

Capello, Roberta; Lenzi, Camilla

Conference Paper

Knowledge, innovation and economic growth: spatial heterogeneity in Europe

52nd Congress of the European Regional Science Association: "Regions in Motion - Breaking the Path", 21-25 August 2012, Bratislava, Slovakia

Provided in Cooperation with:

European Regional Science Association (ERSA)

Suggested Citation: Capello, Roberta; Lenzi, Camilla (2012) : Knowledge, innovation and economic growth: spatial heterogeneity in Europe, 52nd Congress of the European Regional Science Association: "Regions in Motion - Breaking the Path", 21-25 August 2012, Bratislava, Slovakia, European Regional Science Association (ERSA), Louvain-la-Neuve

This Version is available at:

<https://hdl.handle.net/10419/120481>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

**KNOWLEDGE, INNOVATION AND ECONOMIC GROWTH:
SPATIAL HETEROGENEITY IN EUROPE**

Roberta Capello and Camilla Lenzi

Politecnico di Milano

Building, Environment, Science and Technology (BEST) Department

Abstract

This paper aims at re-assessing the relationship between innovation and economic growth by questioning the view equating knowledge to innovation and to regional growth. We rather propose that these linkages are highly differentiated at the regional level and explore this relationship for 262 NUTS2 European regions.

Our results confirm that knowledge and innovation are both important drivers of economic growth. However, this hides a larger territorial heterogeneity. Whereas the growth benefits accruing from knowledge look rather selective and concentrated, the growth benefits accruing from innovation look greater and do not always match the strength of the formal local knowledge basis.

JEL codes: R11, O30

Keywords: knowledge, innovation, economic growth

1. INTRODUCTION¹

This paper studies the role played by knowledge and innovation on regional economic growth. Much has already been written in the literature on this relationship and opinions largely converge on the importance of knowledge and innovation for regional performance (see Cooke et al., 2011 for reviews).

This paper stands in this well documented literature tradition but aims at reconsidering this relationship by moving from the somehow counter-intuitive observation that fast-growing regions (especially in Eastern Europe) are those with the least endowment in terms of local formal knowledge. This sharply contrasts the common understanding of knowledge equating innovation equating growth as well as the current policy efforts of increasing R&D spending to raise competitiveness and growth in Europe.

In particular, this paper claims that the growth benefits stemming from innovation do not necessarily match the strength of local formal knowledge basis and less knowledge intensive innovative regions can succeed as much as more knowledge intensive regions in exploit knowledge and innovation to achieve higher economic performances.

By drawing on the conceptual and empirical distinction between knowledge and innovation, this paper specifically looks for spatial heterogeneity in the way regions are able to successfully exploit (and mix) them to achieve higher paces of economic growth. In particular, the paper shows that, on average, both knowledge (i.e., R&D expenditures) and innovation are crucial, albeit different, drivers of economic growth; however, knowledge and innovation can mix in space in a variety of ways. More importantly, and differently from most of the literature focusing on the relationship between knowledge and regional growth, this paper shows that the growth benefits accruing from innovation do not always match the strength of the formal local knowledge basis.

In so doing, this paper adds to the literature on knowledge, innovation, and regional growth in mainly three directions.

Firstly, the paper contributes to research on the conceptualization of innovative processes at the local level. Our approach, in fact, directly questions the much diffused knowledge-

¹ Financial support the from ESPON KIT project is gratefully acknowledge. More on the project can be found at the website: http://www.espon.eu/main/Menu_Projects/Menu_AppliedResearch/kit.html

innovation-performance equivalence interpreting knowledge, innovation and economic growth as necessarily overlapping processes at the spatial level. Indeed, most of the literature takes for granted that locally created knowledge unavoidably leads to local innovation and local innovation takes place because of local knowledge availability. Similarly, productivity increases are expected when creative efforts, learning processes, an interactive and cooperative atmosphere characterize the local economy.

Differently, the distinction between the knowledge and innovation stages paves the ground to a conceptual framework interpreting not only a single phase of the innovation process, but the *different modes of performing the different phases of the innovation process* (Capello, 2011).

Secondly, the interplay between knowledge, innovation and economic growth has been discussed limitedly so far mostly, but not exclusively, because of the paucity and/or low quality of innovation data. The contribution of this paper is, in this respect, on the methodological ground by providing brand new data on knowledge, innovation and growth patterns for 262 regions of the 27 European Union Member states.

Lastly, our results are also of importance for the current efforts of designing research and innovation policies within the frame of the EU2020 strategy of making the European Union and its regions growing smartly. Whereas previous policy efforts have mostly concentrated on supporting knowledge creation activities as chief enablers of higher economic performance, and, implicitly on knowledge-intensive regions as prominent players in this regard, our results suggest that innovative regions should not be neglected as they show comparable growth potential. Targeting these regions with dedicated innovation policies looks therefore crucial to make them fully contributing to the achievement of the EU2020 strategy goals.

The reminder of the paper is articulated as follows. Section 2 comments on the relevant literature about knowledge, innovation and regional growth and, accordingly, formulates our research hypotheses. Section 3 presents our data and describes knowledge and innovation patterns in European regions. Section 4 sets out our empirical framework and section 5 reports and discusses our empirical findings. Section 6 concludes and outlines some policy implications deriving from our results.

2. KNOWLEDGE, INNOVATION AND REGIONAL GROWTH: THEORETICAL ACHIEVEMENTS AND A NEW INTERPRETATIVE FRAMEWORK

2.1. Theoretical achievements on knowledge, innovation and regional growth: a synthesis

Since the end of the 1960s, innovation at the regional level attracted the interest of regional economists and geographers, by questioning the view that innovation is “manna from heaven” and is equally distributed among firms and in space, contributing to generate a long term process of convergence across countries and regions (Solow, 1957; Borts and Stein, 1962).

An endogenous approach to regional innovation was soon considered as a crucial and necessary step towards the conceptualization of innovation processes in space.

Innovation was, firstly, interpreted as the production of high-tech goods or services, by assuming a straightforward link between invention and innovation, mainly taking place within firms in advanced sectors (and their territories). R&D facilities are, in fact, strictly linked to production facilities, while firms tend to cluster inside high-tech districts in order to take advantage of all sorts of proximity externalities. The mere presence of high-tech sectors was considered as a pre-condition for a region to innovate and, implicitly, to grow. The availability of advanced education facilities was also invoked as a crucial enabler of innovation capacity together with accessibility, advanced urban atmosphere, specialization advantages in distinctive sectors and related functions (Malecki, 1980; Saxenian, 1994). Accordingly, the presence of pervasive and horizontal functions like R&D and high education (MacDonald, 1987; Massey et al. 1992; Monk et al., 1988; Storey and Tether, 1998) was indicated as a key source of differential new knowledge creation capacity. Innovation, in the end, was considered as a direct result of local knowledge (and proxied by knowledge indicators). In this approach, therefore, knowledge equates innovation, as the latter straightforwardly follows from localized R&D investments that, in turn, explain regional growth.

It soon became evident that R&D activities were not the only explanation for innovation.

Despite a low R&D intensity, different areas proved to be able to introduce process and managerial innovations that were driving the rejuvenation of traditional sectors, as in the cases of the adoption of new CAD/CAM and ICTs technologies in mid-eighties. The interest in

the theoretical approaches moved, therefore, to the identification of territorial conditions that are likely to support local innovation creation and adoption, keeping however the equivalence between knowledge and innovation. Soft elements like interaction, synergy and cooperation among local actors, gained much attention and were increasingly addressed as fundamental sources of collective learning processes and, hence, new knowledge creation at the local level, driving straightforwardly to innovation. Local "milieu", where network relations (long-distance, selective relationships), interaction, creativity and recombination capability, nourished by spatial proximity and atmosphere effects can take place, were considered the loci for the creation of knowledge. Social capital and agglomerations economies were indicated as important enablers of local knowledge and innovation (Camagni, 1991; Perrin, 1995; Keeble and Wilkinson, 1999 and 2000; Capello 1999; Cappellin, 2003). Similarly, the "learning" region, the region able to combine existing but dispersed know-how, interpretations of market needs, information flows with intellectual artifacts such as theories and models and to allow the mutual exchange of experiences and co-operation, was identified as the place where such cognitive processes play a vital role (Lundvall and Johnson, 1994). Likewise, the regional innovation system theory emphasized the importance of an efficient combination of a sub-system of knowledge generation and diffusion (knowledge infrastructure dimension) and a sub-system of knowledge application and exploitation (business dimension), which is made up of the companies located in the region. Also, this approach identified in the intense interactions and in a circulation of knowledge, human capital and resources within and between the sub-systems the success conditions for local innovation (Trippi, 2010).

However, in these theoretical approaches, innovation is too easily interpreted as a proxy for regional growth, giving for granted that if local conditions are innovation-prone, and innovation takes place, regional growth is the outcome of the whole process. Differently, the capacity of exploiting innovation for strategic purposes is not equally distributed among firms, institutions and, in general, regions (Capello, 1994).

