatory's website: www.clusterobservatory.eu

Specialisation Quotient

$$SQ_{r,s} = \frac{e_{r,s}/E_s}{E_r/E}$$

SQr,s = the specialisation quotient for region r and cluster sector s
er,s = the number of employees for region r and cluster sector s
Es = the total number of employees in all regions for sector s
Er = the total number of employees in all cluster sectors for region r
E = the total number of employees in all regions and all cluster sectors

Put in a simpler way the Specialisation Quotient is given by

$$\frac{\text{(Employment in a region in a category) / (Total employment in a region)}}{\text{(Employment in a category in Europe) / (Total employment in Europe)}}$$

Focus:

$$F_{r,s} = \frac{e_{r,s}}{E_r}$$

er,s = the number of employees for region r and cluster sector s
Er = the total number of employees in all cluster sectors for region r

ANNEX 2 - PCA analysis

In this annex, the results of the three Principal Components Analyses are given

Principal Component Analysis for Social Filter

Table A1a - Eigenanalysis of the Correlation Matrix – Social Filter

Component	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8
Eigenvalue	3.09646	1.56254	1.11289	0.80251	0.518857	0.439485	0.34847	0.118794
Proportion	0.3871	0.1953	0.1391	0.1003	0.0649	0.0549	0.0436	0.0148
Cumulative	0.3871	0.5824	0.7215	0.8218	0.8867	0.9416	0.9852	1

Table A1b - Coefficients of the PCA- Social Filter

Variable	Comp1	Comp2
LT unemployment	-0.2879	-0.1887
Agriculture Employment	-0.4096	0.2502
Corporate tax rate	-0.0119	-0.7014
Young people	-0.3441	0.4336
Total population	0.1056	0.3473
Education	0.4435	0.1291
Life long learning	0.4175	0.2867
HR in Science and Technology	0.4986	-0.0495

Principal Component Analysis for Clusterisation Index

Table A2a - Eigenanalysis of the Correlation Matrix – Clusterisation Index

Component	Comp1	Comp2	Comp3
Eigenvalue	1.48376	0.807631	0.708606
Proportion	0.4946	0.2692	0.2362
Cumulative	0.4946	0.7638	1

Table A2b - Coefficients of the PCA- Clusterisation Index

Variable	Comp1	Comp2
Specialisation	0.6046	-0.2846
Focus	0.5899	-0.4676
Diversification index	0.5352	0.8369

Table 1. Definition of the variables and data sources

Variable	Definition	Sources
	Dependent variable	
Growth of GDPpc	GDP PPS per inhabitant	Eurostat
	R&D Filter	
R&D expenditure	% of GDP	Eurostat
Patents	Applications per million inhabitants	Eurostat
	Social Filter	
Long term unemployment	% of total unemployment	Eurostat
Agriculture employment	% of total employment	Eurostat
Corporate tax rate	% of corporate benefits (national proxy)	Eurostat
% of young	people aged 15-24 as % of total population	Authors' calculations based on Eurostat data
Total population	% of national population	Eurostat
Education	% total population with tertiary education (levels 5-6 ISCED 1997)	Eurostat
Life long learning	% of Adults (25-64) participating in education and training	Eurostat
Human Resources in Science and Technology	% of active population	Eurostat
	ClusterIndex	
Specialisation	cf Annex I	European Cluster Observatory
Focus	cf Annex I	European Cluster Observatory
Diversification	number of clustered industries in the region per 100 000 of employed people	Authors' calculation based on European Cluster Observatory data