More recently, theoretical reflections took into consideration spillover mechanisms, and knowledge outputs at the local level and posited their importance to achieve higher economic performances (Jaffe, 1989; Acs et al., 1994; Audretsch and Feldman, 1996). Importantly, this

approach indicated geographical proximity as the main channel through which knowledge spillovers spreads across space. As in the innovation diffusion models developed in the 1960s (Hägerstrand, 1967), the pure likelihood of contact between a knowledge creator (e.g. an R&D laboratory) and a potential recipient (e.g. a firm, a university, another R&D centre) was seen as the main vehicle for knowledge transmission, in a pure epidemic logic (Acs et al., 1994; Audretsch and Feldman, 1996; Anselin et al., 2000). Localized knowledge/technological spillovers can therefore explain the tendency of innovative activities to cluster in space: firms co-locate to reap the potential benefits arising from knowledge flows.

However, knowledge creation and innovation are highly cumulative processes leading to much differentiated cognitive base, absorptive capacity and potential for learning across actors and regions. Different concepts of proximity, ranging from social to institutional, from cultural to cognitive, were later added to geographical proximity as interpretative tools to enrich the explanation of knowledge spillovers, diffusion and creation (Boschma, 2005; Rallet and Torre, 1995; Capello, 2009).

Over time, these theoretical and empirical approaches have considerably expanded and augmented the scientific understanding of knowledge and innovation processes in space and have been highly successful in the identification of those territorial pre-conditions and local elements that can support them. Despite their different perspectives, they are all characterized by a common element; namely, they concentrate on the link between knowledge and regional growth and share the idea that locally created and used knowledge can justify local economic performance. However, this reasoning risks to hide a conceptual ambiguity and to neglect the much more complex variety of knowledge and innovation propensity and mix across regions, as it will be discussed in the next section.

2.2. A new interpretative framework

Much of the existing conceptual and empirical efforts focus on one specific phase of the innovation process, often interpreted as the crucial one and mostly meant as knowledge creation or knowledge diffusion only. Some theories also interpret knowledge and innovation as overlapping (frequently synonymous) processes, assuming that knowledge created locally

inevitably leads to local innovation, or, conversely, that local innovation is exclusively due to local knowledge availability. This conceptual ambiguity is clearly manifest in the use of knowledge indicators such as R&D or patent intensity as proxy for innovation outputs. Moreover, some theories interpret innovation as equating regional growth, while context conditions exist that can make a region able to exploit innovation to grow more than others. In fact, knowledge and innovation are not necessarily overlapping processes in space nor necessarily sequential at the local level.

From an empirical point of view, the geography of knowledge, the geography of innovation and the geography of productivity and economic growth can be overlapping in space or not, according to the availability at the local level of specific enabling mechanisms that allow to translate new knowledge into commercially viable innovations and efficiency gains.

Firstly, factors that enhance the creation and implementation of new knowledge can be quite different from the factors which stimulate innovation and regions may exhibit larger endowments either of the former or of the latter.

Secondly, locally created knowledge does not automatically nor necessarily turn into local innovation, or, conversely, local innovation does not inevitably come out from locally produced knowledge. In many cases, the link between basic knowledge and innovation is not very manifest and several regions innovate on the basis of external knowledge, acquired through networking with leading regions, and of specific know-how in local application sectors. The history of technology and innovation is rich of similar examples; the fax machine, first developed in Germany, was turned into a worldwide successful product by Japanese companies. Similarly, the anti-lock brake systems (ABS) was invented by US car makers but became prominent primarily due to German automotive suppliers (Licht, 2009). More in general, there might be regions with weak internal knowledge creation capacity but able to leverage upon external knowledge sources and to develop innovation so to achieve higher economic growth rates. In short, regions can show different advantages and specialization in different phases of the innovation process.

A simple and somehow sketchy taxonomy can help to better capture these different attitudes towards knowledge and innovation and modes of integrating them across regions. Regions, in

fact, can be classified according to their positioning in terms of knowledge and innovation activities with respect to the European average, as displayed in Figure 1 below. Accordingly, one can identify regions with a greater than EU average knowledge and innovation intensity. These type of regions can be defined as *knowledge-based innovative regions*. Differently, there can be regions where a greater knowledge intensity than the European average does not match a larger innovation outcome than the European average, meaning that the locally produced knowledge is not fully exploited at the local level to achieve higher innovative performances and there can be some knowledge leakages or inefficiencies in the use of the locally created knowledge. Accordingly, these regions can be defined as *knowledge donors regions*. Differently, there can be regions able to achieve greater innovative performances than the European average although their local knowledge endowment is below the European average. These regions are therefore very successful and efficient in the use of local knowledge and in accessing external knowledge sources to achieve greater than the average innovative performances. Accordingly, these regions can be defined as *external-knowledge based innovative regions*. Lastly, there can be regions with lower knowledge and innovation propensity than the European average in which the locally available knowledge base can be sufficient for the limited innovative outputs or, possibly, innovation occur through an imitative process of innovations developed elsewhere. These regions can be, accordingly, defined as *imitative innovative regions*.

This simple dichotomy can provide an useful conceptual framework to read innovation processes in space by emphasizing the different propensity towards knowledge and innovation across regions and, more importantly, the *different modes of mixing and performing them*.

[Insert Figure 1 about here]

2.3. Testable assumptions

Building on the conceptual (and empirical) distinction between knowledge and innovation, the ultimate goal of this paper is to assess their impact on regional growth and how their different impacts vary across space.

In particular, following the literature tradition shortly reviewed above, the paper aims, firstly, at confirming the importance of knowledge inputs (namely, the share of R&D expenditures on GDP) as a driver of regional growth. Consistently with previous research, the first testable assumption is that *knowledge has a positive and significant effect on regional growth*.

Next, by distinguishing innovation from knowledge, the paper aims at assessing the impact of the former on regional growth. Similarly, the second testable assumption is that *innovation has a positive and significant effect on regional growth*.

Contrary to general beliefs, we expect that knowledge and innovation do not necessarily overlap at the local level; accordingly, their effects are expected to be neither equivalent nor to substitute one another. The third hypothesis, then, posits that *knowledge and innovation do not equate and have statistically different effects on regional growth*.

Lastly, as discussed in the previous section, regions can be differently positioned in terms of knowledge creation potential and innovation creation potential and, consequently, can show different advantages in different stages of the innovation process. The existing literature, however, has so far stressed only that higher than average knowledge endowments are chief for higher than average growth potentials due to a higher efficiency in exploiting knowledge. Framing this statement with reference to the typology previously introduced, the existing literature has firstly equated knowledge-based innovative regions and knowledge donors regions, and, secondly, it has consistently shown their superior efficiency in using knowledge for growth with respect to external-knowledge based regions and imitative innovative regions. Whereas the link between knowledge endowment and regional growth is barely disputable, this approach overlooks the fact that regions can be highly innovative albeit lacking strong local knowledge sources. The fourth hypothesis, then, posits that *the growth benefits accruing from innovation do not necessarily match the strength of the formal local knowledge basis*. In particular, with reference to the typology previously introduced, external-knowledge based innovative regions are expected to display a similar elasticity of economic growth rate to innovation to knowledge donors regions and knowledge-based regions.

To empirically support these conjectures, we firstly present some descriptive evidence on European regions and classify them according to their knowledge and innovation potential

(section 3) and we next test them in a regional growth econometric regression framework (sections 4 and 5).

3. KNOWLEDGE AND INNOVATION TRENDS IN EUROPEAN REGIONS: SOME DESCRIPTIVE EVIDENCE

To capture the knowledge and innovation propensity of European regions, we rely upon two crucial indicators. As to the former, we measure it as the share of R&D expenditures (both private and public) on GDP. As to the latter, innovation data have been compiled by the authors on the basis of data from the Community Innovation Survey (CIS) EUROSTAT database. In particular, these are based on national CIS4 wave figures (covering the 2002-2004 period), next developed at the NUTS2 level (for an in-depth explanation of the estimation strategy, see Capello, Caragliu and Lenzi, 2012), and capture the share of firms introducing product and/or process innovations in a region.