Table 2 - Pooled (HC-OLS) regressions of regional log GDP/capita

	1	2	3	4(*)	5	6	7	8	9	10	11	12	13	14
Constant	2.157***	0.955***	1.288***	0.691***	2.048***	0.561***	1.459***	1.086	2.165***	2.327***	2.032***	2.012***	2.008***	2.067***
	0.350	*0.256*	*0.2674*	*0.132*	*0.261*	*0.195*	*0.292*	*0.154*	*0.281*	*0.346*	*0.367*	*0.329*	*0.340*	*0.356*
log GDPpc	0.757***	0.947***	0.901***	0.988***	0.896***	0.979***	0.854***	0.9101***	0.722***	0.738***	0.770***	0.770***	0.769***	0.766***
	0.038	*0.027*	*0.0297*	*0.014*	*0.029*	*0.021*	*0.035*	*0.006*	*0.030*	*0.0373*	*0.040*	*0.036*	*0.037*	*0.039*
R&D Filter	0.009	0.034***	0.036***	0.006	0.027***	0.038***	0.019**	0.024***	0.003			0.004	0.008	0.008
	0.008	*0.006*	*0.006*	*0.006*	*0.007*	*0.006*	*0.008*	*0.006*	*0.008*			*0.009*	*0.008*	*0.008*
Social Filter	0.049***									0.0494***	0.051***	0.049***	0.048***	0.049***
	0.005									*0.0046*	*0.005*	*0.005*	*0.005*	*0.005*
Clusterisation index	0.013**	-0.004	0.002	-0.003	-0.007	-0.003	0.010*	0.000	0.016***	0.014**	0.011**			
	0.005	*0.004*	*0.003*	*0.003*	*0.004*	*0.003*	*0.006*	*0.003*	*0.004*	*0.005*	*0.005*			
National dummies	x	x	X		x	x	X	x	X	x	x	X	X	X
Social Filter														
long term unemployment		-0.002***												
		0.001												
Agriculture employment			-0.007***											
			0.001											
corporate tax rate				-0.010***										
				0.001										
% of young					-0.045***									
					0.005									
total population						-0.001								
						0.001								
Education							0.025***							
							0.004							
lifelong learning								0.047***						
								0.005						
HR in science & techno									0.019***					
									0.001					
R&D Filter														
patent application										0.000**				
										0.000				
R&D expenditure											-0.009			
											0.007			
Clusterisation index														
Specialisation												0.0126*		
												0.0065		
Focus													0.011*	
													0.006	
Diversification														0.011
														0.007
R^2	0.925	0.883	0.885	0.898	0.895	0.880	0.914	0.905	0.916	0.926	0.925	0.924	0.924	0.924
F	614.21	1012.33	546.29	1737.74	493.00	1313.86	533.36	1104.96	418.44	538.64	773.24	561.30	705.68	517.31
Number of observations	1756	1760	1760	1760	1760	1760	1760	1760	1756	1756	1756	1756	1756	1756

*,**,*** indicates significances at 10%, 5% and 1% respectively

(*) this regression has been run without national dummies since a national proxy has been used for the Corporate tax rate.

Table 3 - Dynamic Analysis

	Lag 0	**Lag 1**	**lag 2**	**lag 3**	**lag 4**	**lag 5**	**lag 6**
Constant	2.157***	1.956***	1.689***	1.683***	1.283***	1.159***	1.392***
	0.350	*0.314*	*0.282*	*0.243*	*0.253*	*0.256*	*0.248*
Log GDPpc	0.757***	0.785***	0.820***	0.853***	0.874***	0.891***	0.899***
	0.038	*0.034*	*0.031*	*0.028*	*0.0270*	*0.027*	*0.028*
R&D Filter	0.009	0.015**	0.017***	0.017***	0.016***	0.014**	0.015**
	0.008	*0.007*	*0.006*	*0.006*	*0.006*	*0.006*	*0.007*
Social Filter	0.049***	0.043***	0.037***	0.031***	0.030***	0.025***	0.024***
	0.005	*0.005*	*0.004*	*0.004*	*0.004*	*0.004*	*0.005*
Clusterisation Index	0.013**	0.011**	0.009*	0.006	0.004	0.002	0.002
	0.005	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*
R^2	0.925	0.932	0.940	0.947	0.956	0.964	0.968
F	614.21	582.94	630.35	705.77	763.65	927.23	1281.37
Number observations	1756	1596	1436	1276	1116	956	796

Table 4 - Dynamic Analysis with interaction terms between the different filters

		Lag 0	**Lag 1**	**lag 2**	**lag 3**	**lag 4**	**lag 5**	**lag 6**
Interaction between R&D Filter and Social Filter	Coefficient	0.0023***	0.0028***	0.0025***	0.0025***	0.0021***	0.0018**	0.0016*
	Standard Error	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*
	R^2	0.879	0.898	0.916	0.931	0.943	0.9542	0.9590
	F	2244.47	1778.56	1405.31	1208.18	1049.95	860.57	732.72
Interaction between R&D Filter and Clusterisation Index	Coefficient	-0.0007	-0.0013	-0.0007	-0.0001	0.0010	0.0030	0.0042
	Standard Error	*0.004*	*0.004*	*0.004*	*0.004*	*0.005*	*0.005*	*0.005*
	R^2	0.8775	0.8965	0.9144	0.9291	0.9420	0.9537	0.9588
	F	2214.27	1827.81	1362.87	1143.91	947.89	751.51	638.85
Interaction between Social Filter and Clusterisation Index	Coefficient	-0.0008	-0.0010	-0.0010	-0.0011	-0.0011	-0.0012	-0.0012
	Standard Error	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*
	R^2	0.8787	0.8976	0.9153	0.9299	0.9428	0.9540	0.9589
	F	2428.88	1933.90	1555.65	1384.80	1141.24	957.06	818.87
Number observations		1756	1596	1436	1276	1116	956	796