The Lisbon Agenda, reinforced by the Europe2020 Strategy, has declared the importance of research and innovation to guarantee a competitive and smart growth in Europe and has set a specific target on R&D expenditures that should be raised up to 3% of GDP. As of 2007, R&D spending on GDP in Europe showed a strong variation across regions, ranging from values lower than 0.5% to values more than 6% (Map 1). A very small number of regions (i.e. 32 representing 12% of NUTS2 European regions) in Europe achieved (and overcome) the 3% R&D expenditures on GDP target, witnessing that this is still an ambitious aim. Also, its spatial distribution looks strongly concentrated: more R&D intensive regions are located in Scandinavian countries, southern UK and central Europe, with the exception of the French region of Midi-Pyrénées. Eight European countries attract the most R&D intensive regions, namely Austria, Belgium, Germany, Denmark, Finland, France, The Netherlands, Sweden and the UK. Importantly, a very high number of regions belongs to the lowest class, with R&D on GDP lower than 0.5%. Last but not least, there is a clear East-West dichotomy; Eastern regions in fact show a much more limited capacity of R&D spending than Western countries. By contrast, the map displaying the share of firms with product and/or process innovations (Map 2) looks more scattered and innovation patterns more pervasive than R&D expenditures

on GDP. However, product and/or process innovation still displays remarkable levels of concentration, with the bulk of innovative activities taking place in the strongest portion of Europe (Germany, the UK and Ireland, Scandinavian countries) with a few but relevant exceptions represented by some capital or metropolitan regions and single-region countries outside the core (Madrid, Lisbon, Ile-de-France, Lombardy, Athens, Estonia, and Cyprus). Importantly, the comparison between the two maps (i.e. Maps 1 and 2) suggests that the ranking of R&D expenditures on GDP and ranking of the share of firms with product and/or process innovation do not always go hand in hand. Although the correlation coefficient between R&D and innovation is slightly above 0,5 (as shown in the correlation matrix in Annex 1), and statistically significant at conventional levels, there are several regions with higher than European average innovation performance but lower than European average R&D expenditures or the other way round. In fact, by applying the taxonomy developed in section 2.2., we can classify European regions in four groups, according to their knowledge and innovation performance with respect to the European average, as displayed in Map 3. Interestingly, 25% of regions (i.e. 66 out of 262) can be classified as *knowledge-based innovative regions* showing both knowledge and innovation propensity higher than the European average. Somehow counter intuitively, almost 20% of regions (51 out 262) show a greater innovative profile than the average, which however does not match a higher than average knowledge profile. These regions can be accordingly classified as *external knowledge-based innovative regions*. Only a minor group (11% of regions, namely 30 out of 262) shows a knowledge propensity greater than the average but an innovation propensity lower than the average and are therefore classified as *knowledge donors regions*. Lastly, the largest group of regions (almost 44% of them, i.e. 115 out of 262) are *imitative innovative regions*, with both knowledge and innovation intensity below the EU average. The size of this last group confirms once again the embryonic stage of development of the so-called 'knowledge-based' economy in Europe.

[Insert Maps 1-3 about here]

Table 1 also shows that the four groups statistically and significantly differ in their average knowledge and innovation behaviors, as confirmed by the significance level of the ANOVA p-value for the R&D and innovation variables. More relevantly, these groups statistically and significantly differ in their average growth patterns. Quiet surprisingly, a greater knowledge intensity does not always match a larger growth potential as the cases of *external knowledge-based innovative regions* and *imitative innovative regions* show.

Additionally, *external knowledge-based innovative regions* seem able to achieve similar economic growth rates to *knowledge-based regions* with comparable innovation propensity but with a far lower knowledge propensity (the R&D propensity in the former is about 1/3 of the latter). In short, only some regions show a pattern of innovation that goes from *R&D to innovation* and a patterns of growth that goes from *R&D to GDP*.

This somehow striking empirical evidence not only questions the simplistic view that knowledge equates innovation and knowledge equates growth but also suggests that there is a larger heterogeneity across regions in the modes in which knowledge and innovation activities are performed and mixed and how efficiently they are used to achieve higher economic growth rates, as we are going to show in the next sections.

[Insert Table 1 about here]

4. THE MODEL SPECIFICATION: SEPARATING KNOWLEDGE FROM INNOVATION

The different strands of literature presented in section 2.1 rely on two main groups of factors for the explanation of regional growth: (local or external) knowledge inputs, and territorially embedded elements that facilitate the creation of innovation.

Starting from these two strands of theories, in order to empirically assess the impact of knowledge and innovation on economic growth and to unravel the heterogeneity of these relationships across European regions, we estimate a regional growth model that combines knowledge inputs - such as R&D expenditures and knowledge embedded into human capital - with socio-economic local factors that enable knowledge and innovation to take place, while controlling for the region's economic dynamics and development stage. As a novelty of our

approach, we also insert innovation as a separate variable from R&D expenditure, expecting an additional explanatory power of the innovation variable with respect to pure knowledge.²

The model to be estimated, therefore, is as follows:

$$\Delta GDP_r = \alpha_0 + \beta_1 \Delta Emp_r + \beta_2 EU17_r + \beta_3 SocialCapital_r + \beta_4 Infrastructure_r + \beta_5 FDI_r + \beta_6 StructuralFunds_r + \beta_7 FunctionalSpecialization_r + \beta_8 AgglomerationEconomies_r + \beta_9 Capabilities_r + \beta_{10} R \& D_r + \beta_{11} Innovation_r + \varepsilon_r$$

where ΔGDP_r is the regional annual GDP growth rates of regions, explained by three groups of variables. The first group is made of three variables capturing the intensity of:

- formal, basic knowledge, measured through R&D expenditures on GDP;
- informal knowledge embedded into human capital, measured through capabilities;
- innovation to directly account for the impact of new products and/or processes introduced in the market.

The second group of variables included describes knowledge and innovation territorial enabling factors, namely:

- social capital, as a measure of trust, cooperation capabilities and collective actions within a region. Higher cooperative attitudes should promote knowledge and innovation circulation and socialization thus enhancing local growth potentials;
- infrastructural endowment, as a measure of accessibility to the area. The higher the accessibility of an area, the higher the probability for the area to acquire new knowledge, new ideas, new information, and therefore the higher the probability of growth;
- functional specialization of a region, as a measure of presence of innovation prone activities. High-level functions are more inclined to stimulate knowledge and innovation than low level activities, and therefore growth;
- agglomeration economies, meant to capture the synergetic effects, complementarities, collective learning effects and local knowledge spillovers arising in dense agglomerations of economic activities, which are at the basis of knowledge and innovation creation, and local growth.

Lastly, the third group of variables controls for a region's economic dynamism as well as for the nature and pattern of development, namely:

² The empirical results will demonstrate that multi-collinearity between knowledge and innovation is very limited, and that the introduction of the innovation variable adds explanatory power to the regional growth model.

- employment growth rate in manufacturing to directly account for the dynamics of the regional labour market;
- foreign direct investments (FDI) penetration rate as a measure of economic attractiveness, which is expected to positively affect GDP growth rate, and is supposed to generate a push effect on the local economy;
- EU12 to control for the distinctive growth patterns characterizing Eastern and Western European regions;
- structural funds to control for the likely positive impact of public expenditures aimed at stimulating growth in developing regions.

Table 2 reports the description of the variables and their sources and Table 3 their descriptive statistics. The correlation matrix is available in Annex 1.

[Insert Tables 2 and 3 about here]

To capture the heterogeneity of knowledge and innovation propensity across regions, we next interact the R&D and innovation variables with four dummies each aimed at capturing respectively knowledge-based innovative regions, external knowledge-based innovative regions, knowledge donors regions, imitative innovative regions as defined in section 2.2. and empirically identified in section 3.

The enlarged model to be estimated therefore becomes as follows:

$$\Delta GDP_r = \alpha_0 + \beta_1 \Delta Emp_r + \beta_2 EU12_r + \beta_3 SocialCapab_r + \beta_4 Infrastructure_r + \beta_5 FDI_r + \beta_6 StructuralFunds_r + \beta_7 FunctionsSpecialization_r + \beta_8 Agglomerations_r + \beta_9 Capabilities_r + \beta_{10} D_r * R \& D_r + \beta_{11} D_r * Innovation_r + \epsilon_r$$

where D represents the dummy variable for the different groups of regions presented in Figure 1.

Lastly, as we are aware of possible economic interactions across regions, we control for spatial dependency with appropriate econometric techniques (namely spatial lag and spatial error models, indicated as SAR and SEM respectively in Table 4 and Annex 2) when statistically relevant. Moreover, we control for endogeneity that might occur, by running 2SLS instrumental variable regressions that could boost our confidence in causal sequence. Variables are

instrumented with lagged predictors as it is customary in the growth literature in absence of adequate instruments correlated to the explanatory variables but indirectly correlated to the dependent variable (Temple, 1999). Importantly, the Durbin – Wu – Hausman test does not allow to reject the null hypothesis that regressors are exogenous suggesting that OLS estimates are more efficient than 2SLS estimates. Still, results remain robust to this control, as described in Annex 2.

5. EMPIRICAL RESULTS

Table 4 reports the estimates of our baseline and enlarged models. The results for the variables capturing knowledge and innovation territorial enabling factors and the variables capturing regions economic dynamism as well as for the nature and pattern of development are overall statistically significant and with the expected sign. More interestingly, our results indicate that both knowledge and innovation do play a crucial role in explaining growth patterns in European regions, thus supporting the efforts to enlarge and strengthen the European knowledge base proposed in the Lisbon agenda and re-launched by the EU2020 strategy. However, our findings also suggest some caution in the interpretation of this result and highlight a greater heterogeneity across European regions.

In what follows, we comment our results in relation to the hypotheses formulated in section 2.3 in turn.

First assumption

Increasing the average R&D spending at the EU level is certainly beneficial to achieve superior GDP growth rates, also after controlling for spatial interdependencies across regions (Table 4, Models 1 and 2). By computing GDP growth rate elasticity to R&D³, on average, 1 percentage point increase in R&D spending yields a 0.12% increase in GDP growth rate (Table 6). This result therefore is largely consistent with previous findings in the literature and supports our first hypothesis that knowledge is a crucial ingredient for faster regional growth.

³ The regional elasticity of GDP growth rate to R&D ($E_{GDP_gr,R\&D}$) is obtained by multiplying the R&D estimated coefficient ($\beta_{R\&D,EU}$) times the ratio between the EU average R&D level and the EU average GDP growth rate, as the formula below summarizes: $E_{GDP_gr,R\&D} = \beta_{R\&D,EU} * (R\&D_{EU}/GDP_gr_{EU})$

[Insert Table 4 about here]

However, this mechanism takes place with different intensity across different groups of regions (Table 4, Models 3 and 4). To better understand the spatial heterogeneity in GDP growth rate response to R&D spending, we firstly replaced the R&D variable by interacting it with the four dummies each aimed at capturing respectively knowledge-based innovative regions, external knowledge-based innovative regions, knowledge donors regions, imitative innovative regions. Simple coefficients, however, do not allow to assess the magnitude of the impact of R&D in the four groups of regions, and, accordingly, we next computed the relative elasticity values (Figure 2). The arrow in Figure 2 shows the increasing elasticity among the four groups: from imitative innovative regions to external knowledge-based innovative regions, to knowledge-based innovative regions and lastly to knowledge donor regions.

[Insert Figure 2 about here]

Not surprisingly, knowledge donors and knowledge-based innovative regions are better positioned to reap the growth benefits stemming from extra investments in R&D being their GDP growth rate elasticity to R&D greater than 0.3%. External knowledge-based innovative regions follow with an elasticity value of 0.25 and, lastly, imitative innovative regions conclude this ranking with an elasticity value of 0.15. Therefore, these results support the idea that further investments in new formal knowledge creation should be concentrated in those regions with greater R&D spending that, likely, are able to take the greatest advantages from it (Figure 2).

Second assumption

Similarly, increasing innovation at the EU level has a positive effect on GDP growth rates, also after controlling for spatial interdependencies across regions (Table 4, Models 5 and 6), thus

supporting our hypothesis 2. By computing GDP growth rate elasticity to innovation⁴, on average, 1 percentage point increase in innovation yields a 0.38% increase in GDP growth rate, a three times greater elasticity than that of R&D.

Third assumption

Jointly introducing R&D and innovation as explanatory variables (Table 4, Models 7 and 8) shows that they both retain their significance and explanatory power. Given their relatively high correlation (more than 0.5), both R&D and innovation coefficients lower (and so their elasticity). However, especially R&D is penalized as the magnitude of its coefficient almost halves and its significance shrinks from 1% to 10%, whereas innovation preserves its significance albeit with a smaller reduction of the magnitude of its coefficient. This suggests that innovation is likely to bear a larger explanatory power than knowledge, possibly because to its larger variance and spatial dispersion.

Importantly, Chi2 tests (implemented on Model 8) do not allow to accept the null hypothesis that the effect of innovation and R&D are jointly equal to zero (Chi2=19.54, $p < 0.001$) and that their coefficient are equal (Chi2= 2.32, $p < 0.10$). This stresses once more the importance of both variables in a regional growth model and supports our third hypothesis that knowledge and innovation have considerable effects on their own. As highlighted by the descriptive analysis (maps 1 to 3 and table 2), they do not necessarily overlap in space and their effects are not equivalent nor substitute one another.

Fourth assumption

Similarly to R&D, to better understand the spatial heterogeneity in GDP growth rate reaction to innovation, we replaced the innovation variable by interacting it with the four dummies each aimed at capturing respectively knowledge-based innovative regions, external knowledge-based innovative regions, knowledge donors regions, imitative innovative regions and we next

⁴ The regional elasticity of GDP growth rate to innovation ($E_{GDP_gr, Innovation}$) is obtained by multiplying the innovation estimated coefficient ($\beta_{Innovation, EU}$) times the ratio between the EU average innovation level and the EU average GDP growth rate, as the formula below summarizes: $E_{GDP_gr, Innovation} = \beta_{Innovation, EU} * (Innovation_{EU} / GDP_gr_{EU})$

computed the relative elasticity values to assess the magnitude of the impact of innovation in the four groups of regions.

The effects of innovation on GDP growth rate look of larger magnitude and spatially more distributed than those stemming from formal knowledge (Figure 3). Interestingly, external knowledge-based innovative regions seem to benefit the most from increases in innovation, almost comparably to knowledge-based innovative regions and knowledge donors regions. In fact, the direction of the arrow in Figure 3 - showing the increasing elasticity among the four groups - differs from that of Figure 2.

[Insert Figure 3 about here]

Similarly to R&D, however, innovation as well appears to show some sort of scale advantages and to require a certain critical mass to unfold its full potential. It seems likely that imitative innovative regions have not reached yet a critical mass of innovation to be able to turn its benefits into higher growth rate. All in all, these findings are highly consistent with the descriptive analysis presented in section 3 and lend support to our fourth hypothesis. In fact, the growth benefits accruing from innovation do not necessarily match the strength of the formal local knowledge basis and regions innovating in absence of a strong local knowledge base (e.g. external knowledge-based innovative regions) can be as successful as more knowledge intensive regions (e.g. knowledge-based innovative regions and knowledge donors regions) in turning innovation into higher growth rate. As a consequence, knowledge intensity *per se* is not an universal predictor of higher economic growth for all types of regions but, rather, this seems to be the case for a relatively smaller group of regions. These results, therefore, strongly enter the current policy debate on how to make Europe transiting and becoming a knowledge-based economy and growing smartly, as discussed in the next section.

6. Conclusions: policy implications

Interesting policy implications can be drawn from this empirical analysis. If the results do not deny the importance of R&D activities for regional growth, and therefore the right focus put

forward by the Europe 2020 on a “smart growth” based on knowledge and innovation, they call for a particular attention when the Europe 2020 goal is translated into a regional setting. Our results summarised in Figures 3 and 4 suggest that a “one-size-fits-all” policy of achieving a target of 3% of R&D over GDP is neither convincing nor efficient when it is applied at regional level. The elasticity of GDP growth to knowledge is very different in the different types of regions, and its difference at spatial level is much wider than the elasticity of GDP to innovation. Moreover, the group that exploits R&D the most is not the knowledge-based innovative regions, but the knowledge donor regions. In economic terms, this means that decreasing returns exist in the local exploitation of R&D capacity; in policy terms, this suggests that supporting R&D spending in areas that are able to feed also other regions with their local knowledge is not a wrong policy.

Figure 4 tells also another story: elasticity of GDP growth to innovation is much higher and not so strongly differentiated among groups of regions as in the case of GDP growth elasticity to R&D. Also the imitative innovative region registers a high elasticity of GDP growth to innovation, signalling the importance of an imitative innovation process in early stages of regional development. Moreover, knowledge spillovers in some regions like the external knowledge-based innovative regions play a major role, giving these areas the possibility to register the highest GDP growth elasticity to innovation.

[Insert Figure 4 here]

In normative terms these results suggest that a single overall strategy is likely to be unfit to provide the right stimuli and incentives in the different contexts; it is instead necessary to develop ad-hoc, thematically/regionally focused innovation policies.

In a recent work, smart innovation policies have been suggested, defined as those policies able to increase the innovation capability of an area and to make local expertise in knowledge and innovation more efficient, acting on the local specificities and on the characteristics of already established innovation modes in each region. The two key concepts of “embeddedness” and “connectivity” - put forward in the recent debate on smart specialization (McCann, Ortega-

Argilés, 2011) – are a starting point: policies have to be embedded in the local context, in local assets (“embeddedness”), and have to guarantee the achievement of external knowledge through strong and virtuous linkages with the external world (“connectivity”). Smart innovation policies go a step forward, since they adapt the two concepts of “embeddedness” and “connectivity” to the specificities of each mode of innovation. Smart innovation policies look for ad-hoc interventions aimed at reinforcing regional innovation process and at enhancing the virtuous aspects and efficiency of each innovation mode (Camagni and Capello, 2012).

Targeted innovation policies on each mode of innovation would certainly be the right policy to implement the “smart specialization policies” in the field of innovation - called for by the EU in its official document Regional Policy Contributing to Smart Growth in Europe (EU, 2010) - and to achieve a “smart Europe” in the years to come.

References

- Acs Z., Audretsch D. and Feldman M. (1994), “R&D Spillovers and Recipient Firm Size”, *Review of Economics and Statistics*, vol. 76, n. 2, pp. 336-340
- Anselin L., Varga A. and Acs Z. (2000), “Geographic and Sectoral Characteristics of Academic Knowledge Externalities”, *Papers in Regional Science*, vol. 79, n. 4, pp. 435-443
- Audretsch D. and Feldman M. (1996), “R&D Spillovers and the Geography of Innovation and Production”, *American Economic Review*, vol. 86, n. 3, pp. 630-640
- Balconi M., Brusoni S. and Orsenigo L. (2010), “In Defense of a Linear Model”, *Research Policy*, vol. 39, pp. 1-13
- Borts G.H. and Stein J.L. (1962), “Regional Growth and Maturity in the United States: a Study of Regional Structural Change”, *Schweizerische Zeitschrift für Volkswirtschaft und Statistik*, vol. 98, pp. 290-321
- Boschma R. (2005), “Proximity and Innovation. A Critical Survey”, *Regional Studies*, vol. 39, n. 1, pp. 61-74
- Camagni, R. (1991), “Technological Change, Uncertainty and Innovation Networks: Towards Dynamic Theory of Economic Space”, in Camagni R. (ed.), *Innovation networks: spatial perspectives*, Belhaven-Pinter, London, pp. 121-144
- Camagni R. and Capello R. (2012), “Regional Innovation Strategies and the EU Regional Policy Reform: Towards Smart Innovation Policies”, Paper to be presented at the 52nd ERSA Congress, Bratislava 21-25 August
- Capello R. (1994), *Spatial Economic Analysis of Telecommunications Network Externalities*, Ashgate, Aldershot
- Capello R. (1999), “Spatial Transfer of Knowledge in High-technology Milieux: Learning vs. Collective Learning Processes”, *Regional Studies*, vol. 33, n. 4, pp. 353-365
- Capello R. (2009), “Spatial Spillovers and Regional Growth: A Cognitive Approach”, *European Planning Studies*, vol. 17, n. 5, pp. 639-658
- Capello R. (2011), “Territorial Patterns of Innovation”, paper presented at the Tinbergen Institute Seminar, held in May 2011 in Amsterdam, and submitted to International Journal of Urban and Regional Research

- Capello R., Caragliu A., Lenzi C. (2012), "Is innovation in cities a matter of knowledge intensive business services? An empirical investigation", *Innovation: The European Journal of Social Science Research*, 25(2): 147-170
- Cappellin R. (2003), "Territorial Knowledge Management: Towards a Metrics of the Cognitive Dimension of Agglomeration Economies", *International Journal of Technology Management*, vol. 26, n. 2-4, pp. 303-325
- Cooke Ph., Asheim B., Boschma R., Martin R., Schwartz D. and Tödtling F. (eds.) (2011), *Handbook of Regional Innovation and Growth*, Edward Elgar, Cheltenham
- EU (2010), *Regional Policy Contributing to Smart Growth in Europe*, COM(2010)553, Brussels
- Hägerstrand T. (1967), *Innovation Diffusion as a Spatial Process*, University of Chicago Press, Chicago
- Jaffe A.B. (1989), "Real effects of academic research", *American Economic Review*, 79(5), 957-970.
- Keeble D. and Wilkinson F. (1999), "Collective Learning and Knowledge Development in the Evolution of Regional Clusters of High-Technology SMS in Europe", *Regional Studies*, vol. 33, n. 4, pp. 295-303
- Keeble D. and Wilkinson F. (2000), *High Technology Clusters, Networking and Collective Learning in Europe*, Aldershot, Ashgate
- Lundvall B.A. and Johnson B. (1994), "The Learning Economy", *Journal of Industry Studies*, vol. 1, n. 1, pp. 23-42
- MacDonald S. (1987), "British Science Parks: Reflections on the Politics of High Technology", *R&D Management*, vol. 17, n. 1, pp. 25-37
- Malecki E. (1980), "Corporate Organisation of R&D and the Location of Technological Activities", *Regional Studies*, vol. 14, n. 3, pp. 219-234
- Massey D., Quintas P. and Wield D. (1992), *High Tech Fantasies: Science Parks in Society, Science and Space*, Routledge, London
- McCann P. and Ortega-Argilés R. (2011), "Smart specialisation, regional growth and applications to EU cohesion policy", Document de treball de l'IEB 2011/14, Institut d'Economia de Barcelona
- Monk C.S.P., Porter R.B., Quintas P., Storey D. and Wynarczyk P. (1988), *Science Parks and the Growth of High Technology Firms*, Croom Helm, London
- Perrin J.-C. (1995), "Apprentissage Collectif, Territoire et Milieu Innovateur: un Nouveau Paradigme pour le Développement", in Ferrão J. (ed.), *Políticas de Inovação e Desenvolvimento Regional et Local, Edição do Instituto de Ciências Sociais de Universidade de Lisboa*, republished in Camagni R. and Maillat D. (eds.) (2006), *Milieux Innovateurs*, Economica-Anthropos, Paris, pp. 99-128
- Rallet A. and Torre A. (eds.) (1995), *Économie Industrielle et Économie Spatiale*, Economica, Paris, pp. 273-293
- Saxenian A. (1994), *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*, Harvard University Press
- Solow R. (1957), "Technical Change and the Aggregate Production Function", *Review of Economics and Statistics*, vol. 39, n. 3, pp. 312-320
- Storey D.J. and B.S. Tether (1998) "Public Policy Measures to Support New Technology-Based Firms in the European Union", *Research Policy*, vol. 26, n. 9, pp. 1037-1057
- Temple J. (1999), "The new growth evidence", *Journal of Economic Literature*, 37, 112-156.
- Trippel M. (2010), "Developing Cross-Border Regional Innovation Systems: Key Factors and Challenges", *Tijdschrift voor Economische en Sociale Geographie (TESG)*, vol. 101, n. 2, pp. 150-160

Annex 1. Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11
GDP growth rate 2005-2007	1	--										
Employment growth rate in manufacturing (2002-2004)	2	0,196*	--									
EU12	3	0,515*	0,186*	--								
Trust	4	-0,107	-0,072	-0,374*	--							
Accessibility (infrastructure endowment)	5	-0,121*	-0,173*	-0,132*	0,089	--						
FDI	6	0,073	-0,183*	-0,022	0,024	0,354*	--					
Structural funds expenditures	7	-0,491*	-0,136*	-0,980*	0,311*	0,078	-0,018	--				
% of blue collar functions	8	0,149*	0,322*	0,412*	-0,349*	-0,256*	-0,114	-0,337*	--			
Megas	9	0,166*	-0,034	0,085	0,055	0,271*	0,223*	-0,118	-0,144*	--		
Capabilities	10	0,128*	0,099	-0,060	-0,284*	-0,139*	-0,019	0,177*	0,166*	-0,120	--	
R&D	11	-0,073	-0,233*	-0,351*	0,347*	0,203*	0,135*	0,260*	-0,450*	0,173*	-0,336*	--
Innovation	12	-0,099	-0,143*	-0,447*	0,311*	0,251*	0,123*	0,352*	-0,286*	0,108	-0,306*	0,534*

** p < 0.05

Annex 2. Robustness check

To control for potential sources of endogeneity, we re-run our baseline and enlarged models by means of 2SLS instrumental variable techniques. Endogenous variables have been instrumented by using predictors lagged values, when available. Unfortunately, due to lack of data, we could pursue this strategy only for the following independent variables: Employment growth rate in manufacturing, Trust, FDI, Share of blue collar functions, Capabilities and R&D, whereas this was not possible for the Accessibility, Structural funds expenditures and Innovation variables.

Table A1 reports the estimates of the second stage. Results are qualitatively unchanged, especially for the R&D and innovation variables, and lend further support to our hypotheses. Interestingly, the Durbin- Wu – Hausman test does not allow to reject the null hypothesis that regressors are exogenous, but in model 4, suggesting that endogeneity is not a major concern in our estimates of Table 4, and OLS estimates are more efficient than 2SLS.

Also, we expanded the IV-models to control for potential sources of regional inter-dependencies. Table A2 reports the estimates of the SEM and SAR models obtained by implementing the 2SLS estimator. Again, results are qualitatively unchanged and support further our hypotheses.

Lastly, we computed the elasticity of GDP growth to R&D and innovation both at the EU level and for the four groups of regions as in Figures 2 and 3. Elasticity values are computed on the basis of the SEM coefficients reported in Table A.2, namely in models 1, 3, 6 and 8, that look more conservative especially in terms of the innovation variable. Results are qualitatively unchanged.

Table A.1. Determinants of GDP growth rate (2005-2007) – 2SLS estimates

Dependent variable: GDP growth rate 2005-2007	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS
Employment growth rate in manufacturing (2002-2004)	0.027 (0.292)	0.108 (0.329)	0.030 (0.275)	-0.013 (0.276)	0.052 (0.279)
EU12	0.059 (0.045)	0.056 (0.053)	0.068 (0.044)	0.067 (0.045)	0.067 (0.042)
Trust	0.028** (0.013)	0.040** (0.016)	0.033*** (0.011)	0.024** (0.012)	0.034*** (0.011)
Accessibility (infrastructure endowment)	-0.005** (0.003)	-0.006** (0.003)	-0.006** (0.003)	-0.005* (0.003)	-0.006** (0.003)
FDI	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)	0.000 (0.000)
Structural funds expenditures	0.002 (0.003)	0.001 (0.004)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)
% of blue collar professions	-0.010 (0.030)	-0.030 (0.034)	-0.018 (0.029)	-0.013 (0.029)	-0.018 (0.028)
Capabilities	0.020 (0.034)	0.042 (0.033)	0.037 (0.029)	0.017 (0.031)	0.038 (0.029)
Megas	0.005 (0.003)	0.004 (0.002)	0.004 (0.003)	0.004 (0.003)	0.003 (0.002)
R&D	0.285* (0.163)		0.185 (0.177)		0.306 (0.187)
Innovation		0.044*** (0.009)	0.039*** (0.011)		
R&D*KBIR				0.354** (0.177)	
R&D*EKBIR				0.862** (0.428)	
R&D*KDR				0.350 (0.350)	
R&D*IIR				0.679 (0.661)	
Innovation					0.050*** (0.016)
Innovation*KBIR					0.056*** (0.016)
Innovation*EKBIR					0.066** (0.028)
Innovation*KDR					0.080*** (0.027)
Constant	-0.009 (0.034)	-0.017 (0.044)	-0.030 (0.035)	-0.015 (0.033)	-0.038 (0.034)
Lagrange multiplier (spatial lag)	22.018***	4.803**	5.286**	19.505***	5.325***
Robust Lagrange multiplier (spatial error)	9.024***	0.726	0.918	7.177***	0.805
Lagrange multiplier (spatial lag)	13.299***	5.586**	5.748**	12.858***	6.130***
Robust Lagrange multiplier (spatial lag)	0.304	1.483	1.380	0.529	1.610
R2	0.37	0.39	0.41	0.36	0.42
Durbin – Wu- Hausman Test	1.46	1.63	1.55	2.35**	1.64
p-value	0.19	0.15	0.16	0.02	0.14
Observations	262	262	262	262	262

* p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses.

Note: SEM and SAR estimates are based on a row-standardised continuous distance matrix.

Table A.2. Determinants of GDP growth rate (2005-2007) – 2SLS estimates of SEM and SAR models

Dependent variable: GDP growth rate 2005-2007	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SEM	SAR	SEM	SAR	SEM	SEM	SAR	SEM
EU12	0.048 (0.047)	0.027 (0.054)	0.048 (0.055)	0.042 (0.047)	0.063 (0.047)	0.050 (0.048)	0.041 (0.044)	0.061 (0.045)
Accessibility (infrastructure endowment)	-0.005 (0.003)	-0.004 (0.003)	-0.006* (0.003)	-0.005 (0.003)	-0.006* (0.003)	-0.005 (0.003)	-0.004 (0.003)	-0.006* (0.003)
Structural funds expenditures	0.001 (0.003)	-0.000 (0.004)	0.001 (0.004)	0.001 (0.003)	0.002 (0.003)	0.001 (0.003)	0.001 (0.003)	0.002 (0.003)
Megas	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.003 (0.003)	0.003 (0.003)
Trust - Fitted values	0.036** (0.016)	0.039** (0.017)	0.044** (0.019)	0.031** (0.014)	0.036** (0.016)	0.034** (0.017)	0.031** (0.014)	0.037** (0.016)
Employment growth rate in manufacturing (2002-2004) - Fitted values	0.119 (0.289)	0.206 (0.328)	0.158 (0.335)	0.112 (0.280)	0.068 (0.285)	0.093 (0.288)	0.139 (0.288)	0.076 (0.293)
FDI - Fitted values	0.000** (0.000)	0.000* (0.000)	0.000** (0.000)	0.000 (0.000)	0.000* (0.000)	0.000* (0.000)	0.000 (0.000)	0.000* (0.000)
% of blue collar professions - Fitted values	-0.006 (0.031)	-0.033 (0.035)	-0.026 (0.035)	-0.018 (0.030)	-0.010 (0.030)	-0.006 (0.030)	-0.018 (0.029)	-0.010 (0.030)
Capabilities - Fitted values	0.040 (0.035)	0.048 (0.035)	0.046 (0.036)	0.043 (0.032)	0.041 (0.033)	0.037 (0.034)	0.044 (0.032)	0.042 (0.032)
R&D - Fitted values	0.321** (0.152)			0.226 (0.160)	0.238 (0.164)		0.336** (0.171)	0.358** (0.172)
Innovation		0.037*** (0.010)	0.033*** (0.012)	0.031*** (0.012)	0.026** (0.013)			
R&D*KBIR - Fitted values						0.368** (0.150)		
R&D*EKBIR - Fitted values						0.627* (0.372)		
R&D*KDR - Fitted values						0.386* (0.255)		
R&D*IIR - Fitted values						0.752* (0.433)		
Innovation* KBIR							0.042*** (0.013)	0.036** (0.015)
Innovation* EKBIR							0.049*** (0.013)	0.042*** (0.015)
Innovation* KDR							0.064** (0.025)	0.049* (0.026)
Innovation*IIR							0.072*** (0.021)	0.066*** (0.022)
Constant	-0.012 (0.038)	-0.008 (0.045)	-0.013 (0.047)	-0.023 (0.038)	-0.028 (0.040)	-0.014 (0.038)	-0.032 (0.035)	-0.036 (0.037)
Lambda(SEM) / Rho (SAR)	0.683*** (0.138)	0.342** (0.147)	0.519*** (0.193)	0.346** (0.147)	0.541*** (0.189)	0.683*** (0.139)	0.353** (0.146)	0.539*** (0.188)
Squared correlation	0.33	0.40	0.37	0.39	0.37	0.34	0.40	0.38
Observations	262	262	262	262	262	262	262	262

* p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses.

Note: SEM and SAR estimates are based on a row-standardised continuous distance matrix.

Table A.3. Elasticity of GDP growth to R&D and innovation by regional typologies

Regional typologies	Elasticity of GDP growth rate to R&D	Elasticity of GDP growth rate to innovation
EU average	0,12	0,32
Knowledge-based innovative regions (KBIR)	0,30	0,52
External knowledge-based innovative regions (EKBIR)	0,16	0,54
Knowledge donors regions (KDR)	0,28	0,51
Imitative innovative regions (IIR)	0,11	0,41

FIGURES

Figure 1. A proposed taxonomy

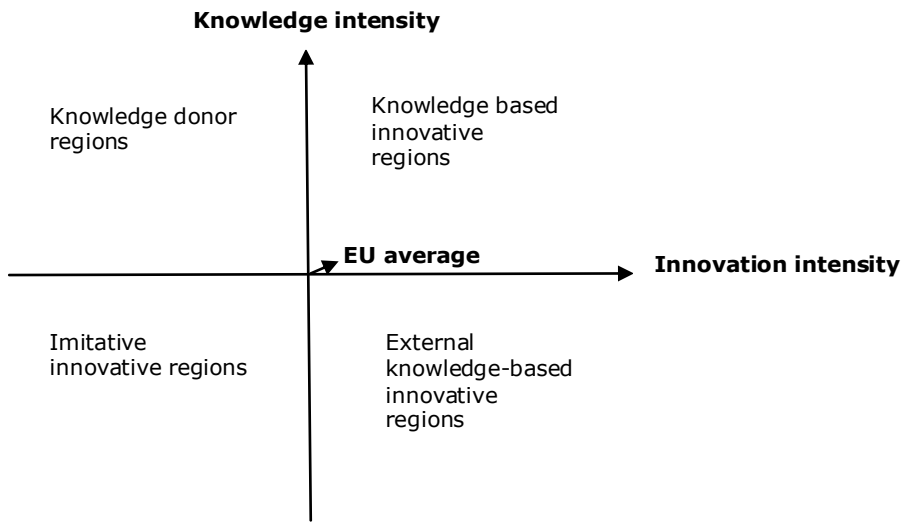
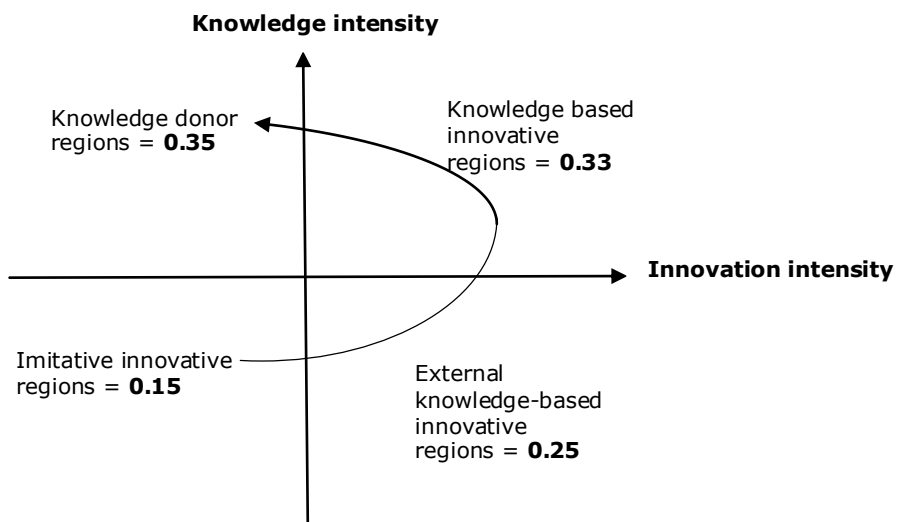
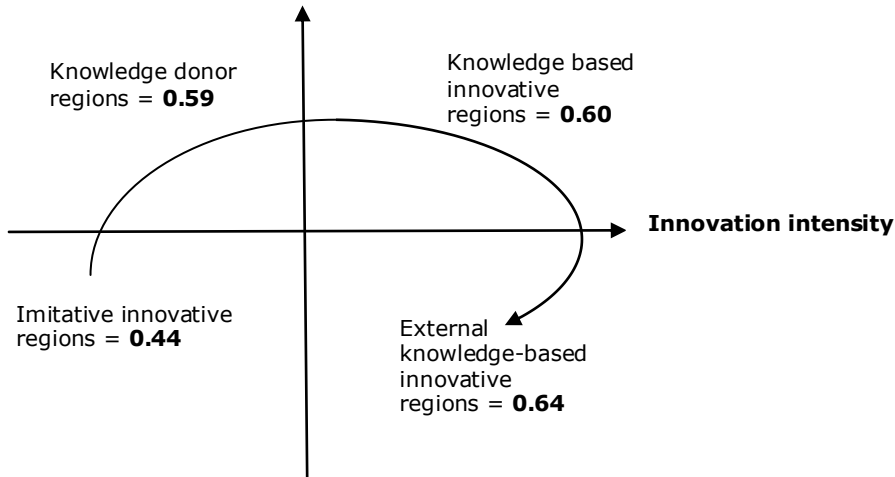


Figure 2. Elasticity of GDP growth to knowledge by groups of regions



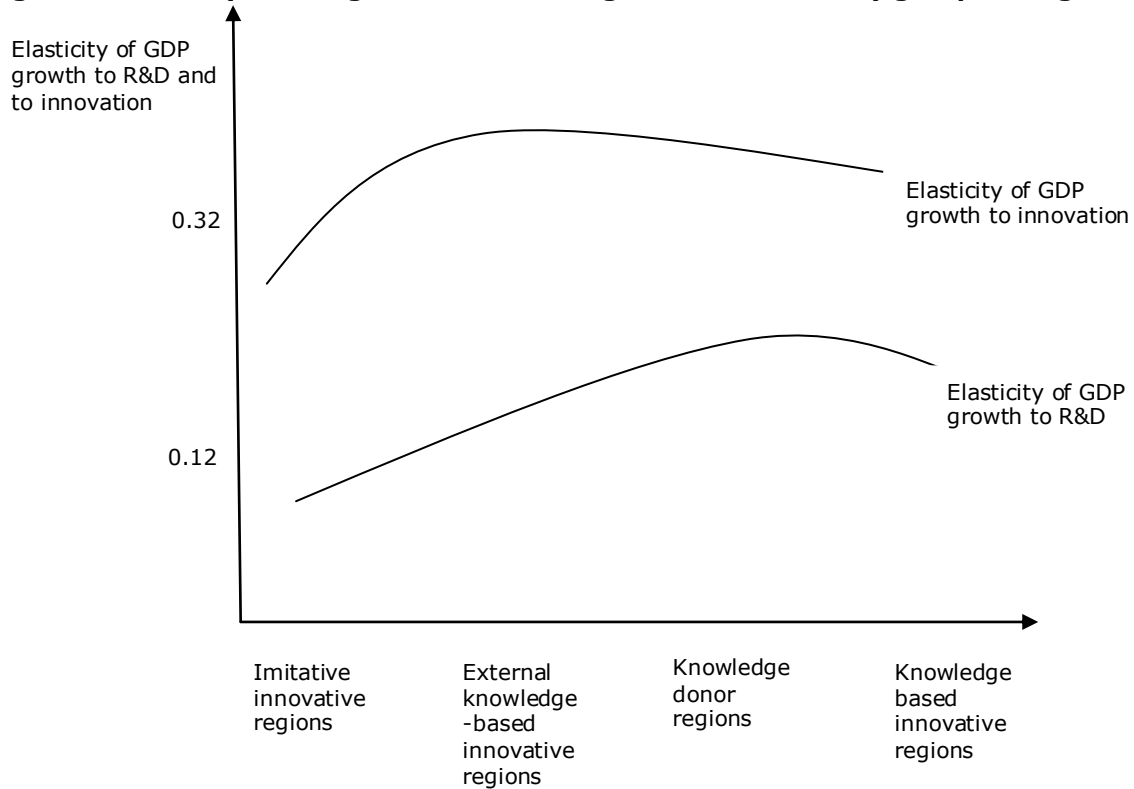
Note: elasticity values are computed according to the estimated coefficients reported in table 4, model 4.

Figure 3. Elasticity of GDP growth to innovation by groups of regions



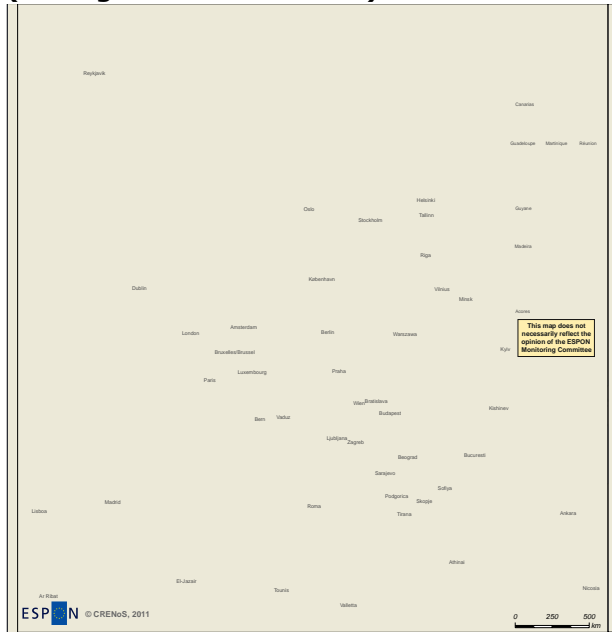
Note: elasticity values are computed according to the estimated coefficients reported in table 4, model 10.

Figure 4. Elasticity of GDP growth to knowledge and innovation by groups of regions



MAPS

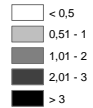
Map 1. R&D Expenditures on GDP (average value 2000-2002)



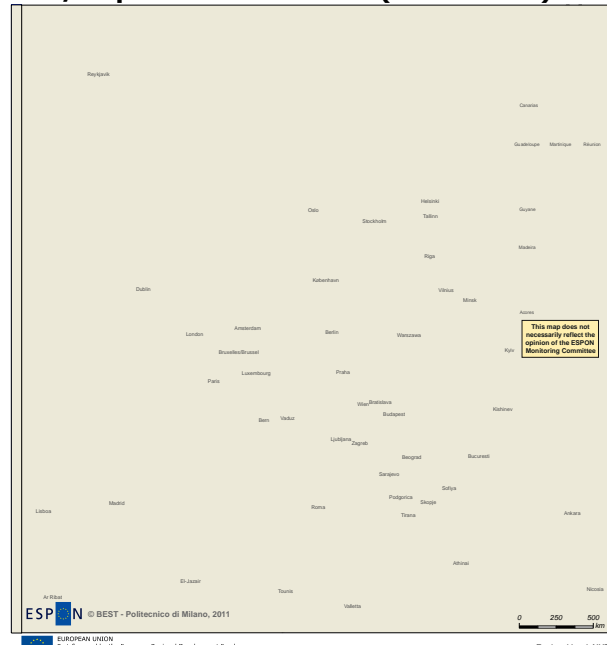
EUROPEAN UNION
Part-financed by the European Regional Development Fund
INVESTING IN YOUR FUTURE

Regional level: NUTS2
Origin of data: CRENoS
© EuroGeographics Association for administrative boundaries

Legend



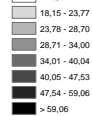
Map 2. Share of firms with product and/or process innovation (2002-2004)



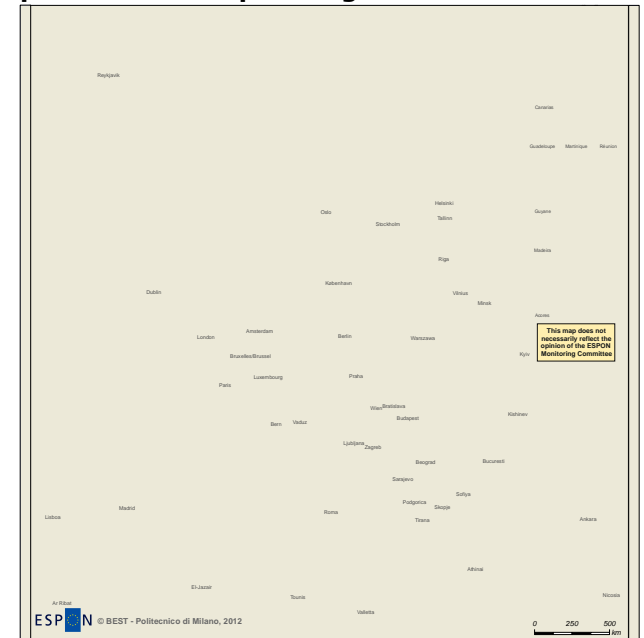
EUROPEAN UNION
Part-financed by the European Regional Development Fund
INVESTING IN YOUR FUTURE

Regional level: NUTS2
Source: EUROSTAT, own calculation, 2011
Origin of data: BEST - Politecnico di Milano, 2011
© EuroGeographics Association for administrative boundaries

Legend



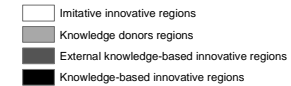
Map 3. Knowledge and innovation patterns in European regions



EUROPEAN UNION
Part-financed by the European Regional Development Fund
INVESTING IN YOUR FUTURE

Regional level: NUTS2
Source: EUROSTAT, own calculation, 2011
Origin of data: BEST - Politecnico di Milano, 2012
© EuroGeographics Association for administrative boundaries

Legend



TABLES

Table 1. Mean values by group of regions and in EU and ANOVA test statistical significance (p-value)

Variable	Knowledge-based innovative regions	External knowledge-based innovative regions	Knowledge donors regions	Imitative innovative regions	EU average	p-value
GDP growth rate 2005-2007	3,41	3,46	3,01	4,03	3,64	<0,01
R&D (average 2000-2002)	2,77	0,86	2,16	0,59	1,37	<0,01
Innovation (2002-2004)	49,02	44,20	31,14	25,11	35,54	<0,01
Number of observations	66	51	30	115	262	n.a.

Note: n.a. = not applicable.

Table 2. Variable description

Indicators	Measures	Computation	Year	Source
GDP growth	Economic growth	Annual rate of growth	2005-2007	EUROSTAT
Employment growth rate in manufacturing	Employment dynamics	Annual rate of growth	2002-2004	EUROSTAT
EU12	Bulgaria, Cyprus, Czech Republic, Hungary, Estonia, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia	Dummy variable equal to 1 if the regions is located in a EU12 country	2004	EUROSTAT
Social capital	Trust	Share of people trusting each other	2000	European Value Survey
Accessibility (infrastructure endowment)	Rail and road network length by usable land	Km of rail and road network on usable land	2000	ESPON
FDI	Foreign direct investments	Number of FDI on total population	Average value 2003-2005	FDI-Regio, Bocconi-ISLA
Structural funds expenditures	Millions (Euro) of expenditures on population	Natural logarithm	1994-1999	ESPON
Functional specialisation	% blue collars professions	Share of craft and related trades workers, plant and machine operators, and assemblers on total employment	Average value 2002-2004	European Labour Force Survey
Mega (agglomeration economies)	FUAs with the highest scores on a combined indicator of transport, population, manufacturing, knowledge, decision-making in the private sectors	Dummy variable equal to 1 if the region is classified as mega	2000	ESPON
Capabilities	Share of SMEs managers and technicians	Factor analysis on the share of managers of SMEs and technicians; factor score min-max normalized	Average value 1997-2001	European Labour Force Survey
R&D	R&D expenditures	Share of R&D expenditures on GDP	Average value 2000-2000	CRENoS database
Innovation (product and/or process)	Firms introducing a new product and/or a new process in the market	Share of firms introducing product and/or process innovations	One value for the period 2002-2004	Authors' estimation on CIS (EUROSTAT) data

Table 3. Descriptive statistics

Variable	Obs	Mean	Dev.Std.	Min	Max
GDP growth rate 2005-2007	262	3,64	2,05	-1,33	12,41
Employment growth rate in manufacturing (2002-2004)	262	-2,01	3,41	-21,32	13,41
EU12	262	0*	--	0	1
Trust	262	30,97	15,77	0	82
Accessibility (infrastructure endowment)	262	27,03	39,48	0	453,51
FDI	262	0,19	0,40	0,00	4,29
Structural funds expenditures	262	33454030	56140880	0	434866600
% of blue collar functions	262	33,3	7,1	16,33	58,73
Megas (agglomeration economies)	262	0*	--	0	1
Capabilities	262	0,40	0,16	0	1
R&D	262	1,37	1,21	0,10	6,60
Innovation	262	35,54	13,27	7,97	87,10
Knowledge-based innovative regions (KBIR)	66	0*	--	0	1
External knowledge-based innovative regions (EKBIR)	51	0*	--	0	1
Knowledge donors regions (KDR)	30	0*	--	0	1
Imitative innovative regions (IIR)	115	0*	--	0	1

*modus value.

Table 4. Determinants of regional GDP growth rate (2005-2007)

Dependent variable: GDP growth rate 2005-2007	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	SEM	OLS	SEM	OLS	SAR	OLS	SAR	OLS	SAR
Employment growth rate in manufacturing (2002-2004)	0.075** (0.033)	0.072** (0.032)	0.076** (0.034)	0.072** (0.032)	0.064** (0.032)	0.058* (0.031)	0.068** (0.033)	0.061** (0.031)	0.068** (0.033)	0.062** (0.031)
EU12	0.043*** (0.015)	0.051*** (0.019)	0.043*** (0.015)	0.047** (0.019)	0.063*** (0.016)	0.051*** (0.019)	0.066*** (0.016)	0.053*** (0.018)	0.067*** (0.016)	0.054*** (0.018)
Trust	0.017** (0.007)	0.009 (0.009)	0.015** (0.007)	0.007 (0.009)	0.007 (0.007)	0.015** (0.007)	0.017** (0.007)	0.014* (0.007)	0.018*** (0.007)	0.015** (0.007)
Accessibility (infrastructure endowment)	-0.005** (0.002)	-0.006** (0.003)	-0.005* (0.003)	-0.006** (0.003)	0.007*** (0.002)	-0.006** (0.003)	-0.007*** (0.002)	-0.006** (0.003)	-0.006** (0.002)	-0.005* (0.003)
FDI	0.005*** (0.002)	0.007*** (0.003)	0.004** (0.002)	0.006** (0.003)	0.005*** (0.002)	0.005** (0.003)	0.005*** (0.002)	0.005* (0.003)	0.005** (0.002)	0.005* (0.003)
Structural funds expenditures	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002* (0.001)	0.001 (0.001)	0.002** (0.001)	0.002 (0.001)	0.002* (0.001)	0.002 (0.001)
% of blue collars professions	-0.022 (0.017)	-0.003 (0.020)	-0.025 (0.017)	-0.003 (0.020)	-0.039** (0.017)	-0.033* (0.017)	-0.032* (0.017)	-0.025 (0.018)	-0.031* (0.017)	-0.024 (0.017)
Capabilities	0.031*** (0.007)	0.040*** (0.010)	0.034*** (0.007)	0.043*** (0.010)	0.031*** (0.006)	0.031*** (0.008)	0.033*** (0.007)	0.033*** (0.008)	0.034*** (0.007)	0.033*** (0.008)
Megas	0.005** (0.002)	0.006** (0.002)	0.005** (0.002)	0.006** (0.002)	0.005** (0.002)	0.005** (0.002)	0.005** (0.002)	0.005** (0.002)	0.004* (0.002)	0.005** (0.002)
R&D	0.318*** (0.099)	0.310*** (0.101)					0.191* (0.115)	0.198* (0.105)	0.306** (0.141)	0.313** (0.135)
R&D*KBIR			0.431*** (0.114)	0.409*** (0.113)						
R&D*EKBR			1.134*** (0.325)	0.998*** (0.360)						
R&D*KDR			0.453** (0.187)	0.486*** (0.164)						
R&D*IIR			0.916** (0.436)	1.014*** (0.382)						
Innovation					0.044*** (0.009)	0.039*** (0.010)	0.039*** (0.010)	0.033*** (0.010)		
Innovation*KBIR									0.048*** (0.016)	0.042*** (0.013)
Innovation*EKBR									0.056*** (0.016)	0.050*** (0.013)
Innovation*KDR									0.063** (0.026)	0.057*** (0.020)
Innovation*IIR									0.076*** (0.027)	0.070*** (0.020)
Constant	0.006 (0.011)	-0.013 (0.018)	0.003 (0.011)	-0.014 (0.017)	-0.015 (0.012)	-0.018 (0.015)	-0.020 (0.012)	-0.023 (0.015)	-0.030** (0.014)	-0.033** (0.016)
Lagrange multiplier (spatial lag)	13.612***		12.230***			1.934		2.608		1.793
Robust Lagrange multiplier (spatial error)	4.325***		2.881***			0.039		1.078		0.002
Lagrange multiplier (spatial lag)	10.284***		11.074***			3.761**		4.108**		4.196**
Robust Lagrange multiplier (spatial lag)	0.997		1.725			1.867		1.678		2.405
R2 (OLS) - Squared correlation (SEM and SAR)	0.38	0.36	0.40	0.37	0.41	0.42	0.42	0.43	0.43	0.44
Lambda(SEM) / Rho (SAR)		0.701*** (0.132)		0.708*** (0.131)		0.286* (0.148)		0.297** (0.147)		0.296** (0.146)
Observations	262	262	262	262	262	262	262	262	262	262

* p < 0.10, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses.

Note: SEM and SAR estimates are based on a row-standardised continuous distance matrix.